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Education-health relationship: New evidence from a distributional perspective

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Abstract

Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), this paper identifies the education gradient in health and explores its underlying factors using a distributional approach. We start by constructing a separate health distribution for two education subgroups – the lower and higher educated – and compare the difference in the level of health between them at each point of the distribution. As a next step, we perform a semi-parametric decomposition exercise to explore which factors lie behind the observed health differential. In line with previous studies we find that, on average, higher educated people enjoy better health than those who are lower educated. We show, however, that the difference is not constant along the health distribution, with the gap being several times bigger at the top of the distribution than at its bottom. We also find that around 65 percent of the health gap between the lower and higher educated can be explained by the subgroup differences in demographic, labor market, and behavioral characteristics.

Keywords: health inequality, educational gradient, health differential, distributional approach, decomposition

JEL classification: D30, I10, I14.

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This paper uses data from SHARE Waves 6 (Börsch-Supan, 2018, Malter and Börsch-Supan, 2017), see Börsch-Supan, Brandt, Hunkler et al. (2013) for methodological details. The SHARE data collection has been primarily funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812) and FP7 (SHARE-PREP: N°211909, SHARE-LEAP: N°227822, SHARE M4: N°261982). Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged (see www.share-project.org). The authors would also like to thank the participants of the SHARE Users Workshop in Luxembourg and the Workshop on Labour Economics in Trier for numerous useful comments.

Introduction

There is extensive evidence that higher educated people, on average, have better health and live longer than those who are less educated. This evidence persists across countries and over time, and holds for various health measures (Kunst et al., 2004; Kunst et al., 2005; Cutler and Lleras-Muney, 2008; Conti et al., 2010; Jürges, 2010; Goldring et al., 2016). According to a recent OECD report, the gap in life expectancy at age 25 between the lower and higher educated is 7.7 years for men and 4.6 years for women, with some variation across the OECD countries (OECD, 2017). Depending on the country, individuals with a lower level of education are also 10 to 40 percent more likely to report poor health compared to their higher educated counterparts (Balaj et al., 2017).

Although the relationship between education and health is well established, it relies on evidence from aggregate measures of socio-economic inequality in health (e.g. a relative risk ratio, between-group differences in the average level of health, the concentration index).[1] These measures provide information on the level of health inequality in the population, but they tell us little about the difference in health outcomes between the lower and higher educated in different parts of the health distribution. For example, would we find a larger difference in the levels of health between the lower and higher educated when comparing the healthiest 10 percent as opposed to the sickest 10 percent of individuals? Is there a point in the distribution of health outcomes at which education gradient in health disappears?

Recent studies have shown the importance of taking a distributional approach towards the inspection of health inequalities. The existing evidence, however, is limited to the analysis of income-related inequalities in health and relies on regression techniques, which allow the association between income and health to vary along the health distribution. Carrieri and Jones (2018), for example, use the unconditional quantile regression approach to analyze the income gradient across the distribution of blood-based biomarkers. They find a strong gradient with respect to income at the highest quantiles of the biomarker distributions, whose values signal that people suffer from severe diseases. Similarly, Silberdorff et al. (2018) apply the additive distributional regression to explore the income-health relationship and find that this relationship

[1] For extensive summary on the measurement of socioeconomic inequalities in health see Wagstaff et al. (1991), Wagstaff and van Doorslaer (2000), Kakwani et al. (1997), and Van Doorslaer and van Ourti (2011).

varies substantially along the health distribution, with poor individuals facing greater health risk in the lower tail of the distribution than in its upper tail.

In this paper, we aim to identify the education gradient in health and explore its underlying factors using a distributional approach. We start by constructing a separate health distribution for two education subgroups – lower and higher educated – and then compare the difference in health outcomes between these subgroups at each point of the distribution. As a next step, we perform a semi-parametric decomposition exercise in order to identify which factors underlie the observed subgroup differences in health. Among potential explanatory factors, we consider the sub-group differences in demographic, labor market, and health behavior characteristics.

The analysis relies on data from wave 6 of the Survey of Health, Ageing and Retirement in Europe covering 17 European countries and Israel. Following Pi Alperin (2016), we use health related information present in the survey to construct a set of synthetic measures of health, which summarize health status of individuals across multiple dimensions. We derive these measures separately for physical, mental, and global (combining physical and mental) health and analyze education gradient in each of these health domains.

Our paper contributes to the literature on education-related health inequalities in several ways. Firstly, it inspects the education-health relationship from the distributional perspective. Rather than relying on differences in the average level of health between education subgroups or aggregate health inequality measures, we analyze the gap between the entire distributions of health constructed for individuals with different levels of education. This approach allows us to identify whether the education gradient in health remains stable along the health distribution or whether it varies in its upper and lower parts. This, in turn, is vital to understand whether education matters more for avoiding light health limitations or severe health limitations, with the latter being more costly for the health care system (Carrieri and Jones, 2017).

Secondly, following DiNardo, Fortin, Lemieux (1996), we perform a semi-parametric distribution decomposition exercise, which allows us to shed light on the factors underlying the gap between the health distributions of the lower and higher educated. So far, the literature has focused on the decomposition of health inequality indices or identification of the channels via which education influences health outcomes using regression techniques. At the same time, no evidence exists on the factors lying behind the education gradient in health, when the latter is analyzed from the distributional perspective. The advantage of our approach is that it allows us to partition the entire distributional difference in health outcomes due to education into a set of components attributable to various socio-economic characteristics of individuals and their health-related behavior.

Lastly, we provide evidence on education gradient in health for a composite measure of health, which accounts for multiple diseases and health limitations. While studying the education gradient in health, existing literature focuses mainly on self-assessed health measures.[2] The main disadvantage of self-assessed health measures lies in their subjectivity, which limits their interpersonal and inter-country comparability (O'Donnell, 2009). Bago d'Uva et al. (2008, 2011), for example, show that the reporting of health status differs substantially by education with higher educated people being more likely to rate their health negatively than the lower educated. This underreporting leads to underestimation of health differential between the lower and higher educated and, as a consequence, underestimation of the degree of health inequality in the population. In a similar spirit, Jürges (2007) provides convincing evidence that reporting styles also vary across countries and taking this fact into account leads to a reduction in cross-country variations in general health. The advantage of our health measure is that it utilizes reported information on the multiple diagnosed diseases and limitations in daily activities. Therefore, the measure is expected to be more comparable across subgroups and countries than the measure of self-reported health.

In line with previous literature, we find that, on average, higher educated people enjoy better health than those who are lower educated. We show, however, that the difference in the levels of health between the lower and higher educated is not constant along the health distribution: it is relatively small if we compare the healthiest 10 percent of the lower and higher educated but multiplies in size for the sickest 10 percent. We also find that the main factors standing behind this gap are the subgroup differences in demographic, labor market, and health behavior characteristics.

The remaining part of the paper is structured as follows. Section 2 presents data and definitions of the constructs (i.e. health, education, other variables) used in the paper. Section 3 describes the methodology. Section 4 provides the results and Section 5 concludes.

[2] Among the exceptions see Jürges (2007) and Jürges (2010).

2. Data and definitions

In this paper, we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE).[3] SHARE is a multidisciplinary multiple-country panel survey, which collects harmonized data on health, socio-economic characteristics, and life-styles of individuals aged 50 years and more. The survey started in 2004 covering 12 countries and expanded over time to 18 countries (17 European countries and Israel). So far, six waves of SHARE have been collected and made available for scientific use. In the paper, we use data from the most recent sixth wave of the SHARE based on interviews conducted in 2015.[4] The list of countries covered in this wave include Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, Frances, Germany, Greece, Israel, Italy, Luxembourg, Poland, Portugal, Slovenia, Spain, Sweden, and Switzerland. The number of observations vary by country reflecting, among other things, the country size and the response rate (see Table A1 in Appendix A). To make sure that the sample data represent country-specific population, we apply weights throughout the analysis.

The main advantage of the SHARE for our study is that it contains a wide range of health indicators referring to both physical and mental health. Among other things, the survey collects information on the diagnosed diseases, limitations in physical activities, depression symptoms, physical and memory measurements. The richness of this information makes SHARE a unique dataset for studying health-related questions, including socio-economic inequalities in health (O'Donnell, 2009). Besides health indicators, SHARE also collects information on socio-economic and behavioral characteristics of individuals (e.g. gender, age, employment status, income, health behavior, life-styles). This information is vital for measuring the education gradient in health and identifying the channels via which differences in education translate into differences in health outcomes.

2.1. Definition of the health status

We measure health status of each individual using a multidimensional approach proposed by Pi Alperin (2006), which is described in detail in Appendix B of this paper. This approach allows aggregating health items, which reflect different aspects of individual health, in a synthetic indicator describing the general level of his or her health. By the way it is constructed, the synthetic

[3] For a detailed description of the SHARE see Börsch-Supan et al. (2013).
[4] For a thorough overview of the SHARE wave 6, see Malter and Börsch-Supan et al. (2017) and Börsch-Supan (2018).

health indicator derived at the individual level is quasi-continuous in nature and can take any value between 0 (absolutely healthy) and 1 (absolutely sick). This allows us to capture even small differences in the level of health across individuals.

In this paper, we first compute the synthetic indicators for two domains of individual health – mental and physical health – and then combine them in a composite indicator of global health, which represents the weighted mean of these two domains.[5] Table 1 below provides an overview of the health items included in each of these indicators and Figure 1 presents the distributions of mental, physical and global health in all countries pooled together.

Table 1. Health items included in synthetic indicators of health

Synthetic health indicator		Dimensions of health	Health items
Global health	Mental health	Depression	Depression, concentration, guilt, loss of interest, sleep, irritability, appetite, stress, pessimism, suicide, enjoyment, tearfulness
		Memory	Orientation regarding: date, day of the week, month, year
		Cognition	Capacity to memorize a given number of words (first trial and delayed)
	Physical health	Long-term illness	Heart attack, stroke, cancer, UIcer, cataract, fracture of the femur, other fractures, rheumatism, hyper tension, high cholesterol, diabetes, pneumonia, Parkinson's, Alzheimer, anxiety, arthrosis, renal problems
		Limitation activities 1	Daily activities: dressing, bathing or showering, eating, cutting up the food, walking across a room, getting in or out of bed
		Limitation activities 2	Instrumental activities: telephone calls, taking medications, managing money, shopping for groceries, preparing a hot meal
		Limitation activities 3	Mobility: walking 100 meters, walking across a room, climbing several flights of stairs, climbing one flight of stairs
		Eyesight	Farsighted, nearsighted
		Hearing	Hearing difficulties

Note: This table is composed from the items, available in the SHARE.

[5] The system of weights is computed following Betti and Verma (2008). More precisely, the weight is the product of two weights, the one that accounts for the prevalence of a given health limitation in the population and the other one that limits the influence of highly correlated health limitations on the synthetic index.

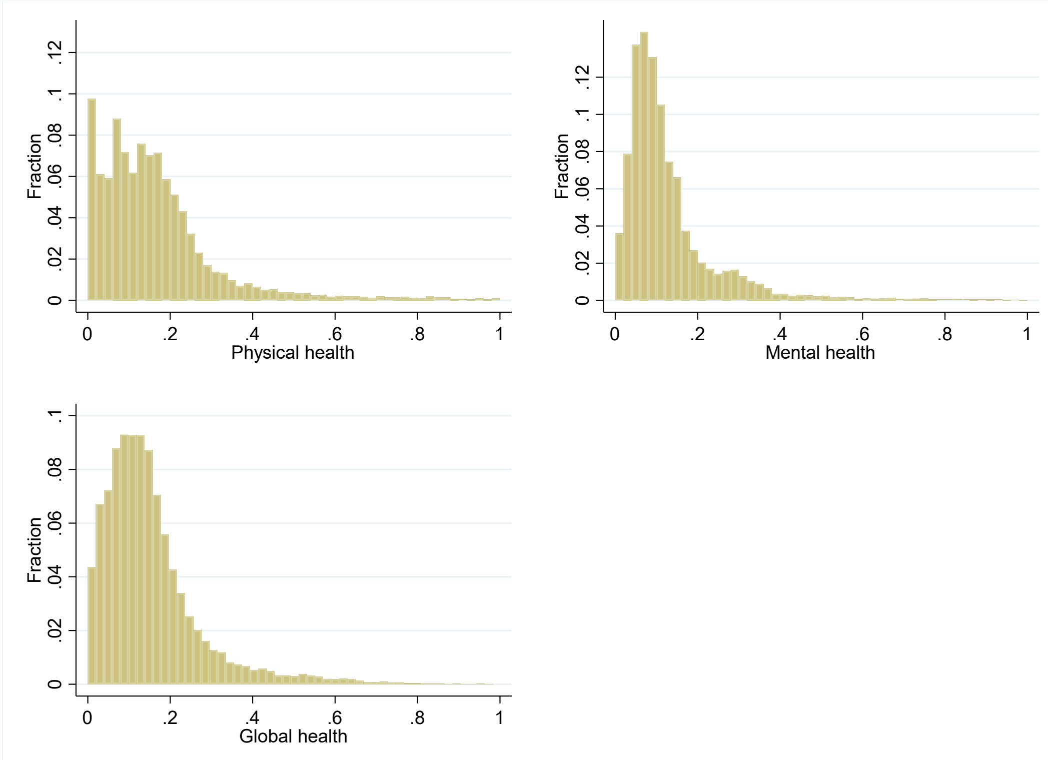

Figure 1. Distributions of general, physical, and mental health, all countries

Note: Weighted estimates.

Figure 1 shows that around 10 percent of the respondents do no experience problems with their physical health and around 4 percent of the respondents also do not have any problems with mental health. In general, all three distributions of health are not symmetric, with most of the respondents having health scores between 0 and 0.2. By contrast, only a small fraction of individuals has health scores between 0.6 and 1, which imply extremely bad health.[6]

2.2. Definition of education

Using information on the highest educational degree received according to the 1997 version of the International Standard Classification of Education (ISCED), we classify all SHARE respondents in two groups – those who are lower educated and those who are higher educated. The group of the lower educated comprises individuals who have upper secondary education or any level below

[6] As discussed in Silbersdorff et al. (2018), skewedness is a typical feature of health distributions based on continuous health measures.

it (corresponding to ISCED categories 0-3). The group of the higher educated includes individuals with any type of post-secondary education (corresponding to ISCED categories 4-6). The main reason behind this gradation is to reach a cross-country comparability in educational levels.[7] Although the ISCED classification is designed to ensure that educational levels are comparable across countries, countries still differ substantially in terms of the types and the scope of educational degrees offered, especially at the post-secondary level. For example, Germany has a well-developed high-quality vocational education and training system whereas in other countries this type of education is less developed (Jacob and Solga, 2015).

Figure 2 provides graphical evidence on the distribution of the SHARE respondents by the two levels of education. It shows that the proportion of higher educated people among the respondents varies substantially across countries, being as low as 10 percent in Italy and Portugal and as high as 42 percent in Denmark and Sweden.[8]

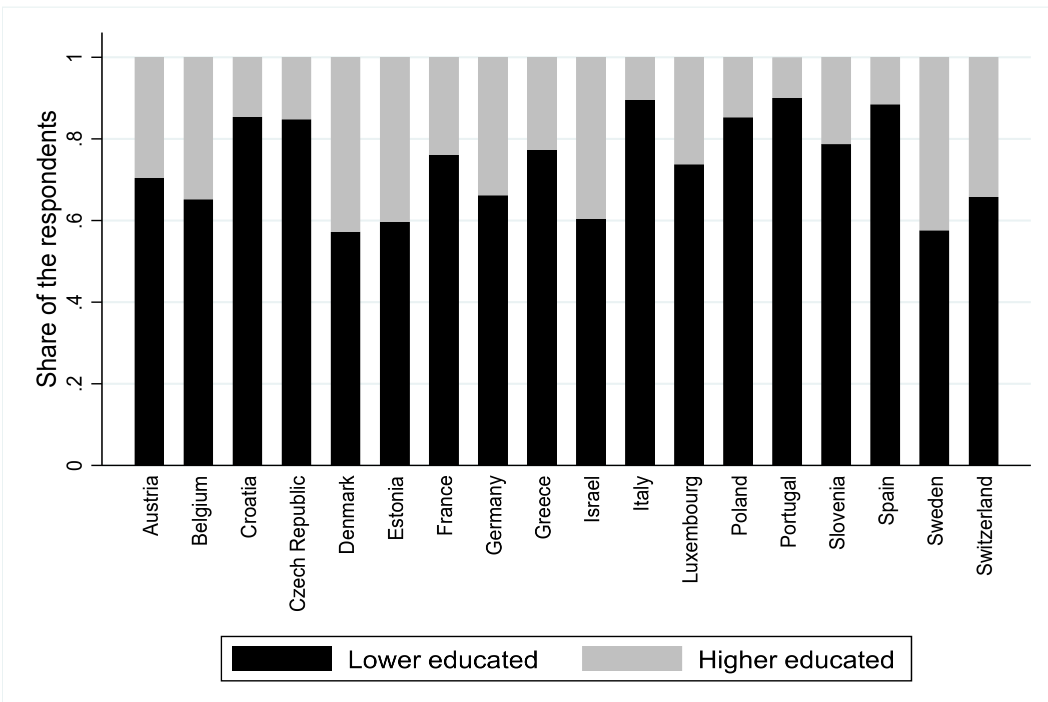

Figure 2. Distribution of the respondents by education

Note: All estimates are weighted using individual cross-sectional weights.

[7] Initially, we were considering the possibility of constructing three educational categories (lower, medium, and higher educated) but a more detailed gradation did not work out for all the countries, due to the differences in the availability and popularity of some types of post-secondary degrees.

[8] The differences in the size of categories would generate a problem for parametric analysis because smaller shares of the lower educated in some countries might signify the presence of a stronger negative selection of these people from the population. For a non-parametric distributional analysis employed in this paper, this issue is of a smaller concern.

2.3. Other variables

In order to investigate what lies behind the education gradient in health, we explore the contribution to it of three groups of factors, i.e. demographic characteristics (age, gender, country of birth, and whether someone lives with or without a spouse), labor market characteristics (employment status and total net equivalized household income), and health behavior (smoking, drinking, doing sports and BMI index as a proxy for eating habits). Previous literature has shown that all these factors are important determinants of health in general and the education gradient in health in particular (for a summary, see Cutler and Lleras-Muney, 2008).

Table 2 shows the distribution of these characteristics across education subgroups in all countries pooled together. In our sample, lower educated people are predominantly female, born in the country of residence, less likely to live with a spouse, and, on average, are a bit older than those who are higher educated.[9] The lower educated are also more likely to be retired or inactive on the labor market and have much lower income than the higher educated. Compared to the higher educated, lower educated individuals are less likely to do sports or have a normal weight but they are also less likely to be heavy drinkers or have ever smoked.

[9] Empirical evidence suggests that people with low levels of education, on average, live a shorter life than people with high levels of education (Hummer and Lariscy, 2011). The fact that in our sample the lower educated are, on average, older than the higher educated can be explained by the expansion of post-secondary education over time, which results into a higher level of education among younger cohorts, as compared to older ones (see Braga et al., 2013).

Table 2. Differences in demographic, labor market, and behavioral characteristics between the lower and higher educated, all countries

Socio-economic characteristics	Lower educated	Higher educated	Difference
Demographic characteristics			
Age (mean)	66.8	63.7	+ 3.1***
Female (%)	56.1	48.0	+ 8.1***
Born in the country of residence (%)	93.0	88.3	+ 4.7***
Living with a spouse (%)	62.1	66.1	- 4.0***
Labor market characteristics			
Total net equivalized household income (mean)	14224	24828	- 10604***
Employment status			
Retired (%)	52.6	47.0	+ 5.6***
Employed (%)	25.1	44.2	- 19.1***
Other (%)	22.3	8.8	+ 13.5***
Health behavior characteristics			
Ever smoked (%)	45.4	48.6	- 3.2***
Doing sport			
More than once a week (%)	29.0	40.4	- 11.4***
Once a week (%)	11.6	17.1	- 5.5***
One to three times a month (%)	8.3	9.1	- 0.8**
Hardly doing any sport (%)	51.0	33.4	+ 17.6***
Body mass index (BMI)			
Underweight	1.2	1.2	0
Normal	34.9	43.7	- 8.8***
Overweight	41.2	39.5	+ 1.6***
Obese	22.7	15.5	+ 7.2***
Drinking habits			
≥ 6 drinks at least once per week	5.9	7.3	-1.4***
≥ 6 drinks 1-2 times per month	10.8	16.9	-6.1***
Not at all in the last 3 months	83.3	75.8	+7.5***
Number of observations	48481	17274	65755

Note: All estimates are weighted using individual cross-sectional weights. * stands for significant at 0.05 level, ** stands for significant at 0.01 level, and *** stands for significant at 0.001 level.

3. Methodology

3.1. Modeling the health gap between the lower and higher educated

Consider sample *S* consisting of *N* individuals, where each individual belongs to one of the two mutually exclusive education subgroups, *E*, where *E* takes the value of 0 if a person belongs to the group of the lower educated and 1 if a person belongs to the group of the higher educated. Let h_i be the individual health status, so that $0 \le h_i \le 1$. Then, health outcomes across all individuals in the sample belonging to a given educational sub-group *E* can be summarized with the cumulative distribution function, $F_H^E(h)$, as follows:

$$F_H^E(h) = \Pr(H \le h) = \int_0^H f_H^E(h)dh \quad , \qquad (1)$$

where $f_H^E(h)$ is the probability density function of health for education sub-group *E*.[10]

The cumulative distribution function of health in Equation (1) summarizes the chances of a randomly taken individual with education *E* to have a health score below or equal to a certain level, *H*. The gap in health scores between the lower and higher educated, $\Delta F_H(h)$, can then be expressed as the difference between their cumulative health distribution functions:

$$\Delta F_H(h) = F_H^0(h) - F_H^1(h) = \int_0^H f_H^0(h)dh - \int_0^H f_H^1(h)dh \qquad (2)$$

3.2. Decomposing the health gap between the lower and higher educated

In order to explore what lies behind the health gap between the lower and higher educated, we perform a decomposition exercise based on the construction of counterfactual distributions of health that would prevail among the lower educated if they had the same demographic, labor market, and health behavior characteristics as the higher educated.

To account for the presence of covariates, the cumulative health distribution function in Equation (2) can be re-written as an integral of the cumulative health distribution function

[10] The probability density function contains a set of probabilities that a randomly taken individual in group *E* will have health status at level *h*.

conditional on individual characteristics, X, over the distribution of those characteristics in a given education subgroup:

$$F_H^E(h) = \int_{\Omega_X} F_{H|X}^E(h \mid x) f_X^E(x) dx \,, \tag{3}$$

where $F_{H|X}^E(h \mid x)$ is a cumulative health distribution function conditional on characteristics of individuals belonging to education subgroup E, $f_X^E(x)$ stands for the density distribution of these characteristics, and Ω_X is their domain.

By separating the distribution of individual covariates from the conditional health distribution function, Equation (3) allows us to construct a set of counterfactual distributions that would prevail among the lower educated if they had the same distribution of characteristics as the higher educated. There are different ways to construct such counterfactual distributions.[11] In this paper, we employ a semi-parametric approach developed by Fortin et al. (1996) which relies on a re-weighting procedure. This procedure allows imposing the distribution of covariates from one population subgroup on another without changing the conditional health distribution function. The main advantage of this approach, as compared to others, is that it does not require a parametric specification of the health function, which makes it less susceptible to the misspecification bias.

Following Fortin et al. (1996), we derive a re-weighting factor, Ψ_X, which accounts for the difference in the distribution of covariates among the lower and higher educated subgroups as follows:

$$\Psi_x = \frac{dF_X^1(x)}{dF_X^0(x)} = \frac{\Pr(E=1 \mid X)}{\Pr(E=0 \mid X)} \cdot \frac{\Pr(E=0)}{\Pr(E=1)} \,. \tag{4}$$

This re-weighting factor allows us to construct a counterfactual distribution of health that would prevail among the lower educated if they had exactly the same distribution of demographic, labor market, and health behavior characteristics as the higher educated:

[11] For an overview of the existing decomposition techniques based on the construction of counterfactuals, see Fortin et al. (2011).

$$F_H^{0'}(h) = \int_{\Omega_X} F_{H|X}^0(h \mid x) \cdot \Psi_X \cdot f_X^0(x) dx \,, \qquad (5)$$

where $F_H^{0'}(h)$ is a counterfactual distribution of health that would prevail among the lower educated if they had exactly the same distribution of characteristics as the higher educated.

The aggregate decomposition can then be performed as follows:

$$\begin{aligned} \Delta F_H(h) &= \int_{\Omega_X} F_{H|X}^0(h \mid x) f_X^0(x) dx - \int_{\Omega_X} F_{H|X}^1(h \mid x) f_X^1(x) dx = \\ &= \left[\int_{\Omega_X} F_{H|X}^0(h \mid x) f_X^0(x) dx - \int_{\Omega_X} F_{H|X}^0(h \mid x) \cdot \Psi_X \cdot f_X^0(x) dx \right] + \\ &+ \left[\int_{\Omega_X} F_{H|X}^0(h \mid x) \cdot \Psi_X \cdot f_X^0(x) dx - \int_{\Omega_X} F_{H|X}^1(h \mid x) f_X^1(x) dx \right] = \\ &= \Delta F_H^{Comp}(h) + \Delta F_H^{Un\exp}(h) \end{aligned} \qquad (6)$$

In the equation above, the first term captures the difference in the health distributions between the lower and higher educated attributable to the differences in their demographic, labor market, and health behavior characteristics (the composition effect), $\Delta F_H^{Comp}(h)$. The second term captures the education gradient in health, which is not explained by the differences in the observed characteristics, $\Delta F_H^{Un\exp}(h)$.

In order to identify which characteristics are especially important for explaining the education gradient in health, a detailed decomposition is needed. There are three ways to perform such a decomposition (Fortin et al., 2011).[12] The first approach (marginal decomposition) relies on the construction of a counterfactual distribution that would prevail among the lower educated if only one characteristic of interest had been distributed among them in exactly the same way as among the higher educated. By taking the difference between the actual health distribution for the lower educated and the counterfactual one, one can identify the direct contribution of the characteristic of interest to the education gradient in health. The main limitation of this approach is that it does not result into an exact decomposition (the sum of the contributions attributable to

[12] For a nice demonstration of the performance of these three approaches in the context of health inequality, see Mazeikaite et al. (2017).

separate factors is not equal to the total composition effect) because of its inability to account for interactions between decomposition components.

The second approach (sequential decomposition) relies on the construction of counterfactual distributions in a sequential manner, where characteristics are introduced in the calculation of weights one by one (for example, first demographic characteristics, then both demographic and labor marker characteristics, and so on). The main shortcoming of this approach is that the decomposition results become path-dependent if the factors interact with each other. If this is the case, the contributions of those factors, which are introduced earlier, capture their interaction effects with the factors, which are introduced at a later stage. A strong interrelationship between decomposition components is especially profound in the context of this paper, where age, for example, might predefine whether someone is employed and both these characteristics might also predefine individual health behavior.

To overcome this shortcoming and identify the true contribution of a given characteristic to the total composition effect, Fortin et al. (2011) proposed an alternative approach to the ones described above. This approach (conditional decomposition) foresees computation of a counterfactual distribution that would prevail among the lower educated if all their characteristics except the one of interest were distributed in the same way as among the higher educated. By comparing this distribution with the counterfactual distribution in Equation (5) one can derive the contribution of the characteristic of interest to the difference in health outcomes between the lower and higher educated. The logic behind this approach is that the contribution of the last factor to be introduced is not affected by the omitted variable bias because all other factors have already been taken into account (Fortin et al., 2011). This allows overcoming the path dependence problem but the contributions of separate components still do not sum up to the total composition effect due to interaction effects, which are not accounted for.

In this paper, we present the results of the detailed decomposition derived according to the third approach.[13] In particular, we quantify the contribution of three group of factors to the observed education gradient in health, i.e. demographic characteristics, labor market outcomes, and health-related behaviors. In order to identify how interactions between various characteristics

[13] We also performed a detailed decomposition following the first two approaches, but the contributions were overestimated in the case of marginal decomposition and they were found very sensitive to the order of decomposition in the case of sequential decomposition. This is to a large extent driven by strong interaction effects between demographic, labor market, and health behavior characteristics of individuals.

contribute to the education gradient in health, we follow Biewen (2014) and calculate the contributions of all possible interactions between decomposition components to the observed subgroup differences in health. To identify, for example, the contribution of the interaction between demographic and labor market characteristics, one needs to construct a counterfactual health distribution that would prevail among the lower educated if both their demographic and labor market characteristics were distributed as among the higher educated. The difference between this distribution and the counterfactual distribution specified in Equation (5) yields the contribution of both factors and the interaction between them to the education gradient in health. By subtracting the direct contributions of demographic and labor market characteristics from this joint contribution, one can obtain the effect of the interaction between these factors to the education gradient in health:

$$\Delta F_H^{(d,l)}(h) = \Delta F_H^{(d+l)}(h) - \Delta F_H^{(d)}(h) - \Delta F_H^{(l)}(h) \qquad (7)$$

where $\Delta F_H^{d,l}(h)$ is the contribution of the interaction between demographic and labor market characteristics to the education gradient in health; $\Delta F_H^{(d+l)}(h)$ is the joint contribution of the demographic and labor market characteristics to the health differential; $\Delta F_H^{(d)}(h)$ and $\Delta F_H^{(l)}(h)$ are direct contributions of the demographic and labor market characteristics to the health differential between the lower and higher educated.

The total composition effect can then be decomposed as follows:

$$\begin{aligned} &\Delta F_H^{Comp}(h) = F_H^0(h) - F_H^{0'}(h) = \\ &\Delta F_H^d(h) + \Delta F_H^l(h) + \Delta F_H^b(h) + \Delta F_H^{d,l}(h) + F_H^{d,b}(h) + \Delta F_H^{l,b}(h) + \Delta F_H^{d,l,b}(h) \end{aligned} \qquad (8)$$

where $\Delta F_H^{(b)}(h)$ is the direct contribution of behavioral characteristics; $\Delta F_H^{(d,b)}(h)$, $\Delta F_H^{(l,b)}(h)$, and $\Delta F_H^{(d,l,b)}(h)$ are the contributions of interactions between respective components to the total differences in health between the lower and higher educated.

4. Results

4.1. The differences in the level of health by education

Figure 3 below presents the differences in the distributions of global, physical, and mental health between the lower and higher educated in all countries pulled together.

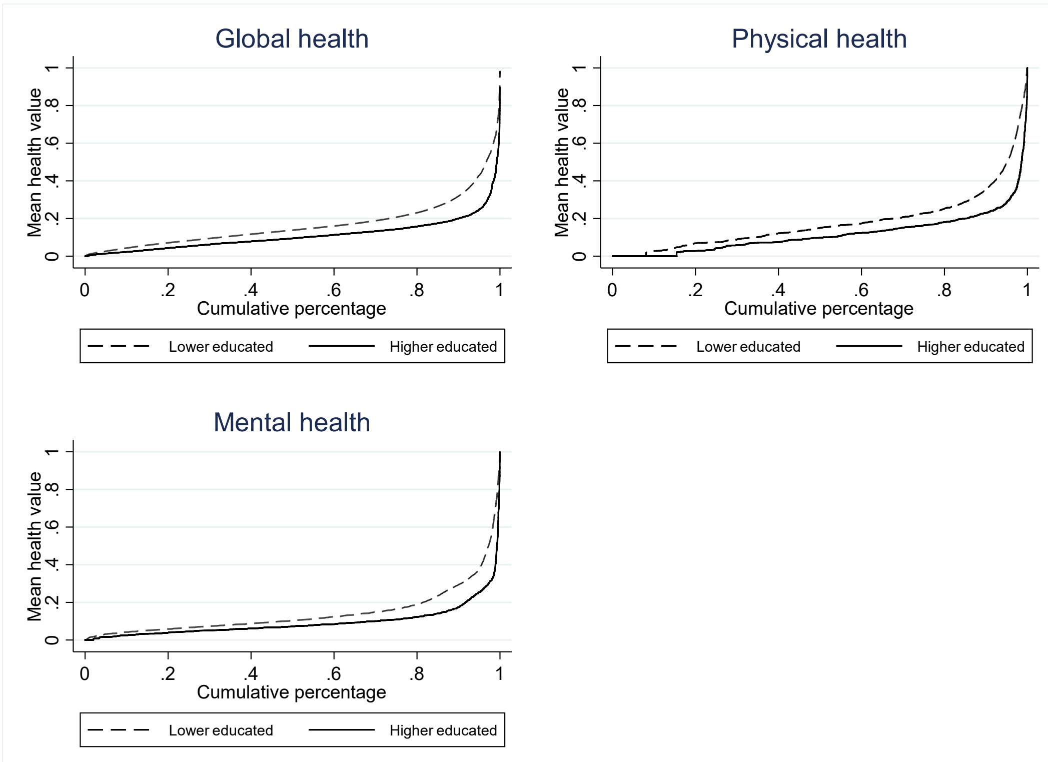

Figure 3. Differences in the cumulative distributions of global, physical, and mental health between the lower and higher educated, all countries

Note: All estimates are weighted using individual cross-sectional weights.

Three important messages come from this figure. First, lower educated people have worse health than those who are higher educated along the entire health distribution. Regardless of whether we compare the healthiest 10 percent or the sickest 10 percent of the lower and higher educated, individuals with lower levels of education will always suffer from more diseases or limitations in daily life activities than those who have higher levels of education. This evidence holds for both physical and mental health, and consequently for global health. Second, the gap in the levels of health between the lower and higher educated is not constant throughout the distribution regardless of the health domain. Whereas it is relatively small at the bottom of the distribution, it increases substantially towards the top. This implies that among the healthiest lower and higher educated the difference in health scores is relatively small but it is several times bigger if we compare the sickest ones. Lastly, the education gradient is slightly larger for physical health than for mental health, especially in the upper tail of the distribution.

Table 3 below quantifies the differences in the health scores between the lower and higher educated at various points of the health distributions depicted in Figure 3.

Table 3. Differences in the levels of health between the lower and higher educated at different points of the health distribution, all countries

Educational category	Percentiles of the health distribution					
	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Mean
			Global health			
Low	0.043	0.082	0.138	0.207	0.318	0.166
High	0.023	0.053	0.094	0.143	0.200	0.109
Difference	+0.020 (0.001)***	+0.029 (0.002)***	+0.044 (0.002)***	+0.064 (0.002)***	+0.118 (0.005)***	+0.057 (0.002)***
			Physical health			
Low	0.028	0.075	0.150	0.228	0.355	0.179
High	0.000	0.042	0.098	0.164	0.229	0.117
Difference	+0.028 (0.001)***	+0.033 (0.004)***	+0.052 (0.002)***	+0.064 (0.002)***	+0.126 (0.005)***	+0.062 (0.002)***
			Mental health			
Low	0.042	0.067	0.104	0.165	0.293	0.142
High	0.025	0.045	0.072	0.109	0.175	0.093
Difference	+0.017 (0.001)***	+0.022 (0.001)***	+0.032 (0.002)***	+0.056 (0.002)***	+0.118 (0.006)***	+0.049 (0.002)***

Note: All estimates are weighted using cross-sectional individual weights. Bootstrapped standard errors in the parentheses (derived from 500 boostrapped replications). *** stands for the significance at 0.001 level.

The results for global health indicate that the gap in health scores between the lower and higher educated at the 10th percentile of the health distribution is only 0.02 points whereas at the 90th percentile it increases in almost 6 times up to 0.118 points. This evidence implies that higher levels of education are especially important for avoiding extremely bad health outcomes. The fact that the average size of the gap is only 0.057 points also suggests that without a distributional analysis we would substantially overestimate the size of the education gradient in health at the bottom of the health distribution and underestimate it at the top. Even at the 50th percentile, the gradient is only 0.044 points, implying that the increase in the health differential due to education happens to a larger extent in the upper part of the distribution than in its lbottom part.

The described patterns of the education-health relationship also hold for the domains of physical and mental health when they are considered separately from each other. The health differential between the lower and higher educated is, however, somewhat larger for physical health than for mental health at all points of the distribution and not only in its upper tail as suggested by Figure 3. For example, at the bottom of the distribution the differential between the lower and higher educated is only 0.017 points in metal health but it is 0.028 in physical health. Moreover, around 10 percent of higher educated individuals do not experience any problems with physical health, which is not the case for the lower educated. This evidence implies that education matters slightly more for physical health than for mental health.

Table 4 presents country-specific distributional differences in the level of global health between the lower and higher educated.[14] It shows that in all countries without exception, the education gradient in health increases along the health distribution. The relative difference between the bottom and the top (p90/p10) is especially large in Croatia, Israel, and Italy, where it is two-three times higher than the cross-country average.

Table 4 also provides further arguments in support of the distributional approach to studying education gradient in health in the context of cross-country analysis. It shows that some countries with a similar average difference in the levels of health between the lower and higher educated face very different health differentials due to education at different points of the health distribution. For example, in France and Slovenia, the average health gap due to education is 0.057, which is also the average for all countries pooled together. The gradient, however, is only 2.7 times higher at the top compared to the bottom of the distribution in Slovenia whereas it is 4.8 times higher in France. Similarly, in Austria, Denmark, and Switzerland the average health differential is smaller than the cross-country average, but these countries, nevertheless, experience a steeper than average increase in the education gradient in health along the distribution. Hence, from the comparative perspective, focusing on the mean differences in the levels of health among individuals with different levels of education might lead to somewhat misleading conclusions about the degree of education inequality in health.

[14] The estimates for physical and mental health domains are summarized in Tables C1 and C2 in Appendix C.

Table 4. Country-specific differences in the levels of global health between the lower and higher educated

Educational category	Percentiles of the health distribution						
	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Mean	90th/10th, %
Austria	0.009***	0.032***	0.023***	0.039***	0.064***	0.035***	7.3
Belgium	0.022***	0.028***	0.034***	0.048***	0.088***	0.045***	3.9
Croatia	0.010**	0.030***	0.045***	0.072***	0.163***	0.063***	16.5
Czech Repub.	0.010	0.019**	0.029***	0.031***	0.053***	0.027***	5.5
Denmark	0.012***	0.039***	0.029***	0.046***	0.088***	0.044***	7.5
Estonia	0.022***	0.036***	0.036***	0.055***	0.104***	0.051***	4.8
France	0.023***	0.027***	0.047***	0.071***	0.111***	0.057***	4.8
Germany	0.019***	0.024***	0.035***	0.047***	0.087***	0.042***	4.7
Greece	0.018***	0.033***	0.044***	0.053***	0.109***	0.055***	5.9
Israel	0.013	0.014	0.047***	0.087***	0.182***	0.065***	14.2
Italy	0.016**	0.026***	0.042***	0.064***	0.149***	0.062***	9.1
Luxembourg	0.018***	0.043***	0.042***	0.063***	0.096***	0.054***	5.4
Poland	0.027***	0.038***	0.037***	0.063***	0.118***	0.059***	4.4
Portugal	0.000***	0.031*	0.051**	0.072	0.124	0.039	-
Slovenia	0.037***	0.039***	0.047***	0.067***	0.100***	0.057***	2.7
Spain	0.032***	0.042***	0.048***	0.080***	0.162***	0.074***	5.1
Sweden	0.013***	0.032***	0.036***	0.045***	0.067***	0.040***	5.3
Switzerland	0.005*	0.013***	0.022***	0.024***	0.038***	0.024***	7.9
Total	0.020***	0.029***	0.044***	0.064***	0.118***	0.057***	5.9

Note: All estimates are weighted using individual cross-sectional weights. * stands for significant at 0.05 level, ** stands for significant at 0.01 level, and *** stands for significant at 0.001 level. The significance levels are derived via the bootstrapping procedure based on 500 replications within each country.

4.2. Decomposition results of the health differential due to education

Table 5 below presents the results of the aggregate decomposition of the health differential between the lower and higher educated derived for global, physical, and mental health measures. The results for global health indicate that differences in demographic, labor market, and health behavior characteristics between the lower and higher educated can explain around two thirds of their differences in the level of health. The unexplained difference constitutes around 35 percent and is related to either unobserved characteristics of individuals or structural effects of the characteristics included in the model (for example, being employed might imply different things for the lower and higher educated due to different types of jobs they occupy).

Table 5. Aggregate decomposition of the health gap between the lower and higher educated, all countries

Educational category	Percentiles of the health distribution					
	10^{th} percentile	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile	Mean
Panel A: Global health						
Total difference	+0.020	+0.029	+0.044	+0.064	+0.118	+0.057
Total explained difference	+0.012 (61.4%)	+0.020 (67.1%)	+0.028 (64.7%)	+0.041 (64.5%)	+0.077 (65.1%)	+0.036 (62.7%)
Panel B: Physical health						
Total difference	+0.028	+0.033	+0.052	+0.064	+0.126	+0.062
Total explained difference	+0.028 (100%)	+0.019 (56.6%)	+0.034 (65.8%)	+0.042 (66.3%)	+0.092 (73.3%)	+0.041 (66%)
Panel B: Mental health						
Total difference	+0.017	+0.022	+0.032	+0.056	+0.118	+0.049
Total explained difference	+0.007 (41.8%)	+0.012 (54.9%)	+0.019 (59.6%)	+0.031 (55.5%)	+0.052 (43.8%)	+0.026 (53.7%)

Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country.

Table 5 also indicates that the explanatory power of the observed socio-economic characteristics is somewhat larger for physical health than for mental health. Whereas, on average, we can assign 66 percent of the subgroup differences in physical health to the differences in their observed socio-economic characteristics, for mental health it is only 54 percent. Further inspection of the results in Panels B and C of Table 5 reveal that the explanatory power of the observed individual characteristics is not constant along the distribution of health. The differences in these characteristics are especially important for explaining the education gradient in physical health at the very bottom and at the very top of the distribution. In particular, the education gradient at the 10^{th} percentile of the physical health distribution would completely disappear if the lower educated had exactly the same distribution of demographic, labor market, and health behavior characteristics as the higher educated. At the top of the health distribution, the gap would also decrease by more than 73 percent had the lower educated the same distribution of characteristics as the higher educated. By contrast, for mental health the explanatory power of the observed socio-economic characteristics is the largest in the middle of the distribution and the smallest in its tails.

The results of the aggregate decomposition derived separately for each country (see Figures D1-D3 in Appendix D) largely mirror findings from Table 5. Although there is a substantial variation in the percentage of the explained difference in health due to education across countries, the message remains the same – the role of the observed characteristics varies along the health distribution and these characteristics explain the subgroup differences in physical more than subgroup differences in metal health.

Table 6 presents the results of the detailed decomposition for all countries together, where we identify the contributions of separate factors (demographic characteristics, labor market characteristics, and health behavior) and their interactions with each other to the differences in health between the lower and higher educated. Looking at the direct contributions of the factors first, we can see that labor market characteristics contribute the most to the education-related differences in health. The contribution of the health behavior to the education gradient in health is the second in size whereas demographic characteristics do not contribute much to this gradient. The findings hold at different points of the distribution and apply to all three measures of health.

A further inspection of Table 6 reveals that albeit differences in demographic characteristics between the lower and higher educated do not explain much of the health differential if considered separately from other factors, they interact substantially with labor market outcomes reinforcing their positive contribution to the education gradient in health. This reinforcement is not very surprising given what this set of characteristics includes. For example, although the civil status not always have a direct effect on individual health, it predefines the size of household income a person has, which, in turn, reflects on health outcomes. Apart from interacting with each other, demographic and labor market characteristics interact with health behavior, the interaction, which also explains a substantial part of the education gradient in health.

The comparison of the estimates in Panels B and C shows that the direct contribution of the subgroup differences in the labor market characteristics to the education gradient in health is much bigger for mental health than for physical health. Net of other factors, these characteristics can explain around 35 percent of the subgroup difference in the average value of mental health and only around 17 percent of the subgroup difference in the average value of physical health. The higher direct contribution of labor market characteristics to the education gradient in mental health, as compared to physical health, is compensated by a lower contribution of the three-way interaction between labor market characteristics, demographic characteristics, and health behavior.

Table 6. Decomposition of the health gap between the lower and higher educated, all countries

Educational category	Percentiles of the health distribution					
	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Mean
Panel A: Global health						
Total explained difference	+0.012	+0.020	+0.028	+0.041	+0.077	+0.036
Contribution of						
Demographics (D)	+0.000	+0.001	0.000	+0.000	+0.002	+0.001
Labor market (LM)	+0.004	+0.005	+0.007	+0.009	+0.014	+0.008
Health behavior (HB)	+0.001	+0.003	+0.004	+0.005	+0.007	+0.004
Interaction D & LM	+0.003	+0.005	+0.009	+0.012	+0.024	+0.011
Interaction D & HB	0.000	0.000	+0.001	+0.001	+0.003	+0.001
Interaction LM & HB	+0.001	+0.001	+0.003	+0.004	+0.006	+0.003
Interaction D&LM&HB	+0.003	+0.005	+0.004	+0.010	+0.021	+0.008
Panel B: Physical health						
Total explained difference	+0.028	+0.019	+0.034	+0.042	+0.092	+0.041
Contribution of						
Demographics (D)	0.000	+0.001	0.000	+0.001	+0.003	+0.001
Labor market (LM)	0.000	+0.004	+0.006	+0.011	+0.013	+0.007
Health behavior (HB)	0.000	+0.003	+0.005	+0.009	+0.010	+0.005
Interaction D & LM	+0.021	+0.009	+0.008	+0.006	+0.026	+0.013
Interaction D & HB	0.000	-0.001	+0.001	+0.001	+0.002	+0.001
Interaction LM & HB	+0.021	+0.007	0.000	-0.005	+0.009	+0.004
Interaction D&LM&HB	-0.014	-0.006	+0.014	+0.019	+0.029	+0.010
Panel B: Mental health						
Total explained difference	+0.007	+0.012	+0.019	+0.031	+0.052	+0.026
Contribution of						
Demographics (D)	0.000	0.000	-0.001	0.000	-0.003	0.000
Labor market (LM)	+0.003	+0.004	+0.008	+0.012	+0.016	+0.009
Health behavior (HB)	0.000	+0.002	+0.002	+0.004	+0.006	+0.002
Interaction D & LM	+0.001	+0.003	+0.005	+0.006	+0.019	+0.007
Interaction D & HB	0.000	0.000	+0.001	+0.001	+0.006	+0.001
Interaction LM & HB	+0.001	+0.001	+0.002	0.000	0.000	+0.002
Interaction D&LM&HB	+0.002	+0.002	+0.002	+0.009	+0.008	+0.005

Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country.

The results of the detailed decomposition derived for each country separately (Figure E.1-E3 in Appendix E) reveal a lot of heterogeneity across countries in terms of the contributions attributable to the differences in demographic, labor market, and behavioral characteristics of individuals. In particular, demographic characteristics have a negative contribution to the health gap in more than a half of the countries studied. This finding implies that if the lower educated had exactly the same distribution of demographic characteristics as the higher educated, the health gap between these subgroups would be even bigger. By contrast, the contributions of labor market characteristics to the observed global health gap due to education are always positive and relatively large. Depending on the country studied, one can assign between 7 and 31 percent of the subgroup differences in health to differences in labor market characteristics. For health-related behavior, the contributions are also positive (with the exception of Greece) but smaller as compared to labor market characteristics.

5. Conclusions

Recent studies emphasize the importance of taking a distributional approach to the analysis of socio-economic inequalities in health. Although some evidence already exists with respect to income-related differences in the level of health along the health distribution, to the best of our knowledge, not much has been done to inspect the education-health relationship from the distributional perspective. This paper aims to close this gap in literature by (1) identifying the gap in the level of health between the lower and higher educated in different parts of the health distribution, and (2) by investigating to what extent subgroup differences in demographic, labor market, and behavioral characteristics of individuals can explain this gap. We measure individual health using a multidimensional approach, which combines multiple health dimensions in synthetic indicators of mental and physical health with their further aggregation in one single indicator of individual global health.

In line with previous literature, our results indicate that, on average, higher educated people enjoy better health than those who are lower educated. We show, however, that this gradient is not constant along the health distribution: it is relatively small if we compare the healthies 10 percent of the lower and higher educated but it multiplies in size if we compare the sickest 10 percent of individuals. On average, the education-related difference in the level of health at the 90th percentile of the health distribution is almost 6 times bigger than the difference at the 10th percentile of the same distribution. These findings stress the importance of going ‘beyond the mean’ while studying education gradient in health.

The results of the decomposition exercise reveal that differences in demographic, labor market, and behavioral characteristics between the lower and higher educated can explain around

65 percent of their differences in the level of global health (with a slightly bigger explanatory power for physical health as compared to mental health). Out of these three factors, differences in labor market characteristics have the largest direct effect on the education gradient in health, driving this gradient upwards. Labor market characteristics also substantially interact with demographic characteristics, inducing further increase in the health differential along the distribution.

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Appendix A

Table A1. Number of observations per country

Country	Number of observations
Austria	3284
Belgium	5593
Croatia	2413
Czech Republic	4706
Denmark	3602
Estonia	5488
France	3774
Germany	4274
Greece	4778
Israel	1841
Italy	5134
Luxembourg	1540
Poland	1647
Portugal	1632
Slovenia	4152
Spain	5402
Sweden	3778
Switzerland	2717
Total	65755

Appendix B

We measure health status of each individual using a multidimensional approach proposed by Pi Alperin (2006). This approach allows aggregating various health limitations at the individual level in one synthetic health indicator, h_i, as follows:

$$h_i = \sum_{j=1}^{M} h_{ij} \cdot w_j / \sum_{j=1}^{M} w_j$$

where h_{ij} is defined as the health status of individual i in the j-th health item (with $j = 1,\ldots, M$) and w_j stands for the weight attached to this health item. By the way it is constructed, the synthetic health indicator, h_i, can take any value between 0 (absolutely healthy) and 1 (absolutely sick) being, thus, quasi-continuous in nature.

To derive the item-specific weights, we follow Betti and Verma (2008), who propose to calculate w_j as a product of two weights, the one that accounts for the prevalence of a given health limitation in the population, w_j^a, and the other one that limits the influence of highly correlated health limitations on the synthetic index, w_j^b. Although being item specific, these weights are the same for each individual in the sample.

The first weight, w_j^a, is calculated as the coefficient of variation of a given health item:

$$w_j^a = \sum_{i=1}^{N} (h_{ij} - \bar{h}_j)^2 / (\bar{h}_j \cdot N)^{1/2}$$

where $\bar{h}_j$ is the mean of the j-th health item in the sample.

By construction, when only a small proportion of individuals suffer from a given disease, the weight given to this disease is larger. The logic behind is that rare diseases (health limitations) are perceived as more critical than widely spread diseases (limitations). As an example, think about eyesight limitation: a substantial share of elderly people suffer from it, but it is still considered as less critical than, for example, a cancer.

The second weight, w_j^b, is calculated as follows:

$$w_j^b = (1 + \sum_{j=1}^{M} p_{j,j'} I(p_{j,j'} \prec p_H)^{-1} \cdot (1 + \sum_{j=1}^{M} p_{j,j'} I(p_{j,j'} \geq p_H)^{-1},$$

where $p_{j,j'}$ is the correlation coefficient between items j and j' and I(.) is the indicator function taking value 1 if the expression in the brackets holds and 0 otherwise. p_H is a predetermined correlation cut-off, which separates low correlated items from highly correlated ones. Betti and Verma (2008) suggest setting this threshold at the point that reflects the largest gap between the ordered set of correlation values, the suggestion that we also follow in the paper.

By construction, w_j^b is the inverse of the average correlation of health item j with all other health items. This implies that the bigger is the correlation of a given health item with other items, the smaller is its weight.

As mentioned above, the final weight for each health item is defined as a product of w_j^a and w_j^b weights:

$$w_j = w_j^a \cdot w_j^b$$

Appendix C

Table C1. Country-specific differences in the level of physical health between the lower and higher educated

Educational category	Percentiles of the health distribution						
	10^{th} percentile	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile	Mean	$90^{th}/10^{th}$, %
Austria	0.000	0.039*	0.024	0.050***	0.074***	0.043***	-
Belgium	0.033***	0.052***	0.034***	0.048***	0.099***	0.052***	3.03***
Croatia	0.000*	0.040***	0.037***	0.075***	0.143***	0.066***	-
Czech Repub.	0.004	0.010	0.029*	0.023**	0.057**	0.023**	13.2**
Denmark	0.000	0.060***	0.032***	0.051***	0.096***	0.049***	-
Estonia	0.027***	0.039***	0.046***	0.062***	0.133***	0.058***	4.9***
France	0.028***	0.031***	0.034***	0.063***	0.118***	0.062***	4.2***
Germany	0.028	0.016	0.033***	0.043***	0.098***	0.046***	3.58***
Greece	0.000	0.038***	0.053***	0.057***	0.100***	0.064***	-
Israel	0.029*	0.029*	0.033	0.037	0.181***	0.059***	6.20
Italy	0.021***	0.029***	0.053***	0.062***	0.148***	0.070***	7.08***
Luxembourg	0.000	0.044***	0.056***	0.067***	0.103***	0.060***	-
Poland	0.043	0.043**	0.038**	0.065***	0.126***	0.066***	3.0ns
Portugal	-0.031	0.033	0.028	0.037	0.133	0.032	-
Slovenia	0.048***	0.029***	0.053***	0.069***	0.121***	0.062***	2.5**
Spain	0.027*	0.027	0.053***	0.070***	0.141***	0.070***	5.14
Sweden	0.000	0.033**	0.035***	0.058***	0.080***	0.050***	-
Switzerland	0.000	0.002	0.029***	0.021***	0.038***	0.026***	-
Total	+0.028***	+0.033***	+0.052***	+0.064***	+0.126***	+0.062***	4.5***

Note: All estimates are weighted using individual cross-sectional weights. * stands for significant at 0.05 level, ** stands for significant at 0.01 level, and *** stands for significant at 0.001 level. The significance levels are derived via the bootstrapping procedure based on 500 replications within each country.

Table C2. Country-specific difference in the level of mental health between the lower and higher educated

Educational category	Percentiles of the health distribution						
	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Mean	90th/10th, %
Austria	0.011***	0.014***	0.013***	0.025***	0.017	0.021***	1.6
Belgium	0.019**	0.019***	0.028***	0.038***	0.046***	0.035***	2.5*
Croatia	0.007	0.022***	0.030***	0.060***	0.144***	0.056***	19.6*
Czech Repub.	0.014**	0.014**	0.021***	0.038***	0.082***	0.034***	6.0
Denmark	0.015***	0.017***	0.020***	0.046***	0.070***	0.034***	4.7***
Estonia	0.016***	0.021***	0.026***	0.038***	0.122***	0.043***	7.7***
France	0.018***	0.026***	0.034***	0.052***	0.106***	0.048***	5.7***
Germany	0.016***	0.024***	0.032***	0.049***	0.097***	0.037***	5.9*
Greece	0.011***	0.017***	0.027***	0.039***	0.075***	0.040***	6.8***
Israel	0.018**	0.009	0.036***	0.081***	0.187*	0.076***	10.4
Italy	0.010***	0.016***	0.026***	0.051***	0.127***	0.049***	12.9**
Luxembourg	0.004	0.015***	0.029***	0.042***	0.117***	0.043***	29.5*
Poland	0.010*	0.021***	0.027***	0.050***	0.142***	0.049***	13.7
Portugal	0.032***	0.036	0.025	0.037	0.081	0.052***	2.5
Slovenia	0.023***	0.026***	0.036***	0.050***	0.111***	0.049***	4.7***
Spain	0.024***	0.028***	0.057***	0.127***	0.162***	0.082***	6.8**
Sweden	0.015***	0.015***	0.015***	0.019***	0.058***	0.022***	3.8***
Switzerland	0.015***	0.015***	0.015***	0.023***	0.023*	0.020***	1.5
Total	+0.017***	+0.022***	+0.032***	+0.056***	+0.118***	+0.049***	6.9***

Note: All estimates are weighted using individual cross-sectional weights. * stands for significant at 0.05 level, ** stands for significant at 0.01 level, and *** stands for significant at 0.001 level. The significance levels are derived via the bootstrapping procedure based on 500 replications within each country.

Appendix D

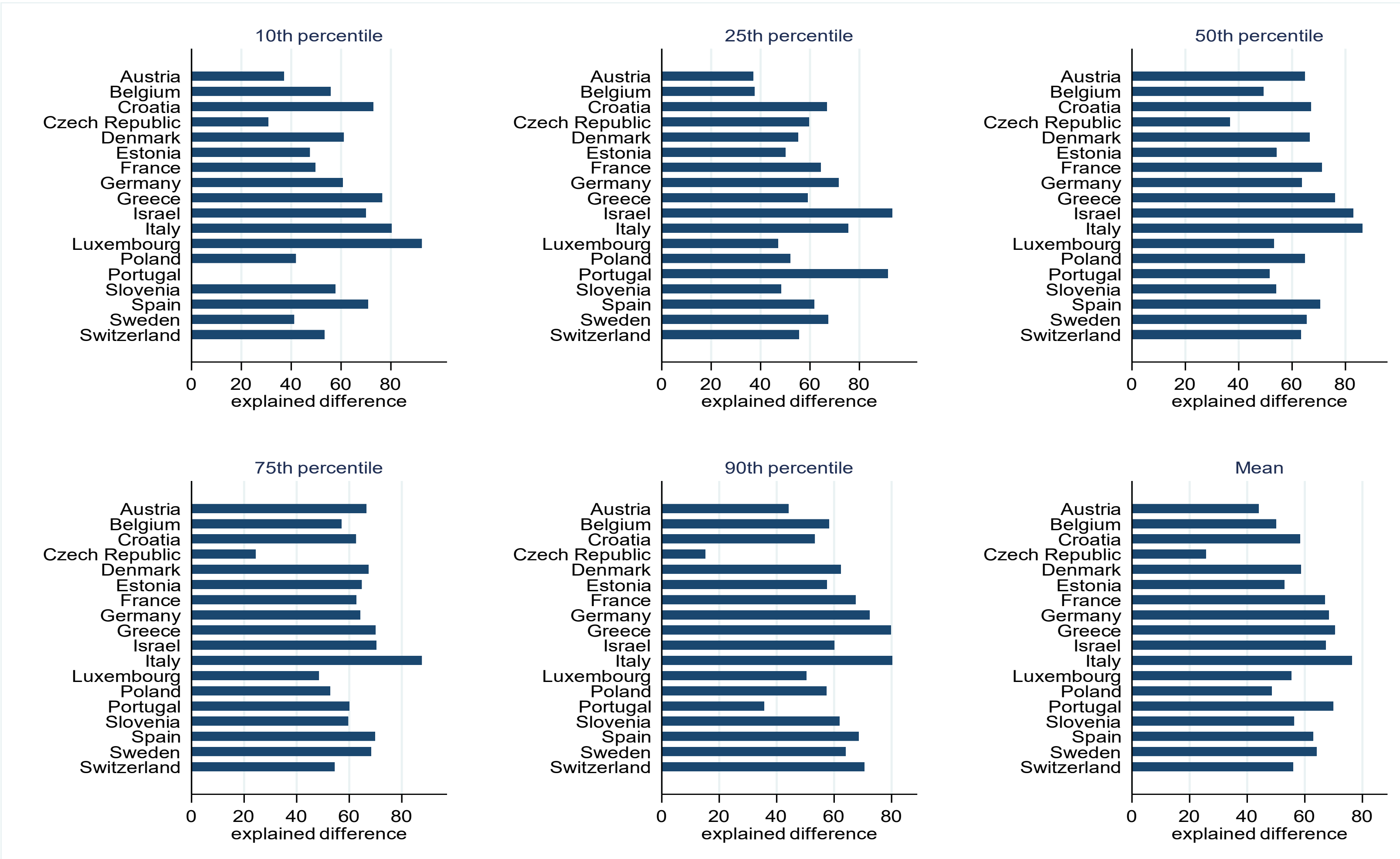

Figure D.1. Aggregate decomposition results for global health, by country

Note: Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country. The X-axis represents the percentage of the education gradient in health, which is explained by the differences in the observed characteristics between the lower and higher educated.

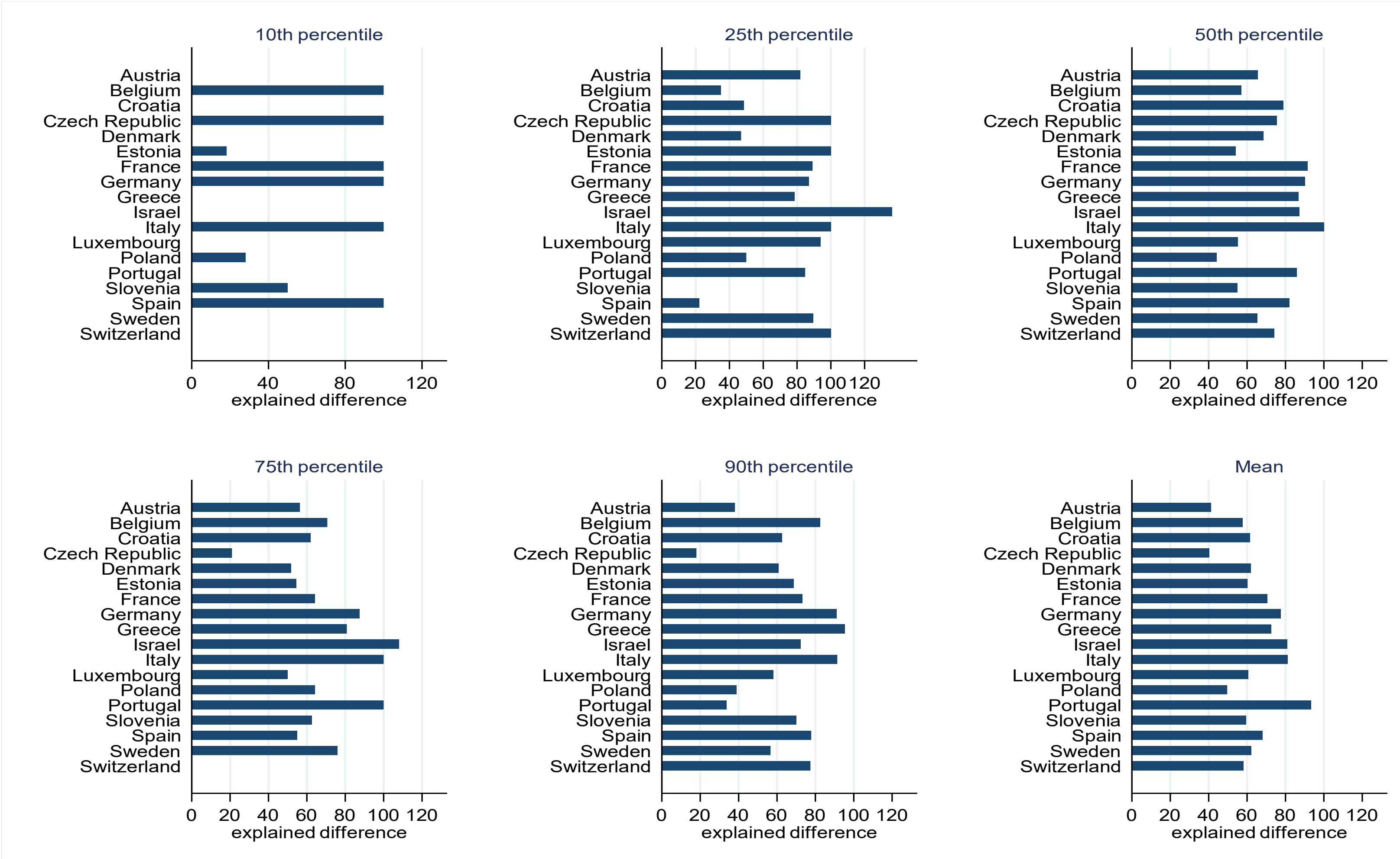

Figure D.2. Aggregate decomposition results for physical health, by country

Note: Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country. The X-axis represents the percentage of the education gradient in health, which is explained by the differences in the observed characteristics between the lower and higher educated. For Portugal, the value at the 10^{th} percentile is negative and quite large (around -80). We recorded it to zero for illustration purposes (to make the scale comparable across different points of the health distribution).

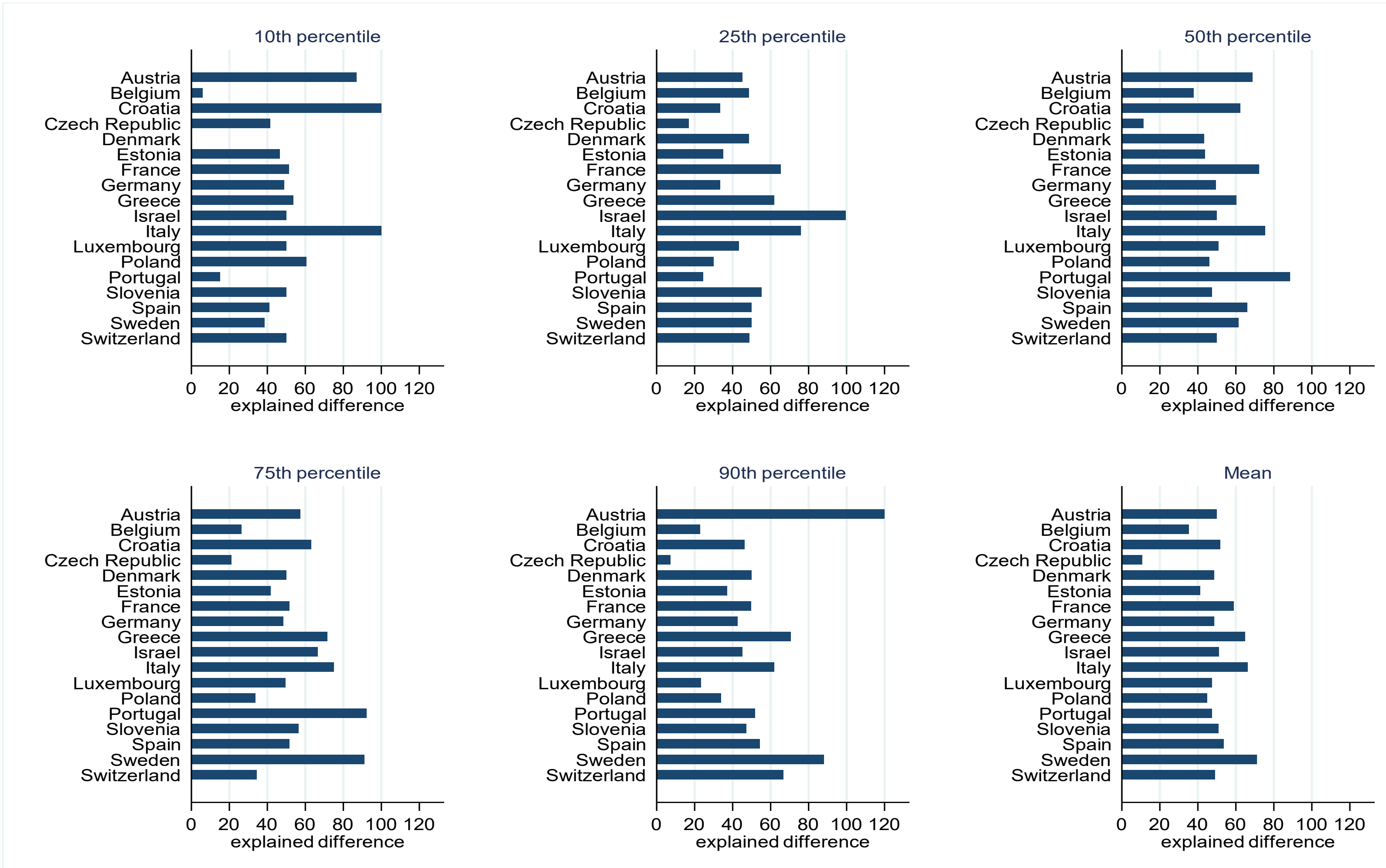

Figure D.3. Aggregate decomposition results for mental health, by country

Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country. The X-axis represents the percentage of the education gradient in health, which is explained by the differences in the observed characteristics between the lower and higher educated. For Austria, the value at the 90th percentile is quite large (187 percent). We recorded it to zero for illustration purposes (to make the scale comparable across different points of the health distribution).

Appendix E

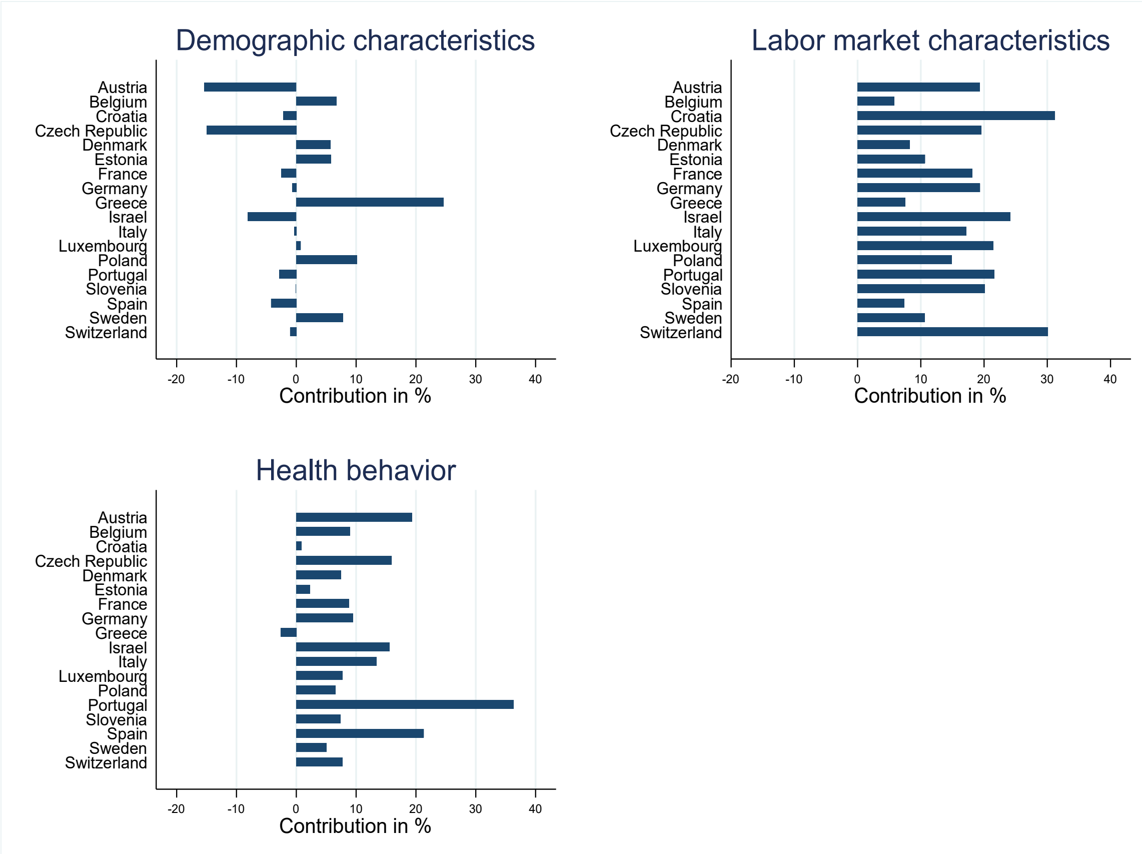

Figure E.1. Detailed decomposition of the subgroup differences in global health at the 50th percentile of the health distribution, by country

Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country. The X-axis represents the percentage of the education gradient in health, which is explained by the differences in the observed characteristics between the lower and higher educated.

Figure E.2. Detailed decomposition of the subgroup differences in physical health at the 50^{th} percentile of the health distribution, by country

Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country. The X-axis represents the percentage of the education gradient in health, which is explained by the differences in the observed characteristics between the lower and higher educated.

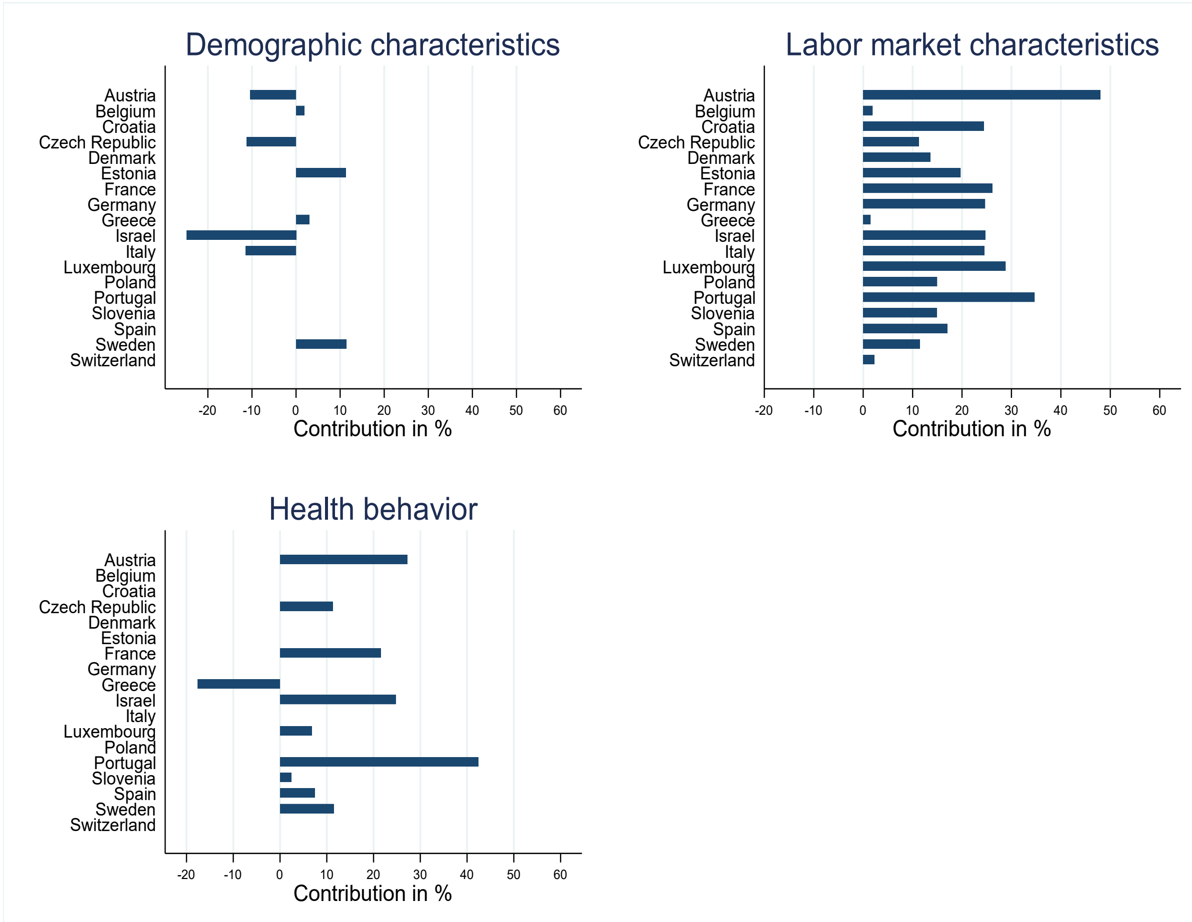

Figure E.3. Detailed decomposition of the subgroup differences in mental health at the 50th percentile of the health distribution, by country

Note: All estimates are derived using individual cross-sectional weights. The re-weighting for the construction of counterfactual distributions is performed separately within each country. The X-axis represents the percentage of the education gradient in health, which is explained by the differences in the observed characteristics between the lower and higher educated.

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