Decomposing Income Inequality by Education in Romania

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ABSTRACT

As long as education is not consolidated a sustainable society no longer grows. All components of education are of most importance when analysing their contributions to wage inequalities in Romania. Decomposition analysis is an essential tool that provides insights into the social dimension of income inequality. The current study aims to explore the role of education and its influence in the decomposition of income inequality in Romania, by using both multivariate regression-based and Theil decomposition. First, to measure the inequality in the distribution of individual income, Gini index, two Theil indices and Variance of log are used. Then, a multivariate regression-based decomposition function is applied on the dataset. As a well-known econometric measure of investigating economic inequality, due to its properties, the Theil index is employed to decompose both overall income inequality in Romania into the between and within components and furthermore by Education. The data subset relies on the UK Data Service collection - European Working Conditions Survey for 2015. The analysis reveals consistent results for the computed indices. The Theil decomposition analysis results regarding the income inequality in Romania indicate that by the attained level of education the main contributing groups to the inequality are people with medium education and high education. The group of people with high education contributed with 40% to the inequality while for Theil L. decomposition the same group contributed with 28.72%. These findings are also consistent with the fact that a higher level of education is better rewarded.

Keywords: *Romania, Theil index, entropy, group inequality, decomposition*
JEL Classification: *C1, J7*

1. INTRODUCTION

Access to equal income opportunities is an essential dimension of residential differentiation in the context of population dynamic and social change, presenting new global challenges. The interplay between population growth, family structure and education will create potential income imbalances for the Europe population over the coming decades (Guerin, 2013).

Many research studies conclude that the rise in income inequality is mainly due to the increase of two driving factors: earnings inequality and the number of single-mother families (Cholezas and Panos, 2007; Kollmeyer, 2013). Earnings inequality increases as a reward for educational certifications, work experience and digital skills, required for the new jobs where new technologies, automatization, robotics and communication tend to replace traditional working (Cholezas and Panos, 2007; Castellano, 2017). In respect to the second factor, the observed increase in single-mother families has altered the income distribution (Kollmeyer, 2013). These social changes in family structure heightens income inequality in the long run. Findings across countries reveal that single-parent households are at greater risk of poverty than households with regular families (Brady and Burroway, 2012; Maldonado and Nieuwenhuis, 2015). Moreover, Maldonado and Nieuwenhuis (2015) point out that single mothers are more likely to be poor than single fathers. In the past decade, European economies experienced changes in labour market conditions (Huber, 2007) and in population patterns (Botev, 2012; Gerőházi et al., 2011) due to the accelerating economic requirements and due to the global Great Recession started in autumn 2007 (Cho, and Newhouse, 2013). According to Matysiak et al. (2021), it is seen a fertility decline strongly corelated to unemployment increase. Therefore, as the crisis impacts the economic performance, youth unemployment rate increases (Cho, and Newhouse, 2013; OECD, 2013), with mixed results for young adult workforce in Europe (O'Higgins, 2012). Crises in the past millennia had a periodic occurrence affecting independently different parts of the world. With the increase in the interdependence between the major global regions the resiliency to crises shifted to the lower end, requiring increased efforts. Furthermore, the emergency measures and lockdowns based on social distancing to contain the spread of COVID-19, contributed to the rise in the wage inequality and poverty in all European countries (Palomino et al., 2020) with grater increases in Eastern and Southern Europe. In this respect, the authors highlight an increase in the average of Gini coefficient and underline that lockdowns contributed to the rise in inequalities both between and within countries.

Paulus and Tasseva (2017) emphasize that changes in population characteristics and market income increase poverty and inequality in EU countries. In addition, their results indicate that one of the largest inequality-reducing policy effects is in Romania. There are however still limited studies in the inequality of income distribution and its decomposition in Romania. One of the most popular inequality indexes, from the class of generalized entropy indexes, developed by the economist Henri Theil (1967) measures inequality of population between groups. Andrei et al. (2017) conducted a study on the inequality of income distribution by the source of income at the country level in Romania. Their results showed significant differences in the income distribution of the three sources of income: wages, capital income, and other sources. Also, using income tax data, Oancea et al. (2018) highlight that the capital income is Pareto distributed in the upper tail. Moreover, decomposition analysis studies for Romania identify education, labour market status (Molnar, 2010) and remittances (Zamfir et al., 2010) as divers for income inequalities. In their study, Militaru and Stanila (2015) investigate the income inequality determinants in Romania. Education and status in employment are amongst the main determinants of income variability between households. However, the increased prevalence of single-mother families is only one of the major changes in the structure of the family over the years. It is well known that in Romania, mothers tend to have lower earnings compare to childless women (Glăvan, 2018). Such changes in the dynamic of the population add burden to the overall income inequalities between countries.

The aim of this research is to explore the role of education and its influence in the decomposition of income inequality in Romania. The present study adds knowledge in the literature by analysing the decomposition of individual net monthly income from main paid job using data for 2015 in Romania. In particular, a multivariate regression-based decomposition method is used to estimate the inequality contribution of variables included in the model. Socio-demographic factors, such as area of residency, age and education level are analysed for their impact on the income inequality. Furthermore, Theil indices are introduced through their belonging in the general entropy family and their decomposition into two components, one referring to the between groups and the other to the within groups part.

2. METHODOLOGY AND DATA

In this modelling study, microdata from UK Data Service collection (Eurofound, 2017), is used to examine the differences in income levels and inequality between individuals in Romania. A selection from the original dataset is carried out and several variables are computed mapping the employed work force, between 18 to 63 years of age. This selection includes the following variables depicted in Table 1.

Although there are a multitude studies following techniques that measure inequality, such as Lorenz curves, Blinder-Oaxaca decomposition (Glăvan, 2016), Generalized Entropy indices (Andrei et al.,2017), Atkinson indices (Atkinson, 2005; Gradín, 2020) and other scalar transformations. The Generalized Entropy decompositions class, and more specifically through Theil L. and Theil T. indexes, are of interest in the present study due to their straight interpretation and their additively decomposable measures (Shorrocks 1980) for which inequality is the sum of inequality between groups and the weighted sum of inequality within groups.

The widely used Gini coefficient proposed by Corrado Gini in 1912 ranks income distribution on a scale theoretically from 0 to 1, where 0 denote total equality of income and 1 total inequality. In respect to the General Entropy Indexes - $GEI(\alpha)$, two popular members of its class are: $GEI(0)$ -Theil L. or mean logarithmic deviation and $GEI(1)$ or Theil T. index. In addition to these measures, the variance of log income is another useful tool to measure income inequality.

Defined variables

Table 1

Variable name	Definition
wage	Wage in national currency [RON]
weights	Population weights
age_cat	Age (categorical), with levels: <25, 25-34, 35-44, 45-54, >=55
education_cat	Number of years in school, factor with levels: Low education, Medium education, High education
area_cat	Area, factor with levels: urban, rural
sex	Factor with levels: woman, man

The Theil index is an inequality measure, and its principle is related to the generalised entropy indices to calculate inequality or difference (Bellù and Liberati, 2006). Compared to the widely used Gini coefficient, the Theil index is decomposable, and therefore can be linked on the source of the inequalities. When the parameter α, driving the weights given to distances between cases in different parts of a distribution for the generalized entropy, is 1, it is obtained Theil's first measure or commonly known "Theil T.". When α takes the value of 0, Theil's second measure of inequality is obtained, also known as "Theil L." or the mean log deviation. Furthermore, with α taking the value of 2, the measure is called coefficient of variation.

Partitioning a population into $K \geq 1$ disjoint groups with *k* referring to *k*-th group, each group of population size n^k and mean income (wage) μ^k has a distribution of $y^k = \left(y_1^k, \dots, y_{n^k}^k\right)$ and *i* identifies the *i*-th individual of vector *y*. According to Shorrocks (1980) the Generalised Entropy family $I_\alpha(y)$ is written as:

$$GEI(\alpha) = I_\alpha(y) = \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\mu}\right)^\alpha - 1\right] \quad (1)$$

with $w_{I_\alpha}^k$ as index specific weights being a function of group population shares n^k/n and relative wages μ^k/μ.

$$w_{I_\alpha}^k = \frac{n^k}{n}\left(\frac{\mu^k}{\mu}\right)^\alpha \quad (2)$$

With $\alpha = 0$, Mean log deviation or Theil L. index (Theil, 1967) is defined as:

$$I_0 = T_L = \frac{1}{n}\sum_{i=1}^{n} ln\frac{\mu}{y_i} \qquad (3)$$

with its index specific weights $w_{I_0}^k = \frac{n^k}{n}$.

For $\alpha = 1$, it should be noted that the Theil T. index or the first measure (Theil, 1967) is defined as:

$$I_1 = T_T = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i}{\mu} ln\frac{y_i}{\mu} \qquad (4)$$

with its index specific weights $w_{I_1}^k = \frac{n^k}{n}\frac{\mu^k}{\mu}$, where *n* is the population size, y_i is the income or wage of the individual *i*, μ is the overall mean wage of the population.

Both Theil L. and Theil T. indices can be decomposed into 2 parts, between-group $(T_b\ or\ L_b)$, and within-group $(T_w\ or\ L_w)$, components. The first term, $(T_b\ or\ L_b)$, captures the inequality of distribution of population incomes due to the differences of income distribution existing between the disjoint groups, while the second term, $(T_w\ or\ L_w)$, measures the inequality of income distribution as a result of the differences in the distribution of incomes within the disjoint groups of population.

Equations (5) and (6), further reflect both Theil T. and Theil L. decomposition (Akita, 2003; Liao, 2019):

$$T_T = T_b + T_w = \sum_{k=1}^{K} w_k ln\frac{\mu_k}{\mu} + \sum_{k=1}^{K} w_k \sum_{n=1}^{n_k} w_{ik} ln\frac{y_{ik}}{\mu_k} \qquad (5)$$

where μ_k or μ^k is the mean income of disjoint group *k*, w_k is the *k*-th group's income share represented as a proportion of sample or population total income, w_{ik} is the income share of the *i*-th individual in the *k*-th group, and y_{ik} is the *i*-th individual's income in group *k*.

$$T_L = L_T = L_b + L_w = \sum_{k=1}^{K} n_k ln\frac{\mu}{\mu_k} + \sum_{k=1}^{K} n_k \sum_{n=1}^{n_k} n_{ik} ln\frac{\mu_k}{x_{ik}} \qquad (6)$$

where n_k or n^k represents *k*-th group's group size proportion of the overall sample and respectively, n_{ik} is the proportion of the *i*-th case out of the *k*-th group.

Generalised Entropy family indices are more sensitive to differences in income shares among the poor or among the rich depending on the α parameter defining the $GEI(\alpha)$. The lower the α parameter value the more sensitive the index is to the differences at the bottom of the distribution (Jenkins and Van Kerm, 2008). Among the two indices Theil L. is known to be more sensitive to income differences in the lower end of the distribution with better decomposability properties, while Theil T. is more sensitive to the differences in the top end of the distribution. Therefore, a smaller Theil index denotes a smaller degree of inequality, and vice versa (Gradín, 2020).

In the present research the income inequality is computed using four different popular indexes: Gini, Theil L., Theil T. and variance of log income. To further inspect income inequality a regression-based decomposition method is applied following the methodology covered by Fields (2003) and Brewer and Wren-Lewis (2016).

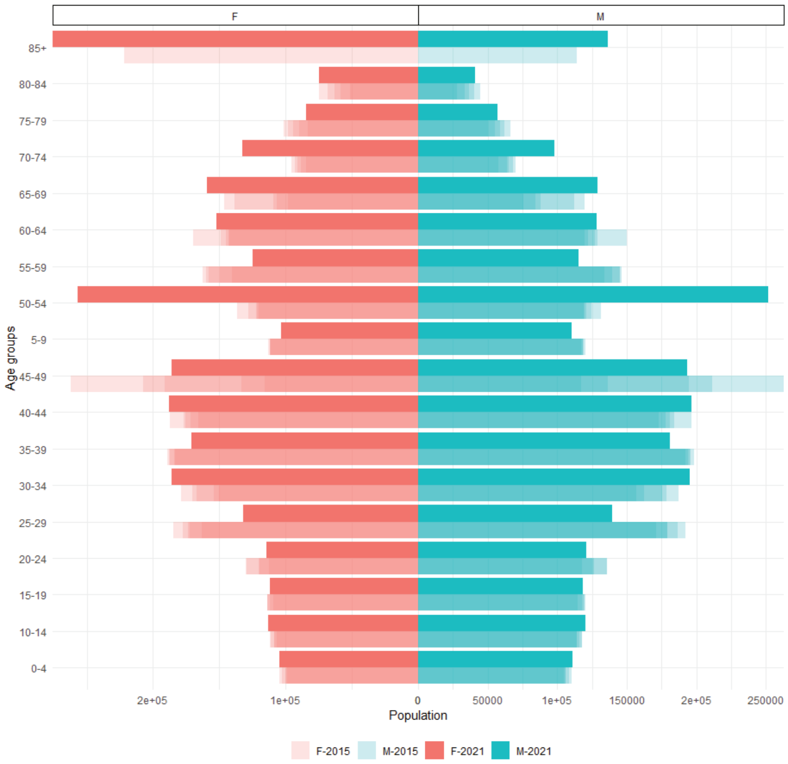
The analysis is performed using R software packages “dineq” (Schulenberg, 2018) and “IC2” (Plat, 2012). The regression-based decomposition method incorporates multiple variables to compute each variable’s contribution to the wage inequality. Socio-economic along with demographic and territorial characteristics (such as. education, age, area and sex) of individuals are added to the function. A key feature of this method is its usage of value logarithmic transformation in the dependent variable, thus, only non-zero values are kept. The decomposition of both Theil L. and Theil T. indices follow the mathematical framework covered by Cowell (2000) and Elbers et al. (2005).

3. RESULTS

Using data provided by Romania NIS, Figure 1 shows that the share of population aged 65 and over was rising in 2021 compared to 2015, while the population under 25, respectively the working-age population is decreasing.

Population pyramid by age group and sex (in thousands), Romania in 2015 and 2021

Figure 1



Source: designed by the author based on data provided by the Romania NIS online database

Furthermore, the old-age dependency ratio is rising from 25.2 percent in 2015 to estimated 29.7 percent in 2021 (Eurostat, 2022a). Under the base line scenario, the old-aged dependency ratio is projected to rise at 57.8 percent by 2100 (Eurostat, 2022b). These changes in the structure of population foretell abrupt changes in the distribution of wages, thus increasing the burden of existing inequalities.

Table 1 illustrates, based on individual monthly income, the results for the inequality measured by four indices.

Results of the of 4 inequality measures

Table 1

Inequality measures	Gini	Theil L. (Mean log dev.)	Theil T.	Variance of log
Values	0.2640	0.1138	0.1296	0.2030

Source: designed by the author based on EWCS 2015 selection data

Considering the case when individuals are grouped according to several variables such as age, sex, area, educational level. Table 2 presents the decomposition of the inequality into the selected variable with education highlighting its main contribution.

The (relative) decomposition of the inequality into the different variables

Table 2

Variables	Age	Education	Area	Sex	Residual
Values	0.0098	0.1977	0.0596	0.0847	0.6482

Source: designed by the author based on EWCS 2015 selection data

To conclude this section, Table 3 helps in understanding the Ordinary Least Squares (OLS) estimates from the fitted regression equation used to decompose wage inequality.

OLS regression estimation used in the decomposition of inequality

Table 3

Variable	Estimate	Standard Error
intercept	7.04023***	0.06780
Age 25-34	0.14851*	0.05983
Age 35-44	0.18532**	0.05768
Age 45-54	0.17457**	0.05831
Age >=55	0.14310*	0.06596
Low education	-0.64735***	0.06704
Medium education	-0.40929***	0.03515
Urban area	0.20748***	0.03038
Masculine	0.27938***	0.02833

*Source: designed by the author based on EWCS 2015 selection data; Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Next, with equations (5) and (6) the overall degree of the inequality of wage distribution is explored through its two components, the within-group inequality and the difference between the groups of population. Furthermore, computing both Theil T. and Theil L. decomposition, the results of the wage distribution for the three disjoint groups categorized by the educational level are presented in Table 4.

Theil indices and decomposition by education for Romania

Table 4

Education	Theil T.	Theil L.
Within-Educational Groups		
Low education	0.06	0.06
(% Contrib.)	(1.70)	(2.97)
Medium education	0.08	0.07
(% Contrib.)	(35.92)	(44.39)
High education	0.14	0.12
(% Contrib.)	(40.48)	(28.72)
Decomposition		
Within-Educational Groups	0.10	0.09
(% Contrib.)	(78.10)	(76.08)
Between-Educational Groups	0.03	0.03
(% Contrib.)	(21.90)	(23.92)
Total	0.13	0.11

Source: designed by the author based on EWCS 2015 selection data; % Contrib. is the share contribution of each group to the overall inequality.

Theil decomposition analysis by the attained level of education shows that the main contributing groups to the inequality are people with medium education and high education. The group of people with high education contributed with 40% to the inequality while for Theil L. decomposition the same group contributed with 28.72%. This contribution occurs through within-group component which contributes with 78.10% to the total inequality for Theil T. and 76.08% for Theil L. Educational groups with low education, on the contrary, contributed marginally to inequality with 1.7%.

4. CONCLUSIONS

In this research income inequality in Romania is computed based on a subset of microdata from UK Data Service collection. New perspectives linking the importance of education is revealed through analysing the decomposition of income inequality in the country.

First, to measure overall wage inequality four well known indices, Gini, Theil L., Theil T and Variance of log are computed. Second, the data are analysed using a multivariate regression-based decomposition method. As a result, education has the main contribution to the income inequality in Romania.

Next, using entropy class techniques, an individual-based decomposition of inequality applying Theil T and Theil L measures is performed. The two parts of inequality given by the between-group and within-group components are revealed. The first component, T_b with abs. value 0.03 and contribution 21.90% or L_b with same abs. value and 23.90% contribution, known also as the between-groups inequality term, captures the inequality of distribution of population incomes due to the differences of income distribution existing between the disjoint groups. The second component, T_w with abs. value 0.10 and contribution 78.10% or L_b with abs. value 0.09 and 76.08% contribution, noted as within-group term, measures the inequality of income distribution as a result of the differences in the distribution of incomes within the disjoint groups of population. Although the results for Theil T. and Theil L. are not far apart, it should be noted that in particular, the Theil's T. is more sensitive for change in the upper tail, while Theil's L. is more sensitive to changes that affect the lower end of the distribution.

In a next study more focus will be on investigating new data sources and larger series. An interesting further approach is to decompose the change of the mean log deviation between two data sets by population subgroups and examine its inequality components, changes between and within groups and the changes in the relative size of the groups. Moreover, the data will be re-examined using other entropy techniques and RIF decomposition as generalization of the Blinder-Oaxaca methodology to estimate the marginal effect of covariates on income distribution.

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