GLOBAL WELL-BEING AND ECONOMIC INEQUALITY

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Abstract. *The objective of this paper is to find the efficiency of computational methods, namely multinomial logistic regression (MLR) in predicting four classes of human development index (HDI) for 98 world countries for year 2018. In this paper we apply MLR to study the impact of GDP per capita, Net Income Gini index, Wealth Gini index and poverty rate on Human Development Index, for 98 world countries. The MLR model emphasized the nonlinear relationship between economic inequality (measured by GINI indices and poverty rate) and HDI. The logistic regression model achieved 92,9% accuracy and R-square values over 90%. The results of our research have generated a series of suggestions for the future that can be considered by both international organizations and state governments.*

Keywords: Human development index, Economic inequality, Logistic regression

JEL classification: I31, I32, C38.

DOI: 10.24818/ie2020.05.05

1. Introduction

Since its introduction in 1990, HDI was aimed to measure human development. It was proved that economic growth and income growth are not the only factors to contribute to well-being [1], [2], [3]. There is a big debate on the supremacy of GDP versus HDI in measuring development. Paper [4] establishes a correlation between GDP and HDI. GDP has been for long a measure of social welfare, measuring a country's output relative to the population. HDI with its three components health, education and income has become the main alternative to GDP [5]. Paper [5] emphasizes how by its three dimensions, HDI assumes the individual participation to the general well-being, e.g. how healthcare access leads to a longer life [6].

The paper is structured as follows. Section 2 describes the relevant basic concepts in literature, followed by section 3 with a theoretical approach to multinomial logistic regression and its application to the dataset. In subsection 3.1, the used data is presented and summarized. The logistic regression approach is applied in subsection 3.2 and the results are interpreted. Section 4 concludes the paper and presents some suggested directions for future research.

2. Literature Review

Globalization causes large-scale changes in technological, economic, political and social fields of social development. These changes have a contradictory impact on the development of national economies and their competitiveness [7]. Economic inequalities and poverty both directly and indirectly influence people's well-being [8], [9]. Economic inequalities are the most obvious, as they show different positions of people in the distribution of income, wealth, goods, including wages [10]. Although the basis of the distribution of income is based on the principles of global economic distribution, the issue of economy, welfare at country and individual level is imperative and can be centered on the policy of equal opportunities for all members of a society [11], [12], [13]. If a state government decides to reduce the level of economic inequality [14], [15], it may apply a few sets of tools: (1) redistribution - from those with high incomes to those with low incomes; (2) the grid of opportunities widely available and (3) social responsibility. Redistribution involves taking from the income of those with higher incomes and supplementing the incomes of those with lower incomes [16]. The opportunity grid is a state policy that consisted of offering different opportunities to the vulnerable, in difficulty and helpless. The social responsibility of the organizations [17] is constituted by responsible social initiatives of the economic agents in response to the expectations of the employees, customers, investors and of the company as a whole with regard to the business environment focused on the provision of high quality services, respecting the rights of the employees and solving social problems [18]. The application of these tools by the state governments would allow a reduction of economic inequalities, but at the same time, it should not affect the economic productivity, the labor market and the incentives for investments respectively. The main causes of economic inequalities [19] are: wage inequalities (when some highly skilled workers earn more than those with lower or no qualifications, including gender wage inequalities), the process of globalization, monopolizing certain market segments, technological changes and computerization, fiscal policy, education, political reforms, labor market failures, wealth growth. In this context emphasize the importance to focusing on increasing R&D expenditures, especially in the higher education sector, as it has a significant influence on improving the global competitiveness development [20]. There are different conceptual approaches to economic inequalities. Some authors [21], [22], [23] believe that economic inequalities are necessary for economic growth. Other authors [24], [25] consider that an analysis of the factors (components) of inequalities is needed to understand why they exist and how their impact on the well-being of the population is reflected.

By using the data for the year 2018 we analyze the correlation between the well-being of the population and the economic inequalities between the selected countries.

3. Research Methodology

3.1 Data Analysis

In this paper we collected data for 98 world countries available for 2018 from The World Economic Forum's Inclusive Development Index 2018. The dependent variable is HDI and the explanatory variables are GDP per capita (PPP2011), Net Income Gini index, Wealth Gini index and Poverty rate [*]. HDI is a composite index built by United Nations Development Programme (UNPD) used to measure the development of a country. HDI has three components: life expectancy at birth, standard living measured by the natural logarithm of GNI per capita and education (namely, expected years of schooling). Based on 2018 data, HDI is divided into four categories: 0.8-1 (*Very High*), 0.7-0.799 (*High*), 0.550-0.699 (*Medium*), 0.350-0.545 (*Low*). Of the 98 countries in the analysis, 42 fall into the *Very High* HDI category, 27 into the *High* HDI category, 15 into the *Medium* and 14 into the *Low* categories.

The Gini indices help ranking the countries according to their income distribution. When Gini index is close to 1, it shows perfect inequality. Lower values of GINI index indicate an equal distribution of poverty. It is widely known there is a direct relationship between GDP per capita and the Gini index. GDP per capita is a measure of the welfare of a country; if GDP per capita increases, then the standard of living is better and several people will benefit from the country's economic output. If at the same time the GINI index increases, people will not have increased income. By economic policies, governments will take actions to redistribute wealth.

Figure 1 plots the averages of the used data and shows how in the top *Very High* HDI class (>75th percentile value) with an average HDI=0.885, the GDP per capita is also the highest, USD 37715 (in 2011 purchasing power parity terms) and consistently over HDI classes decreases to USD 2255 in the bottom *Low* HDI class with an average HDI=0.488. The top HDI countries are Norway (HDI=0.954, Income gini=24.9, wealth gini=80.5, and poverty rate of 8.5%) and Switzerland (0.946, 24.9, 80.5 and 7.8, respectively) and Ireland (0.942, 30.3, 81.3, and 9.1%, respectively). The top-3 countries have GDP per capita of over USD50000 (PPP, 2011). The only other countries reach GDP of USD50000 in our data set. Are Luxembourg (USD 93734, HDI=0.909, income gini=28.4, wealth gini=68.1, and poverty rate 8.1%) and United States (USD55681, 0.92, 37.8, 85.9, and 16.8%). The United States has the second highest wealth gini (85.9) after only Kazakhstan (92.6). The lowest wealth inequality is seen in Hungary, Slovakia and Iceland (45.3-46.7); the highest income gini is found in Chile (45.9) and Russia (43.0), while the lowest income inequality being found in Iceland, Norway, Denmark and Finland (24.4-25.6) in the group of 42 countries in the *Very High* HDI category.

Figure 1. Wealth and income inequality, poverty and GDP per capita in HDI classes

Source: Authors' own research

The *High* HDI class is topped by countries like Serbia, Iran and Panama, with HDI between 0.795-0.799 and GDP from USD16035 to USD22674, while the category's lowest income inequality is in Ukraine (26.3) and the highest in South Africa (57.7) and lowest wealth gini in Albania (44.8) and highest in Egypt (0.91).

The *Medium* HDI class ranges from Pakistan (HDI=0.56) and Zimbabwe (0.563) to Vietnam. The groups GDP ranges from USD2688 of Zimbabwe to Namibia's USD9898. The largest income inequality is in Kyrgystan (34.1) and the smallest in Namibia (55), which also has the lowest wealth inequality (91), Pakistan showing the largest (52.6).

The *Low* HDI category's HDI ranges from Chad's 0.401 to Rwanda's 0.536 and GDP per capita ranges from Burundi's USD660 to Nigeria's USD5316. The highest income inequality is found in Mauritania (30.3) and the highest wealth inequality in Tansania (55.2).

Poverty rate shows opposite, but consistent relation to HDI: It is 7,9% in the top HDI class on average, while 75,6% in the bottom HDI class; *High* HDI countries have 11,0% poverty rate, which increases to 39,7% on average, when a country falls under the *Medium* HDI class.

Economic inequality on the aggregate level do not show as consistent behavior as GDP per capita as seen in figure 1: For both, Income gini and Wealth gini, the highest average values are seen in *High* HDI class (HDI between 50th and 75th percentile), while being only slightly lower in the *Medium* HDI class (HDI between 25th and 50th percentile), i.e. countries belonging the *High* and *Medium* HDI classes are the most economically equal; the greatest wealth inequality is found in the *Low* HDI countries, while the *Very High* HDI countries show the highest income inequality. This may reflect the most functional market economy and property rights of the developed countries, where income inequalities work as incentives in labor markets, while the high wealth inequality in the least developed countries may result from less competitive markets with some actors able to accumulate wealth by the expense of other actors. The non-linear relationship between HDI and economic inequalities is handled by multinomial logistic regression, which relaxes the linearity assumption of linear regression models.

3.2 Multinomial Logistic Regression

Multinomial Logistic Regression (MLR) is a case of linear regression when the dependent variable is nominal and it has more than two levels. In this section we recall from [26] some well-known formulas on MRL which will be used later in modelling our HDI classification problem. Denote by Y the categorical variable with K levels $\{1, \dots, K\}$ and the predictors $\{X_1, \dots, X_s\}$. The probability of the level j of Y , for $j=1, \dots, K-1$, is $p_j(x) = P(Y = j | X_1 = x_1, \dots, X_s = x_s)$. The last level K is usually taken as the reference level, even if it can be a different level, where $\sum_{j=1}^K p_j(x) = 1$. $p_K(x) = P(Y = K | X_1 = x_1, \dots, X_s = x_s)$. Dividing the relations and applying logarithm, one obtains:

$$\ln \frac{p_j(x)}{p_K(x)} = \beta_{0j} + \beta_{1j}x_1 + \dots + \beta_{sj}x_s \quad (1)$$

HDI is the dependent variable and GDP per capita, Net Income Gini, Wealth Gini and Poverty rate are explanatory variables. The objective of MLR is to find the best model between HDI and the independent variables. The reference category of the class variable HDI is High.

Table 1. Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	257,579	265,334	251,579			
Final	53,204	91,978	23,204	228,375	12	,000

Source: Authors' own research

Table 1 compares the null model (only the intercept) and the final model which includes the predictors and the intercept. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are based on information theory and compare the quality of the null model and the final model. Lower values indicate better models; in our case the final model is preferred since $53,204 < 257,549$ and $91,978 < 265,334$. The -2 Log Likelihood test finds the least possible deviation between the observed and predicted classes of HDI; The lower value 23,204 of the -2 Log Likelihood indicates a better fit for the final model. The likelihood ratio test is an

alternative to the previous goodness-of-fit tests. The model fit is significant $\chi^2(12) = 228,375$, $p < 0,01$, consequently the final model predicts better than the null model.

The goodness-of-fit model by Pearson (Chi-square 20,05) and Deviance (Chi-square=23,20) statistics has the p-values of $1,000 > 0,05$ (lack of significance) indicating a good fit. Similarly, pseudo- R^2 s have very high values all $> 0,90$; the best one is Nagelkerke pseudo R^2 with the highest value of 0,978, therefore, they confirm the good fit.

The statistics of table 2 Likelihood Ratio Tests show that both the intercept and the Wealth Gini display p-values less than 0,05, meaning that they do not have a significant contribution to the full effect.

Table 2. Likelihood Ratio Tests for the Reduced Model

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Sq.	df	Sig.
Intercept	52,702	83,722	28,702	5,498	3	,139
GDPperCapPPP2011	124,800	155,820	100,800	77,597	3	,000
IncomeGini	61,316	92,336	37,316	14,112	3	,003
WealthGini	51,194	82,214	27,194	3,990	3	,263
PovertyRate	63,981	95,000	39,981	16,777	3	,001

Source: Authors' own research

Table 3. Parameter Estimates

HDI ^a		B	Std. Error	Wald	df	Sig.	Exp(B)
Low	Intercept	42,981	47,771	,810	1	,368	
	GDPperCapPPP2011	-,004	,003	1,911	1	,167	,996
	IncomeGini	-2,304	2,902	,630	1	,427	,100
	WealthGini	,460	,572	,646	1	,422	1,584
	PovertyRate	,734	,799	,843	1	,358	2,083
Medium	Intercept	4,298	7,956	,292	1	,589	
	GDPperCapPPP2011	-,001	,001	4,046	1	,044	,999
	IncomeGini	,112	,296	,143	1	,705	1,118
	WealthGini	-,013	,126	,010	1	,920	,987
	PovertyRate	,088	,094	,883	1	,347	1,092
Very High	Intercept	-12,094	20,109	,362	1	,548	
	GDPperCapPPP2011	,004	,006	,502	1	,478	1,004
	IncomeGini	-2,782	4,217	,435	1	,509	,062
	WealthGini	,513	,721	,506	1	,477	1,670
	PovertyRate	-,096	,920	,011	1	,917	,908

a. The reference category is: High.

Source: Authors' own research

The logistic coefficients Beta (B) are interpreted as the change in logit for a unit change in the predictor. Small values of Beta are given by GDP per capita, meaning that this predictor has the least influence on predicting HDI. Exp(B) (table 3) is the odds ratio of each predictor. Predictors with Exp(B) greater than 1 will increase the logit and predictors with Exp(B) lower than 1 will decrease it. According to (1), the three MLR equations are:

$$\ln \frac{P(HDI=low)}{P(HDI=high)} = 42,981 - 0,004GDP - 2,304IGini + 0,460WGini + 0,734PR. \quad (2)$$

From Exp(B) values for Low HDI category in table 3, one notices that for a one-point increase in GDP per capita, the chances that a country has a low HDI rather than a high HDI decrease with 0,4% (1-0,996); for a one-point increase in Income Gini, the chances that a country has a low HDI rather than a high HDI decrease with 90% (1-0,100); for a one-point increase in WealthGini, the chances that a country has a low HDI rather than a high HDI increase with 58,4% (1,584-1); and for a one-point increase in PovertyRate, the chances that a country has a low HDI rather than a high HDI increase with 108,3% (2.083-1).

$$\ln \frac{P(HDI=medium)}{P(HDI=high)} = 4,298 - 0,001GDP + 0,112IGini - 0,013WGini + 0,088PR. \quad (3)$$

Exp(B) values for Medium HDI category in table 3 show that: for a one-point increase in GDP per capita, the chances that a country has a medium HDI rather than a high HDI decrease with 0,1%; for a one-point increase in Income Gini, the chances that a country has a medium HDI rather than a high HDI increase with 11,8%; for a one-point increase in WealthGini, the chances that a country has a medium HDI rather than a high HDI decrease with 1,3%; and for a one-point increase in PovertyRate, the chances that a country has a medium HDI rather than a high HDI increase with 9,2%.

$$\ln \frac{P(HDI=veryhigh)}{P(HDI=high)} = -12,094 - 0,004GDP - 2,782IGini - 0,513WGini - 0,096PR. \quad (4)$$

Exp(B) values for Very High HDI category in table 3 show that: for a one-point increase in GDP per capita, the chances that a country has a very high HDI rather than a high HDI increase with 0,4%; for a one-point increase in Income Gini, the chances that a country has a very high HDI rather than a high HDI decrease with 93,8%; for a one-point increase in WealthGini, the chances that a country has a very high HDI rather than a high HDI increase with 67%; and for a one-point increase in PovertyRate, the chances that a country has a very high HDI rather than a high HDI decrease with 9,2%.

Table 4 shows the performance of the MLR classifier. The overall accuracy is 92,9%, which means that the full model (with coefficients and intercept) correctly classifies the 98 countries.

Table 4. Classification

Observed	Predicted				Percent Correct
	High	Low	Medium	Very High	
High	25	0	2	0	92,6%
Low	0	12	2	0	85,7%
Medium	1	1	13	0	86,7%
Very High	1	0	0	41	97,6%
Overall Percentage	27,6%	13,3%	17,3%	41,8%	92,9%

Source: Authors' own research

4. Conclusions

The predictive power of economic inequalities (measured by the wealth and income gini) with respect to the United Nations' human development index, HDI, has been studied together with

the gross domestic product (GDP per capita) in 98 world countries. The logistic regression model achieved 92,9% accuracy and >90% R-square values. Thus, the MLR captured the non-linear relationship of inequalities and HDI. In this study, only cross data was considered for year 2018. The statistical significance levels are expected to be higher with time-series data. Further, more elaborate models, e.g. based on neural networks may even further enhance the predictive performance of inequalities on well-being measures. Income inequalities seem to work as incentives in the relatively functioning market economies and the related established institutions of the most developed countries [27], [28], while rent seeking and negotiation power in the lowest HDI countries may have resulted in the highest wealth inequalities depending on political and other institutional structures [29]. The decile-wise wealth and income inequality data may prove useful with other mega-trends, such as digitalization [30], which generate well-being with unknown inequality effects.

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