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Education level and income attainment inequalities: A service ecosystem perspective

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Abstract

Purpose. The ecosystem view is a fascinating perspective, which provides managerial scholars with innovative conceptual tools to investigate the functioning of complex service systems. This paper focuses on the education service ecosystem "mega" level to explain the relationship between education attainments and income disparities across Europe.

Methodology. Data were collected from the European Union Statistics on Income and Living Conditions (EU-SILC). Data trends over the time period (2007-2010) were investigated, involving 27 European Countries; unobserved time-invariant heterogeneity was controlled and dynamics over time were followed. A random effects model was estimated for each Country: in particular, random effects model allow to conduct regression analysis, especially when the units of analysis are randomly selected from a large population, as in the instance of dataset. The semi-log functional form is informed by Mincer (1974) human capital models, which this study extended to other explanatory variables.

Findings. Education levels were found to be a predictor of income inequality in all the Countries included in this research, *i.e.* higher education level leads to higher income and *vice versa*. However, the effect of education attainments on individual earnings was irregular. Eastern European Countries, *inter alia*, revealed a strong relationship between education attainments and individual earnings, whereas Scandinavian Countries showed a weak link between education levels and income.

Practical implications. Education has the potential to affect income inequalities in Europe. Policy makers should devise tailored strategies to deal with the consequences of education attainment on individual earnings. Both education services' quality and the interaction between education and other socio-demographic variables may influence income inequality in European Countries.

Originality/value. This is one of the first attempts to investigate the relationship between education levels and income inequalities in light of the service ecosystem perspective. Further conceptual and practical developments are needed to better explain the effects of education attainment on income inequality from an ecosystem point of view.

Keywords
education services; income inequality; ecosystem view; awareness; patient empowerment

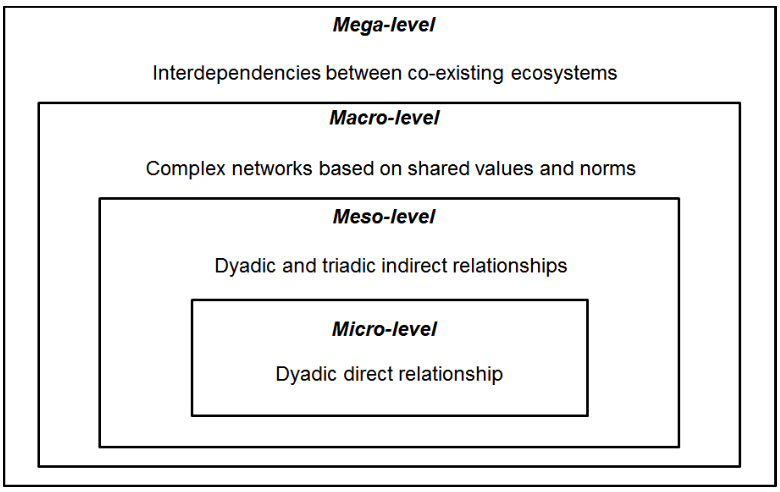
1. Introduction: an ecosystem-based interpretation of education services

Service ecosystems have been presented as the next step in the evolution of the Service Dominant (SD) Logic (Vargo & Lusch, 2017). Ultimately, a service ecosystem could be understood as a self-regulated community of interdependent actors, which share resources and exchange services in an attempt to achieve value co-creation and increase their ability to survive their environment (Akaka, Vargo, & Lusch, 2012; Vargo & Lusch, 2011). To date, the ecosystem perspective has been used to investigate the functioning of various service contexts, including health care (Beirão, Patrício, & Fisk, 2017), cultural services (Minkiewicz, Bridson, & Evans, 2016), social media services (Kim, 2016), and recycling services (Mastrogiacomo, Barravecchia, & Franceschini, 2016). In addition, education services seems to be fitting with the ecosystem perspective, since they rely on strong interdependencies between different actors, who interact to co-create value (Davis & Ostrom, 1991; Redding, 1991; Brandsen, Pestoff, & Verschuere, 2014).

The conceptual lens of service ecosystem has been used for heterogeneous purposes. On the one hand, the contribution of the ecosystem perspective in fostering the creation of the "common good" has been emphasized (Bonomi, Ricciardi, & Rossignoli, 2017). On the other hand, the risks of value co-destruction arising from enhanced interdependencies have been stressed, in order to point out the importance of actor engagement in an ecosystem approach to value co-creation (Prior & Marcos-Cuevas, 2016). It is worth noting that value co-creation and value co-destruction dynamics may happen at different service ecosystem levels, involving different categories of actors (Ciasullo, et al., 2016; Frow, McColl-Kennedy, & Payne, 2016).

In fact, as depicted in Figure 1, scholars have identified four ecosystem levels, each of which catch a specific shade of the broader service system functioning (Chandler & Vargo, 2011; Frow, et al., 2014). The micro level focuses on dyadic actor-to-actor relationship and deals with the exchange of resources and services for creating value. The meso level goes beyond direct service-for-service exchanges, taking into consideration indirect relationships established by actors which operate in the same ecosystem. At the macro level complex networks arises, which rely on norms and values shared by the actors involved in the service ecosystem. Last but not least, at the mega level wider interdependencies between coexisting ecosystems are taken into account to figure out how they interact to enact a value co-creation or a value co-destruction dynamic.

Figure 1. The four ecosystem layers



Source: Authors' elaboration

To the authors' knowledge, scholars have focused most of their attention on the "micro", "meso", and "macro" levels of service ecosystems, overlooking the distinguishing dynamics which animate the mega level. For the sake of the argument, Hardyman, Daunt and Kitchener (2015) investigated the micro-level requisites to realize the full potential of value co-creation in the health care service system. Looking at the meso level, Horbel et al. (2016) delved into the role of context in influencing value co-creation for sport events, while, investigating the macro level, Nesse et al. (2016) recently performed an in-depth analysis of ecosystem service innovation in the field of contactless communication technologies. From this point of view, there is a strong need for further research aimed at examining how mega level dynamics shape value co-creation in service ecosystems. This is especially true when education services are concerned. In fact, there is a dearth of research adopting the ecosystem approach to explore the functioning and the outcomes of education.

This paper strives for contributing to fill this gap in the current scientific knowledge, delving into the complex and dynamic relationship which links the education service ecosystem and the work ecosystem. Going more into details, the effects of education attainments on income inequalities is investigated. It is assumed that disparities in terms of education levels pave the way for disparities in terms of work earnings. In turn, individual income is able to affect the access to education services and – consequently – to influence education levels. Sticking to these arguments, the education service ecosystem and the work ecosystem are argued to be strictly related. The following research questions inspired this paper:

R.Q. 1: Is there a relationship between education attainments and income levels? And, if so, how does education influence income inequalities?

R.Q. 2: Sticking to a service ecosystem interpretation, how could income inequalities be handled acting on education levels?

R.Q. 3: And, last but not least, are there mediating variables which could confound the relationship between education attainments and income levels?

A quantitative approach has been taken to provide a tentative answer to these research questions. In particular, drawing on the European Union Statistics on Income and Living Conditions (EU-SILC) for the period 2007-2010, a random effects model was estimated for 27 European Countries in an attempt to delve into the link between education and income inequalities. The remainder of the paper is organized as follows. The second section provides some details about the research strategy which was used to collect and analyse data. Then, the third section depicts the research findings, pointing out the relationship between education attainments and income inequalities across the European countries involved in this study. The fourth section critically discusses the findings, in light of the research questions at the basis of this paper. The fifth and concluding sections emphasizes the twofold relevance of this article which, on the one hand, contributes to advance the scientific knowledge in the field of service ecosystem and, on the other hand, suggest intriguing insights to inspire the education policies of the future.

2. Research strategy and design

This study relies on the EU-SILC data, which currently represents the main European source for comparable statistics on income distribution and living conditions at household and individual levels. The EU-SILC survey, coordinated by Eurostat, was launched in 2003 through a gentlemen's agreement in seven European countries and then extended to most of EU (and some extra-EU) States. It is a flexible instrument, aimed at promoting the idea of international comparability in each National Statistical System: for this purpose, a common framework in terms of harmonised target variables, common guidelines, classifications and procedures is established.

Sticking to the Eurostat guidelines, which suggest an integrated design, based on four-year rotational groups at least, this study is carried out in a longitudinal perspective for the period 2007-2010. The attention was focused on currently earners, observing their educational level based on International Standard Classification of Education – ISCED. Both employees and self-employed who have been continuously and successfully interviewed from 2007 to 2010 were taken into consideration, irrespective of their activity sector. They were aged minimum 18 years in 2007 and maximum 65 in 2010. If multiple jobs were held, the main job – e.g., the one with the greatest number of worked hours – was contemplated.

In this work, the potential of panel data for controlling unobserved time-invariant heterogeneity in cross-sectional models and for following the dynamics over time was exploited through a panel data regression model in which "*…very large cross sections consisting of thousands of micro-units are followed through time, but the number of periods is often quite small*" (Greene, 2003, p. 283). To handle time-invariant regressors (e.g., gender, race, place of birth), panel data regression model with random effects (Balestra and Nerlove, 1966) was performed. Allison (2009) provides perspective on the use of fixed- versus random-effects estimators. As compared with the latter, fixed effects do not allow to estimate time-invariant regressors and between the individual effects α_i and the observed covariates there is correlation. Also, random effects models are an appropriate specification if individuals are drawn randomly from a large population, which is usually the case of individual panel studies (Baltagi, 1985; 2009).

More specifically, the balanced panel model with random effects is written as:

$$\ln y_{it} = x_{it}\beta + \alpha + v_i + \varepsilon_{it} \quad t = 1,2,...,T \;\; i = 1,2,...,n \qquad [1]$$

where:

- $\ln y_{it}$ is the logarithm of gross individual income;
- x_{it} is the 1xk vector of covariates;
- α_i is the time-constant, individual-specific effect; it is also named unobserved heterogeneity and its role is to capture time-invariant unobservable effects. It is composed of two parts:
  - the first (α) is constant and independent from i and t;
  - the second (v_i), the unit-specific residual, is random and differs between units;
- ε_{it} is the disturbance term with zero mean, homoscedastic, not auto-correlated and uncorrelated with regressors and v.

Random effects models are derived under the further assumption of strict exogeneity and uncorrelation between the individual effects α_i and the observed covariates:

$$E(\varepsilon_{it}|\mathbf{X}_i, \alpha_i) = 0 \text{ .... } t = 1,2,...,T \qquad \text{and } E(\alpha_i|\mathbf{X}_i) = 0 \qquad [2]$$

The opportunity of estimating the time-invariant unobservable effects derives from the hypothesis of absence of correlation between α_i and x_{it} and, therefore, from the assumption of strict exogeneity unconditional on unobserved heterogeneity (Wooldridge, 2010; Verbeek, 2012). This is fundamental to estimate time-invariant unobservable effects, since it allows the explicit inclusion as regressors of time-invariant variables (such as gender and race). In such a way, the random effect estimator gains in efficiency. In particular, the random effect model considers all the individual effects as stochastic, even though the choice between fixed effect and random effect estimators does not rely on the different nature of individual effects (deterministic rather than stochastic), but on the hypothesis that imposes if the correlation between effects and regressors exists or not (Arellano, 2003).

Panel data models for 26 Countries are estimated through maximum likelihood random effects method, which allows to consider the personal longitudinal weights.

The log likelihood for the *i*th unit is:

$$l_i = -\frac{1}{2}\left(\frac{1}{\sigma_e^2}\left[\sum_{t=1}^{T_i}(y_{it}-x_{it}\beta)^2 - \frac{\sigma_u^2}{T_i\sigma_u^2+\sigma_e^2}\left\{\sum_{t=1}^{T_i}(y_{it}-x_{it}\beta)\right\}^2\right] + \ln\left(T_i\frac{\sigma_u^2}{\sigma_e^2}+1\right) + T_i\ln\left(2\pi\sigma_e^2\right)\right) \quad [3]$$

Basically, the maximum likelihood estimator and the random estimator yield the same results, except when total $N = \Sigma_i T_i$ is small (200 or less) and the data are unbalanced, but in this analysis we have more than 2000 individuals and panels built are all strongly balanced. In brief, the consistency of model estimation depends on the hypothesis of orthogonality between individual effects (α_i) and observed explanatory variables (x_{it}). This means that all regressors are assumed to be exogenous. The individual effects (α_i) are treated as a random variable that adds to error terms ε_{it}.

Finally, yet importantly random effects models control for "individual heterogeneity" (Hsiao, 2003), that is the variability across individuals (*between*) and the variability over time (*within*). Hence, these models allow to estimate the coefficients of the regressors that do not vary at all over time (null within variation) and to measure, with no efficiency loss, the effects of regressors that display a small within variation, such as education levels, the key explanatory variable in this analysis.

3. Findings

As anticipated in the previous section, panel data models, with the (log of) gross individual income as dependent variable, were estimated through the maximum likelihood random effects method, which allowed to consider personal longitudinal weights. The semi-log functional form was informed by Mincerian human capital models, extended to other explanatory variables (Mincer, 1958; 1974). The analysis of personal income disparities was motivated by the interest to explain the determinants of inequality in the individual capacity to earn income, regardless of how such resources are obtained and how individuals share them within own household (Manna & Regoli, 2012). The main aim was to shed light on the rate of schooling return for European Countries according to an ecosystem perspective.

Going more into details, random effects models, separately estimated for 26 European Countries, were conceived as income-generating models tested on a range of personal characteristics (gender, marital status, consensual union, age, general health), human capital (educational attainment, ISCED97) and job background variables, namely employment status (self-employed vs employee), employment contract (full-time vs part-time) and occupation types (ISCO-88) scaled according to skill levels.

As reported in Table 1, X^2-values, with degrees of freedom equal to the number of restrictions, confirm the statistical significance of regressions. In the same way, the high values of "chibar2" of likelihood-ratio (LR) tests, which compare the ordinary linear regression model (without individual effects) and the model with random effects, denote that both random effects models, for the European Countries included in this study significantly take into account the set of characteristics which distinguish each individual: the random effect in all models are significant.

Table 1. Random effects models' estimation by European Countries

Country	Variable:	Coefficients	Std Err	Model Results	Random Effects
Austria (AT)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1583***	(0.0013)	N=3332; T=4; LR test of sigma_u=0:	Sigma_u=0.5129*** (0.0005)
	High (ISCED97: 5, 6)	0.3386***	(0.0016)	chibar2(01)=6.7e+05 *p-value*= 0.0000	Sigma_e=0.8478*** (0.0002)
	Gender:(1 if *male*)	0.5864***	(0.0010)	LR chi2 (16)= 833671.82 *p-value*=0.0000	rho= 0.2680*** (0.0004)
Belgium (BE)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.0150***	(0.0011)	n=3,474; T=4; LR test of sigma_u=0:	Sigma_u= 0.3740***(0.0005)
	High (ISCED97: 5, 6)	0.3482***	(0.0013)	chibar2(01)=2.1e+05 p-value=0.000	Sigma_e)=0.9774***(0.0003)
	Gender:(1if *male*)	0.4184***	(0.0008)	LRchi2(16)=806263.52 p-value=0.000	rho= 0.1277***(0.0003)
Bulgaria (BG)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.2110***	(0.0009)	n=2,259; T=4; LR test of sigma_u=0:	Sigma_u= 0.3409***(0.0005)
	High (ISCED97: 5, 6)	0.2673***	(0.0014)	chibar2(01)=1.5e+05 p-value=0.000	Sigma_e= 0.9023***(0.0003)
	Gender:(1if *male*)	0.4072***	(0.0018)	LRchi2(16)=84298.33 p-value=0.000	rho= 0.1249***(0.0004)
Cyprus (CY)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1722***	(0.0041)	n=2,854; T=4; LR test of sigma_u=0:	Sigma_u= 0.6935***(0.0012)
	High (ISCED97: 5, 6)	0.5230***	(0.0053)	chibar2(01)=5.4 e+05 p-value=0.000	Sigma_e= 0.4789***(0.0004)
	Gender:(1if *male*)	0.5843***	(0.0034)	LRchi2(14)=102133.77 p-value=0.000	rho= 0.6771***(0.0009)
Czech Republic (CZ)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.3314***	(0.0015)	n=6, 684; T=4; LR test of sigma_u=0:	Sigma_u= 0.5079***(0.0003)
	High (ISCED97: 5, 6)	0.6835***	(0.0018)	chibar2(01)=5.4 e+05 p-value=0.000	Sigma_e= 0.6478***(0.0001)
	Gender:(1if *male*)	0.3588 ***	(0.0007)	LRchi2(16)= 931212.86 p-value=0.000	rho= 0.3807***(0.0003)
Denmark (DK)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0. 0964***	(0.0027)	n=1,976; T=4; LR test of sigma_u=0:	Sigma_u= 0. 8651***(0. 0008)
	High (ISCED97: 5, 6)	0. 1045***	(0.0033)	chibar2(01)=7.3 e+05 p-value=0.000	Sigma_e= 1. 1279***(0. 0004)
	Gender:(1if *male*)	0. 0826 ***	(0.0021)	LRchi2(14)= 162625.17 p-value=0.000	rho= 0. 3704***(0. 0005)
Estonia (EE)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.0540***	(0.0041)	n=2,996; T=4; LR test of sigma_u=0:	Sigma_u= 0.4265***(0.0015)
	High (ISCED97: 5, 6)	0.0050***	(0.0053)	chibar2(01)=2.9 e+04 p-value=0.000	Sigma_e= 1.0017***(0.0008)
	Gender:(1if *male*)	0.0028***	(0.0034)	LRchi2(15)=185044.63 p-value=0.000	rho= 0.1535***(0.0010)
Finland (FI)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1632***	(0.0029)	n=2,540; T=4; LR test of sigma_u=0:	Sigma_u= 0.7619***(0.0007)
	High (ISCED97: 5, 6)	0.5316***	(0.0031)	chibar2(01)=1.2 e+06 p-value=0.000	Sigma_e= 0.6914***(0.0003)
	Gender:(1if *male*)	0.2630***	(0.0019)	LRchi2(15)=486766.41 p-value=0.000	rho= 0.5484***(0.0005)
France (FR)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1838***	(0.0002)	n=4,003; T=4; LR test of sigma_u=0:	Sigma_u= 0.8414***(0.0001)
	High (ISCED97: 5, 6)	0.4882***	(0.0003)	chibar2(01)=1.4 e+08 p-value=0.000	Sigma_e= 0.8141***(0.0000)
	Gender:(1if *male*)	0.4773***	(0.0002)	LRchi2(16)=3.39e+07 p-value=0.000	rho= 0.5165***(0.0000)

Greece (GR)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.3576***	(0.0013)	n=3,460; T=4; LR test of sigma_u=0:	Sigma_u= 0.7888***(0.0004)
	High (ISCED97: 5, 6)	0.5264***	(0.0019)	chibar2(01)=2.8 e+06 p-value=0.000	Sigma_e= 0.8496***(0.0002)
	Gender:(1if *male*)	0.6315***	(0.0012)	LRchi2(16)=1.45e+06 p-value=0.000	rho= 0.4629***(0.0003)
Hungary (HU)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1670***	(0.0009)	n=5022; T=4; LR test of sigma_u=0:	Sigma_u= 0.3864***(0.0003)
	High (ISCED97: 5, 6)	0.5290***	(0.0013)	chibar2(01)= 1.4e+06 p-value=0.000	Sigma_e= 0.5019***(0.0001)
	Gender:(1if *male*)	0.2153***	(0.0007)	LRchi2(16)= 953145.10 p-value=0.000	rho= 0.3722***(0.0004)
Iceland (IS)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.0322***	(0.0043)	n=1906; T=4; LR test of sigma_u=0:	Sigma_u= 0.4081***(0.0016)
	High (ISCED97: 5, 6)	0.0251***	(0.0052)	chibar2(01)= 4.2e+04 p-value=0.000	Sigma_e= 0.5670***(0.0008)
	Gender:(1if *male*)	0.4067***	(0.0058)	LRchi2(15)= 39953.55 p-value=0.000	rho= 0.3413***(0.0020)
Italy (IT)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1942***	(0.0005)	n=2981; T=4; LR test of sigma_u=0:	Sigma_u= 0.5435***(0.0002)
	High (ISCED97: 5, 6)	0.4705***	(0.0008)	chibar2(01)=3.8 e+06 p-value=0.000	Sigma_e= 0.9763***(0.0001)
	Gender:(1if *male*)	0.4175***	(0.0004)	LRchi2(15)=4.23e+06 p-value=0.000	rho= 0.2633***(0.0001)
Lithuania (LT)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.5284***	(0.0043)	n=3,357; T=4; LR test of sigma_u=0:	Sigma_u= 0.8329***(0.0010)
	High (ISCED97: 5, 6)	0.8302***	(0.0048)	chibar2(01)=3.2 e+05 p-value=0.000	Sigma_e= 1.2602***(0.0005)
	Gender:(1if *male*)	0.5936***	(0.0023)	LRchi2(16)=408254.57 p-value=0.000	rho= 0.3031***(0.0006)
Luxembourg (LU)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1911***	(0.0039)	n=3,357; T=4; LR test of sigma_u=0:	Sigma_u= 0.4667***(0.0016)
	High (ISCED97: 5, 6)	0.3788***	(0.0058)	chibar2(01)= 4.7e+04p-value=0.000	Sigma_e= 0.7710***(0.0009)
	Gender:(1if *male*)	0.4919***	(0.0036)	LRchi2(16)= 78306.82 p-value=0.000	rho= 0.2681***(0.0014)
Latvia (LT)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.2699***	(0.0037)	n=2,590; T=4 LR test of sigma_u=0:	Sigma_u= 0.5972***(0.0010)
	High (ISCED97: 5, 6)	0.6265***	(0.0046)	chibar2(01)=1.6 e+05 p-value=0.000	Sigma_e= 0.9911***(0.0006)
	Gender:(1if *male*)	0.3481***	(0.0026)	LRchi2(16)=235692.34 p-value=0.000	rho= 0.2664***(0.0008)
Malta (MT)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.3721***	(0.0048)	n=2,192; T=4; LR test of sigma_u=0:	Sigma_u= 0.4715***(0.0024)
	High (ISCED97: 5, 6)	0.2243***	(0.0054)	chibar2(01)= 1.5e+04 p-value=0.000	Sigma_e= 1.0283***(0.0013)
	Gender:(1if *male*)	0.4735***	(0.0070)	LRchi2(10)= 29539.38p-value=0.000	rho= 0.1737***(0.0016)
Netherland (ND)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1097***	(0.0021)	n=4,323; T=4; LR test of sigma_u=0:	Sigma_u= 0.9838***(0.0004)
	High (ISCED97: 5, 6)	0.4970***	(0.0024)	chibar2(01)=3.1 e+06 p-value=0.000	Sigma_e= 0.9920***(0.0002)
	Gender:(1if *male*)	0.4741***	(0.0016)	LRchi2(16)=377069.99 p-value=0.000	rho= 0.4958***(0.0002)
Norway (NO)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.0470***	(0.0020)	n=5,368; T=4; LR test of sigma_u=0:	Sigma_u= 0.5492***(0.0004)
	High (ISCED97: 5, 6)	0.1225***	(0.0023)	chibar2(01)=7.8 e+05 p-value=0.000	Sigma_e= 0.7044***(0.0002)
	Gender:(1if *male*)	0.3847***	(0.0014)	LRchi2(16)= 408488.32 p-value=0.000	rho= 0.3781***(0.0004)

Poland (PL)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.7335***	(0.0020)	n=9,155; T=4; LR test of sigma_u=0:	Sigma_u= 1.3651***(0.0004)
	High (ISCED97: 5, 6)	1.2164***	(0.0024)	chibar2(01)=1.3e+07 p-value=0.000	Sigma_e= 1.2874***(0.0002)
	Gender:(1if *male*)	0.7875***	(0.0010)	LRchi2(16)=6.79e+06 p-value=0.000	rho= 0.5292***(0.0002)
Portugal (PT)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.2217***	(0.0016)	n=3,036; T=4; LR test of sigma_u=0:	Sigma_u= 0.9257***(0.0005)
	High (ISCED97: 5, 6)	0.6978***	(0.0024)	chibar2(01)=2.5e+06 p-value=0.000	Sigma_e= 0.9625***(0.0002)
	Gender:(1if *male*)	0.4725***	(0.0014)	LRchi2(16)=1.24e+06 p-value=0.000	rho= 0.4805***(0.0003)
Romania (RO)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	N/F	N/F	n=6,032; T=4; LR test of sigma_u=0:	Sigma_u= 1.0037***(0.0003)
	High (ISCED97: 5, 6)	N/F	N/F	chibar2(01)=6.8e+06 p-value=0.000	Sigma_e= 1.1013***(0.0002)
	Gender:(1if *male*)	0.6174***	(0.0009)	LRchi2(7)=4.78e+06 p-value=0.000	rho= 0.4537***(0.0002)
Spain (SP)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1242***	(0.0008)	n=8,614; T=4; LR test of sigma_u=0:	Sigma_u= 0.7342***(0.0001)
	High (ISCED97: 5, 6)	0.3016***	(0.0009)	chibar2(01)=1.6e+06 p-value=0.000	Sigma_e= 1.6993***(0.0002)
	Gender:(1if *male*)	0.3544***	(0.0008)	LRchi2(16)= 7.17e+06p-value=0.000	rho= 0.1573***(0.0004)
Sweden (SE)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1923***	(0.0027)	n=3,142; T=4; LR test of sigma_u=0:	Sigma_u= 0.9516***(0.0006)
	High (ISCED97: 5, 6)	0.0221***	(0.0030)	chibar2(01)=3.6e+06 p-value=0.000	Sigma_e= 0.6528***(0.0002)
	Gender:(1if *male*)	0.1919***	(0.0017)	LRchi2(16)=251222.23 p-value=0.000	rho= 0.6799***(0.0003)
Slovenia (SL)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1138***	(0.0031)	n=2,524; T=4; LR test of sigma_u=0:	Sigma_u= 0.3886***(0.0008)
	High (ISCED97: 5, 6)	0.5023***	(0.0039)	chibar2(01)=2.5e+05 p-value=0.000	Sigma_e= 0.3651***(0.0003)
	Gender:(1if *male*)	0.3217***	(0.0020)	LRchi2(16)=151719.26 p-value=0.000	rho= 0.5312***(0.0011)
Slovak Republic (SR)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.0891***	(0.0040)	n=5,443; T=4; LR test of sigma_u=0:	Sigma_u= 0.5431***(0.0006)
	High (ISCED97: 5, 6)	0.0030***	(0.0042)	chibar2(01)=3.9e+05 p-value=0.000	Sigma_e= 1.0701***(0.0003)
	Gender:(1if *male*)	0.4078***	(0.0013)	LRchi2(16)=373589.08 p-value=0.000	rho= 0.2048***(0.0004)
United Kingdom (UK)	**Education (ref: low, ISCED97: 1;2)**				
	Medium (ISCED97: 3;4)	0.1079***	(0.0008)	n=3,743; T=4; LR test of sigma_u=0:	Sigma_u= 0.5659***(0.0002)
	High (ISCED97: 5, 6)	0.4442***	(0.0009)	chibar2(01)= 6.29e+06 p-value=0.000	Sigma_e= 1.1434***(0.0001)
	Gender:(1if *male*)	0.5504***	(0.0006)	LRchi2(16)= 2.4e+06 p-value=0.000	rho= 0.1968***(0.0001)

**** significant at 1%*

Source: Authors' elaboration

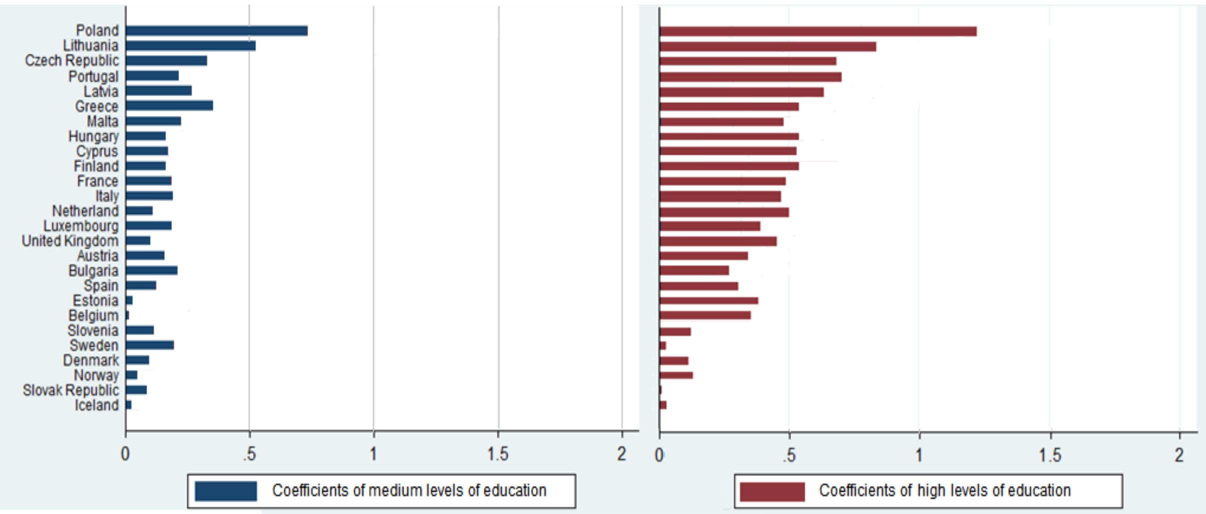
The data included in Table 1 are summarized in Figure 1, which provides a snapshot of the coefficients of random effects models' estimation for mediums and high education levels. Firstly, it is worth noting that, in general, the coefficients of high education levels are higher ass compared with medium education levels. This confirms that better education paves the way for greater work-related earnings. Moreover, in all cases, medium education levels show positive correlates with income, suggesting that education performs as an important determinant of income inequalities. It is possible that education mixes its effects on income levels with gender, which was found to be an important co-determinant of income inequalities in the European Countries.

Interestingly, European countries may be categorized in four groups according to the role played by education in generating income inequalities. A first group of European countries – including Poland, Lithuania, Czech Republic, Portugal, Latvia, and Greece – reveals higher correlates, ranging from 0.22 for medium education levels to 1.22 for high education levels. In these countries, people living with medium levels of education are likely to earn an income which is a quarter higher as compared with people with basic education; alternatively, those with higher education could earn an average an income which is about 120% greater as compared with low educated people.

Malta, Hungary, Cyprus, Finland, France, and Italy showed medium-high correlates. In these cases, the effect of education on work-related incomes was found to be still relevant, but weaker, ranging from 0.17 for medium education levels to 0.53 for high education levels. Netherland, Luxembourg, United Kingdom, Austria, Bulgaria, Spain and Estonia seemed to suffer less from income inequalities generated by education levels. In fact, correlates ranged from 0.05 for medium education levels to 0.38 for high education levels. These results suggested that countries belonging to the second and the third groups succeeded to implement ecosystem interventions at the meso and macro levels, aimed at contrasting the effects of education on work-related income.

Lastly, Belgium, Slovenia, Sweden, Denmark, Norway, Slovak Republic and Iceland were included among the virtuous European countries: the role of education in anticipating income inequalities was found to be quite weak, ranging from 0.01 for medium education levels to 0.35 for high education levels. It could be maintained that this was the consequence of tailored policies implemented at the mega, macro, and meso levels, in an attempt to reduce the gap in terms of work-related earnings between highly educated people and their lowly educated counterparts.

Figure 1. Coefficients of medium and high education levels



Source: Authors' elaboration

4. Discussion

The service ecosystem perspective allows to shed light on the relationships between individual education attainments and income inequalities. Going more into details, sticking to the service ecosystem theoretical framework, the education level may be conceptualized as a micro-level variable, which is able to affect the individual behaviors and, consequently, to influence direct dyadic relationship between different actors who operate within the ecosystem. In turn, education attainments shape interactions at the meso level; among others, employment could be conceived as a meso-level variable, since it involves both dyadic (employee-employer) and triadic (user-employee-employer) relationships. Obviously, the better the knowledge, skills and attitudes of the employee, the greater his or her own ability to obtain a higher income within the work market, which is a macro-level area of the ecosystem. In fact, it relies on complex networks of relationships, based on common norms and values. From this point of view, a link between education levels and employment opportunities could be envisaged. People with higher education attainments are considered to show a greater ability to navigate the ecosystem and to achieve better employment opportunities. It follows that the better the employment opportunities, the higher the individual income.

The research findings support these arguments, pointing out that a statistically significant relationship exists between education attainments and income. Even though this was true for all the European Countries involved in the research, several peculiarities could be figured out. In several countries, such as Poland and Lithuania, education attainments have been found to explain strong income inequalities within the ecosystem (Checchi, Peragine & Serlenga, 2010). Such inequalities have been stressed by the inability to intervene at the mega ecosystem level to counteract the consequences of inadequate education on income. In other circumstances (*i.e.* Italy and Finland), education levels are still likely to produce significant income differences; however, it seems that they are slightly constrained by interventions at the mega level, which are intended to relieve income inequalities through social cushions (Goeslin, 2001).

Some Western European Countries, including Netherland and UK, were found to be able to contain income inequalities produced by education levels. However, they showed strong inequalities when differences between people reporting either higher or medium education levels as measured by the ISCED scale and those living with poor education were concerned. In other words, their macro-level intervention were effective, but unable to prevent income inequalities when people living with pre-primary and primary education levels were concerned (Brown & Tannock, 2009). Lastly, in several cases (*i.e.* Scandinavia Countries) macro-level interventions were effective in preventing income inequalities produced by education attainments. In this circumstance, it seemed that social interventions were aimed at addressing the root causes of income inequalities generated by education levels: both social and individual initiatives have been argued to be useful in an attempt to minimize the side-effects of basic education (Huijts, Eikemo & Skalickà, 2010).

Gender was found to perform as an important co-determinant of income inequalities in all of the Countries included in this study. Indeed, men were likely to show a higher income than women did; in particular, the gap ranged between 20% and 79%. Only in two circumstances, namely Denmark and Estonia, gender did not perform as a relevant and significant co-determinant of income inequalities. In light of these considerations, the role of gender in confounding the effects of education levels on income inequalities should be investigated in depth, in an attempt to illuminate how gender and education concur in generating inequalities.

5. Conclusions

Education outcomes should not be conceived as a province of the education system. The adoption of an ecosystem perspective induces to discuss the effects of education attainments on other ecosystem variables, including – *inter alia* – employment and incomes. The findings of this research emphasizes that education attainments are able to deeply affect the individual work opportunities and, consequently, to influence income levels. Even though other variables – such as gender – may confound the relationship between education and income, it seems that the former performs as a significant and strong determinant of income inequalities in all European Countries.

Drawing on these considerations, a rethinking of education according to a service ecosystem perspective is required. In light of the link existing between education levels and income, policy makers should implement appropriate cushions, aimed at containing the effects of education levels on disparities. This is crucial to improve the individual and collective well-being, since income inequalities themselves could pave the way for health and social inequalities.

There is a strong need for further developments, aimed at better explaining the relationship between education and income inequalities and at conceptualizing education services through an ecosystem perspective. On the one hand, panel studies may provide more intriguing and reliable evidence on the interplay between education and income inequalities. On the other hand, a grand theory intended to figure out the role of education within a complex ecosystem may be crucial to arrange the steps forward to enhance the scientific knowledge in the field of service ecosystems.

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