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RESEARCH ARTICLE

Will Outbreaks Increase or Reduce Income Inequality? the Case of COVID-19

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Abstract

The effects of economic contractions experienced during pandemic periods on different income sectors and country groups in terms of income inequality are not homogeneous. Due to the fact that COVID-19 has deeply affected the lives of the poor, immigrants, refugees, the homeless, seasonal workers and people with no health insurance, the relationship between the pandemic and income inequality is of great significance. This study aims to find an answer to the question of whether the recent pandemic increased or decreased income inequality. In the study, the effect of COVID-19 on income inequality in 38 countries with different income levels is analyzed with the Artificial Neural Networks (ANN) and Linear Regression (LR) method. In this context, Gini index values for 2020 were estimated using unemployment, inflation and growth data, which are determinants of income distribution, for the periods 2000-2019. According to the analysis findings, while COVID-19 reduces income inequality in some countries, it increases it in others. However, in general, the results of our study show that the overall effect of COVID-19 on income levels in both developed and developing countries has been to increase income inequality.

Keywords

COVID-19, Pandemic, Income inequality, Gini, Artificial neural networks, Linear regression

Introduction

Covid-19, which emerged in China's Hubei province in December 2019 and which has shown its impact all over the world, continues to deeply shake both public health and the economic contraction which it has caused. With the effect of strict isolation policies, the social consequences of the pandemic became quite asymmetrical and its negative effects, especially on low socio-economic groups, continued to increase (O'Donoghue et al., 2020).

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COVID-19 has brought about a human development crisis. With the pandemic, some dimensions of human development, such as health, education, individual economy, housing, social participation, human security, social justice, environmental sustainability and social life have regressed, and some of these parameters have fallen to the low levels seen in the mid-1980s. This is because the crisis caused by the pandemic has badly affected all elements of human development. The main affected areas are income (which has seen the biggest contraction in economic activity since the Great Depression), health (the pandemic that has already killed over 1 million 500 thousand people is expected to cause more deaths with the effect of a second wave) and education (which has been affected in regards to restriction of access to the internet, increasing inequality of opportunity in education, and the decline of primary education to the levels of the mid-1980s). The scale of the effects of the outbreak is expected to be yet more devastating, given the deterioration in many parameters, including an increase in gender-based violence (UNDP, 2020).

To control the spread of COVID-19, governments are implementing different degrees of isolation policies that can lead to a sharp contraction in economic activity, a decrease in employment and income, and an increase in poverty and inequality (Lustig et al., 2020). The mentioned income inequality is an issue that needs to be discussed because income inequality and the pandemic are closely related. In this framework, the pandemic, which determines income inequality, is also directly affected by income inequality. The vicious circle between the pandemic and inequality can be explained as follows: With the onset of a health crisis, economic contractions can trigger chronic diseases due to insufficient care and treatment, and this process, which affects productivity in all aspects, increases health care costs and poverty, and this subsequently brings more diseases.

Countries with relatively higher income inequality are likely to report more COVID-19 cases and deaths (Bonacini et al., 2020; Fisher & Bubola, 2020; Clarke & Whiteley 2020). Moreover, disadvantaged groups, which are exposed to high income inequality, have to work to survive, making them vulnerable in terms of the risk of developing the disease and making them more exposed to high treatment costs. This situation is even more brutal for low-income groups which are employed informally without health insurance to survive.

Although many factors act as a driving force in the relationship between the pandemic and income inequality, the prominent factor is the labor markets. This is because, with the COVID-19 crisis, human beings, the dominant factor of the production process, are under a global health threat (Campello et al., 2020). The effect of the pandemic on the workforce differs depending on the parameters of the workforce, such as age, income, gender, and education, and this is determinant in income inequalities. While the majority of the highly skilled workforce has the opportunity to work from home, there is not much opportunity to work remotely for low skilled workers (Neidhöfer, 2020). In addition, the strict isolation policies implemented to control the pandemic have led to a decrease in employment and a significant increase in unemployment rates. This effect is expected to be more devastating, especially in low-income countries. In low-income countries, poor individuals who can only meet their basic needs have had to choose between the pandemic and hunger. For example, although very drastic measures were not taken in Kenya, as a result of the current practices, most of the informal workers who make up more than 80% of the workforce remained unemployed. Recently, Ebola in West Africa, Hurricane Idai in Mozambique, the Desert Grasshopper invasion in Somalia and Ethiopia, and migration waves in these geographies have further weakened these countries economically. Therefore, the expansion of the pandemic in these countries means that poverty and inequality affect the whole society more deeply (Maffioli, 2020). The extent of informal employment in low-income countries also plays an important role in affecting the labor market's income distribution. In these countries, particularly the poor living in rural areas are employed informally, and percentages of informal employment exceed 90 in the agricultural sector. Informal employment mostly means excluding these individuals from social aid and allowances. Therefore, the pandemic is expected to play a significant role in increasing inequality by further affecting the living conditions of these people (FAO & UN, 2020; FAO, 2020; ILO, 2018). However, due to the employment of the poorest in the agricultural and daily life services sector, and due to these sectors being relatively less affected by the pandemic, the poorest households face lower levels of unemployment. On the other hand, it is expected that many households with middle and middle-high income levels who do not have the opportunity to work from home will be deeply affected by the pandemic through the unemployment channel. Therefore, although the pandemic shakes the living conditions of the poorest more deeply, the issue of which households have the greatest income loss differs. Therefore, it remains uncertain how the pandemic will affect inequality through the labor channel.

As important as employment conditions, another factor which plays a part in the pandemic's impact on income inequality is the sectoral effect of the pandemic. In this context, the wealth of billionaires, who are owners or shareholders of digital giants and large pharmaceutical companies, has increased several times due to the increase in stock prices (Van Barneveld et al., 2020). For example, between 1st January , 2020 and 10th April, 2020, 34 of the USA's 170 richest billionaires increased their fortunes by tens of millions of dollars, and eight of these billionaires - Jeff Bezos (Amazon), MacKenzie Bezos (Amazon), Eric Yuan (Zoom), Steve Ballmer (Microsoft), John Albert Sobrato (Silicon Valley real estate), Elon Musk (Tesla and SpaceX), Joshua Harris (Apollo Global Management) and Rocco Commisso (Mediacom) saw a huge increase in fortunes. The wealth increase of Amazon founder and CEO Jeff Bezos is particularly unprecedented in the history of modern finance and is increasing day by day. His wealth has increased by an estimated \$ 25 billion since January 2020, as of April 15, which is greater than the Honduras GDP, which was \$ 23.9 billion in 2018.

However, although the pandemic has increased the wealth of some billionaires, there was a slight decrease in the total number of billionaires on Forbes' global billionaires' list published on 7 April 2020 (Collins et al., 2020). This situation shows that in countries where companies with relatively high technological power are clustered, income inequality will deepen further.

With the pandemic, working from home has become widespread and the limited opportunity to work from home on an individual or sectoral basis affects inequalities. Compared with high-income individulas, low-income individuals have limited opportunities to work remotely. Also, while high-income individuals can earn a wage bonus by working from home, the earnings of low-income workers are much more limited. For example, in European countries, 74% of employees in the highest wage quintile can work remotely, but this rate is 3% in the lowest quintile. In the UK, 60% of high-income people are able to work from home, but this rate is only 20% for low-income people. Similarly in the USA, the potential for working from home increases as the wage distribution goes up. Therefore, if the rise and spread of working from home becomes the norm, it could be a new vector of inequality (Stantcheva, 2021; Adams-Prassl et al., 2020; Sostero et al., 2020; Bonacini et al., 2020; Van Barneveld et al., 2020).

One of the prominent parameters in explaining the relationship between the pandemic and income inequality is productivity. In this framework, the pandemic affects income inequality by affecting the productivity of different income groups in different dimensions. For example, Etheridge et al., (2020) suggested that women and individuals in low-wage jobs experienced the greatest declines in productivity in the United Kingdom. In the study, the way in which income inequality through productivity was affected by working from home during the pandemic was also discussed. In the study, they found that the level of productivity of homeworkers during the lockdown was related to the intensity of working from home and how it changed from the previous period. Those who used to work at least occasionally from home and then increased the intensity of working from home or who had never worked from home before the pandemic reported significant decreases in productivity.

Remittances, another factor in the relationship between the pandemic and income inequality, are an important source of income in low- and middle-income countries, especially in rural households. Although most rural residents have relatively safe access to land, livestock or natural resources, they rely on various sources of income, including wage labor and non-agricultural activities, to survive. For example, about 40% of poor households in Nigeria receive either domestic or international remittances. Therefore, fluctuations in remittances will create a serious income shock for these households. In addition, given the share of remittances, particularly in education spending, a sharp decline in these is expected to reduce investment in human capital development, which is usually financed by remittances (FAO & UN, 2020; World Bank, 2020). The cost of accessing healthcare is a factor which illustrates how the pandemic will change the income distribution. Particularly in countries where access to healthcare services is costly, healthcare bills can further deepen inequality due to large-scale borrowing on the part of the poor which leads to greater poverty. Individuals with the lowest income do not have health insurance, as they mostly work in the informal employment sector. Hence, high healthcare costs increase income inequality by cutting into a larger share of the budgets of poor households.

COVID-19 is expected to affect inequalities between countries as well as domestic inequalities. For example, Maffioli (2020) emphasized that poor countries could be more affected by the pandemic due to the insufficient infrastructure as well as to insufficient resources to strengthen public health policies. The fact that low-income countries direct their limited resources to health expenditure may further deepen the income differences between developed and underdeveloped countries. FAO & UN (2020) emphasized that COVID-19 could worsen inequalities both between countries and within the country. It is also possible that the consequences of inequalities from the pandemic are long-term because greater inequality weakens the impact of economic growth on poverty reduction. This causes growth to have less impact on the poor and other marginalized groups, and hence the economic recovery is reflected only on a certain part of society. Consequently, the process can lead to greater inequality in society as a whole (FAO & UN, 2020).

In the literature, the effect of the pandemic on income distribution is mostly discussed in developed countries. However, one of the questions waiting to be answered is how the pandemic affects the distribution of income in countries with different levels of development. What is the power of the social support policies implemented by the countries to affect this trend? It is expected that this study will contribute to the literature in this sense. In this study, the effect of COVID-19 on income inequality in 38 countries with different income levels is investigated using ANN and LR simulation methods. The plan of the study is as follows: In the section following the introduction, the literature review is discussed and in the third and fourth sections, the methodology and analysis findings are presented.

Literature

COVID-19 affects society in many ways, but undoubtedly one of the most controversial issues is its effect on household income. How is the pandemic affecting the income of we althy households or poor households? It is impossible to talk about a single direct effect on this subject. The epidemic, which affects households with high income levels in some sectors, may affect poor households more strongly in others. It is important to know how the pandemic is affecting households with different income levels. This is because the effectiveness of social assistance policies to be implemented depends on a knowledge of how the epidemic,

which has already greatly affected social discontent, has changed income distribution. At this point, public support can minimize the impact of the pandemic, but knowing how it affects or will affect the incomes of households with different incomes can both bring an effective public policy and play an important role in reducing income inequalities by supporting the segment most affected by the epidemic.

Studies focusing on the relationship between COVID-19 and income inequality are mostly limited to specific countries, so this study, which includes both developed and developing countries, is expected to contribute to the literature by showing the trend of income inequality to be caused by the pandemic in both developed and developing countries.

Some studies on how COVID-19 will affect income inequality suggest that the pandemic will increase this inequality (Komatsu & Menezes-Filho, 2020; Van Barneveld et al., 2020; Bonacini et al., 2020; Kyyrä et al., 2021). However, other studies emphasize that income inequality will tend to decrease (Lustig et al., 2020; O'Donoghue et al., 2020; Grabka, 2021).

Studies suggesting that the pandemic will affect income distribution deal with the fact that the opportunity to work from home is not offered to the educated and low-educated workforce at the same rate (Bonacini et al., 2020) and with the fact that the lockdown restrictions affect households at different rates (Perugini & Vladisavljević, 2020). Other studies cover the distribution of social support benefits and tax reductions (Kyyrä et al., 2021; Almeida et al., 2021) and the fact that the pandemic affects women and low-income individuals more deeply (Etheridge et al., 2020).

Considering the studies suggesting that the pandemic will increase income inequality, Delaporte et al. (2020) in their study of 20 Latin American and Caribbean (LAC) countries argued that the social distance applied to the pandemic led to an increase in income inequality in many of these countries. Perugini & Vladisavljević (2020) argued that restriction policies applied to control the pandemic in 31 European countries will increase inequality and poverty, and the magnitude of change will be greater in more unequal countries. Bonacini et al. (2020) argued that working from home has increased with the pandemic in Italy, and this practice, which benefits upper-middle income people, may deepen income inequalities. According to Van Barneveld et al. (2020) , a skilled and high-wage workforce that can work from home in the Information Technology (IT) field is more advantageous than the millions of low-wage workers in the low-wage retail and service sectors, and thus the unskilled workforce may be more affected by the pandemic. Therefore, according to the authors, COVID-19 will increase income inequality. Aina et al. (2021) investigated the effect of Covid-19 on wage distribution in Italy. According to the findings of the study, the pandemic affects the wages of all workers, but this effect is higher for those at the lower end of the wage distribution.

In addition, the fact that the fortunes of billionaires affiliated to digital giants and large

pharmaceutical companies increase more and more as the stock prices increase is one of the determining factors in the deepening of inequalities. Duman (2020) suggested that isolation policies due to Covid-19 can increase wage inequality depending on supply shocks in Turkey. Similarly, Bayar et al. (2020), in their study of labor market indicators in Turkey due to Covid-19, reached the findings that low-income groups lost more income than high-income groups. In summary, the findings are based on the argument that the rich lose proportionally less income than the poor.

However, looking at studies suggesting that inequalities will tend to decrease with the pandemic, O'Donoghue et al. (2020) mentioned that the pandemic could play a balancing role in income inequality with the effect of social assistance and taxes in Ireland. According to the study, they claimed that with the pandemic, the highest income losses were seen in high-income individuals, and the poorest part of the society received the least damage from the process with the introduction of tax cuts and social assistance. According to Grabka (2021), income inequality decreased in Germany with the pandemic. According to the study, the reason for the decrease in relative income inequality in Germany is directly related to the income losses suffered by the self-employed because self-employed people in Germany are richer than other labor force groups.

In some studies, the effect of the pandemic on income distribution was examined by including the process of public support policies. For example, Lustig et al. (2020) argued that the devastating impact of COVID-19 in Argentina, Brazil, Colombia and Mexico was stronger on middle-income households than on the poorest segment of society. In this framework, the study, in which the expanded social assistance provided by governments in response to the crisis was included in the analysis, revealed that the aid had a low level impact in Colombia and a large balancing effect in Brazil and Argentina. Almeida et al. (2021) investigated the impact of the pandemic in 27 European countries and the effects of the policies implemented due to the pandemic. Accordingly, the pandemic is expected to increase income inequality, but support policies are expected to reduce this effect relatively. According to Angelov & Waldenström (2021), Covid-19 has increased earnings inequality in Sweden because the epidemic has affected low-paid individuals more in the country. In the study, it was emphasized that public support had a positive effect on income distribution, but could not completely eliminate inequality. Kyyrä et al. (2021) suggested that the pandemic increased income inequality in Finland. According to the study, it was emphasized that tax support played a balancing role in these inequalities, otherwise inequality might be much higher.

Methodology

In the study, firstly, missing Gini values in 102 countries were calculated based on the available UTIP data, and the values obtained by both the UTIP data and the simulation met-

hod are given in Table 2 and Table A1 (see appendix). While the light-colored Gini values in Table 2 and Table A1 show the UTIP data, the dark-colored values are the values obtained by the ANN simulation method based on the UTIP data. The graphics showing the trend and deviation of the real and simulated values of these calculations are also given in Annex 2.

In this study, how the COVID-19 epidemic will affect income inequality in 38 countries is examined using ANN and LR methods. The Gini values for 2020 were estimated using growth, unemployment and inflation data which affect income inequality. For this, the Gini index for 2020 was predicted by using unemployment, growth and inflation for the 2000-2019 period. Here, the effect of the change that these variables will cause in the Gini index is utilized. The inputs and outputs used in the model are given in Table 1.

Table 1	
Input and output variables for ANN and LR Method	
Inputs	Outputs
InGDP, Inflation, Unemployment and Year	Gini index for 2020

The development of artificial neural networks (ANN) was formed by combining many simple computing elements, namely neurons, in a highly interconnected system. And so the ANN emerged from an attempt to simulate biological nervous systems, hoping that an "intelligence" would give rise to complex phenomena as a result of self-organization. While artificial neural networks rarely have a few hundred or more than a few thousand neurons, the human brain has about a hundred billion neurons. Resembling a complex human brain, these networks are still far beyond the fastest, highest-capacity parallel computers in existence (Warren, 1995). ANN consists of neuron-like elements which are called nodes. These nodes are arranged in layers as shown in Figure 1. Generally, ANN is used to approximate a nonlinear mapping between system inputs and outputs (Willis et al., 1992).



Figure 1. Artificial neural network.

The basic unit of a multilayer perceptron is the neuron, which has the function of subjec-

ting the weighted sum of signals to the input to a transfer function (Kubat, 2017). Where \sum is the weighted sum of the inputs, calculated using the formula:

$$f(\Sigma) = \frac{1}{1 + e^{-\Sigma}} \tag{1}$$

The Artificial Neural Network in Fig. 1 is known as the multilayer perceptron, input, output and hidden layers represented by neurons. For two-layer perceptron the formula is as given,

$$y_{i} = f\left(\sum_{j} W_{ji}^{(1)} f\left(\sum_{k} W_{kj}^{(2)} x_{k}\right)\right)$$
(2)

The j-th hidden neuron takes the weighted sum, $\sum_{j} W_{kj}^{(2)} x_{k}$, as input and subjects it to the sigmoid function $(\sum_{k} W_{kj}^{(2)} x_{k})$, with the values x_{k} multiplied by the weights included with the links. The i-th output neuron then obtains the weighted total of the hidden neurons' values and applies the transfer function to it once more. This is how the i-th output is obtained. Forward propagation is the process of propagating attribute values from the network's input to its output in this manner (Aggarwal, 2018). Artificial Neural Networks are the most well-regarded and widely used machine learning techniques.

Machine learning (Er et al., 2021; Farsad & Goldsmith, 2018; Kubat, 2017) is widely utilized in a variety of fields to address complex issues that are difficult to solve using traditional computer methods. One of the most basic and widely used machine learning methods is linear regression. It is a method for performing predictive analysis that is based on mathematics. Linear regression (LR) allows for projections of continuous/real or mathematical variables. Linear regression (Chen et al., 2019; Maulud & Abdulazeez, 2020) is a typical mathematical research tool that allows you to test and estimate anticipated effects versus numerous input variables. It is a data analysis and modeling technique that develops linear relationships between dependent and independent variables. From the quantitative perspective, machine learning such as ANN and LR often consists of optimum combinations which permit better prediction and more accurate estimations than occur with other types of models. One of the benefits of using ANNs is that it may make models from complex natural systems with massive inputs easier to use and more accurate. The artificial neural network (ANN) has been discovered to be a very new and valuable model for problem-solving and machine learning (Abiodun et al., 2018; Isik et al., 2021).

In the simplest terms, Linear Regression is a supervised Machine Learning model that identifies the best fit linear line between the independent and dependent variables, i.e. it discovers the linear relationship between the two variables. There are two forms of linear regression: simple and multiple. Only one independent variable is present in simple linear regression, and the model must identify a linear relationship between it and the dependent variable. Multiple Linear Regression, on the other hand, uses more than one independent variable to find a relationship. In the equation of simple linear regression, b_0 is the intercept, b_1 is the coefficient or slope, x is the independent variable, and y is the dependent variable.

$$y = b_0 + b_1 x \tag{3}$$

Multiple Linear Regression Equation, where b_0 is the intercept, b_1 , b_2 , b_3 , b_4 ,..., b_n are the coefficients or slopes of the independent variables x_1 , x_2 , x_3 , x_4 ,..., x_n , and y is the dependent variable.

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \dots + b_n x_n \tag{4}$$

The basic goal of a Linear Regression model is to determine the best-fit linear line and the appropriate intercept and coefficient values such that the error is minimized. The discrepancy between the actual and predicted values is called error, and the goal is to reduce it (Chen et al., 2019; Maulud & Abdulazeez, 2020).

ANN and LR models have the ability to learn and can learn with different learning algorithms (Kubat, 2017). They can produce results (information) for unseen outputs. There is unsupervised learning. They can make pattern recognition and classification. They can complete the missing patterns. They have fault tolerance and can work with incomplete or ambiguous information (Chen et al., 2019; Wang et al., 2018). In faulty cases, they show graceful degradation and can work in parallel and process real-time information so are used in this study.

All data is statistically compared for training and testing results once all estimated values are produced with ANN and LR models. To compare the results, the coefficient of determination (R²) and Mean squared error (MSE) approaches are used. The following equations show how to calculate Formulation of MSE and R².

$$MSE = \frac{\sum_{i} (Real \ Data_{i} - Sim_{i})^{2}}{N}$$
(5)

$$R^{2} = 1 - \frac{\sum_{i} (Real \ Data_{i} - Sim_{i})^{2}}{\sum_{i} (Sim_{i})^{2}}$$
(6)

Real data, Sim and N denote to the value of real data, the value of simulated results, and the number of samples in the suggested model, respectively. The coefficient of determination and the MSE are proposed to become around 1 and 0 correspondingly. Although R² values for the model's training and testing outcomes are around 1, MSE values are greater than 0, notably for the model's testing section (Hecht-Nielsen, 1989). The similarity between experimental and simulation results is 99 % for all of the glow curve data (Lee, 2004; Basheer & Hajmeer, 2000; Willis et al., 1992).

Results

In this study, ANN and LR models were used to estimate the Gini index for 2020 using Gini index of 38 countries. The growth, inflation, unemployment, which are determinants of income inequality, and years are chosen as input and the Gini index of all years is selected as output for the prediction of the Gini index of 2020. The model findings obtained using these variables are presented in Table 2. The table also includes simulated Gini values based on both UTIP Gini data and UTIP data for the 2000-2019 periods in order to see past trends. The change in the Gini index is analyzed on the basis of the previous year's data and if the change is positive, a (+) sign is placed in front of the value, and a (-) sign is placed in front of the value if it is negative, thus indicating the direction of the change.

Table 2Gini index for 38 countries

	Countries	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020- ANN	2020- LR
	Australia	40.77	41.55	40.75	41.84	41.79	42.08	42.76	43.37	42.50	42.52	-42.11	-42.44
	Austria	36.36	36.86	36.97	36.81	36.61	36.49	35.95	35.64	36.59	36.58	+36.61	+36.84
	Belgium	41.27	41.10	42.46	42.84	42.63	42.64	42.96	42.02	42.02	41.52	+41.74	+41.80
	Canada	39.30	38.34	38.76	38.75	38.83	38.85	38.34	38.13	38.53	38.27	+41.27	+41.82
	Cyprus	36.18	36.81	35.56	36.94	36.98	36.91	36.80	36.98	35.28	36.18	-35.09	-35.45
	Czech Rep.	31.94	31.14	31.96	32.01	31.74	30.87	32.57	31.51	31.82	31.61	-31.24	-31.38
	Denmark	37.14	36.15	34.16	34.08	34.31	34.18	34.01	33.96	34.15	33.55	+34.48	+34.26
	Finland	36.04	35.88	36.03	35.86	36.41	35.96	35.26	36.45	36.26	36.86	-36.84	+36.87
	France	38.15	37.57	37.33	38.03	38.00	37.94	37.91	37.46	37.78	37.13	-36.23	-36.14
	Germany	38.51	38.86	38.31	38.37	38.29	38.22	38.44	37.54	38.55	38.25	+40.14	+39.37
ies	Greece	41.23	40.88	45.11	45.51	45.47	45.44	45.41	45.41	45.51	45.91	-45.75	-44.96
ntri	Israel	44.37	44.69	44.27	43.88	43.47	43.41	43.04	43.79	43.58	43.28	+43.98	+43.82
0u	Italy	37.08	37.06	37.37	37.36	37.33	37.23	37.16	37.23	37.42	37.62	-36.19	-37.00
) po	Japan	43.88	46.50	43.45	43.83	43.02	43.87	44.91	43.79	43.38	43.78	+44.45	+44.30
ope	Latvia	42.50	42.62	41.84	41.04	40.93	40.67	40.81	40.71	40.60	41.70	+41.94	+41.81
evel	Lithuania	44.25	43.21	42.48	41.43	41.11	40.69	40.62	41.92	41.23	41.83	-41.17	-41.59
Õ	Netherlands	38.42	39.65	39.16	39.13	38.89	38.88	39.56	39.39	37.38	37.58	+38.43	+38.70
	Norway	36.81	36.79	37.24	37.15	34.42	37.16	38.35	38.81	39.08	39.20	+39.57	+39.42
	Portugal	43.11	42.77	42.76	42.83	42.57	42.45	42.62	42.46	42.21	42.14	-41.56	-41.99
	R. of Korea	38.90	39.19	39.02	39.80	39.07	39.54	39.25	39.21	39.06	39.37	+39.68	+39.88
	Singapore	39.02	39.81	39.14	39.20	40.42	40.84	40.35	40.44	39.50	39.93	-39.82	-39.11
	Slovakia	36.85	36.67	36.89	37.36	37.03	36.4	37.08	37.56	37.72	38.00	+39.58	+39.69
	Slovenia	34.70	34.55	34.10	34.46	33.39	33.36	33.59	32.35	31.34	32.04	+32.76	+32.37
	Spain	40.90	40.9	41.52	42.04	42.35	42.21	42.00	41.83	40.92	40.81	+41.93	+42.49
	Sweden	33.77	33.11	34.28	34.46	34.44	32.82	33.48	33.40	33.10	33.20	-33.13	-32.83
	UK	38.42	40.33	38.53	41.27	39.81	39.87	40.68	38.87	37.30	37.08	+38.69	+40.14
	USA	42.20	42.31	42.08	42.02	42.00	41.98	41.94	41.93	41.93	41.93	+42.08	+42.46

	Countries	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020- ANN	2020- LR
	Brazil	47.70	47.48	47.15	47.06	47.16	47.58	47.39	47.51	47.12	47.22	+47.28	+47.40
	Bulgaria	43.12	42.18	42.69	42.45	41.88	41.56	41.37	42.35	41.85	42.15	+42.31	+42.18
	China	38.78	38.99	37.68	37.53	37.42	38.26	38.47	38.94	38.25	38.56	+41.20	+41.38
	Colombia	42.44	41.76	41.47	45.15	44.81	44.8	44.84	44.73	44.99	43.73	+43.87	+43.83
ies	Croatia	42.29	42.37	42.73	42.82	41.68	41.76	42.01	42.01	42.01	42.03	-39.73	-39.07
ntr	Hungary	41.45	41.11	40.86	40.43	40.49	39.87	40.34	39.42	40.42	40.42	-38.27	-39.63
Cou	Malaysia	39.70	39.38	39.31	39.29	39.62	39.42	40.47	40.67	40.87	39.07	+39.85	+39.73
^b	Philippines	47.68	47.63	48.46	49.74	49.68	49.67	49.84	49.91	50.02	50.42	-50.34	-50.06
opii	Poland	40.32	40.49	40.27	39.97	39.73	39.43	38.41	37.75	37.35	37.18	+38.00	+38.02
vel	Romania	42.56	42.66	42.35	44.09	41.78	42.52	42.78	43.86	43.90	43.52	-42.92	-43.19
De	Turkey	47.16	46.61	45.74	45.13	44.78	44.70	45.91	46.97	46.67	46.07	+46.57	+46.65

Note: Light colored values show UTIP data, while dark-colored values show Gini values obtained by a simulation method based on UTIP data.

When the Gini index values and changes estimated by the ANN and LR simulation method in Table 2 are examined, it is seen that the results vary from country to country. Therefore, it becomes difficult to make a preliminary judgment that the pandemic increases or decreases income inequality. However, in general, it can be said that the pandemic increases the income inequality mainly in developed countries and in developing countries, but this effect is more uncertain.

It is observed that inequality is increasing, especially in countries such as the USA, Germany, UK and China, where leading vaccine producing countries are located. In these countries where digital giants and large pharmaceutical companies are strong, inequality is expected to increase. The lack of strong transnational companies in sectors with increased profit margins in developing countries with the pandemic and the deterioration in living conditions of households with middle-income levels are the main parameters that can lead to a decrease in inequalities. According to Forbes's list of billionaires for 2021 (Dolan et al., 2021), it can be seen that the pandemic has led to a significant increase in the number of billionaires. According to the report, the USA is the country with the most billionaires with 724 and China comes second with 698 billionaires. As can be seen from Table 2, the mentioned countries are among the countries where inequalities have increased. Similarly, inequalities are expected to increase in Brazil, which has the highest number of billionaires in Latin America. According to the Forbes report, the USA ranks first in the number of billionaires emerging with the pandemic in the world, followed by Canada. As can be seen in Table 2, the increase in inequalities is expected to be higher in Canada.

The size of social assistance programs is undoubtedly as important as the sectoral shares of the countries in the formation of these results. For example, is the support provided by governments mostly to the poor or to big companies? However, when the social assistance policies of these countries are examined, it can be seen that, contrary to expectations, these policies are limited in most of these countries. On the other hand, it is expected that the relative inequalities will decrease or show a slower increase in countries that implement a relatively strong and fairer social policy. For example, Germany is one of the countries where the big global technology companies and the vaccine-pharmaceutical industry that benefit from the pandemic are strong, and therefore the number of billionaires is increasing rapidly. However, the increase in inequality is expected to be lower than expected. Because Germany has been successful in its social aid policies, it provides for the society in general. According to the ILO (2020) report, the main social support policies implemented by Germany to reduce the effects of COVID-19 are: i) continuation of benefit for workers from short-term work allowance even if they work in additional jobs, ii) support for single parents who are caring for children, iii) reduction of VAT rates , iv) suspension of bankruptcy applications due to excessive indebtedness, v) provision of privileges to seasonal workers in addition to the support provided in the agricultural sector, vi) income support for low-income households and individuals working alone, vii) Family Premium Payment per child for all parents, viii) free one-off support payment to those who have a profession, ix) provision of financial support to companies that are particularly severely affected by the pandemic (ILO, 2020). All of this has allowed support against the effects of COVID-19 to be distributed throughout the entire community.

France and Italy, which are among the countries with the highest number of COVID-19 cases, are expected to balance inequalities by maintaining support for low-income house-holds and by implementing policies to prevent unemployment. For example, France mostly prioritizes employment sustainability in its policies to reduce the effects of the pandemic. Some of these policies include cash assistance within the framework of unemployment guarantees, solidarity funds provided to companies in the sectors that experience a very sharp decline in their activities, and giving a certain percentage of monthly turnover as compensation. Italy, on the other hand, has focused directly on low-income individuals. For example, bonus supports for low-income workers, mortgage repayment (for residency house) for low and middle-income households, income support to companies during periods of temporary or permanent interruption of production (80% of gross salary and full social security contribution) to minimize unemployment. Support provided to low-income households, such as the provision of services, and policies to reduce unemployment may be effective (ILO, 2020).

When we look at Turkey, which has a relatively high number of cases, inequalities are expected to show an increasing trend. Some of the support provided in Turkey included a delay in payment of taxes, configuring the taxes and interest owed, a delay for trade credit, and low income cash assistance to households. The strongest policy used by the government in minimizing the impact of the epidemic on households was the prohibition of layoffs for a certain period of time and support of this with short-time work allowance. Thus, it is aimed to partially control unemployment.. However, the higher level of benefits provided to medium

and large-scale companies caused small tradesmen to be more severely affected by the epidemic. Therefore, an improvement in income distribution is not expected. On the other hand, the sharp increase in exchange rate and gold prices led to a significant increase in the wealth of households with foreign currency and gold deposits in their accounts. This is one of the determining parameters in income inequality. In summary, although the aim was to minimize the destructive effect of the epidemic, the effect of the increase in gold prices in exchange rates in addition to the economic contraction experienced all over the world, has meant that the support provided in the country was insufficient to mitigate the impact of the epidemic.

Conclusions

Income inequality is an important area of discussion within the framework of the effects of the COVID-19 crisis, which has affected the whole world with its health and economic dimensions. Countries that want to reduce the number of pandemic-related cases and patient and mortality rates due to the pandemic turn to strict isolation policies. This situation leads to problems such as a serious decrease in the production process and the loss of employees' jobs and income. COVID-19 affects all segments of society, albeit in different forms and degrees. The pandemic has caused changes in the income level of the skilled workforce as well as the unqualified workforce. Again, the continuation of the employment of a significant portion of the unskilled labor force who work in the agricultural sector and daily casual jobs, and the opportunity to work from home to the educated qualified workforce, makes it difficult to reveal which segment is affected relatively more by the pandemic. Thus , the pandemic affects the employment of both the qualified and unqualified workforce in multiple ways. Every segment of society is affected by this process, though in different dimensions.

In this study, an ANN and LR simulation method was used to study the effect of CO-VID-19 on income inequality in 38 countries. The results obtained in this study, which deals with the effects on income inequality of parameters such as unemployment, inflation and growth, differ by country. According to this study, inequality is generally expected to increase in developed countries and this effect is more uncertain in developing countries. Although the pandemic has deeply affected the living conditions of the poor, the relative decline in the wealth of individuals in middle and upper-income levels may be higher. Because there are rich people whose wealth has increased exponentially due to the pandemic, there is also a segment whose wealth is rapidly disappearing. Therefore, a single argument that suggests that inequality will decrease or increase around the world would not be realistic. At this point, many parameters, from the social assistance policies of countries to the shares of sectors in the national economy, will be decisive in how far the pandemic will affect inequality.

Another parameter that determines inequalities is the number of billionaires in the country increasing with the pandemic, because in countries where the number of billionaires has inc-

reased due to the pandemic, inequalities are expected to increase. When Table 2 is examined, it is seen that inequalities have increased in most of the countries that are at the forefront in the number of new billionaires after pandemic in the Forbes list (for example USA, Canada, Germany, Japan and Spain, Brazil).

Our findings show that inequalities may show an increasing trend, especially in developed countries where billionaires have increased after the pandemic. In addition, the findings also support the limited number of studies that focus on the impact of the pandemic on inequalities, mostly in developed countries. (Kyyrä et al., 2021; Adams-Prassl et al., 2020; Almeida et al., 2021; Brewer & Tasseva, 2020; Clark, 2021)

In conclusion, it is important to design social policies in a way that prioritizes basic rights to life such as housing, nutrition and health. In this context, the following policies are important to reduce income inequality: (i) Providing access to free health services for those who have to work informally in order to survive and who are not under the umbrella of social security. (ii) Providing tax cuts to companies, tax restructuring, financial assistance to sectors directly affected by COVID-19 in order to prevent income losses due to unemployment. (iii) Additional taxation of companies whose profitability has increased due to the pandemic process, to be transferred to the households most affected by this process. (iv) In order to prevent isolation policies from locking the economy, arrangements should be made for flexible and different time schedules such as shift systems and different working hours so as to to reduce human density.

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APPENDIX

Table A1 GINI Index for 1963-2019 in 102 Countries

> 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1989 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 42 1028 41 Stul 41 2228 44 Stul 41 2228 44 Stul 41 2228 44 Stul 41 2228 44 Stul 41 228 45 Stul 41 28 Stul 41 58 Stul 41 58 Stul 41 28 Stul 41 58 Countryname dighanistar Albanin Algerin Argentina Argentina Australia Australia Austria Azerbaija Banglades *2,000 * 7,001 * 7,001 * 7,001 * 7,000 31,2151 31,4177 31,2007 31,2111 31,2008 31,6466 31,4827 31,5240 31,4584 31,7044 31,6316 31,4854 31,5488 31,1374 31,2297 31,9573 32,2100 32,5786 32,7008 33,2864 33,873 34,2326 34,5855 35,0019 35,6458 35,2276 **06,5112 36,330** 34,4566 34,8314 34,0176 34,8024 35,0302 35,3555 35,3466 34,4673 34,4716 34,4162 33,2880 33,6136 34,3017 33,705 33,6115 33,2014 34,0276 34,3103 34,6871 34,8890 45,9500 35,0444 35,0167 35,2047 34,871 34,200 1017 B HOLT 2018A Belgium Belgium Bolivia 12498 12482 94999 112400 11490 84713 11240 854771 94814 8448 25471 95470 8499 14041 94474 134914 134914 13491 13494 12491 12494 13491 13491 12494 13491 134991 13491 134 Canardo Canada Chia Chia Chia Coago Control Coago Coago Control Coago Control Coago Control Egopt Estres Es Section 19, 201 (2011) 19, 2013 (2011) 19, 2011 (2011) 19, 2011) 19, 2013 (2011) 19, 2013 (2011) 19, 2013 (2011) 19, 2011 (2011) 19, 2013 (2011) 19, 2013 (2011) 19, 2013 (2011) 19, 2013 (42,559 41,365 40,007 42,855 42,154 42,4166 41,000 40,421 41,259 42,626 42,222 43,151 44,617 45,001 46,138 47,318 46,756 47,009 42,600 44,660 44,660 43,001 90,227 49,564 33,001 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,601 31,622 31,626 31,600 31,620 3 44.815 0 0/01 0 0/312 0 0/00 0 1/242 51.842 5 0/807 5 0/219 0 0/213 1 1/119 0 0/043 0 0/055 0 0/219 1 0/219 0 0/203 0 0/203 0 1/220 1 0/203 0 Jordan Gazakhstar Kenya Kuwait Kyrgyzstan Latvia Lesotho Lithuania 54,1125 53,5616 53,2591 53,1835 52,9997 52,0660 53,1465 52,0561 52,0551 50,5769 51,1363 51,9700 51,0458 51,5767 50,0610 50,7241 51,6998 50,4756 50,9888 50,8250 50,2785 51,0017 52,0866 51,7248 51,245 50,6709 51,2454 50,769 48,0031 50,0003 48,3450 51,4755 52,2592 51,7659 51,5750 51,6036 51,966 31,7587 30,5640 30,7233 28,7321 28,9412 29,2999 29,9766 31,9777 31,1315 30,4744 30,0861 30,6755 29,7178 29,3799 29,488 30,6465 31,7388 31,0645 31,7388 31,0647 31,0687 axembourg Macao dacedonia dadagascar Malawi Makaysin Mata Manitias Menico Mongolia Morocco Myanmar Nepal Vaturdard 4,0001 45,241 45,101 47,000 44,000 55,000 75,000 45,000 14,000 44 51 2261 50 6220 50 2026 50 5275 51 0065 50 5077 50 2224 50 0121 47 5012 47 6672 49 4175 40 2175 40 6225 50 2015 50 660 4288 51,030 11,045 32,1051 31,047 33,146 33,770 33,686 33,922 33,756 33,656 33,923 32,756 33,650 33,960 33,960 33,971 32,915 34,968 34,978 34,968 34,971 33,670 33,686 33,970 34,686 33,972 33,766 33,970 34,986 34,970 34,970 34,986 34,970 34,970 34,986 34,970 34,970 34,986 34,970 34,970 34,970 34, letherlands ew Zealand Nigeria Norway Oman Pakistan Pakistan Parama Peru Philippines Poland Portugal Qatar —whijc of Ko 45,024 4,485 4,590 453171 45,126 46,0071 4,721 45,124 4,027 4,819 4,807 4,941 4,119 4,775 46,391 17,80 4,391 47,809 4,360 4,321 47,919 4,9118 4,222 4,9176 4,0014 4,687 9,212 4,800 4,929 4,800 4,929 4,900 4,929 4,900 4,929 4,900 4,929 4,900 4,929 4,900 4,929 4,900 4,929 4,900 4,929 4,900 FUEL CONTROL HOUSE NOT AND ADDRESS AND Senegal Singapore Slovakia Stovrnin South Africa Spain Sri Lanka Swaziand Sweden Syrian Arab Republic Tairan 41/16 50/46 84/07 84/07 94/07 40/07 9/07 20/07 a Arab Reput Taiwan Thailand Tunisia Turkey Uganda Ukraine ited Kingdom 20048 35,588 35,219 35,685 10,718 22044 24,120 2250 2505 83,085 10,001 29,810 26,414 10,008 91,018 25,212 10,217 10,581 31,0181 32,181 32,912 33,414 35,6910 4,2174 14,618 4,688 14,601 34,921 35,918 4,618 34,910 4,121 ed Republic of Tanzania 46,1150 45,6869 45,5674 46,3938 45,8661 45,4878 45,6272 45,0497 45,1791 45,4181 45,1493 44,9004 44,2433 44,3229 44,7212 44,9004 45,4579 44,5818 43,0088 43,2079 43,5265 44,7013 44,1238 43,7555 43,7156 44,7990 44,4524 45,2190

Countraname	1001 1002 1003 1004 1005 1006 1007 1008 1000 2000 2001 2007 2003 2005 2005 2006 2007 2008 2000 2010 2011 2012 2013 2014 20	15 2016 2017 2018
Achemister	20 7001 47 9946 44 2669 46 931 49 6056 43 0147 43 2973 44 0555 44 0430 46 2400 47 9309 47 6100 26 710 126 555 24 0201 21 6730 40 912 62 7210 43 0551 44 1917 42 710 13 5146 45 592 45 7	P25 42 7812 42 2022 41 00c0
Albacia	14 1364 13 9419 24 0070 57 0051 51 7705 45 151 61 0 2724 42 0161 44 0174 45 0051 44 5172 42 0075 40 0010 47 0175 47 0175 47 1010 47 0175 45 0010 46 0774 44 7641 42 1020 47 700 44 124 52 0	274 42 9555 42 2201 43 2320
Aconta	34,1374 33,0476 3,0571 31,175 43,1201 42,1734 43,0401 44,0224 44,317 43,0577 44,0620 46,04710 47,4252 47,1012 47,8123 40,0505 40,0274 44,061 43,057 44,0274 44,061 43,050 44,021 44,041 43,050 44,021 44,041 43,050 44,021 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 44,041 43,050 44,041 43,050 44,041 44,041 43,050 44,041 4	274 42,9353 42,2201 43,2320
Augena	38,49/0 39,810/ 39,3924 39,4050 ++,1515 39,0801 39,0514 40,0811 41,0935 49,285 44,2445 44,269 42,260 41,0952 49,352/ 39,6526 39,4415 39,497/ 39,781 40,162/ 40,0895 40,252 59,7020 359	953 38,5117 38,3026 38,2301
Argentina	47,7231 46,5660 46,7293 46,6930 46,7177 47,1906 45,7619 48,6425 48,4616 48,7400 49,5270 50,2793 50,1231 48,4822 46,7531 46,7567 48,9674 49,8197 48,7159 46,6057 44,3666 43,5559 43,5899 43,1050 42,7	808 45,8585 45,7159 46,7095
Armenia	47,8971 55,2644 57,2357 57,2655 47,3893 47,4417 48,0431 51,8535 55,4879 50,6276 48,5228 48,6450 52,0170 51,2504 55,7847 53,2598 50,3595 48,2960 46,7853 47,3037 46,7889 46,3	522 45,6088 45,1250 44,8337
Australia	35,9768 35,9664 36,5611 37,2816 37,2955 36,7075 36,2915 37,2949 36,6300 36,8320 36,7161 37,9195 38,2453 38,6575 37,8680 37,9452 39,5032 40,4697 40,2879 40,7733 41,5479 40,7514 41,8423 41,7922 42,0	838 42,7621 43,3696 42,4984
Austria	35,6848 35,8062 35,8369 35,8270 35,0822 35,2731 35,6405 35,6196 35,7693 36,2112 35,4973 35,5397 35,7414 35,4732 35,9783 35,8322 35,5324 35,5134 36,0035 36,3618 36,8623 36,9670 36,8111 36,6108 36,4	908 35,9505 35,6410 36,5858
Azerbaijan	42,1134 47,7253 48,7908 49,4470 50,8084 51,6388 54,2875 55,7682 54,9015 56,4938 56,5631 54,7491 53,3039 53,3072 51,5452 51,2924 51,0078 48,2752 45,6519 48,9638 47,3276 46,6688 45,7	572 48,7962 49,6258 47,6108
Bangladesh	48,8789 49,2394 48,0709 47,5068 47,8223 48,0393 48,6601 50,1643 49,2925 48,0775 48,7130 47,9691 49,7579 49,7680 50,5117 49,8649 48,9552 49,8665 48,6283 49,3381 47,1332 48,0436 49,0402 48,1231 47,3	303 49,6582 48,9747 50,1666
Beleium	38,2361 38,1200 38,2895 38,0917 38,0585 38,6493 39,0895 38,8383 38,4337 38,4986 38,9725 39,0865 40,0039 40,0823 40,4997 40,3052 40,0340 40,7533 41,3960 41,2744 41,1015 42,4561 42,8364 42,6310	372 42.9642 42.0158 42.0224
Bolinia	50 8697 50 4755 50 9059 51 0686 51 0842 50 8397 50 0583 50 6675 50 8631 51 4207 51 6984 51 3824 51 2463 51 1869 51 1635 51 3425 51 9844 52 3257 51 6347 49 8028 48 9538 48 7813 48 7686 49 3678 52 0	952 52 1958 52 0093 51 8969
Dotropos	10 100 10 2550 40 1507 47 0051 40 4017 10 7005 10 001 51 470 50 00 25 40 0025 40 0051 41 105 47 050 4 105 41	073 46 5787 46 2400 46 0510
Basel	ער איז	763 47 3990 47 5133 47 1333
Dealer	C. H. CCL, P. CON, P. PCL, P. PCR, P. CCC, P. DUROSP. D1 0, 69 UD1, 69 LOCC, P. LOCC, P. CL, CP. D10, 79 D10, 79 UD0, 244, 50 UD0, 79 UD0, 70 U 70 UD0, 70	152 47,5330 47,5123 47,1232
Bulgara	32,9517 36,9548 38,5776 41,3599 39,5714 40,5541 40,9117 41,059 41,4458 42,5678 42,5858 42,4959 42,4795 42,6218 42,5166 42,0585 42,6228 45,0004 42,5492 43,1212 42,1808 42,0872 42,4489 41,5849 41,5	564 41,3/15 42,3520 41,8506
Burundi	52,1029 52,9832 53,2611 53,8922 52,3233 51,2474 50,5523 50,0137 50,0619 52,3473 53,5241 51,1292 52,8574 50,3589 55,8591 56,8885 56,0050 58,0404 57,4785 56,4213 56,2013 55,4092 55,6217 56,7	617 57,4544 56,2197 56,4826
Cameroon	54,8261 55,5225 55,2974 55,2847 56,8971 56,6102 56,2390 56,7137 56,4421 55,8857 54,4579 55,1299 53,38976 52,4467 50,8368 53,2656 55,3026 55,3072 55,5401 55,9264 55,2791 54,5203 53,1145 55,6368 55,0	971 55,8614 56,0811 56,0910
Canada	37,5950 37,5662 38,3057 38,3385 38,1697 37,9467 38,1168 37,8897 38,1394 38,4729 38,5232 38,5660 38,5385 38,4711 37,9647 37,8978 38,4575 38,9568 38,9381 39,3034 38,4433 38,7589 38,7547 38,8266 38,8	513 38,3433 38,1289 38,5262
Chile	46,9572 46,5505 46,4149 46,2907 46,5519 46,7574 47,0583 48,8014 48,2128 47,7307 48,5959 48,9103 48,8874 49,8697 50,3217 47,9969 47,1912 48,3736 48,3590 47,9460 48,0332 48,9411 49,6049 49,8689 49,9	507 47,9849 48,7496 48,7809
China	38.8434 42.3640 40.7309 39.5001 41.7957 39.8188 38.6445 38.3301 38.0241 38.8162 39.6422 39.3642 42.6938 41.6262 40.9967 40.7280 40.0308 38.8695 39.9983 38.7789 38.9917 37.6775 37.5286 37.4162 38.2	562 38,4680 38,9352 38,2537
Colombia	45 8807 47 1317 46 9046 46 8184 46 7499 46 6133 46 5918 46 5607 47 2819 47 0725 47 6000 47 5060 47 5060 47 6065 46 9945 46 8754 46 4573 44 7761 44 2018 43 8690 42 4379 41 7555 41 4729 45 1461 44 8083 44 8	036 44 8388 44 7794 44 9867
Conto	48 4010 48 2560 46 1016 47 6151 48 1021 48 6055 48 2018 47 1514 47 1658 47 1205 47 4804 48 0771 50 5500 50 0111 48 7518 40 1600 40 3661 48 5507 46 0001 48 2567 47 0240 47 8147 48 4050 48 6558 47 7	954 48 6162 49 7876 48 4871
Contro		100 40,0102 40,1010 40,4071
Costa roca	+,555/ +5,0162 +2,9656 +4,5591 +1,5170 +4,1757 +2,0557 +2,0557 +5,8522 +5,907 +4,1706 +4,0231 +4,0472 +3,4003 +5,2105 +2,6177 +4,4120 +4,077 +4,52524 +4,0759 +4,0759 +5,0651 +4,079	583 43,1858 43,0780 44,0702
Croana	38,3000 30,9201 33,3089 30,8390 37,8540 39,4161 39,3005 41,3409 41,8431 42,3106 42,8677 42,9058 42,7189 42,6211 42,7175 42,1178 41,720 41,6142 42,2906 42,5718 42,7317 42,8168 41,613 41,7	508 42,0132 42,0133 42,0148
Cuba	35,5205 35,4213 34,6242 33,329 33,930/ 32,5271 32,6870 32,6514 32,5263 32,6663 33,4132 33,1592 32,7/56 32,9808 33,6026 33,7/44 33,5089 34,6769 32,9850 32,485/ 33,8597 35,0114 34,7830 34,6128 33,9	320 33,6221 34,9120 35,4829
Cyprus	39,1407 39,3001 39,6192 38,9641 39,3479 39,7906 39,7702 39,7175 40,5581 38,4183 38,3879 37,5459 38,7079 38,6224 36,4649 36,5535 36,5672 36,8464 35,8593 36,1816 36,8108 35,5616 36,9426 36,9794 36,9	105 36,7976 36,9781 35,2766
Czech Republic	26,9376 28,5493 29,6252 29,3104 29,3595 29,6906 29,9145 30,4044 30,9709 31,1198 30,7155 30,6912 31,0832 30,3206 30,6110 30,5785 29,9059 30,2942 31,9585 31,9414 31,9620 32,0113 31,7406 30,8	710 32,5650 31,5098 31,8180
Denmark	31,3462 30,6374 30,3259 30,6696 30,7686 31,3563 29,8636 30,8726 31,0786 31,8077 31,3681 32,5201 32,9575 31,7880 32,8959 33,7872 33,2248 33,2055 36,0305 37,1394 36,1508 34,0767 34,3130 34,1	764 34,0150 33,9559 34,1508
Dominican Republic	2 48,6107 50,3985 50,4073 50,0099 50,3628 52,9788 51,6593 51,3009 50,2446 52,0335 49,3912 48,6107 51,1561 51,2387 51,6004 51,4169 50,0037 50,8187 50,3985 50,4073 50,0099 50,3628 52,9788 51,6593 51,3	009 50,2446 52,0335 49,3912
Ecuador	48.4089 49.0535 49.5487 50.6801 48.6084 51.1338 50.8882 50.3570 50.3978 48.7518 45.7473 44.4664 43.9490 48.6682 49.9533 48.0803 47.0529 46.8302 46.8860 46.5266 46.9359 46.1062 47.2313 47.7345 47.7	742 46,1279 46,9054 46,4893
Egynt	47,4070 47,6519 48,4286 48,8065 48,8170 49,5737 50,1984 49,1249 50,4961 50,7699 50,9993 52,9214 52,0495 53 3187 53,4030 53,4030 53,95801 53,5138 52,6072 52,5620 53,8786 53,6714 51,8335 53,7700 53,9	365 52,9768 52,8191 52,9738
FI Salvador	46 4105 48 0170 40 0100 10 6180 40 8651 40 4058 47 0741 48 1501 50 5818 50 0545 50 7481 48 6815 40 6042 40 0473 50 0133 50 7664 50 5749 50 110 40 055 50 505 51 55 156 156 160 113 50 1	095 49 7075 49 0531 49 5117
Fritran	46 7571 46 1457 14 5071 48 4158 45 6701 14 7524 45 6560 14 7514 45 6560 15 610 61 7614 45 6560 15 6173 45 6173 14 8673 45 6173 45 6173 45 6173 45 751	507 51 0111 50 6584 40 6476
Land Ca.	1,2,2,2,1,0,2,2,2,2,2,2,2,2,2,2,2,2,2,2,	TOF 26 0841 26 1880 27 78426
Estona	+++++2 +	163 30,0341 30,1330 36,7550
Pup	21,4211 49,4020 49,0021 40,9101 42,0009 41,0299 40,0210 44,1203 42,4120 45,2452 41,5587 40,4092 42,2510 46,1088 44,2821 44,8802 47,4191 45,7598 45,2215 45,4827 45,2421 45,9428 45,0816 45,6	450 45,482/ 45,5895 45,1689
Finland	34,3300 33,740 33,8744 33,3900 33,120 32,9787 33,1858 33,1868 32,7314 32,8658 33,2683 33,1641 33,6531 34,2578 33,7815 54,1897 34,1949 34,2044 35,6922 36,0371 35,8753 36,0303 35,8597 36,4096 35,9	352 35,2599 36,4462 36,2634
France	36,383/ 36,9003 57,5544 57,8754 57,8754 56,353 36,4971 36,6073 36,7468 36,9391 36,6533 36,9629 36,9956 36,2435 37,2039 37,4539 37,3573 35,9760 37,7834 38,1459 37,5739 37,3274 38,0298 37,9971 37,9	598 37,9110 37,4577 37,7840
Georgia	48,9490 47,5495 52,4865 50,3510 50,7547 50,2689 49,8806 48,2135 48,1024 47,3584 46,8598 45,9544 45,4066 44,5263 44,7280 45,4137 47,1939 47,3	454 46,5766 45,2774 45,0179
Germany	33,0006 33,7481 34,2608 35,5964 35,9036 35,3751 34,9611 36,5194 35,9019 36,2706 36,9739 37,2363 37,8040 38,0888 37,7032 37,6689 37,8226 38,5056 38,8606 38,3148 38,3704 38,2915 38,2	236 38,4397 37,5427 38,5516
Ghana	50,8912 50,9054 49,3209 49,3175 49,3118 48,3773 48,8664 48,0773 47,2420 47,1400 47,1655 47,6388 47,7171 47,4338 47,3943 47,2429 48,9081 49,3360 50,5668 50,6253 50,9661 46,4810 50,6808 50,8912 50,9	054 50,7572 49,0069 50,2641
Greece	44,7204 44,7819 43,9292 43,9291 44,2915 44,8490 44,1161 44,1763 43,9766 43,9408 45,3388 45,3595 45,0179 45,0365 45,1541 44,2302 44,2801 44,4090 44 5744 41 2291 40,8831 45,1006 45 5105 45 4743 45 4	353 45,4066 45,4086 45,5088
Guatemala	55,1736 54,5451 55,2533 54,3145 53,5328 49,5653 48,9984 50,0040 50,2699 51,3077 53,1299 55,6704 55,6617 57,6650 51,0771 49,7715 40,7669 51,0077 51,1769 55,6704 55,67000 50,6700000000000000000000000000000000000	273 50.2589 50 1055 49 0010
Hondway	50 5075 40 1733 50 7777 50 7300 48 1843 45 7847 46 0781 48 1540 48 770 5 45 837 46 6645 46 0783 45 560 44 783 46 560 46 777 55 730 46 9174 45 918 46 1781 48 1781 48 1781 48 1	337 46 0645 46 0783 45 2620
riveduras	21 2014 2017 2017 2017 2017 2017 2017 2017 2017	
Hungary	34,3944 36,6121 39,1539 39,6616 39,6450 40,2401 40,5020 40,2066 40,1198 39,3161 39,8858 39,9577 40,2075 40,1125 41,6655 40,5788 40,2045 39,9150 41,0937 41,4515 41,1119 40,8598 40,4504 40,4907 39,8	/30 40,340/ 39,4168 40,4222
India	50,0995 50,5398 50,2465 50,7340 50,9104 50,4405 51,0466 50,9748 51,0859 51,9401 52,1760 52,5457 52,7767 52,2028 51,9454 51,7154 51,8158 51,7211 50,8496 50,8534 50,8534 50,8534 50,4595 50,4481 50,4	396 50,1977 50,4447 50,7480
Indonesia	48,2103 47,8126 46,6497 47,4748 49,9268 48,2102 48,2307 51,4419 50,4402 47,8817 52,9578 47,1586 50,5296 48,8693 49,8274 47,7762 46,5993 51,1336 50,3000 50,6019 45,9982 47,9994 48,7734 48,6927 48,6	362 49,7329 48,7289 48,7286
Iran	41,4069 44,1965 45,5415 43,8682 42,5182 44,6355 45,4586 46,1608 46,2513 46,9371 46,3407 46,1789 46,6744 46,8589 46,6255 48,3568 48,4630 46,8498 46,5126 46,3967 46,9751 47,0403 48,4323 48,3521 48,3	365 48,4505 48,1461 48,7242
Ireland	37,4593 37,5218 37,4652 37,0499 37,5714 37,0260 36,3939 35,8899 35,2548 34,5055 34,8224 34,8764 34,5166 34,6791 36,5165 36,3832 36,7274 37,9009 39,2674 39,5264 39,7100 39,7444 39,6105 39,7090 38,7	097 38,6284 38,7461 39,6545
Israel	42,4391 42,6019 42,4653 41,8308 42,0368 42,2784 42,3955 42,6981 42,9763 43,3270 42,9224 43,4171 43,4226 44,3725 44,2843 44,9878 44,2806 43,6657 44,1243 44,3653 44,6950 44,2674 43,8758 43,4660 43,4	142 43,0424 43,7904 43,5790
Italy	37,9998 38,6464 38,7431 38,5941 37,3852 36,4351 37,7487 37,1461 37,1256 36,9696 36,6897 36,7715 36,8192 36,5645 37,0002 36,8740 36,6335 36,6641 36,4255 37,0803 37,0556 37,3724 37,3622 37,3349 37,2	270 37,1581 37,2292 37,4192
Jamaica	51 8740 49 4993 48 8050 48 1572 47 9646 47 7982 48 1255 49 8091 50 6369 51 2460 51 2935 51 4049 49 9721 50 6851 51 1216 49 6950 47 7374 46 3767 48 2537 49 5663 46 8440 47 5530 47 6773 48 0914 50 8	608 51 3918 49,7160 48,7393
Ianan	37 3631 37 1894 37 1754 41 4007 41 5018 41 7075 41 8411 42 1241 42 3831 42 6004 43 5021 44 2901 44 4696 44 5042 44 4471 44 4255 44 2188 43 9836 43 7878 43 8795 46 5039 43 4463 43 8262 43 0274 43 8	747 44 9144 43 7918 43 3830
Inches	40 450 47 4117 16 2000 40 0051 46 2100 46 5266 47 1031 57 560 10 000 50 7465 10 5000 50 7465 10 5000 50 1265 50 1001 50 10 651 40 0450 10 0070 50 0010 52 1115 51 160 57 5770 51 2022 51 5	721 50 5005 50 2646 50 6640
Varakhetan	17 121 20 40 10 10 10 10 10 10 10 10 10 10 10 10 10	245 47 0242 46 0996 45 0607
Kazaknistan	+//361 +2/052 +3	243 47,0343 40,9880 43,9607
Kenya	50,8940 30,4742 49,8212 49,4950 49,958 47,811 47,572 49,499 30,9990 49,0550 48,7083 53,1408 48,0013 50,0520 30,045 30,041 51,4018 54,1740 51,999 51,9881 52,007 52,5483 52,0019 52,5923 52,8	169 51,4312 50,9924 52,9585
Kuwan	59,1596 50,1794 55,0460 55,510 55,254 54,060 54,542 55,5210 55,5210 55,460 54,252 5 62,52,05 05,252 51,2520 51,411 00,241 50,253 56,156 25,26,051 54,262 10,159 01,241 00,241 50,254 54,050 54,054 54,050 54,054,054 54,054 54,054 54,054 54,054 54,054 54,054 54,05	488 39,0003 38,8801 37,9769
Kyrgyzstan	40,2758 45,5322 45,7940 45,3693 46,8153 44,3047 49,7428 47,9377 48,2987 58,5295 56,3892 61,4185 61,2868 61,8365 59,9966 60,6185 62,4198 62,2826 62,8504 60,8292 61,8698 62,3284 60,7	524 59,4837 60,9336 60,4110
Latvia	43,9346 41,7549 41,7909 42,1144 41,6523 38,7079 39,5133 39,0992 38,1164 37,6633 37,1163 37,4458 37,8849 38,5360 38,1401 40,1322 42,1628 42,4988 42,6171 41,8381 41,0353 40,9314 40,6	668 40,8125 40,7083 40,5992
Lesotho	52,5826 52,8379 52,5106 53,3517 51,8326 49,8573 48,1207 49,5360 49,9589 49,3228 51,9618 52,1415 52,0199 48,7366 51,0742 52,0275 50,8400 52,5486 54,3167 52,7774 51,7540 51,3553 51,9259 53,5330 52,0	044 48,7662 52,5653 51,5562
Lithuania	35,8468 39,2448 39,8813 41,8060 41,8027 42,0657 42,5485 43,7070 44,2978 43,1175 43,1547 42,0190 42,2143 41,2286 40,9680 41,3882 44,0662 44,2533 43,2076 42,4824 41,4313 41,1076 40,6	885 40,6207 41,9162 41,2295
Luxembourg	34,3065 34,3659 35,0949 35,4534 35,4792 35,2565 35,3318 35,2216 35,3728 36,2876 34,3876 34,6878 36,2900 36,9705 36,5190 37,5537 37,1818 41,0965 38,9601 39,6895 39,4974 39,2260 39,7231 40,0332 39,9	200 39,5749 39,1030 39,5665
Macao	25 2686 27 0633 31 9975 32 4000 32 9592 33 6054 33 7491 33 4966 34 1920 34 2537 34 5996 35 6894 36 8408 36 5056 39 2363 41 4606 42 5770 41 9351 43 0201 43 1611 43.8733 44 1262 44 6569 44 5482 44.9	670 44.5789 44.2523 44.2359
Macadonia	10 0105 16 T112 17 4201 18 1822 1 20 130 530 41 1684 41 2000 41 T711 41 0005 47 1802 47 0005 41 8466 45 1465 44 7650 44 0407 45 8420 44 1563 44 7506 44 0200 44 0707 44 1663 45 84200 45 842005 45 84200000 45 842000 45 8420000000000000000000000000000000	580 44 7720 44 8467 44 9501
Madagaran	45 6510 46 0112 46 7373 47 6438 46 0614 46 7007 46 9930 40 0154 47 9247 46 0250 47 0054 44 9964 45 1550 47 0000 45 0075 45 0726 45 3705 44 7026 43 4103 40 555 46 7551 43 9647 47 3108 44 0947 46 9	774 45 7565 45 9090 46 9779
Maland		
Malawi	52,220 94,005 94,121 32,000 53,137 52,730 94,122 53,204 00,004 35,0451 53,0451 54,042 33,542 34,040 52,535 20,1152 50,045 50,0112 50,1142 50,245 30,0013 50,0112 50,1142 50,045 50,0414 00,045 50,0414 00,045 50,0414 50,045 5	332 37,7004 30,4707 33,9302
Maraysta	40,8390 39,8613 39,1600 39,3101 38,9110 39,1344 39,4503 39,1603 38,8520 40,9089 40,1510 40,8107 40,8205 40,4799 39,9622 39,9730 40,0214 40,4011 39,1015 39,3804 39,3089 39,2895 39,6249 39,4	231 40,4653 40,6673 40,3674
Malta	34,6105 34,4531 35,3557 35,2472 37,3952 35,6712 36,6968 36,1399 38,0745 37,7333 37,3794 37,7342 38,0669 38,0992 37,3524 42,2930 41,0299 40,9978 39,3456 39,7736 41,1101 39,3800 38,5861 38,9344 41,8	702 39,7506 38,5458 37,8263
Mauritius	37,4306 36,2882 36,3262 36,6998 37,1447 37,1862 38,9502 38,9944 37,8619 37,3632 37,3785 36,8153 38,4152 40,2186 40,5695 39,3977 42,1910 41,7119 40,2079 40,2714 38,4983 38,5840 39,0639 38,9387 38,7	291 38,5410 39,5211 40,5198
Mexico	45,3874 46,4863 46,6917 45,2497 46,3570 46,9990 47,4335 47,3077 47,2865 47,2343 46,8036 46,5478 47,6686 48,8326 47,6988 49,7219 49,2776 49,3345 48,3895 48,0450 48,5000 47,8679 47,7700 48,1692 49,2	558 49,9514 48,9406 49,5314
Mongolia	47,4941 49,7361 51,7828 51,1350 49,7740 46,3975 48,0234 44,7854 43,8549 45,5602 49,4958 52,9575 50,3993 49,2621 53,8176 52,0506 46,5557 56,1441 47,8388 51,9064 56,6017 52,9116 48,5	919 51,5798 52,5910 53,5911
Morocco	49,7360 48,7272 48,5934 48,5250 47,7827 47,5506 48,1922 49,0255 50,0962 51,1718 51,3493 51,5794 51,9864 51,3896 52,3178 53,4998 53,1041 52,6569 52,4890 53,4499 54,9488 55,5800 55,9349 55,9997 56,1	366 56,2261 56,6358 56,8365
Myanmar	40,9489 48,9002 44,2445 44,8406 52,0606 51,0645 51,9390 51,2116 48,1758 47,5613 48,2037 45,0994 46,5728 49,1901 49,2667 48,3925 47,4632 44,9517 45,0043 45,5607 49,3849 49,4763 49,7	363 48,8189 48,3616 49,4904
Nepal	50,2000 49,3354 48,4841 45,8687 45,2736 46,6952 47,7420 45,9139 47,9431 51,6102 53,0568 53,7997 54,4095 54,1565 53,5706 50,8807 42,5623 42,9826 47,0616 47,7700 48,1814 50,7884 49,0650 50,8807 42,5623 42,9826 47,0616 47,7700 48,1814 50,7884 49,0650 50,8807 42,5623 42,9826 47,0616 47,7700 48,1814 50,7884 49,0650 50,8807 54,1565 53,5706 50,8807 42,5623 42,9826 47,0616 47,7700 48,1814 50,7884 49,0650 50,8807 54,1565 53,5706 50,8807 42,5623 42,9826 47,0616 47,7700 48,1814 50,7884 49,0650 50,8807 54,1565 53,5706 50,8807 54,2623 54,2986 54,1565 54,1565 54,1566 54,156	917 52.5919 53.6777 49 6818
Netherlands	35 0861 35 2015 35 4165 35 3142 34 9186 35 1998 37 6073 37 8372 36 2649 36 7004 36 3617 36 7107 37 5432 36 2866 36 9552 38 9590 39 3875 36 4101 30 7557 38 4707 30 4576 30 1507 30 1316 38 8014 38 8	810 39.5551 39.3887 37 3817
New Zealand	19 5178 40 4776 38 5858 36 7695 37 9677 38 335 3711 38 3543 38 3711 38 3543 39 9714 38 0171 36 9971 37 0001 37 0001 36 4983 35 5417 36 5401 36 56863 37 4531 37 0511 40 1701 30 4750 30 4751 3	366 39 3210 38 1941 37 1951
Ninesia	17 YECK 18 (1750 56) 11063 50 1065 40 4088 40 0465 48 8806 48 1757 48 7456 48 655 48 5704 48 9304 47 7504 7504 47 7504	653 48 8777 40 4400 50 000
Norma	26 1457 26 1021 25 7042 24 2011 24 6002 21 1001 24 1001 24 1001 24 1001 24 24 04 21 100 1 24 6002 31 1001 24 0001 24 1	620 19 1540 10 0101 10 0000
INCE WILLY	1/12 1/14/14/14/14/14/14/14/14/14/14/14/14/14	0.0 00,3540 38,8101 39,0823
Oman	21,1472 24,0241 22,2301 23,0307 31,1403 20,0904 24,7500 244110 24,830 34,444 49,4085 24,02/4 50,1455 14,2500 47,2249 20,2652 47,1413 47,8843 48,5577 50,8625 49,7116 50,1	11/ 30,3151 49,2655 50,2611
Pakistan	30,5300 30,0197 30,7113 30,0997 30,9440 31,2052 51,4985 52,1923 52,3016 52,8416 52,9665 52,6746 52,8511 51,9225 50,0455 50,7643 52,0025 52,5664 52,7524 52,8522 53,2644 53,3335 53,0735 52,9429 51,6	198 51,3655 51,2688 50,6133
Panama	47,8749 51,2820 50,5074 50,28253 51,7804 50,6871 50,5787 50,6914 50,2506 46,2949 48,8311 51,4639 43,4184 44,3949 48,9623 47,8132 50,5674 44,1235 44,3335 42,2611 41,4959 42,4320 43,9287 46,7	0/4 42,2556 42,8682 43,2133
Peru	49,1479 48,7088 49,4645 51,2521 52,1314 50,9578 50,0501 52,5953 53,2672 54,6386 54,9235 55,3916 55,6804 55,4981 55,4486 55,1495 54,8702 54,7415 55,2968 54,6438 54,1867 54,3625 53,3616 53,7152 53,9	120 53,1420 53,3793 54,1810
Philippines	49,3434 49,2713 49,6369 49,6203 49,2370 47,6858 47,4219 46,7225 47,1782 47,1965 47,4520 47,4966 47,5577 47,5894 48,9433 47,7604 47,8237 48,6707 48,3292 47,6760 47,6288 48,4565 49,7350 49,6764 49,6	673 49,8363 49,9144 50,0200
Poland	33,7375 35,8462 36,5844 37,8467 38,6467 37,0954 37,9120 38,4072 41,7789 41,4862 42,9291 42,3515 41,5356 42,0785 41,7398 41,4888 40,5603 40,1139 40,2919 40,3169 40,4859 40,2718 39,9725 39,7325 39,7	288 38,4135 37,7489 37,3523
Portugal	36,9009 37,7582 38,8649 39,4025 40,1301 40,4176 40,4907 40,5093 40,5854 41,0864 41,4652 41,3701 41,6576 42,1398 41,7174 42,2503 42,4421 42,1034 42,6112 43,1109 42,7677 42,7552 42,8290 42,5694 42,4	489 42,6167 42,4628 42.2111
Qatar	54,0306 54,3122 55,7692 54,0622 55,1680 55,5372 56,9936 55,5039 54,6295 53,9876 54,0972 53,6040 55,3264 51,5479 51,7258 51,1652 50,5216 50,2324 52,2166 56,4026 56 8080 47 7427 46 4684 46 7186 46 8	410 57,7194 57.8370 57,9473
Republic of Kores	37 9589 38 2591 38 0448 38 3582 37 7143 38 2257 38 1676 39 4986 38 8747 39 1738 39 3204 38 9056 39 5921 39 9967 40 0429 39 4495 41 3384 40 3922 30 6077 38 8080 10 100 100 710 70000 10 07714 10 5	354 39.2477 39.2060 39 0647
Republic of Moldows	47 47 47 45 10 4811 50 3877 47 0870 41 4217 41 48 7783 51 1071 46 6311 38 7077 47 0634 40 433 39 6870 39 6671 37 8678 41 0011 41 2011 47 744 46 511 48 7784 46 511 1071 41 647	359 40 1893 40 8337 30 7376
Pomania	11 JUND 33 4578 33 0003 34 J356 35 6600 36 3063 38 0825 38 5106 40 3500 J1 2507 J1 5504 J1 5504 J1 5504 J1 0570 J1 057	187 42 7822 43 8576 42 0022
Desire Fadarat	5,2,4 991,1,1 992,0 100,2 10,2 1	101 42,1022 43,0310 43,9023
sussian rederation	3, 201 4,	0.0 43,/022 43,85/0 43,4023
Senegal	49,0320 46,2003 46,9001 30,9900 46,810 40,0611 50,0501 48,4007 47,0406 48,6942 50,3062 51,2133 49,5009 45,3520 46,2035 48,9974 47,5199 49,3618 50,1702 47,0132 49,1724 47,3958 48,0404 50,9	250 45,5057 49,4249 48,5469
Singapore	34,840/ 34,0432 34,00432 34,0004 34,5390 55,9029 34,0480 34,6519 35,7564 36,6733 36,7019 37,4990 37,7504 38,0488 38,0455 37,6157 37,6269 37,7558 37,7248 38,4409 39,0226 39,8139 39,1444 39,1972 40,4198 40,8	+1+ 40,3473 40,4434 39,5007
Slovakia	35,1482 36,3965 35,9037 36,6212 36,2684 36,4980 36,8796 36,9496 37,2855 37,7869 37,8454 37,9598 38,4376 37,9872 37,0382 35,9209 36,3563 36,8541 36,6707 36,8934 37,3647 37,0298 36,3	981 37,0776 37,5565 37,7231
Slovenia	31,3106 31,6331 31,9993 32,3600 32,6109 32,8994 33,2596 33,5166 32,7906 32,9842 33,1077 32,8802 33,9906 34,3186 34,4885 33,5749 33,4108 33,6505 35,2195 34,6953 34,5479 34,0989 34,4590 33,3916 33,3	644 33,5883 32,3515 31,3408
South Africa		219 49,4538 49,1821 49,9615
	45,425 45,4128 45,5849 46,1935 46,2018 46,4313 46,6218 45,6104 45,5451 46,4511 47,1019 47,0014 47,6797 47,5308 46,7133 46,9003 45,1248 45,2725 45,8575 46,9917 47,1675 47,2808 47,0380 48,0124 48,1	
Spain	12,400 42,4128 45,2889 46,1253 46,208 46,1313 46,218 45,210 45,251 46,211 47,1199 47,1094 47,0197 47,258 46,113 46,209 43,1248 45,212 45,2515 46,2991 41,105 41,208 47,250 46,0154	120 41,9986 41,8255 40,9209
Spain Sri Lanka	10,200 45,24125 45,250 45,200 46,1053 46,200 46,0131 40,0131 40,0101 45,2101 46,1211 47,1079 41,0071 47,0701 47,0701 47,000 46,014 40,014 41,041 47,071 47,010 47,010 47,000 47,010 47,000 47,010 47,000 47,010 47,010 47,000 47,010 47,010 47,000 47,010 47,0	120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44 0748
Spain Sri Lanka Swagland	12/102 64/103 62/109 10/102 10/102 10/102 10/102 10/102 10/101 10	120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44,0248 464 52,7860 53 7971 51 7974
Spain Sri Lanka Swaziland	1242 42435 5246 4255 6256 4255 64255 64255 64255 64255 6425 1245 5245 6425 1245 1245 1245 1245 1245 1245 1245 1	120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44,0248 464 52,7860 53,7921 51,7924 183 31,4907 32,4009 33,000
Sprin Sri Lanka Swaziland Sweden	45952 0.0012 0.0012 0.0012 0.1012 0.1012 0.0012 0.0014 0.0021 0.0021 0.0021 0.0021 0.0001 0.0021 0.00000000	120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44,0248 464 52,7860 53,7921 51,7924 183 33,4807 33,4003 33,0967
Spain Sri Lanka Swaziland Sweden Syrian Arab Republic	CLUCE 42438 C25476 (LDST 96/LDB 96/LDB 96/LDB 96/LDB 92/LDB 96/LDB 92/LDB 96/LDB 96	120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44,0248 464 52,7860 53,7921 51,7924 183 33,4807 33,4003 33,0967 852 47,2929 47,8645 48,2062
Spain Sri Lanka Swaziland Sweden Syrian Arab Republic Taiwan	School	120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44,0248 464 52,7860 53,7921 51,7924 138 33,4807 33,4003 33,0967 852 47,2929 47,8645 48,2062 723 38,8148 38,9012 39,1074
Spain Sri Lanka Swaziland Sweden Syrian Arab Republic Taiwan Thailand		120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44,0248 464 52,7860 53,7921 51,7924 183 33,4807 33,4003 33,0967 852 47,2929 47,8645 48,2062 723 38,8148 38,9012 39,1074 798 38,3798 36,4082 35,4223
Spein Sri Lanka Swaziland Sweden Syrian Arab Republic Taiwan Thailand Tunisia	School	120 41,9986 41,8255 40,9209 929 44,2496 44,6823 44,0248 46 52,7860 53,7921 51,7924 183 33,4507 33,4003 33,0967 852 47,2929 47,8645 48,2062 723 38,8148 38,9012 39,1074 978 33,3798 36,4082 35,4223 834 42,3032 42,9430 42,7377
Spain Sri Lanka Swaziland Sweden Syrian Arab Republic Taiwan Thailand Tunisia Tunisia Tunkey	Note: 1.0012 1.0012 1.0012 1.0013 1.0014 1.0014 1.0014 0.0021 0.00110	1:20 41,9986 41,8225 40,9209 929 44,2496 44,6823 44,0248 446 52,7860 53,7921 51,7924 183 33,4807 33,4003 33,967 852 47,2929 47,8645 48,2062 723 38,8148 38,9012 39,1074 798 38,3798 36,4082 35,4223 834 42,9032 42,9430 42,7377 96 45,9123 46,9673 46,6743
Sprin Sri Lanka Swaziland Sweden Syrian Arab Republic Taiwan Thailand Tunisia Turkey Uganda	A 10 C 1	120 41,9956 41,8255 40,9209 929 42,4264 64,823 44,0243 464 52,7860 53,7921 51,7924 183 33,4007 33,4003 33,0607 822 47,2292 47,5645 48,2062 723 38,8145 38,9012 39,1074 798 38,3798 36,4082 35,4223 83 43,798 36,4082 35,4223 84 42,2003 42,9430 42,7377 966 45,9123 46,9673 46,6743
Spein Sri Lanka Swazland Sweden Syrian Arab Republic Taiwan Thailand Tunisia Tunkey Uganda Ukryine	School	120 41,9956 41,8255 40,9209 929 44,2496 44,6823 44,0248 446 \$2,5766 05,7921 51,7921 183 33,4007 33,4003 33,0967 825 47,2929 47,8645 48,2062 723 38,8148 33,9012 99,107 798 38,5798 36,4082 35,4223 84 42,3032 42,9430 42,737 966 45,9123 46,9673 46,673 983 45,9123 46,9673 46,674 983 45,9123 46,9673 46,674
Sprin Sri Lanka Swadand Sweden Syrin Arab Republic Tairan Thailand Tunizia Tunizia Tunizy Uganda Ustrinie	4592 10491 10492 10492 10492 10491 10494 10496 10496 0050 0050 0050 0050 0050 0050 0050 00	120 41,9956 41,8255 40,9209 929 42,2466 446823 44,0248 464 52,7860 53,7921 51,7924 183 33,4007 33,4003 33,0607 522 47,2292 47,5645 48,2062 723 38,3145 38,9012 39,1074 798 38,3798 36,4082 35,4223 834 42,3032 42,9430 42,7377 796 45,9123 46,9673 46,9743 812 44,7320 44,8467 44,9501 564 40,6731 89,727 57,707
Spain Sei Lanka Swazland Sweden Syrian Arab Republic Tairan Tunkey Uganda Ukraine Ukraine Ukraine	Sector 11, 12, 12, 12, 12, 12, 13, 14, 12, 14, 14, 14, 14, 14, 14, 14, 14, 14, 14	120 41,9956 41,8255 40,9209 929 42,2468 446823 44,0248 446 42,7560 53,7921 51,7924 183 33,4807 33,4003 33,0607 852 47,2929 47,8645 48,2062 723 38,5148 38,9012 94,1074 798 38,3798 36,4082 55,4223 834 42,3032 42,9430 42,7377 96 45,9123 46,0673 46,5743 183 45,9123 46,0673 46,5743 105 45,9123 46,0673 46,5743 105 46,781 38,8727 37,3011 35 469,156 40,774
Spain Sri Lanka Sweden Syrian Arab Republic Tahwan Tunkan Tunkan Uganda Ukraine Ukraine Ukraine of Tunzaia	School 200412 100425 100425 100425 100421 100421 10040 10040 10041 10045 10040 10	120 41,9956 41,8255 40,9209 929 42,246 446823 44,0245 464 52,7860 53,7921 51,7924 133 33,4007 33,4003 33,0867 822 47,2292 47,5645 48,2062 723 38,3148 38,9012 39,1074 798 38,3798 36,4082 55,4223 834 42,3032 42,9430 42,7377 966 45,9123 46,9673 46,673 803 45,9123 46,9673 46,673 803 45,9123 46,9673 46,673 812 42,7720 44,8467 44,9501 566 40,6731 85,727 37,2011 226 59,2153 50,1993 51,1903 84 39,074 40,324 6,257
Sprin Sri Lanka Swadan Sweden Syrin Arab Republic Taiwan Tunkey Uganda United Kingdom Jinted Republic Of Tanzmia United States of America	Here and the second sec	1120 41,998 41,825 49,2920 299 41,246 41,552 49,2920 446 51,756 53,7921 51,7921 813 34,967 33,4960 33,9667 723 38,814 38,901 24,9480 33,9667 723 38,814 38,901 24,9480 42,757 723 38,314 38,901 24,9480 42,757 838 41,2001 24,9480 42,757 845 45,9123 46,967 34,6743 813 42,1212 46,067 34,6743 813 42,1212 46,067 34,6743 813 42,1212 46,067 34,6743 813 42,1212 46,073 45,743 814 42,1374 41,9210 51,908 51,1908 816 41,974 41,921 43,9101 43,9101 43,9101 816 41,974 41,921 44,9710 816 41,974 41,921 44,9710 817 41,974 41,971 44,971 817 41,974 41,971 44,971 817 41,974 41,971 44,971 817 41,974 41,971 44,971 817 41,974 41,971 41,971 817 41,974 41,971 817 41,974 817 41,974
Spain Sei Lanka Swadan Sweden Syrian Arab Republic Tairwan Tankand Tunkin Tunkey Uganda Ukraine Ukrain	Sector 1. 2012 1. 01021 1. 01021 1. 01021 1. 01021 1. 01021 0.	$\begin{array}{c} 120 \; 41,998 \; 41,825 \; 40,203 \\ 929\; 41,246 \; 41,632 \; 44,0243 \\ 446\; 52,760\; 53,7921\; 51,7924 \\ 446\; 52,760\; 53,7921\; 51,7924 \\ 572\; 47,586\; 53,792\; 57,864\; 45,2062 \\ 572\; 47,387,148\; 53,989\; 54,6462\; 55,4223 \\ 42,3921\; 42,904\; 42,904\; 92,7949 \\ 42,3931\; 42,904\; 24,204\; 94,204\; 94,7947 \\ 968\; 45,2912\; 46,9673\; 46,744 \\ 42,1924\; 42,904\; 42,904\; 42,7947 \\ 968\; 45,2912\; 46,9673\; 46,744 \\ 1212\; 44,770\; 44,846\; 44,8490 \\ 44,770\; 44,846\; 44,8490 \\ 122\; 46,731\; 35,837\; 73\; 50,110 \\ 122\; 65,0213\; 50,1933\; 51,1903 \\ 151\; 41,974\; 41,9214\; 42,9210 \\ 42,974\; 41,974\; 44,9214\; 42,9216 \\ 42,976\; 42,976\; 45,2577 \\ 54,976\; 51\; 556\; 52,577 \\ 54,976\; 51\; 556\; 52,577 \\ 54,976\; 54\; 556\; 52,577 \\ 54,976\; 54\; 556\; 52,577 \\ 54,976\; 54\; 556\; 52,577 \\ 54,976\; 54\; 556\; 52,577 \\ 54,976\; 54\; 556\; 52,577 \\ 54,976\; 54\; 556\; 52,577 \\ 54,976\; 54\; 56\; 52,577 \\ 54,976\; 54\; 56\; 52,577 \\ 54,976\; 54\; 56\; 52,577 \\ 54,976\; 54\; 55\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,577 \\ 55,976\; 56\; 52,570\; 56\; 55\; 56\; 52,570\; 56\; 55\; 56\; 55\; 56\; 55\; 56\; 56\; 55\; 56\; 56$
Spain Sei Lanka Swaziland Sweden Sweden Tairwan Tairwan Tairwan Tunkin Tunkey Uganda Ukraine Ukraine Ukraine Ukraine Ukraine Ukraine Ukraine Ukraine Ukraine Ukraine Ukraine Ukraine	Experience 10, 2012 (1), 2012 (1), 2013 (1), 2013 (1), 2013 (2), 2013 (1)	$\begin{array}{c} 120 41,998 41,3255 40,2919 \\ 594 42,964 46,2768 53,7921 51,7924 \\ 454 52,796 53,7921 51,7924 \\ 552 47,292 47,5645 45,2062 \\ 552 47,292 47,5645 45,2062 \\ 552 47,292 47,5645 45,2062 \\ 552 47,292 47,5645 45,2062 \\ 544 2304 24,2912 45,9673 46,574 \\ 544 2304 24,2904 34,2912 34,964 42,7917 \\ 564 45,9121 46,9753 46,574 \\ 544 2304 24,2914 34,2914 $
Sprin Si Laka Swazimd Swazimd Swazimd Takand Thaland Tuskin Uganda United Kaupdon United Kauptok of Tanzania United Kauptok of Tanzania United States of America Uring States of America	Exercise 1.0.012 1.0.012 1.0.012 1.0.012 1.0.012 1.0.01	$\begin{array}{c} 120 41,998 41,825 40,929 \\ 291 42,046 45,06 53,792 15,792 \\ 424 52,766 53,792 15,792 47,564 45,106 \\ 552 47,292 47,564 45,206 \\ 552 47,292 47,564 45,206 \\ 552 35,210 42,930 45,711 \\ 552 47,292 47,564 45,206 \\ 45,212 46,200 45,771 \\ 45,212 46,700 45,771 46,741 \\ 553 45,212 46,673 45,741 \\ 554 45,7512 46,674 45,901 \\ 555 55,751 55,757 $

Note: Light colored values show UTIP data, while dark-colored values show Gini values obtained by a simulation method based on

UTIP data.



Figure A1. Simulation and real data for GINI for 102 Countries



Figure A1. Continued