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ORIGINAL RESEARCH

Inequalities in Talents' Earnings: A Tale of Two European Countries

Tindara Addabbo[1] · **Chiara Mussida**[2]

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Abstract
This paper explores the wage inequalities for the population group of highly talented youth in Italy and Germany, that is the main destination country of Italian talents. We use cross sectional data from the European Union Statistics and Living Conditions Survey for the years 2012 and 2022. We estimate unconditional quantile regression to investigate the wage of Italian and German talents and, within talents, between genders (Italian male versus German male, and Italian female versus German female), across the overall wage distribution. We also apply a decomposition technique of the wage gaps. Our findings suggest a substantial increase in the wage gap at the disadvantage of Italian talents in 2022 largely determined by differences in returns with a higher change for female talents. The gap, indeed, is increasing more for female talents especially at the top of the wage distribution. The gender wage gap within talent shows an increase for talents in Italy (from 10% in 2012 to 22.5% in 2022) and a reduction in Germany (from 27.5% in 2012 to 15% in 2022), with a higher unexplained share of the gender wage gap in Italy than in Germany. An increasing wage gap at the disadvantage of Italian talents, together with better conditions for employed talents in Germany, are consistent with the observed flow of talents from Italy to Germany and call, wishing to increase attractiveness for Italian talents, for policies able to reduce the observed distance within the two countries.

Keywords Talents · Wage distribution · UQR · O-B decomposition · Italy · Germany

JEL Classification C21 · E24 · I24

✉ Tindara Addabbo
tindara.addabbo@unimore.it

Chiara Mussida
chiara.mussida@unicatt.it

[1] Department of Economics 'Marco Biagi', University of Modena and Reggio Emilia, Viale Berengario, 51, Modena, Italy

[2] Department of Economic and Social Sciences, Università Cattolica del Sacro Cuore, Piacenza, Italy

1 Introduction

This paper deals with inequalities concerning a particular group of the population: highly talented youth (hereafter talents) defined as highly educated (holding a Bachelor or higher degree) persons aged from 25 to 40. The questions we seek to answer lie within the framework of two different lines of research: on the one hand, literature analysing wage inequalities by gender within a particular group of the population (young people with a university degree or higher) and on the other hand the literature on inequalities in the labour market at the origin of international mobility and inequalities in countries' attractiveness of young talent.

The reason for this special focus is connected to the potential contribution that talents can provide to the countries in terms of growth and innovation and to understand the reasons for their mobility across countries. Not attracting young talents and seeing them migrate to other countries, can be considered detrimental especially for countries like Italy with a low economic growth, stagnating real wages and real incomes, skill shortages, and characterized by aging and low fertility rates (Adsera, 2005; Ince Yenilmez, 2015; Visco, 2020). Talents' attractiveness sensibly differ across countries. According to the OECD Indicators of Talent Attractiveness (Tuccio, 2019) ranging from 0 to 1 (where 1 indicates the highest attractiveness), the last available report shows that in terms of attractiveness of higher educated workers Italy (score 0.44) lags behind Germany (score 0.55) and the top performer is New Zealand (score 0.64) (OECD, 2023a). Italy (0.47) is less attractive than Germany (0.56) having a score very close to the US (top performer in terms of attractiveness of University students with a score of 0.60, OECD, 2023a).

We compare the condition of Italy's talents with respect to the main country of destination of Italian talents in 2022, that is Germany. The selection of this country is justified as Germany amongst the EU countries, is a high talents' attractive country, and in 2022 the first country attracting Italian youth with a degree (Istat, 2024a), while Italy not only saw a sensible increase of talents migration but also a low degree of talents' attractiveness (OECD, 2023a). Moreover, the Italian labour market is characterized by a high percentage of over-educated workers. In fact, in 2023 the percentage of over-educated graduate workers was about 34% in Italy, with a higher percentage of over-education amongst foreigners, the youngest and women (Istat, 2024b). The inability of the Italian production system to embark on a virtuous path of growth by enhancing the quality of the workforce of the new generations has been highlighted by Migliavacca et al. (2015).

In this analysis on highly talented youth a special attention will then be provided to highly talented women. In terms of gender inequalities in the labour market, Italy, is characterized by seven regions holding a gender gap in employment rates 20 to 64 years age of at least 20.0% points at the disadvantage of women in 2022 (Eurostat, 2023), and by the lowest achievement in the work dimension according to EIGE gender equality index. In fact, Italy holds the latest position in the work domain of the Gender Equality Index with a value of 65.5% well below the EU average of 74.2% (EIGE, 2024).

A complex set of factors can determine the observed flows and the different attractiveness for young talents of the two countries analysed. In this paper, while recognising the importance of a broader set of factors behind mobility in the capabilities and aspirations approach (De Haas, 2021), we concentrate on earnings inequalities and provide descriptive statistics also on other working conditions, variables that young graduates in Italy state to

be important in their job choice, without neglecting the factors that make staying in a labour market characterised by working conditions not in line with the aspirations of young graduates and can therefore motivate their choice of mobility towards countries with perceived better working conditions.

A key element in the choice of mobility together with other dimensions of the quality of work is the evaluation of human capital. We measure wage inequalities between and within countries, by talent status and by gender producing statistical analysis. To explore our aim we use data from the European Union Statistics on Income and Living Conditions Survey (EU-SILC) survey, which is conducted in most European Union countries by the relevant national institutes of statistics using harmonized definitions and survey methodologies. The topics covered by the survey encompass living conditions, income, social exclusion, housing, work, demography, and education. The use of such data, therefore, allows obtaining comparable information across countries of the main variable of interest, i.e. gender wage gap for talents. Our analysis considers the cross-sectional version of the data for Italy and Germany. We will consider the years 2012 and 2022. The time span allows comparing the situation of talents over a decade (including, among others, the COVID-19 shock). Our main research questions are: What is the talent wage gap between Italy and Germany? And, within talents, what is the gender wage gap between Italian male (female) and German male (female)? What are the findings of a decomposition of these wage gaps?

We offer both a descriptive and econometric analysis. For the latter, we estimate an unconditional quantile regression (UQR) proposed by Firpo et al. (2009) to investigate the wage of Italian and German talents and, within talents, between genders (Italian male versus German male, and Italian female versus German female), across the overall wage distribution, i.e. we consider the bottom (10th percentile), the median (50th), and the top (90th). In a second step, we apply a decomposition technique (Oaxaca-Blinder recentered influence function decomposition) on the wage gap between talents in Italy and talents in Germany, and by gender, to better understand the sources of wage inequality. In fact, this methodology helps to break down the overall wage gap into its components and to identify the specific factors—such as differences in characteristics (e.g., gender, education, occupation, sector of economic activity) and differences in returns to those characteristics—that contribute to the wage disparities between talents in the two countries, by looking also at the gender dimension.

The novelties of the paper are at least two. First, the literature about analyses of the wage gap for the population category of talents (neither overall or by gender) is limited. Second, we also investigate the components of the wage gap and their evolution overtime by comparing two relevant countries, Italy and Germany. Our findings suggest a substantial increase in the wage gap at the disadvantage of Italian talents in 2022 largely determined by differences in returns with a higher change occurring for female talents. The gap, indeed, is increasing more for female talents especially at the top of the wage distribution. The gender wage gap within talents shows an increase for talents in Italy (from 10% in 2012 to 22.5% in 2022) and a reduction in Germany (from 27.5% in 2012 to 15% in 2022) with a higher unexplained share of the gender wage gap in Italy than in Germany. An increasing wage gap at the disadvantage of Italian talents together with better conditions for employed talents in Germany are consistent with the observed flow of talents from Italy to Germany and call, wishing to increase attractiveness for Italian talents, for policies able to reduce the observed distance within the two countries.

The paper proceeds as follows. Sect. 2 reviews the existing literature, Sect. 3 describes the data. Sect. 4 presents the empirical models, while Sect. 5 discusses the findings of our descriptive and econometric analyses. Sect. 6 concludes.

2 Literature Review

The potential contribution that young talents can provide to the countries in terms of growth and innovation and also in countries characterized by a highly ageing population and low fertility rates justified an increase in the literature trying to measure the mobility of young talents and to understand the reasons of their mobility across countries. The importance of knowledge workers for each country economy has been highlighted by international organizations like OECD and the European commission stressing also the role of tertiary education institutions in attracting and retaining academic students and researchers and creating space as the European Research Area to reach higher mobility of researchers (Morano-Foadi, 2005). Mobility within Europe has been stimulated by European Union internationalisation policies of higher education as the Bologna and Lisbon processes and specific programmes to enhance university students mobility across EU countries. A new recommendation by the Council of Europe on a European framework to attract and retain research, innovation and entrepreneurial talents in Europe in line with action 4 of the ERA Policy Agenda 2022–2024 on "promoting attractive and sustainable research careers, balanced talent circulation and international, transdisciplinary and inter-sectoral mobility across the ERA" has been shared in 2023 in line with the 2020 Commission Communication on 'A New ERA for Research and Innovation' and the Council Conclusions of May 2021 on 'Deepening the European Research Area: Providing researchers with attractive and sustainable careers and working conditions and making brain circulation a reality'.

Moreover, within talent flows, highly skilled women migration flow has sensibly increased in the last decades (Gonzales Enriques & Triandafyllidou, 2016) also towards male-dominated sectors (Bolzani et al., 2021). Higher attention towards high skilled young women is driven by ethical (Gupta & Bapuji, 2024) and efficiency concerns being gender inequalities in the labour market still persistent (EIGE, 2024; Eurostat, 2023), and highly educated women's skills still underused and under evaluated. Moreover, it has been detected how highly skilled women migrants are more likely to experience losses in their mobility path with negative impact on their well-being due to higher than young men talents experiences of unemployment, deskilling and a career downturn (de Araju, 2023).

The importance of not limiting the analysis of wage differential at the mean has been widely recognized in the literature on the measurement of wage differentials also with reference to different groups of the population in the two countries analysed to highlight the existence of differences across the wage distribution. Addabbo and Favaro (2011) estimate quantile regression models on ECHP 2001 data by education level (compulsory education and higher level of education) detecting a higher gender gap at the disadvantage of women in the lower educated group as well as higher gender wage gap at the top of the wage distribution for women in the group of workers with higher level education. By using 1994–2001 ECHP data, Mussida and Picchio (2014) estimate the gender wage gap across the wage distribution using quantile regression models by education level corrected for selection bias. They found evidence of a higher gender wage gap for the lower educated group of work-

ers that increases when they correct of selection bias especially at the bottom of the wage distribution. The gender wage gap is higher, for the group with higher level of education, at the top of the wage distribution, however the results do not change for this group when the correction of selection bias is applied (Mussida & Picchio, 2014).

Brunetti et al. (2022) analyse the gender wage gap along the whole wage distribution within graduate workers by type of contract (permanent or temporary) on Istat 2015 'Inserimento Professionale dei Laureati' data on individuals graduated in 2011 focussing on their employment conditions four years later. They estimate Unconditional Quantile regressions and apply O-B decomposition finding evidence of a higher wage gap for graduated workers holding a temporary contract detecting a U-shaped pattern across the wage distribution and differences related to the field of studies.

A strand of literature also explores the possible role of occupations in explaining wage inequality and the impact of recent occupational changes (see, for instance, Acemoglu & Autor, 2011; Williams, 2013; Sloane et al., 2021).

Acemoglu and Autor (2011) investigate the U.S. labor market from the 1970s to the 2000s using data from the U.S. Census and the Current Population Survey. They develop a task-based framework to study how technological change influences employment and wages. They argue that occupations are central to explaining wage inequality, as technology has displaced routine middle-skill jobs and boosted demand for both high-skill abstract and low-skill manual non-routine jobs, leading to employment polarization. These occupational shifts, shaped by changing task requirements, have been a key driver of rising wage inequality in the U.S. Williams (2013) provides a complementary perspective by examining the UK labor market over the same period (1970–2000 s) using national survey data. He emphasizes the role of occupational structure in explaining British wage inequality, showing that shifts in the distribution of occupations, especially the growth of high-wage professional jobs and the decline of mid-wage routine jobs, have significantly contributed to widening wage differentials. These dynamics are also closely linked to changes in labor supply and demand, and occupational shifts are likely to influence the evolution of wage inequality over time. Occupations, according to other studies, such as Eurofound (2017), Fernández-Macías and Arranz-Muñoz (2020) and Orfao et al. (2025), account for around 50% of wages' variance or even more in several EU countries.

However, some other works found a reduction of the role of occupation. Sloane et al. (2021), for instance, explore the United States from the 1950s to the 2010s, using data from the American Community Survey. They examine how college majors and occupations shape the gender wage gap. They find that occupational sorting explains a large share of the gap, especially in earlier cohorts, but its impact has declined over time as gender differences in occupations have narrowed—though notable disparities remain. Bovini, De Philippis and Rizzica (2024) find that gender differences in the choice of university majors explain almost 60% of the early career gender pay gap in Italy while sorting across firms and jobs accounts for a limited share of the gender pay gap by using a wide administrative source of data.

2.1 Why Italy vs. Germany

In 2022, amongst the EU-27 countries Italy is the country characterized by the lowest tertiary education attainment level in the population aged from 25 to 34 (see Table 1). The lower presence of young graduates in Italy should make us expect a higher remuneration of

Table 1 Population aged 25–34 with tertiary education level by sex (%)

	M	F	Total	M-F
EU-27	36.5%	47.6%	42%	-11.1%
Italy	23.1%	35.5%	29.2%	-12.4%
Germany	34.4%	39.1%	36.7%	-4.7%

Source: Eurostat metadata: edat_lfse_03

Table 2 Employment rates 2022 25–49 with tertiary education by gender

	M	F	M-F
EU-27	87.1	76.5	10.6
Italy	82.1	62	20.1
Germany	89.1	80.4	8.7

Source: LFS– Eurostat metadata lfsa_ergaed

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young talents in Italy than in countries where the percentage of graduates is higher. However, this is not the case as the evidence gathered in this study shows. Actually, young talents' working conditions in Italy are worse than those found in other European countries characterized by a higher percentage of youth with tertiary education. This difference can be related to the Italian production structure characterized by a higher share or small firms, fewer investment in technologies and innovations and low-tech specialization with respect to other EU countries. The lower dimensions of firms make them more likely not to rely on second-tier company contracts but rather to sectoral collective bargaining agreements that are often not renewed when they expire or renewed with years of delay keeping wages lower and less able to hedge against inflationary growth.

From 2013 to 2022 the net flows in and from Italy of 25–34 graduates is negative with a loss of 87,000 graduated youth. After a decrease in 2021 in the migration flow out of Italy of 25–34 graduated an increase took place in 2022, and the very composition of the migrants from Italy changed: half of them have a degree against one third 10 years before (Istat, 2024b). In 2022, the first country attracting young graduates is for the first time Germany followed by the UK, Switzerland, France and the Netherlands (Istat, 2024a).

Surveys carried out in Italy at the moment of graduation show that the reasons why graduates move abroad are mainly to be found in the better working opportunities abroad, especially in terms of wages and career perspectives (AlmaLaurea, 2023a and 2024). Italian graduates moving abroad are characterized by better academic achievements. Mobility also regards scientific areas, such as computer science and ICT technologies, in which there is a high demand from the national labour market (AlmaLaurea, 2023a and 2024).

Data on the Italian graduates working abroad as compared to those working in Italy one year after the graduation show a significant wage gap in favour of those working abroad (from +32% to +44% more for bachelor and master levels of education), and are more likely to be employed in intellectual and highly specialised professions, and in permanent positions (AlmaLaurea, 2023a).

Labour force survey data show higher employment rates for tertiary educated people aged from 25 to 49 in Germany and the lowest employment rate for women (62%) in Italy with a higher gender gap at their disadvantage (Table 2).

Amongst 25–34 years old with tertiary education attainment, Eurostat data on the proportion of those who are employed in occupations for which a tertiary level of education is not

required (equivalent to ISCO major groups 4–9) show higher rate of overeducation in Italy (Table 3). One has also to consider that overeducation in Southern and Eastern European countries have been found to be more conducive to a trap with persistent effect on the probability of a mismatch later in the career profile (Albert et al., 2021; Meroni & Vera-Toscano, 2017).

3 Data

We use data from the EU-SILC survey, that is based on a methodology and definitions which are standardized across most members of the European Union (Eurostat, 2010). The topics covered by the survey are living conditions, income, social exclusion, housing, work, demographics, and education of individuals. For our analyses, we select cross-sectional data for Italy and Germany in 2012 and 2022. We will compare the condition of talents overall and by gender in Italy with respect to Germany, i.e. the main country of destination of Italian talents. This will allow exploring the evolution of the wage gaps between talents and countries and by gender across a decade. As said above, Italy is among the EU countries in which the relatively lower share of youth with high education and the higher outflows of talents (the outflows increased importantly from 2013 to 2022 with negative net flows of talented youth) coexist. Germany is one of the main countries of destination of Italian talents, i.e. it was the first country attracting young graduates in 2022.

Our samples include employed (employee, not self-employed) young people aged from 25 to 40 years. As suggested by the World Economic Forum (2025), we extended the upper age threshold of young talents up to 40 years old, as Young Global Leaders cohort comprises exceptionally talented individuals under the age of 40, recognized for their outstanding achievements and potential to shape the future across sectors such as business, culture, science, and public leadership. Within this population group, we compare the wage of talents, i.e. those youth with at least a tertiary educational attainment level, between countries and, within talents, the gender wage gap, i.e. Italian male vs. German male, and Italian female vs. German female. We use sampling weights (available in the EU-SILC data) to provide unbiased and representative estimates of the target population. We also used robust standard errors to understand how much sampling variability was likely to affect your estimates. These latter also properly account for complex sample designs.

The variables of interest in our investigation is the gross hourly wage in the respondent's main job, deflated to 2015 prices.[1] The net hourly wage is computed starting from the employees' yearly gross cash income, variable PY010G, and using the number of months at work, obtained from variables PL211A–PL211L in the EU-SILC code, and the number

[1] By using the Harmonized Index of Consumer Prices (HICP) gathered by EUROSTAT.

Table 3 Over-qualification rate 25–34 with tertiary education by gender– 2022

	M	F
EU-27	22.8	23.1
Italy	22.7	27.9
Germany	19.5	18.0

Source: LFS– Eurostat metadata lfsa_eoqgan

of hours usually worked per week, PL060. Considering that on average there are 4.345 weeks in a month, the hourly wage is computed as follows: w = PY010G/(#of months at work × PL060 × 4.345).

Moreover, the information on earnings is retrospectively collected (the income year is the year before the survey year). This means that the survey year 2022 includes income for the year 2021. By contrasting the Italian and German talents' wage and, within talents, by gender, the kernel density estimates offer a visual inspection of both the talent pay gap and the gap by gender over the wage distribution. Figure A1 in the Appendix reports the kernel density estimates for talents (Italy vs. Germany) and by gender between countries for 2012 and 2022. From Figure A1, we see that the gender gap between talents, as well as by gender, increased overtime, that is from 2012 (top Figure A1) to 2022 (bottom Figure A1). The wage premium of talents in Germany over Italy (especially for male), therefore, reinforced overtime.

In the econometric investigation, we estimate UQR and Oaxaca decomposition over the wage distribution (for details, see Sect. 4). The covariates used for the investigation include both individual and household characteristics, that are gender, age and its squared, the number of children of different age range (0–3 and 4–15), tasks of the occupation (apical and supervisory), occupation (variable PL051 in the EU-SILC code), sector of economic activity, part-time job, temporary contract, degree of urbanization.[2] Missing values were dropped as the percentages (incidence on the overall sample) were very low (below 10%) for both countries.

4 Methodology

To understand how the wage of talents (in Italy vs. Germany, overall and by gender) changes across the overall wage distribution, we apply the methodology proposed by Firpo et al. (2009), the Unconditional Quantile Regression (UQR), which allows going beyond the mean in the estimation of explanatory association. Indeed, the UQR is designed to overcome some of the limitations of the linear model: it provides a more flexible approach by estimating relationships at various quantiles of the distribution, offering robustness in the presence of outliers and heteroscedasticity. While Conditional Quantile Regression (CQR) estimates the effect of a covariate on the conditional quantiles of an outcome variable (i.e., given specific values of the covariates), UQR assesses the impact of changes in the distribution of explanatory variables on the quantiles of the unconditional (i.e., marginal) distribution of the outcome variable (Alejo et al., 2025). This distinction is essential when the main interest lies in analyzing the overall distribution of wages. Unlike CQR, which focuses on subpopulations defined by covariates, UQR allows us to estimate the effects of covariates on the wage distribution as a whole, making it particularly suitable in contexts characterized by heterogeneity in wages (variable of interest) across the population. Moreover, UQR is better suited to policy analysis because it provides insights into how explanatory variables influence the overall distribution of an outcome variable like wages — which is typically

[2] The covariates definitions are reported more in depth in the Appendix Table A1. A variable that has been shown in the literature to significantly affect the gender pay gap for early stage graduates is the field of study, however this variable cannot be introduced amongst our covariates since it is not available in the EU-SILC data set.

what policies aim to affect. The UQR moves beyond individual-specific effects (i.e., effects of specific covariates as implied by a CQR) and focuses on population-wide impacts. The UQR method aims to identify how small location shifts in the distribution of explanatory variables affect a statistic of interest (***F***). To be applied, the method introduced by Firpo et al. (2009) involves the calculation of the Recentered Influence Function (RIF) which is defined as:

$$RIF\left(y;v,F\right)=v\left(F\right)+IF\left(y;v,\ F\right)=v\left(F\right)+\frac{v\left(\left(1-t\right)F+t\Delta_{y}\right)-v\left(F\right)}{t}\quad,\quad(1)$$

where $RIF\left(y;v,F\right)$ is the Recentered Influence Function of the statistic v (a quantile, we will consider 10th, 50th, and 90th) for observation y under distribution F. On the right hand side, $v\left(F\right)$ is the value of the statistic of interest (i.e., a quantile); $IF\left(y;v,\ F\right)$ is the influence function, initially introduced by Hampel (1974), which measures how much the observation y affects v; the last term represents the influence function evaluated at a small contamination at point y, normalized by the density. According to Firpo et al. (2009), once the values of $RIF\left(y;v,\ F\right)$ are computed for all observations, the effects of a marginal change in the distribution of the covariates considered (determinants of the wage) on the distributional statistic $v\left(F\right)$ can be correctly calculated through a simple OLS estimation. Following Choe and Van Kerm (2018), we estimate the 'unconditional' of the covariates, i.e. socio-economic characteristics. The core idea of this methodology is: if the described marginal change engenders significant effects on distributional statistics, then the covariate considered influences the wage distribution. In other words, the bigger and more distant from zero the estimated coefficients are, the more the covariate of interest plays an important role in the wage distribution.

The UQR method also allows considering relevant characteristics, which may diverge among young workers employed in different occupations and therefore potentially lead to incorrect effects on the distributional statistics. We then regressed RIFs on a vector of covariates (mentioned also above, see Sect. 3) concerning both individual and household characteristics: gender, age (and age square), number of children of different age ranges ([0, 3] and [4, 15], type of occupation, that is apical and supervisory, type of contract, such as part-time or full-time and temporary or permanent employment, sector of economic activity, and degree of urbanization. In our analysis, we estimate the unconditional effects of the mentioned covariates on the wage distribution focusing on the following distributional statistics: the 10th, 50th and 90th quantile. Therefore, we estimate the following model:

$$RIF\left(Y_{i};\ Q_{\tau}\right)=\alpha_{\tau}+\sum_{k=1}^{n}\gamma_{k\tau}X_{ki}+\epsilon_{i}\quad(2)$$

where Y_i is the outcome variable, the (log) of the gross hourly wage, *i* denotes the employee, Q_τ is τth-quantile, X_{ki} is the vector of n control variables, and ε is the error term.[3]

In a second step, following the methodology of Firpo et al. (2018), we identify the effect of unobserved characteristics on the wage gap between both talents in Italy and Germany,

[3] We use the statistical software STATA and the package/command rifhdreg 'recentered influence function regression with high-dimensional fixed effects'. Quantiles were computed by specifying the recentered influence function (RIF) statistic, in our case the quantiles 10th, 50th, and 90th used as outcomes.

and by gender (male in Italy vs. male in Germany, and female in Italy vs. female in Germany) applying to the RIF-regression the Oaxaca–Blinder (OB) decomposition method. Indeed, the Oaxaca-Blinder (OB) decomposition is a widely used method in economics to decompose differences in mean outcomes between two groups (e.g., talents and non-talents, and within talents male and female workers) into two components: one that reflects differences in characteristics (the "explained" component) and another that reflects differences in returns to those characteristics (the "unexplained" component) (Blinder, 1973; Oaxaca, 1973).[4] However, while the original methodology was created to analyse differences of outcome means, several articles provided improvements to extend the analysis to other distributional statistics (see Fortin et al., 2011 for a review). Firpo et al. (2018) describe the use of RIF regressions, in combination with a reweighted strategy proposed by DiNardo et al. (1996), as a feasible methodology for decomposing differences in distributional statistics beyond the mean. This methodology has several advantages among which the simplicity of implementation, the possibility of obtaining detailed contributions of individual covariates on the aggregate decomposition, and the possibility of expanding the analysis to any statistic for which a RIF can be defined (Rios-Avila, 2020).[5]

5 Results

In this Section, we report our findings for both the descriptive and the econometric analysis. For the former, in Sect. 5.1, we report the raw statistics on talents' wage gap (talents IT/DE) and both male and female talents wage gap between Italy and Germany, as well as the talents gender wage gap for each country. For the latter, in Sect. 5.2, we estimate UQR and the O-B decomposition, by considering the same reference as for the descriptive analysis (talents wage gap by country and gender wage gap within talents) for both countries and years explored.

5.1 Descriptive Analyses

Table 4 reports the raw wage gap between talents/non talents in Italy and Germany and by gender in 2012 and 2022, respectively. Interestingly, we see an increase in the wage gap

Table 4 Unadjusted wage gaps within talents and by gender 2012–2022

	2012			2022		
	IT	DE	Wage Gap*	IT	DE	Wage Gap*
Talents M+F	13.78	18.15	24%	14.37	23.88	40%
Talents F	13.09	15.55	16%	12.65	21.56	41%
Talents M	14.75	20.40	28%	16.93	25.81	34%

*Unadjusted wage gap: (DE-IT)/IT

Source: Authors' calculations from EU SILC data

[4] However, we should notice that since the RIF-Oaxaca approach assumes additive effects of covariates it does not allow to specify interactions between variables and therefore we cannot account for interaction effects in the decomposition.

[5] It is important to note that the decomposition analysis enables us to identify sources that contribute to the wage gap and its components across the wage distribution, but our results cannot be interpreted as causal effects.

Table 5 Unadjusted gender wage gap within talents by country 2012 and 2022

	IT	DE
2012	11%	24%
2022	25%	16%

Source: Authors' calculations from EU SILC data

Table 6 Talents (M+F) wage gap by country in 2012 and 2022

	2012				2022			
	Mean	10th	50th	90th	Mean	10th	50th	90th
Germany	2.784***	2.241***	2.806***	3.354***	3.278***	2.713***	3.293***	3.866***
	(0.016)	(0.023)	(0.016)	(0.026)	(0.014)	(0.024)	(0.014)	(0.020)
Italy	2.558***	1.862***	2.662***	3.173***	2.801***	2.292***	2.805***	3.324***
	(0.037)	(0.123)	(0.033)	(0.042)	(0.039)	(0.062)	(0.036)	(0.052)
Difference	0.226***	0.379***	0.144***	0.181***	0.477***	0.420***	0.488***	0.542***
	(0.040)	(0.125)	(0.037)	(0.049)	(0.041)	(0.066)	(0.038)	(0.056)
Explained	0.00590	-0.000547	-0.00213	0.0187	0.114***	0.0748	0.0965***	0.102***
	(0.022)	(0.025)	(0.022)	(0.027)	(0.030)	(0.047)	(0.028)	(0.035)
Unexplained	0.220***	0.380***	0.146***	0.163***	0.363***	0.345***	0.391***	0.440***
	(0.035)	(0.120)	(0.035)	(0.052)	(0.038)	(0.072)	(0.038)	(0.058)
Observations	1,958				2,233			

Notes: Standard Errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

O-B decomposition. Regressions include age, age squared, number of children 0–3 and 3–14 in the household, type of job (supervisory responsibilities, apical positions, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators, and assemblers, elementary occupations), industry (NACE level 1); type of contract (part-time, temporary job), urban area.
Source: Authors' calculations from EU SILC data

for talents Germany/Italy. The wage gap between talents in Germany and talents in Italy increases from 24% in 2012 to 40% in 2022. This can partly explain the fact that Germany, as said above, is the first country attracting talents in Europe in 2022. Our evidence suggests (and confirms) that in this country there is a relatively high wage premium for highly educated youth.

The advantage of female talents in Germany with respect to Italy increased importantly over time, from 16% in 2012 to 41% in 2022. This explains the increased migration of highly educated women. From Table 5, we note that the gender wage gap within talents sensibly increased over the observed period in Italy, i.e. from 11% in 2012 to 25% in 2022, whereas it decreased in Germany, i.e. from 24% in 2012 to 16% in 2022.

These differences between Italy and Germany stimulated our econometric investigation.

5.2 Econometric Analysis

Table 6 shows the wage gap[6] faced by talents in Italy and Germany in 2012 and 2022. On average the wage gap at the disadvantage of Italian talents increased from 22.6% in 2012 to 54.2% in 2022 with a larger increase in the gap for women's talents (Tables 7 and 8).

[6] As explained in Sect. 3 and as listed in the table notes, we control for a set of individual and household characteristics. For the sake of brevity, we do not report all the set of regressors. Results are available upon request.

Table 7 Male talents wage gap DE vs. IT, 2012 and 2022

	2012				2022			
	Mean	10th	50th	90th	Mean	10th	50th	90th
Germany	2.784***	2.241***	2.806***	3.354***	3.278***	2.713***	3.293***	3.866***
	(0.016)	(0.023)	(0.016)	(0.026)	(0.014)	(0.024)	(0.014)	(0.020)
Italy	2.558***	1.862***	2.662***	3.173***	2.801***	2.292***	2.805***	3.324***
	(0.037)	(0.123)	(0.033)	(0.042)	(0.039)	(0.062)	(0.036)	(0.052)
Difference	0.226***	0.379***	0.144***	0.181***	0.477***	0.420***	0.488***	0.542***
	(0.040)	(0.125)	(0.037)	(0.049)	(0.041)	(0.066)	(0.038)	(0.056)
Explained	0.00590	-0.000547	-0.00213	0.0187	0.114***	0.0748	0.0965***	0.102***
	(0.022)	(0.025)	(0.022)	(0.027)	(0.030)	(0.047)	(0.028)	(0.035)
Unexplained	0.220***	0.380***	0.146***	0.163***	0.363***	0.345***	0.391***	0.440***
	(0.035)	(0.120)	(0.035)	(0.052)	(0.038)	(0.072)	(0.038)	(0.058)
Observations	1,958				2,233			

Notes: Standard Errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

O-B decomposition. Regressions include age, age squared, number of children 0–3 and 3–14 in the household, type of job (supervisory responsibilities, apical positions, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators, and assemblers, elementary occupations), industry (NACE level 1); type of contract (part-time, temporary job), urban area. Source: Authors' calculations from EU SILC data

Table 8 Female talents wage gap DE vs. IT, 2012 and 2022

	2012				2022			
	Mean	10th	50th	90th	Mean	10th	50th	90th
Germany	2.578***	2.040***	2.615***	3.086***	3.127***	2.581***	3.126***	3.706***
	(0.015)	(0.034)	(0.013)	(0.018)	(0.014)	(0.027)	(0.014)	(0.024)
Italy	2.454***	1.878***	2.553***	3.104***	2.577***	1.972***	2.669***	3.154***
	(0.034)	(0.082)	(0.025)	(0.047)	(0.036)	(0.067)	(0.031)	(0.040)
Difference	0.124***	0.162*	0.0615**	-0.0183	0.551***	0.609***	0.457***	0.552***
	(0.037)	(0.089)	(0.028)	(0.050)	(0.038)	(0.072)	(0.034)	(0.046)
Explained	0.00460	0.00771	0.00169	-0.00500	0.0901***	0.121**	0.0446*	0.0460
	(0.018)	(0.040)	(0.016)	(0.018)	(0.028)	(0.051)	(0.025)	(0.033)
Unexplained	0.119***	0.154*	0.0598**	-0.0133	0.0901***	0.488***	0.412***	0.507***
	(0.035)	(0.089)	(0.028)	(0.052)	(0.028)	(0.088)	(0.037)	(0.053)
Obs	2,300				2,189			

Notes: Standard Errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

O-B decomposition. Regressions include age, age squared, number of children 0–3 and 3–14 in the household, type of job (supervisory responsibilities, apical positions, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators, and assemblers, elementary occupations), industry (NACE level 1); type of contract (part-time, temporary job), urban area. Source: Authors' calculations from EU SILC data

Table 7 shows the results of the Oaxaca decomposition of the UQR estimates[7] for male talents in Germany and Italy for 2012 and 2022. From Table 7, we note that male talents perceive an increasing wage over the earnings distribution in both years and both countries. However, in 2012 the wage gap for male talents at the disadvantage of Italian male talents, though not disappearing in the 90th percentile, appears to be higher at the bottom of the wage distribution and to decrease moving towards the top of the wage distribution signalling the presence of a sticky floor effect. This does not appear to be the case when we analyse the 2022 male talents wage gap showing a higher wage gap at the disadvantage of Italian male talents at the top of the wage distribution. As for the mean in each percentile the unexplained part of the differential is found to be the largest share of the gap.

A similar trend can be found for female talents, Table 8 shows that also female talents perceived an increasing wage over the earnings distribution in both years and both countries. However, in 2012 the wage gap for female talents at the disadvantage of Italian, though not disappearing in the 90th percentile, appears to be higher at the bottom of the wage distribution and to decrease moving towards the top of the wage distribution signalling the presence of a sticky floor effect. This does not appear to be the case when we analyse the 2022 female talents wage gap showing a higher wage gap at the disadvantage of Italian female talents at the bottom and the top of the wage distribution, this is consistent also with the lower probability for Italian female talents to be in managerial positions than the German ones. As for the mean in each percentile the unexplained part of the differential is found to be the larger share of the gap.

Analysing the contribution of each variable to the explained and unexplained part of the wage gap living in an urban area positively contributes to the explained part at the disadvantage of Italian male and female talents starting from the 50th percentile, while the return of being employed in the public sector are higher for German male talents at the lowest percentile.

For female talents the returns to age (that not observing seniority or not including past work experience,[8] can be considered as a proxy of past work experience) is higher for women talents in Germany than in Italy.

Comparing the talents' wage gap by country and gender, the higher increase in the gap is at the disadvantage of female talents in Italy with respect to female talents in Germany especially at the top of the wage distribution. This impact can be related to a higher career probability for female talents in Germany than in Italy. The difference in talent wage gap for men is found to increase from 2012 to 2022 starting from the 50th percentile (Table 9).

The observed trend can be explained by an intense effort made by Germany in the period analysed in attracting and retaining skilled workers and in issuing residence permits for study purposes.

[7] As a robustness check, we compare the results of our unconditional quantile regression (UQR) method with a conditional quantile regression (CQR). Results are reported in the Appendix Tables A3/A6 by country and year (2012 and 2022). From these tables, we note only few differences between the UQR and CQR methods. For the reasons clarified in Sect. 4, we use the UQR method as more appropriate than standard (conditional) quantile regression for our purposes.

[8] Past work experience is available in EU-SILC data, however, when included in the model it shows evidence of collinearity or it is not significant in the UQR estimated models for the two countries (apart from Germany 2012). Moreover, introducing this covariate does not significantly change the other estimated coefficients. This could be related also to the less fragmented working profile for talents over their observed relatively short spell of life.

Table 9 Change in the talents' wage gap by gender

	2022 − 2012			
	Mean	10th	50th	90th
DE-IT Male	0.25	0.04	0.34	0.36
DE-IT Female	0.43	0.45	0.40	0.57
DE-IT M + F	0.36	0.35	0.38	0.41

Source: Authors' calculations from EU SILC data

Table 10 Gender wage gap within talents in Germany years 2012 and 2022 at mean and selected percentiles

	2012				2022			
	Mean	10th	50th	90th	Mean	10th	50th	90th
Men	2.900***	2.269***	2.939***	3.466***	3.278***	2.713***	3.293***	3.866***
	(0.024)	(0.043)	(0.023)	(0.040)	(0.014)	(0.024)	(0.014)	(0.020)
Women	2.625***	1.960***	2.703***	3.151***	3.127***	2.581***	3.126***	3.706***
	(0.025)	(0.063)	(0.025)	(0.030)	(0.014)	(0.026)	(0.014)	(0.024)
Difference	0.275***	0.309***	0.236***	0.315***	0.151***	0.132***	0.167***	0.159***
	(0.035)	(0.077)	(0.034)	(0.050)	(0.020)	(0.035)	(0.019)	(0.031)
Explained	0.163***	0.135**	0.162***	0.0641	0.0941***	0.0700**	0.0956***	0.0828***
	(0.029)	(0.068)	(0.032)	(0.062)	(0.013)	(0.035)	(0.017)	(0.022)
Unexplained	0.112***	0.174*	0.0732*	0.251***	0.0566***	0.0615	0.0711***	0.0766**
	(0.034)	(0.100)	(0.039)	(0.072)	(0.021)	(0.048)	(0.023)	(0.033)
Observations	1.238				3.222			

Notes: Standard Errors in parentheses * $p<0.10$, ** $p<0.05$, *** $p<0.01$

O-B decomposition. Regressions include age, age squared, number of children 0–3 and 3–14 in the household, type of job (supervisory responsibilities, apical positions, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators, and assemblers, elementary occupations), industry (NACE level 1); type of contract (part-time, temporary job), urban area. Source: Authors' calculations from EU SILC data

A sign of the attention by Germany in attracting young talents is the increase in the Blue Card (a temporary residence permit for skilled academic workers from non-EU countries) issue. The Blue Card was introduced throughout the EU in 2012 to address the shortage of highly qualified skilled labour. Between 2012 and 2022, around 200,000 people from non-EU countries received a Blue Card for the first time in Germany. Germany issued the majority of all EU Blue Cards in the EU and the highest number of authorisations for students, researchers and other related categories (Eurostat, 2024). The requirements for obtaining the permit were having completed a university degree and a concrete job offer with a gross annual salary of at least 58,400 euros (2023). In the so-called shortage occupations, in which there was a high number of unfilled vacancies in Germany, a lower salary threshold of €45,552 applied (Weißmann & Eberle, 2023).

We estimated selection bias corrected models but the estimates did not support the existence of selection biases in the samples.[9] Tables 10 and 11 report the results of the gen-

[9] Heckman Two Steps Selection Model has also been estimated to correct for potential bias in the estimation due to non random selection of employed individuals with positive wages from the population. However, as shown in the model estimated at mean (Table A2 in the Appendix), evidence of non random sample selection, cannot be ascertained for the talent sample. Indeed the sample of tertiary and over educated individuals shows more homogeneity in terms of employment probability (talents' employment rates being higher than 70% in both countries), the sample selection process does not significantly impact the estimated wage equation, not requiring correction for sample selection in estimating wages for the talent population.

Table 11 Gender wage gap within talents in Italy years 2012 and 2022 at mean and selected percentiles

	2012				2022			
	Mean	10th	50th	90th	Mean	10th	50th	90th
Men	2.558***	1.862***	2.662***	3.173***	2.801***	2.292***	2.805***	3.324***
	(0.037)	(0.122)	(0.034)	(0.041)	(0.039)	(0.060)	(0.037)	(0.054)
Women	2.454***	1.877***	2.553***	3.104***	2.577***	1.972***	2.669***	3.154***
	(0.034)	(0.076)	(0.026)	(0.047)	(0.036)	(0.068)	(0.032)	(0.039)
Difference	0.104*	-0.0156	0.109**	0.0687	0.225***	0.320***	0.136***	0.170**
	(0.050)	(0.143)	(0.043)	(0.063)	(0.053)	(0.091)	(0.049)	(0.067)
Explained	0.0866	0.138	0.0451	-0.0431	0.0402	0.0418	0.0425	-0.0338
	(0.040)	(0.158)	(0.042)	(0.047)	(0.037)	(0.085)	(0.042)	(0.057)
Unexplained	0.0175	-0.154	0.0638	0.112	0.184***	0.278**	0.0933*	0.204**
	(0.044)	(0.193)	(0.053)	(0.075)	(0.051)	(0.115)	(0.053)	(0.086)
Obs	1.048				1.200			

Notes: Standard Errors in parentheses * $p<0.10$, ** $p<0.05$, *** $p<0.01$

O-B decomposition. Regressions include age, age squared, number of children 0–3 and 3–14 in the household, type of job (supervisory responsibilities, apical positions, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators, and assemblers, elementary occupations), industry (NACE level 1); type of contract (part-time, temporary job), urban area. Source: Authors' calculations from EU SILC data

der wage gap Oaxaca decomposition by country at mean and by selected percentiles. As Table 10 shows the gender pay gap in Germany was 27.5% in 2012 and decreased in 2022 (15%), while the gender pay gap increased in Italy from 10.4% in 2012 to 22.5% in 2022.

What is also significant is the difference in the composition of the gap in the two countries. On the one hand, the explained part increased its weight in Germany from 2012 to 2022. On the other hand, the unexplained part dominates in the decomposition of the gender pay gap in Italy representing 82% of the observed gender pay gap in 2022 and 17% in 2012.

By analysing the gender wage gap over the wage distribution, Italy is characterized in 2022 by a higher gender wage gap at the 10th percentiles (0.32) than at the other percentiles of the gender pay gap (0.17 at the top percentile) with a higher weight in the different percentiles of the wage distribution of the unexplained part, while in Germany there is no evidence of the sticky floor effect with a higher gender pay gap at the bottom of the wage distribution. Differently from Italy, for Germany evidence of a larger contribution to the overall gender pay gap can be attributed to being in a part-time job (one of the regressors included in the UQR models) at the 10th percentile of the wage distribution. This is consistent with a higher use of part-time work offering lower career progression and lower wages by women in Germany than in Italy. The increase in the gender gap in working time after maternity leave on the gender wage gap in Germany is also found by OECD (2022).

The lower gender wage gap at mean in Germany can be associated with a relatively higher gender equality in management that, according to de Castro-Romero et al. (2023) analysis of the European Structure of Earnings Survey for year 2018 on the impact of gender equality management on the gender wage gap in 22 EU countries including Germany, shows that a higher gender equality in management reduces the gender wage gap mainly in the middle and lower part of the wage distribution. The decrease of the gender wage gap at the lowest percentile is consistent also with the introduction in 2015 of minimum wage in Germany that has been set at a relatively high level (Caliendo & Wittbrodt, 2022).

Table 12 Type of jobs for talents in Germany and Italy in 2022

	DE			IT		
	M	F	GAP	M	F	GAP
Temporary	8%	10%	-2%	16%	17%	-1%
Permanent	70%	56%	14%	45%	46%	-1%
Apical	6%	2%	3%	2%	1%	2%
FT	92%	67%	25%	89%	80%	9%
PT	8%	33%	-25%	11%	20%	-9%

Source: Authors' calculations from 2022 EU SILC data

The lower gender wage gap in Germany can also be associated with more generous family policies and with a change started in the 2000s with the objective of encouraging greater employment among German mothers (Cooke et al., 2022). During this period, important institutional changes took place on the childcare provision and on the system of parental leaves that can be relevant in the choices of graduates mobility between the two countries.

In Germany, the legal right to Early Childhood Education and Care for all children from the age of one year came into effect in August 2013, while, in November 2014 the parental benefit scheme was redesigned to promote part-time working for mothers and fathers, a reform that can be considered as a further step towards a Nordic dual-earner model (Kraemer, 2015). A further step towards this model will be the introduction of a 10 days paternity leave in 2024, currently fathers in Germany are entitled to two exclusive parental leave benefit months, and most of them take up them or part of them after their child birth (Schober et al., 2023).

In Italy in 2022 the non-experimental nature of the leave and the Paternity leave benefit at the level of 100% of previous wages has been confirmed. However, differently from maternity leave, which includes a prohibition to work during the leave, paternity leave in Italy is a potestative right that can be waived and the majority of fathers do not take advantage of this leave (Addabbo et al., 2023).

The observed differential in wages between talents in the two countries and the different evaluation of graduates' observable characteristics can be related to the observed increase in young graduates flow from Italy to Germany observed over time.

Turning also to other dimensions of quality of work more evaluated by Italian graduates, AlmaLaurea survey for Italian graduates provides information on the graduates' evaluations of the different quality of work dimensions they seek in their jobs (AlmaLaurea, 2023b). Amongst the aspects that Italian graduates considered most relevant are the acquisition of a better professionality through job, job stability, career opportunities, opportunity of earning a living, independence or autonomy in work, flexibility in working hours, and leisure time availability. Characteristics that are differently present in the two countries. As shown in Table 12, talents show a higher percentage of permanent work in Germany than in Italy, as well as a gender gap in the latter and not in the former country (70% for men and 56% for women in Germany, compared to 45% and 46% for men and women in Italy). While men's part-time work is similar across the two countries (8% in Germany, and 11% in Italy), the percentage of women working part-time is higher in Germany (one third of women in Germany works part-time, with respect to one fifth in Italy). The percentage of talents in apical positions is higher in Germany.

6 Conclusions

Attracting young talents can positively contribute to economic growth and innovation and the two countries analysed in this paper have a different degree of talent attractiveness. Inequalities in the degree of attractiveness and retention of high skilled workers request to analyse talents' aspirations and job characteristics that they value more (Walk et al., 2013; Zaharee et al., 2018) both at macro and micro level with a higher attention in HR policies. We have analysed the characteristics of the dimensions of the quality of work that Italian talents consider more important in their job. Descriptive statistics on these dimensions are consistent with the observed increase in mobility of talents from Italy to Germany. Econometric analysis at means and at specific percentiles of the wage distribution within the group of talents lead to accept the hypothesis of higher wages paid to talents in Germany and of a lower gender pay gap in Germany. To analyse to what extent the situation changed in the two countries we have used two cross-Sects. (2012 and 2022) of EU SILC microdata. These data allow us to compare the situation in the two years considered as two separate snapshots but do not allow us to account for long-term trends in the observed variables. Amongst the set of observed covariates included in the model the impact of occupations is lower than shown in previous studies and this result is in line with the declining role shown by Sloane et al. (2021) and the lower impact for graduates shown in Bovini et al. (2024).

Policies that can be implemented to reduce inequalities should be directed to wages and to reduce the observed gender pay gap. The Italian labour market is characterized by lower employment rates of women and the lowest score, as compared to other European countries, in terms of the work dimension of the Gender Equality Index (EIGE, 2024). Real wages in 2024 are lower than 2008 (ILO, 2024) in Italy and for talents the wage gap with respect to Germany at the disadvantage of Italy increased from 2012 to 2022.

With respect to Germany, in Italy, one can observe a higher occurrence of temporary work bearing earnings penalties for talents and lower wages especially at the bottom of the wage distribution (as the explained part of the O-B decomposition by countries show). The very dimensions of work that graduates state to value most are less attainable in Italy.

The higher opportunity of part-time work that characterizes female talents in Germany encourages continuity of the work-experience for main carers at the cost of lower career progression and an increase in the wage gap at the disadvantage of women, especially at the bottom of the wage distribution. To decrease the gender wage gap in both countries, policies aimed at a better work-life balance should be implemented together with actions devoted to incentivising a more equal allocation of domestic and care work within couples to avoid negative impact on the career progression and wages of main carers.

Pay transparency and gender pay gap reporting can produce lower gender pay gap by different channels (Oecd, 2023b, 2021; Bennedsen et al., 2023; Blundell, 2021): raising public awareness of pay inequalities; providing incentives for companies to reflect on horizontal and vertical segregation and the drivers of observable pay gaps; lower attractiveness for women of jobs with high pay gaps to their disadvantage.

Finally, another possible explanation for the lower gender pay gap observed in Germany may lie in the country's stronger institutional support for work-life balance, including more extensive parental leave policies and access to childcare services. Additionally, Germany's vocational training system and more structured school-to-work transitions could contribute to a more equal labour market entry for young men and women.

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Data Availability The data that support the findings of this study are available from Eurostat, but restrictions apply to the availability of these data, which were used under licence for the current study and so are not publicly available. The data are, however, available from the authors upon reasonable request and with the permission of Eurostat.

Code Availability The Stata code for all analyses reported in the manuscript is available.

Declarations

Competing Interests The authors have no financial or proprietary interests in any material discussed in this article.

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