

Istanbul Business Research, 51(2), 583-605

DOI: 10.26650/ibr.2022.51.895431 http://ibr.istanbul.edu.tr/ http://dergipark.org.tr/ibr

Istanbul Business Research

Submitted: 11.03.2021 Revision Requested: 09.09.2021 Last Revision Received: 27.10.2021 Accepted: 27.03.2022 Published Online: 22.09.2022

RESEARCH ARTICLE

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

Esme lşık¹ ©, Ayfer Özyılmaz² ©, Metin Toprak³ ©, Yüksel Bayraktar⁴ ©, Figen Büyükakın⁵ © Mehmet Fırat Olgun⁶ ©

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).

- 1 Esme Işık (Asst. Prof. Dr.), Malatya Turgut Özal University, Optician, Malatya, Turkiye. E-mail: esme.isik@ozal.edu.tr ORCID: 0000-0002-6179-5746
- 2 Ayfer Özyılmaz (Asst. Prof. Dr.), Kocaeli University, Gölcük Vocational School, Foreign Trade Program, Kocaeli, Turkiye. E-mail: ozyilmazayfer@gmail.com ORCID: 0000-0001-9201-2508
- 3 Metin Toprak (Prof. Dr.), Istanbul Sabahattin Zaim University, Faculty of Business and Management Sciences, Department of Economics, Istanbul, Turkiye. E-mail: Metin.toprak@izu.edu.tr ORCID: 0000-0001-9217-6318
- 4 Yüksel Bayraktar (Prof. Dr.), Istanbul University, Faculty of Economics, Department of Economics, Istanbul, Turkiye. E-mail: ybayraktar@istanbul.edu.tr ORCID: 0000-0002-3499-4571
- 5 Figen Büyükakın (Assoc. Prof. Dr.), Kocaeli University, Faculty of Economics and Administrative Sciences, Department of Economics, Kocaeli, Turkiye. E-mail: bfigen@kocaeli.edu.tr ORCID: 0000-0002-0226-7265
- 6 Corresponding Author: Mehmet Fırat Olgun (Lecturer), Kastamonu University, Rectorate, Kastamonu, Turkey. E-mail: mfolgun@kastamonu.edu.tr ORCID: 0000-0002-2728-0714
- To cite this article: Isik, E., Ozyilmaz, A., Toprak, M., Bayraktar, Y., Buyukakin, F., & Olgun, M. F. (2022). Will outbreaks increase or reduce income inequality? the case of covid-19. *Istanbul Business Research*, *51*(2), 583-605. http://doi.org/10.26650/ibr.2022.51.895431



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.

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

$$R^{2} = 1 - \frac{\sum_{i}(Real \ Data_{i} - Sim_{i})^{2}}{\sum_{i}(Sim_{i})^{2}}$$
(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
les	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
ntr	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
Developed Countries	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
o pa	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
lopé	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
Ď	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
les	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
Ountr	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
	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
	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
opin	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
eveloping	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
ñ	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.

References

Aggarwal, C. C. (2018). Neural Networks and Deep Learning: A textbook. Cham, Switzerland: Springer International Publishing AG.

Aina, C., Brunetti, I., Mussida, C. & Scicchitano, S. (2021). Who lost the most? Distributive effects of the Covid-19 pandemic. *INAPP Working Paper*, No. 65, 1-34. Retrieved from https://oa.inapp.org/xmlui/bitstream/handle/123456789/911/INAPP_Aina_Brunetti_Mussida_Scicchitano_Who_lost_the_most_Distributive_effects_of_the_COVID-19_pandemic_WP_65_2021.pdf?sequence=2.

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A. E. & Arshad, H. (2018). Stateof-the-art in artificial neural network applications: A survey. *Heliyon*, 4(11), e00938. doi: https://doi. org/10.1016/J.HELIYON.2018.E00938.

Peer-review: Externally peer-reviewed.

Conflict of Interest: The authors have no conflict of interest to declare.

Grant Support: The authors declared that this study has received no financial support.

Author Contributions: Conception/Design of study: A.Ö., E.I., Y.B., M.T., F.B.; Data Acquisition: M.F.O, E.I.; Data Analysis/Interpretation: E.I., M.F.O.; Drafting Manuscript: A.Ö.; Critical Revision of Manuscript: M.T., Y.B., F.B., A.Ö., M.F.O., E.I.; Final Approval and Accountability: A.Ö., E.I., Y.B., M.F.O.

Adams-Prassl, A., Boneva, T., Golin, M. & Rauh, C. (2020). Work That Can Be Done from Home: Evidence on Variation within and across Occupations and Industries. *IZA Discussion Paper 13374*, 1-60, Institute of Labor Economics (IZA), Bonn. Retrieved from https://www.econstor.eu/bitstream/10419/223816/1/ dp13374.pdf.

- Almeida, V., Barrios, S., Christl, M., De Poli, S., Tumino, A. & van der Wielen, W. (2021). Households' income and the cushioning effect of fiscal policy measures during the Great Lockdown. JRC Working Papers on Taxation and Structural Reforms No 06/2020, 1-42.
- Angelov, N. & Waldenström, D. (2021). COVID-19 and Income Inequality: Evidence from Monthly Population Registers. *IFN Working Paper, No. 1396*, 1-35, Research Institute of Industrial Economics (IFN), Stockholm. Retrieved from https://www.econstor.eu/bitstream/10419/240539/1/wp1396.pdf.
- Basheer, I. A. & Hajmeer, M. (2020). Artificial neural networks : Fundamentals, computing, design and application. *Journal of Microbiological Methods*, 43(1), 3-31.
- Bayar, A. A., Gunçavdı Ö. & Levent H. (2020). COVID-19 salgınının Türkiye'de gelir dağılımına etkisi ve mevcut politika seçenekleri [Covid-19 outbreak of the impact of the income distribution in Turkey and the available policy options]. *Istanpol Politika Raporu*, 7, 1-23.
- Bick, A., Blandin, A. & Mertens, K. (2020). Work from Home after the Covid-19 Outbreak. SSRN Scholarly Paper ID 3650114, Social Science Research Network, Rochester, NY. doi: https://doi.org/10.24149/ wp2017.
- Bonacini, L., Gallo, G. & Scicchitano, S. (2021). Working from home and income inequality: risks of a 'new normal'with COVID-19. *Journal of population economics*, 34(1), 303-360.
- Bonacini, L., Gallo, G. & Scicchitano, S. (2020). All that glitters is not gold. Effects of working from home on income inequality at the time of COVID-19. *GLO Discussion Paper Series No. 541*, 1-32. Retrieved from: https://www.econstor.eu/bitstream/10419/216901/1/GLO-DP-0541.pdf.
- Brunori, P., Maitino, M. L., Ravagli, L. & Sciclone, N. (2020). Distant and unequal. Lockdown and inequalities in Italy. *DISEI, Università degli Studi di Firenze, Working Paper No. 13/2020*. Retrieved from https:// www.disei.unifi.it/upload/sub/pubblicazioni/repec/pdf/wp13_2020.pdf.
- Campello, M., Kankanhalli, G. & Muthukrishnan, P. (2020). Corporate hiring under COVID-19: Labor market concentration, downskilling, and income inequality. *National Bureau of Economic Research, No.* w27208, 1-44. Retrieved from http://www.nber.org/papers/w27208.
- Chen, J., de Hoogh, K., Gulliver, J., Hoffmann, B., Hertel, O., Ketzel, M., Bauwelinck, M., van Donkelaar, A., Hvidtfeldt, U. A., Katsouyanni, K., Janssen, N. A. H., Martin, R. V., Samoli, E., Schwartz, P. E., Stafoggia, M., Bellander, T., Strak, M., Wolf, K., Vienneau, D., ... Hoek, G. (2019). A comparison of linear regression, regularization, and machine learning algorithms to develop Europe-wide spatial models of fine particles and nitrogen dioxide. *Environment International*, 130, 1-14. doi: https://doi.org/10.1016/j. envint.2019.104934.
- Clark, A. E., d'Ambrosio, C. & Lepinteur, A. (2021). The Fall in Income Inequality during COVID-19 in Four European Countries. Retrieved from https://halshs.archives-ouvertes.fr/halshs-03230629.
- Clarke, H. & Whiteley, P. (2020, May 6). Economic inequality can help predict Covid-19 deaths in the US [USApp-American Politics and Policy Blog]. Retrieved from https://blogs.lse.ac.uk/usappblog/2020/05/06/economic-inequality-can-help-predict-covid-19-deaths-in-the-us/.
- Collins, C., Ocampo, O. & Paslaski, S. (2020). Billionaire Bonanza 2020: Wealth, windfalls, tumbling taxes, and pandemic profiteers. *Washington, DC: Institute for Policy Studies*. Retrieved from https://ips-dc.org/ wp-content/uploads/2020/04/Billionaire-Bonanza-2020.pdf.
- Delaporte, I., Escobar, J. & Peña, W. (2020). The Distributional consequences of social distancing on poverty and labour income inequality in Latin America and the Caribbean. *GLO Discussion Paper No: 682*, 1-42. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3710062.

- Dolan, Kerry A., Wang, J. & Peterson-Withorn, Chase (2021). Forbes World's Bilionaries List: The Richest in 2021. Retrieved from https://www.forbes.com/billionaires/.
- Duman, A. (2020). Wage losses and inequality in developing countries: Labor market and distributional consequences of Covid-19 lockdowns in Turkey. Retrieved from http://dx.doi.org/10.2139/ssrn.3645468.
- Er, M. B., Isik, E. & Isik, I. (2021). Parkinson's detection based on combined CNN and LSTM using enhanced speech signals with Variational mode decomposition. *Biomedical Signal Processing and Control*, 70. doi: https://doi.org/10.1016/J.BSPC.2021.103006.
- Etheridge, B., Tang, B. & Wang, Y. (2020). Worker productivity during lockdown and working from home: Evidence from self-reports. *Covid Economics*, *52*, 118-151.
- FAO & UN (2020). Addressing inequality in times of COVID-19. FAO Policy Brief. Retrieved from: http:// www.fao.org/documents/card/en/c/ca8843en/.
- FAO (2020). COVID-19 and rural poverty: supporting and protecting the rural poor in times of pandemic. *FAO Policy Brief*. Retrieved from http://www.fao.org/publications/card/en/c/CA8824EN.
- Farsad, N. & Goldsmith, A. (2018). Neural network detection of data sequences in communication systems. *IEEE Transactions on Signal Processing*, 66(21), 5663–5678. doi: https://doi.org/10.1109/ TSP.2018.2868322.
- Figari, F. & Fiorio, C. V. (2020). Welfare resilience in the immediate aftermath of the Covid19 outbreak in Italy. EUROMOD Working Paper: No. EM 6/20, University of Essex, Institute for Social and Economic Research (ISER), Colchester. Retrieved from https://www.econstor.eu/bitstream/10419/228405/1/1697333176.pdf.
- Fisher, M. & Bubola, E. (2020, March 15). As Coronavirus deepens inequality, inequality worsens its spread. New York Times. Retrieved from https://www.nytimes.com/2020/03/15/world/europe/coronavirus-inequality.html.
- Grabka, M. M. (2021). Income inequality in Germany stagnating over the long term, but decreasing slightly during the coronavirus pandemic. *DIW Weekly Report* 17+18/2021. doi: https://doi.org/10.18723/diw_dwr:2021-17-1.
- Hecht-Nielsen, R. (1989). Theory of the Backpropagation Neural Network. Academic Press, 593–605. Retrieved from http://www.andrew.cmu.edu/user/nwolfe/esr/pdf/backprop.pdf.
- ILO (2020). COVID-19 and the world of work country policy responses. Retrieved from https://www.ilo.org/global/topics/coronavirus/regional-country/country-responses/lang--en/index.htm#DE.
- Isik, E., Isik, I. & Toktamis, H. (2021). Analysis and estimation of fading time from thermoluminescence glow curve by using artificial neural network. *Radiation Effects and Defects in Solids*. doi: https://doi.or g/10.1080/10420150.2021.1954000.
- Komatsu B. K. & Menezes-Filho N. (2020). Simulações de impactos da COVID-19 e da Renda Básica emergencial sobre o Desemprego, Renda, Pobreza e Desigualdade. São Paulo: Policy Paper No.43, 1-31. Retrieved from https://www.insper.edu.br/wp-content/uploads/2020/04/Policy-Paper-v14.pdf.
- Kubat, M. (2017). An Introduction to Machine Learning. Cham: Springer International Publishing. doi: https://doi.org/10.1007/978-3-319-63913-0.
- Kyyrä, T., Pirttilä, J. & Ravaska, T. (2021). The Corona crisis and household income: The case of a generous welfare state. VATT Mimeo 61, 1-22. Retrieved from https://www.doria.fi/bitstream/hand-le/10024/180378/vatt-mimeo-61-the-corona-crisis-and-household-income-the-case-of-a-generous-welfare-state.pdf?sequence=1.
- Lee, Tsong L. (2004). Back-Propagation neural network for long-term tidal predictions. *Ocean Engineering*, 31(2), 225–238.

- Lustig, N., Martinez-Pabon, V., Sanz, F. & Younger, S. D. (2020). The impact of COVID-19 lockdowns and expanded social assistance on inequality, poverty and mobility in Argentina, Brazil, Colombia and Mexico. CGD Working Paper No. 556, 1-36. Retrieved from https://www.cgdev.org/sites/default/files/ impact-covid-19-lockdowns-and-expanded-social-assistance.pdf.
- Maffioli, E. M. (2020). Consider inequality: Another consequence of the coronavirus epidemic. Journal of Global Health. 10(1), 1-3. doi: 10.7189/jogh.10.010359.
- Martinez-Juarez, L. A., Sedas, A. C., Orcutt, M. & Bhopal, R. (2020). Governments and international institutions should urgently attend to the unjust disparities that COVID-19 is exposing and causing. *E-Clinical Medicine. 23*, 1-2. doi: 10.1016/j.eclinm.2020.100376.
- Maulud, D. & Abdulazeez, A. M. (2020). A Review on Linear Regression Comprehensive in Machine Learning. *Journal of Applied Science and Technology Trends*, 1(4), 140–147. doi: https://doi.org/10.38094/ jastt1457.
- Neidhöfer, G. (2020, June 9). Long run consequences of the COVID-19 pandemic on social inequality [UNDP IN LATIN AMERICA AND THE CARIBBEAN]. Retrieved from https://www.latinamerica.undp.org/ content/rblac/en/home/blog/2020/consecuencias-de-la-pandemia-del-covid-19-en-las-desigualdades-s. html.
- O'Donoghue, C., Sologon, D. M., Kyzyma, I. & McHale, J. (2020). Modelling the distributional impact of the COVID-19 crisis. *Fiscal Studies*, 41(2), 321-336.
- Perugini, C. & Vladisavljevic, M. (2020). Social stability challenged: pandemics, inequality and policy responses. *IZA Discussion Paper No. 13249*. Retrieved from https://www.econstor.eu/bitstream/10419/223691/1/dp13249.pdf.
- Sostero, M., Milasi, S., Hurley, J., Fernandez-Macias, E. & Bisello, M. (2020). Teleworkability and the CO-VID-19 crisis: a new digital divide?. *JRC Working Papers Series on Labour, Education And Technology, No. 2020/05*, European Commission, Joint Research Centre (JRC), Seville. Retrieved from https://www. econstor.eu/bitstream/10419/231337/1/jrc-wplet202005.pdf.
- Stantcheva, S. (2021). Inequalities in the times of a pandemic. Retrieved from https://www.economic-policy. org/wp-content/uploads/2021/04/9103_Inequalities-in-the-Times-of-a-Pandemic.pdf
- Stiglitz, J. (2020). Conquering the great divide: The pandemic has laid bare deep divisions, but it's not too late to change course. *Finance and Development*, *57*(3), 17-19.
- UNDP (2020). COVID-19 and human development: Assessing the crisis, envisioning the recovery. 2020 Human Development Perspectives. Retrieved from http://hdr.undp.org/sites/default/files/covid-19_and_human_development_0.pdf.
- Van Barneveld, K., Quinlan, M., Kriesler, P., Junor, A., Baum, F., Chowdhury, A., Junankar P., Clibborn S., Flanagan, F., Wright C. F., Friel, S., Halevi, J. & Rainnie, A. (2020). The COVID-19 pandemic: Lessons on building more equal and sustainable societies. *The Economic and Labour Relations Review*, 31(2), 133-157.
- Wang, D., He, H. & Liu, D. (2018). Intelligent Optimal Control With Critic Learning for a Nonlinear Overhead Crane System; Intelligent Optimal Control With Critic Learning for a Nonlinear Overhead Crane System. *IEEE Transactions on Industrial Informatics*, 14(7), 2932-2940. doi: https://doi.org/10.1109/TII.2017.2771256.
- Warren S. S. (1995). Artificial neural networks and statistical model. Japanese Journal of Applied Statistics, 24(2), 77–88.

- Willis, M. J., Montague, G. A., Di Massimo, C., Tham, M. T. & Morris, A. J. (1992). Artificial neural networks in process estimation and control. *Automatica*, 28(6), 1181–1187.
- World Bank (2020). Poverty and distributional impacts of COVID-19: Potential channels of impact and mitigating policies. Retrieved from https://www.worldbank.org/en/topic/poverty/brief/poverty-and-distributional-impacts-of-covid-19-potential-channels-of-impact-and-mitigating-policies.

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 Azerbaijau Bonzdades *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 31,4686 31,7094 31,6316 31,4854 31,5488 31,1374 31,2297 31,9573 32,2109 32,5786 32,7008 33,2864 33,8733 34,2326 34,5855 35,0019 35,6458 35,2276 **36,5112 36,330** 34,4566 34,8314 34,0176 34,8024 35,0302 35,3555 35,3466 34,4473 34,4716 34,4162 33,2880 33,6136 34,3101 34,5171 33,7705 33,6115 33,29124 34,0276 34,3103 34,6871 34,8890 45,9520 35,0447 34,071 35,2085 35,0657 1017 B HOLT 2018A Belgium Belgium Bolivia 12498 12482 14999 11340 11340 12410 12411 2418 05171 14811 03481 2411 12410 2417 1440 1491 1441 1441 1441 1441 1441 1444 1441 1444 1441 1444 1441 1444 1441 1444 1441 1444 1441 1444 1441 1444 1441 1444 1441 1444 1444 1441 1441 1444 Canardo Canada Chia Chia Coago Control Coago Coago Control Egopt Estres Section 19, 201 (2011) 19, 2013 (2011) 19, 2011 (2011) 19, 2011) 19, 2013 (2011) 19, 2013 (2011) 19, 2013 (2011) 19, 2013 (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 49,556 31,597 33,708 13,622 31,923 53,942 14,098 33,476 33,0004 32,050 23,016 81,572 31,627 31,628 31,460 13,618 13,618 14,618 34,618 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 1/211 1 0/217 0 0/200 0 0/212 0 1/210 0 1/210 0 0/00 0 0/212 0 1/210 0 0/00 0 0/212 0 0/200 0 0/210 0 0/200 0 0/210 0 0/200 0/200 0/200 0 0/200 0/200 0 0/200 0/200 0/200 0/200 0/200 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 30,6735 29,7178 29,3799 29,488 30,6465 31,7388 31,0645 31,7388 31,0647 31,738 31,0667 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 75,100 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 34,978 34,968 34,978 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 4,911 46,775 46,391 17,80 4,391 47,80 4,390 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,390 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,80 4,391 47,3 The second secon 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 80,081 20,819 26,194 80,089 30,108 25,213 10,2197 30,580 1,083 32,113 12,912 33,414 35,6910 4,1214 14,615 4,688 14,603 14,925 35,295 34,645 45,106 5,2109 5,305 5,106 5,2109 5,305 5,106 5,210 5,21 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

Albania		
Afghanistan Albania		
Albania	1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016	
	39,7091 42,8846 44,3668 46,8231 48,6035 42,9142 43,2873 44,0565 44,0420 46,3409 47,8398 43,6100 36,2701 36,5353 34,8394 31,5270 40,8136 36,7312 43,9563 44,2617 44,1817 43,219 43,5146 43,5843 43,2825 42,7813 43,914 14,1817 43,2114 14,1817 43,2114 14,1817 43,2114 14,1817 43,2114 14,1817 43,2114 14,1817 44,	3 42,2933 41,9969 4
	34,1394 33,8425 35,0978 57,8951 51,7785 45,1261 42,3734 43,0461 44,0224 45,9884 44,5173 43,8975 49,6820 48,0036 48,4716 47,4532 47,1012 47,8125 46,9058 46,8274 44,7641 43,4393 42,7200 44,1345 43,9274 42,9555 49,6820 48,0036 48,4716 47,4532 47,1012 47,8125 46,9058 46,8274 44,7641 43,4393 42,7200 44,1345 43,9274 42,9555 49,6820 48,0036 48,4716 47,4532 47,1012 47,8125 46,9058 46,8274 44,7641 43,4393 42,7200 44,1345 43,9274 42,9555 49,6820 48,0036 48,4716 47,4532 47,1012 47,8125 46,9058 46,8274 44,7641 43,4393 42,7200 44,1345 43,9274 42,9555 49,6820 48,0036 48,016 49	
Algeria	38,4970 39,8167 39,5924 39,4686 44,1515 39,3661 39,6514 40,3611 41,6933 43,2363 44,2443 44,5668 44,2869 43,2860 41,6935 40,3327 39,6526 39,4413 39,4997 39,7811 40,1627 40,3693 40,2325 39,7020 38,9953 38,5117 :	7 38,3026 38,2301 3
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 44,8666 43,5559 43,5859 43,1050 42,7808 45,8585	5 45,7159 46,7095 44
Ameria	47 8971 55 2644 57 2357 57 2655 47 3893 47,4417 48,0431 51,8535 55,4079 50,6276 48,5228 48,6450 52,0170 51,2504 55,7847 53,2598 50,3595 48,2960 46 7853 47 3037 46 7389 46,3522 45,6088	8 45.1250 44.8337 4
Australia	47,8971 55,2644 57,2357 57,2655 47,3893 47,4417 48,0431 51,8585 55,4079 50,6276 48,5228 48,6450 52,0170 51,2504 55,7847 53,2596 50,595 48,2960 46,7853 47,3037 46,7389 46,3522 45,0688 435,9768 35,9664 36,5611 37,2915 36,7265 36,7075 36,2915 37,2649 36,6300 36,8320 36,7161 37,9195 38,2453 38,6875 37,8680 37,9452 39,5032 40,4097 40,2879 40,7733 41,5479 40,7514 41,8423 41,7922 42,0838 42,7621	41 1606 47 4984 4
Austria	5,6444 3,5,8062 3,5,807 3,5,827 3,5,640 3,5,693 3,663 3,5,693 3,5,673 3,5,471 3,5,771 3,5,471 3,5,471 3,5,471 3,5,471 3,5,471 3,5,471	25 6410 26 5959 2
Azerbaijan	42.1134 17.7251 48,7908 49,4470 08,088 51,6185 54,2187 55,7682 54,9015 56,631 54,749 13,5309 53,502 51,1224 51,1007 84,82752 45,8519 48,9688 45,7872 48,7892	5 55,0410 50,5555 5
	42,1154 47,1253 48,1908 49,4410 50,8084 51,6385 54,2815 55,1682 54,9015 56,4958 56,5631 54,1491 53,5039 55,5012 51,2424 51,0018 48,2152 45,6519 48,9638 47,5216 46,6688 45,1512 48,1962 4	2 49,6258 47,6108 4
Bangladesh	48,8789 49,2394 48,0709 47,8068 47,8223 48,0393 48,6601 50,1613 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 47,3303 49,6582	2 48,9747 50,1666 49
Belgium	38,2361 38,1200 38,2395 38,0917 38,0855 38,6493 39,0895 38,8383 38,4337 38,4966 38,9725 39,0865 40,0039 40,0823 40,4997 40,3052 40,0434 40,753 41,3960 41,2744 41,1015 42,4561 42,8364 42,6310 42,6372 42,9642 42,010 42,010 42,	2 42,0158 42,0224 4
Bolivia	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 52,0952 52,1958	8 52,0093 51,8969 5
Botswana	48,000 48,855 48,155 47,9651 49,4027 49,7005 48,2940 51,4220 509228 49,9661 49,6521 46,1681 47,0887 45,7798 44,3338 45,1772 47,6047 48,859 51,0741 52,2644 48,7473 45,9129 46,2593 46,244 46,7473 45,973 46,9129 46,2593 46,244 46,7473 45,9129 46,2593 46,244 46,7473 45,9129 46,2593 46,244 46,7473 45,9129 46,2593 46,244 46,7473 45,9129 46,2593 46,244 46,7473 45,9129 46,2493 46,2493 46,2493 46,2493 46,2494 46,2493 46,2494 46,7474 46,2593 46,2494 46,2494 46,2494 46,	2 46,2499 46,0510 43
Branl	48,6951 49,1545 49,0197 48,8222 48,6785 49,2757 49,6876 49,6170 49,9312 49,6135 49,4757 49,6234 49,3961 49,7706 48,6710 48,0436 47,9996 47,6954 47,4776 47,1534 47,0635 47,1555 47,5752 47,3880	47,5123 47,1232 4
Bulgaria	32 9517 36 9348 38 5776 41 3599 39 5714 40 5341 40 9117 41 0759 41 4458 42 5678 42 5678 42 5979 42 6718 42 5166 42 0385 42 6078 42 610 44 5497 42 1308 42 6877 42 4489 41 8849 41 5564 41 3715 4	5 42 3520 41 8506 41
Burundi	52,1029 53,0833 53,0611 53,58922 53,2333 51,2474 59,5523 50,0137 50,0619 53,5473 53,5541 52,2441 51,129 53,8574 59,3589 55,8591 56,8585 56,0050 55,0041 57,4785 56,4213 55,002 55,0012 55,002 55,0012 55,002 55,0012 55,002 55,0012 55,002 55,0012 55,	4 56,2197 56,4826 5
Cameroon	54 82/61 55 5225 55 2074 55 2847 56 8071 56 6102 56 2300 56 7137 56 4421 55 8857 54 4579 55 1200 53 8076 52 4467 50 8368 53 2656 55 3026 55 3027 55 5401 55 9264 55 2701 54 5203 53 1145 55 6368 55 0071 55 8614 2	4 56 0811 56 0910 5
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 38,1433 38,7589 38,7547 38,8266 38,8513 38,1433	1 18 1280 18 5262 1
Chie	46 9572 46 5505 46 4149 46 2907 46 5519 46 7574 47 0583 48 2014 48 2128 47 7107 48 5959 48 9103 48 3874 49 2607 50 3217 47 9969 47 1912 48 3736 48 33590 47 9460 48 0332 48 9411 49 6649 49 3688 49 9507 47 3949 9	AR 7404 48 7800 4
China	35,841 42,3640 40,780 39,5001 41,797 39,5185 38,6445 35,3301 38,0241 38,8162 39,6422 49,3644 14,26938 41,5262 40,9967 40,7180 40,0108 38,8695 39,9983 38,7189 33,9011 37,6775 37,5286 37,4162 38,2562 33,6489 1	3 20 0353 20 3537 3
Colombia	38,3434 42,3640 40,7309 39,3001 41,757 39,3138 33,6445 33,301 33,0241 33,3162 39,6422 39,3642 42,0938 41,0262 40,996 40,7200 40,008 38,8095 39,9983 38,7789 33,5911 37,6775 37,5268 37,4162 38,2562 33,4630 .	38,9352 38,253/ 3
	453802 47,1317 46304 463184 46739 466133 465918 465807 47,210 9170725 47,0000 17,06654 469945 463754 44,751 44,2018 13,8000 42,4379 41,755 43,100 14,3003 44,8016 44,3038 44,3	5 44,7294 44,9867 4.
Congo	48,4919 48,2560 46,1936 47,6153 48,1021 48,6085 48,2818 47,1514 47,1658 47,1205 47,4804 48,0771 50,5800 50,0331 48,7838 49,1600 49,3661 48,5202 48,0003 48,2567 47,9249 47,8347 48,4980 48,6558 47,7954 48,6162	2 49,7876 48,4871 4
Costa Rica	44,3337 44,0162 42,9838 44,6501 41,5176 44,7195 42,6455 42,4887 43,8232 43,9328 43,9672 44,6039 44,7708 44,6472 43,4663 43,2268 42,8797 42,4150 44,7777 43,2382 44,7939 44,6956 43,3651 44,9883 43,1858	\$ 43,0780 44,0702 43
Croatia	38,3000 30,9201 33,3689 36,8390 37,8540 39,4767 39,5069 41,3469 41,8431 42,3105 42,8677 42,9068 42,7189 42,6211 42,7218 42,7175 42,1178 41,7250 41,6142 42,2906 42,3716 42,7317 42,8168 41,6813 41,7618 42,0122 43,5210 35,4213 34,6242 33,9239 33,9307 32,8271 32,6870 32,6874 32,5263 32,6663 33,4132 33,1922 32,7756 32,9808 33,6026 33,7744 33,5089 34,6769 32,9859 32,4857 33,5597 35,0114 34,7830 34,6128 33,9320 33,6211	2 42,0133 42,0148 43
Cuba	35,5203 35,4213 34,6242 33,3239 33,9307 32,8271 32,6870 32,6514 32,5263 32,6663 33,4132 33,1592 32,7756 32,9808 33,6026 33,7744 33,8089 34,6769 32,9850 32,4857 33,8597 35,0114 34,7830 34,6128 33,9320 33,6221	1 34,9120 35,4829 3
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 35,8993 36,1816 36,8108 35,5616 36,9426 36,9794 36,9105 36,7976 1	5 36,9781 35,2766 3
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 1444 31 9620 32 0113 31 7406 30 8710 32 5659 30 5710 32 5710 32 5710 32 5710 32 5710 32 5710 32 5710 32 5710 32 5710 32 571	31.5098 31.8180 3
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 9475 31 7880 32 8949 33 7872 33 2248 33 2055 36 0305 37 1394 36 1508 34 1560 34 0767 34 3130 34 1764 34 0150 3	1 11 0550 14 1508 1
Dominican Republic	48,6107 50,3085 50,4073 50,0099 50,3625 52,9788 51,6909 50,246 52,0335 40,3912 48,6107 51,1561 51,2387 51,6004 51,4169 50,0037 50,8187 50,3085 50,4073 50,0099 50,3628 52,9788 51,6903 51,3009 50,246 54,0535 49,5487 50,6801 47,6529 46,802 46,5850 46,5266 46,9359 46,1062 47,2313 47,7345 47,7714 246,1279 4	52 0225 40 2012 4
Ecuador		AC DOEA AC 1997 4
	42/1002 #0/0223 #0/2024 #0/2004 #0/2004 #0/2004 #0/2025 #0/2027 #0/2024 #0/2027 #0/2024 #0/202	9 40,9034 40,4393 4
Egypt FI Salvador	41,4010 41,0017 46,480 46,8000 46,610 47,5137 30,1964 49,1249 30,4991 30,1099 30,9993 52,9214 32,0495 53,518 53,4030 53,9301 33,8135 32,8001 23,8260 33,6214 53,8355 53,1247 33,8260 53,9240 53,6214 53,8355 53,1247 33,8260 53,9240 53	5 52,8191 52,9738 5.
EI Salvador	46,4805 48,0370 49,9199 50,6389 49,8651 19,1088 47,0741 48,3501 50,5838 50,0545 50,2481 48,6815 49,6042 49,9473 50,0133 50,2664 50,8749 50,1110 49,0539 50,2085 47,8957 46,2163 46,0395 49,4131 50,3995 49,7075 46,2573 46,3487 45,9951 45,6978 48,4158 45,6759 147,524 45,6569 48,6500 50,3944 50,8386 45,3735 44,8533 46,7199 46,7730 46,6861 46,1854 48,729 49,6591 54,126 52,8486 51,9597 52,6108 52,0672 52,2502 51,0111 1	-9,0531 49,5237 49
Entrea	40,273 40,216 (2),2761 (2),276	00,0584 49,0426 5
Estonia	44,4731 43,7433 42,6018 43,6197 44,4796 42,8902 38,5702 37,0083 37,9787 37,6895 37,4433 37,0705 36,9124 36,5495 36,5590 36,0311 37,0000 37,2032 36,9989 36,8217 36,7138 36,2577 36,2785 36,0541	1 36,1550 36,7550 36
	51,4571 49,4626 48,0910 47,8097 46,8167 43,6669 41,6599 46,0510 44,1203 42,4120 45,2455 41,3587 40,4692 42,2570 46,7088 44,2821 44,8802 47,4191 45,7598 45,2215 45,4827 45,2421 45,9428 45,0816 45,6450 45,4827	45,5895 45,1689 44
Finland	34,5565 33,5780 33,8744 33,3906 33,1726 32,9787 33,1858 33,1868 32,7314 32,8658 33,2685 33,2685 33,1641 33,6531 34,2578 33,7815 34,1897 34,1939 34,2094 35,6922 36,0371 35,8753 36,0303 35,8597 36,4096 35,9552 35,2559	9 36,4462 36,2634 3
France	36,3837 36,9003 37,5524 37,8754 37,8527 36,3393 36,4971 36,6073 36,7468 36,9391 36,6535 36,9056 36,2435 37,2009 37,4559 37,3873 35,9760 37,784 38,1459 37,5759 37,3274 38,0298 37,9971 37,9398 37,9110 (45,945) 47,549 42,1455	37,4577 37,7840 3
	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 47,3454 46,5766	6 45,2774 45,0179 4
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 38,5066 38,3148 38,3704 38,2915 38,2236 38,4397	7 37,5427 38,5516 3
Ghana	50 8912 50 9054 49 3709 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 6753 50 9661 46 4810 50 6808 50 8912 50 9054 50 7572 /	2 49 0069 50 2641 50
Greece	44 7704 44 7810 43 0707 43 0701 44 7015 44 8400 44 1161 44 1763 43 0766 43 0408 45 3388 45 3505 45 0170 45 0365 45 1641 44 7307 44 7801 44 40 7307 44 7801 44 17701 40 8811 45 1006 45 5105 45 4743 45 4353 45 4066 4	45 4086 45 5088 4
Gentemala	HY, LUM 44, LUM 25, LU	50 1055 40 0010 4
Honduras	33,138 34,943 32,235 34,2414 32,325 442,0063 46,9764 30,040 30,007 32,001 32,007 30,001 32,0030 34,0213 32,0030 34,0213 32,0030 34,0213 32,0230	5 30,1033 45,0530 4
	20/2012 19/113 20/217 20/103 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	5 40,0755 45,2020 44
Hungary	34,3944 36,6121 39,1539 39,6676 39,6450 40,2401 40,5020 40,2096 40,1798 39,3761 39,8858 39,9577 40,2075 40,7123 41,6635 40,5788 40,2043 39,9150 41,0937 41,4515 41,1119 40,8598 40,4304 40,4907 39,8730 40,3407 3	7 39,4168 40,4222 40
India	50,0995 50,5395 50,2585 50,7340 50,9104 50,4405 51,0466 50,9748 51,0459 51,9401 52,1760 52,2457 52,7767 52,2028 51,9454 51,7154 51,8158 51,7211 50,8466 50,8534 50,8108 50,4595 50,4595 50,4481 50,4396 50,1977 48,2103 47,8126 46,6497 47,4748 49,268 44,2102 42,2307 51,4419 50,4402 47,8817 52,9478 47,1566 50,5296 48,2093 49,8274 47,7762 46,5993 51,1336 50,3000 50,6019 45,9982 47,9994 48,7734 48,6927 48,6492 49,7339	7 50,4447 50,7480 5
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 50,3296 48,8693 49,8274 47,7762 46,5993 51,1336 50,3000 50,6019 45,9982 47,9994 48,7734 48,6927 48,6362 49,7329	9 48,7289 48,7286 4
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 48,3321 48,3365 45,456 46,1789 46,6744 46,8589 46,6255 48,3568 48,4630 46,8498 46,5126 46,3967 46,9751 47,0403 48,4323 48,3321 48,3365 45,456 46,1789 46,6744 46,8589 46,6255 48,3568 48,4630 46,8498 46,5126 46,3967 46,9751 47,0403 48,4323 48,3321 48,3365 45,456 46,1789 46,6744 46,8589 46,6255 48,3568 48,4630 46,8498 46,5126 46,3967 46,9751 47,0403 48,4323 48,3321 48,3365 45,456 46,1789 46,6744 46,8589 46,6255 48,3568 48,4630 46,8498 46,5126 46,3967 46,9751 47,0403 48,4323 48,3365 45,456 46,1789 46,6744 46,8589 46,6255 48,3568 48,4630 46,8498 46,5126 46,3967 46,9751 47,0403 48,4323 48,3365 45,458 48,459 46,5126 46,3967 46,9751 46,975	5 48,1461 48,7242 4
Ireland	37.4593 37.5218 37.4652 37.0499 37.5714 37.0260 36.3939 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 38.7097 38.6284 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.7100 39.7444 39.6105 39.7090 38.7097 38.6284 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.3832 36.7274 37.9009 39.2674 39.5264 39.5165 36.5264 39.5165	4 38,7461 39,6545 31
Israel	42,4391 42,6019 42,4653 41,8308 42,0368 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 43,4142 43,0424	4 43,7904 43,5790 43
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 37,2270 37,1581	37.2292 37.4192 3
Jamaica	37,9998 38,6464 38,7431 38,5941 37,3822 36,4351 37,7487 37,1461 37,1256 36,9695 36,6897 36,7115 36,8192 36,5645 37,002 36,8740 36,6335 36,6641 36,4255 37,0803 37,0556 37,3724 37,3622 37,3349 37,2270 37,1581 151,8740 49,4993 48,8050 48,1572 47,9646 47,7982 48,1255 49,8091 50,6369 51,2460 51,2935 51,4010 49,9721 50,6851 51,1216 49,6950 47,7374 46,3767 48,2357 49,5663 46,5440 47,5510 47,6773 48,0914 50,8618 51,2918	8 49,7160 48,7393 5
Japan	37;3631 37;1894 37;1754 41,4007 41,5018 41,7025 41,8411 42,1241 42,3831 42,6004 43;5021 44,2901 44,4699 44,5042 44,4471 44,4255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4463 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4463 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4463 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4463 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4463 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4463 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4463 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 46,5039 43,4663 43,8262 43,0224 43,5747 44,914 44,255 44,2188 43,9836 43,7878 43,8795 44,2184 43,9836 43,7878 43,8795 46,5039 43,4467 44,914 44,2124 42,2184 43,9836 43,7878 43,8795 46,5039 43,4669 43,5924	4 43 7918 43 3830 4
Jordan	9/4530 47/11 46,248 48,5865 46,2129 46,5565 47,1931 52,2649 48,5919 50,7645 45,505 50,1804 50,015 40,5051 90,6051 50,1805 50,1	E 50 7646 50 6640 5
Kazakhstan	47,7351 49,575 50,520 47,011 40,245 40,001 47,7351 49,575 50,520 49,541 47,6018 46,425 44,955 43,554 4,954 61,520 44,957 43,553 42,546 43,751 42,545 43,604 47,7018 48,124 51,7014 49,124 51,7014 51,7004 51,7004 51,7004 51,7004 51,7004 51,7004 51,7004 51,7004 51,7004 51,7004 51,7004 51,7	3 30,2040 30,0040 3.
Kazaknistan	+1,135 49,232 9,252 49,	3 40,9880 43,900) 4
Kenya	50,8846 50,4742 49,8212 49,4930 49,9883 47,8117 47,5723 49,4499 50,9600 49,8556 48,7083 53,1468 48,0015 50,8520 50,6471 51,4618 54,1746 51,7979 51,9891 52,0077 52,3483 52,6019 52,5923 52,8169 51,4312 59,7598 56,1794 55,6465 55,3701 55,2334 54,5676 54,4432 55,5210 55,5835 54,6519 57,2756 57,2556 57,2550 57,4977 58,2337 57,8633 58,7182 58,9187 59,8141 60,9013 61,1411 60,9488 59,6000	2 50,9924 52,9585 5.
	59,7598 56,1794 55,6486 55,3701 55,2334 54,5676 54,5432 55,5210 55,5835 54,6519 55,9796 57,2756 57,5550 56,8953 57,2520 57,4977 58,2333 58,7382 58,9187 59,8141 60,5013 61,1190 61,5411 60,9488 59,6003 55,5510 55,551	3 58,8801 57,9769 5
Kyrgyzstan	40,2758 45,5322 45,7940 45,3693 46,8153 44,3047 49,7428 47,9377 48,2987 58,5295 56,3892 61,4183 61,2868 61,8363 59,9966 60,6185 62,4198 62,2826 62,8504 60,8292 61,8698 62,3284 60,7524 59,4837 6	7 60,9336 60,4110 6
Latvia	43,9346 41,7549 41,7549 41,7549 42,1144 41,6523 38,7079 39,5133 39,0092 38,1164 37,6633 37,1165 37,4458 37,8549 38,5360 38,1401 40,1322 42,1628 42,6988 42,6171 41,8381 41,0353 40,9314 40,6668 40,8125 52,5816 52,8379 52,5106 53,3317 51,8326 49,8573 48,1207 49,5589 49,9228 51,9618 52,1415 52,0159 48,7565 51,0742 52,0275 50,8400 52,5186 54,3107 52,7774 51,7540 51,3553 51,9259 53,5330 52,0044 48,7662 1	5 40,7083 40,5992 4
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 52,0044 48,7662 52,8578 54,958 54,	2 52,5653 51,5562 53
Lithuaria	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 40,6885 40,6207	7 41,9162 41,2295 4
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 9200 39 5749 1	9 39 1030 39 5665 39
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 44,9670 44,5789	44.2523 44.2359 4
Macedonia	38,9195 36,7112 37,0281 38,3822 39,5350 41,3584 41,2600 41,7711 41,0095 42,3822 42,9005 42,5486 45,1465 44,7658 44,9607 45,8420 44,9077 44,1565 44,7886 44,9299 44,9707 44,2562 45,7885 44,9299 44,9707 44,2562 45,7885 45,7890 44,7710 44,5552 45,847 46,2124 45,7884 45,9124	44 8467 44 9501 4
Madagascar	45 6510 46 9112 46 7373 47 5438 46 9614 46 7987 45 9830 40 0154 47 8747 46 950 47 0054 44 8864 45 1550 47 0000 45 9875 45 0785 44 7036 43 4103 40 5557 45 8547 47 7108 44 9847 46 9754 45 7565	5 45 8080 46 8378 4
Malawi	52,9250 54,7653 54,7727 52,6096 53,5139 52,7910 54,7720 55,2904 56,0764 56,5437 55,0489 55,0891 53,7541 54,3023 55,9823 54,6266 52,8932 56,1792 56,6473 56,0172 55,1142 56,0243 56,0599 55,3414 56,8882 57,7064 10,0000 10,0000 10,0000 10,0000 10,0000 10,0000 10,0000 10,0000 10,0	56 4767 55 9367 54
Malaysia	40,85% 59,8613 39,1866 59,3101 38,9170 39,1344 39,4303 39,7663 39,6160 38,8526 40,0089 40,7370 40,8167 40,8263 40,4799 39,9822 39,9730 40,0214 40,4011 39,7015 39,3804 39,3089 39,2895 39,6249 39,4231 40,4658 - 34,6105 34,4531 35,3557 35,2472 37,3952 35,6712 36,6968 36,1399 38,0715 37,7333 37,3794 37,7342 38,0669 38,0992 37,3524 42,0293 41,0299 40,9978 39,3456 39,7736 41,1101 39,3800 38,5861 38,9344 41,8702 39,7566 1	40 6672 40 9674 2
Malta		C 10 E4E0 17 0161 1
Mata	34,010 34,431 35,3557 35,2472 37,3952 35,0112 30,0908 30,1399 38,0745 37,1343 37,794 37,1342 38,0009 38,0992 37,3524 42,2950 41,0299 40,9978 39,5456 39,7756 41,1101 39,3800 35,5861 33,5344 41,8702 39,7506 1	5 38,5458 37,8203 3
Mauntus	37,4306 36,2882 36,3262 36,6998 37,1447 37,1862 38,9502 38,9944 37,8619 37,3652 37,3785 36,8153 38,4152 40,2186 40,5695 39,3977 42,1910 41,7119 40,2079 40,2714 38,4683 38,5840 39,0639 38,9387 38,7201 38,5410	0 39,5211 40,5198 40
	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 49,2558 49,9514 4	4 48,9406 49,5314 4
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 48,5919 51,5798	
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 52,4850 53,4499 54,9485 55,5800 55,9349 55,9939 56,1366 56,2261 1 40,9489 48,9002 44,2445 44,8406 52,0666 51,0645 51,9390 51,2116 48,1758 47,5613 48,2037 45,0944 46,5728 49,1901 49,2667 48,3925 47,4632 44,9517 45,9043 45,5607 49,3840 49,4763 49,7363 48,8189	
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 45,9043 45,5607 49,3849 49,4763 49,7363 48,8189	56,6358 56,8365 5
Nepal		1 56,6358 56,8365 5 9 48,3616 49,4904 4
Netherlands	50,2060 49,8354 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 42,0616 43,7200 48,1515 50,2385 52,9968 49,0650 50.8917 52,5919 :	1 56,6358 56,8365 5 9 48,3616 49,4904 4 9 53,6777 49,6838 5
	50.2000 49.8354 48.8411 45.867 45.2736 46.6952 47.240 45.9139 47.941 54.8102 43.0548 53.7997 54.4095 54.165 35.7066 53.8376 45.2621 42.9262 42.0614 43.700 48.1515 50.2355 52.9968 49.0659 50.8971 52.5919 55.616 53.1341 43.1018 53.1006 53.1013 75.1013 75.1013 76.1	1 56,6358 56,8365 5 9 48,3616 49,4904 4 9 53,6777 49,6838 5
New Zealand	35,0061 35,2015 35,4165 35,3142 34,9186 35,1998 37,0973 37,8372 36,2649 36,7094 37,8317 36,3617 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,7837 36,201 36,987 39,9187 39,1073 37,8372 36,2649 36,919 39,5531 36,919 36,918 37,919 36,918 36,918 36,919 36,918 36,919 36,918 36,919 36,918 36,919 36,918 3	1 56,6358 56,8365 5 9 48,3616 49,4904 4 9 53,6777 49,6838 5 1 39,3887 37,3812 3 0 38 1941 37 1851 3
Netherlands New Zealand Nizeria	35,0061 35,2015 35,4165 35,3142 34,9186 35,1998 37,0973 37,8372 36,2649 36,7094 37,8317 36,3617 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,7837 36,201 36,987 39,9187 39,1073 37,8372 36,2649 36,919 39,5531 36,919 36,918 37,919 36,918 36,918 36,919 36,918 36,919 36,918 36,919 36,918 36,919 36,918 3	1 56,6358 56,8365 5 9 48,3616 49,4904 4 9 53,6777 49,6838 5 1 39,3887 37,3812 3 0 38 1941 37 1851 3
Netherlands New Zealand Nigeria Norway	35,0061 35,2015 35,4165 35,3142 34,9186 35,1998 37,0973 37,8372 36,2649 36,7094 37,8317 36,3617 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,78372 36,2649 36,7107 37,7837 36,201 36,987 39,9187 39,1073 37,8372 36,2649 36,919 39,5531 36,919 36,918 37,919 36,918 36,918 36,919 36,918 36,919 36,918 36,919 36,918 36,919 36,918 3	1 56,6358 56,8365 5 9 48,3616 49,4904 4 9 53,6777 49,6838 5 1 39,3887 37,3812 3 0 38 1941 37 1851 3
Nigeria Norway	150001 55001 55001 55001 55001 55001 55001 73071 2872 8600 5000 9 18011 5010 75001 8601 5010 7500 9 1800000000	1 56,6358 56,8365 5' 9 48,3616 49,4904 4' 9 53,6777 49,6838 5' 1 39,3887 37,3812 3' 0 38,1941 37,1851 3' 7 48,4489 50,2625 4' 0 38,8101 39,0823 3' 0 38,8101 39,0823 3'
Nigeria Norway Oman	15,000 15,001 55,041 55,154 51,000 17,007 17,007 12,077 54,070 17,007 10,007 17,007 10,000 10,007 10,000 10	1 56,6358 56,8365 5' 9 48,3616 49,4904 4' 9 53,6777 49,6838 5' 1 39,3887 37,3812 3' 0 38,1941 37,1851 3' 7 48,4489 50,2625 4' 0 38,8101 39,0823 3' 0 38,8101 39,0823 3' 1 49,2655 50,2611 5'
Nigeria Norway Oman Pakistan	15,000 15,001 55,010 55,010 55,010 51,000 17,007 12,072 56,000 50,007 13,072 56,000 50,007 14,000 12	1 56,6358 56,8365 5' 9 48,3616 49,4904 4' 9 53,6777 49,6838 5' 1 39,3887 37,3812 3' 1 38,1941 37,1851 3' 7 48,4489 50,2625 4' 9 38,8101 39,0823 3' 1 49,2655 50,2611 5' 5 51,2688 50,613 3' 5 12,688 50,613 3'
Nigeria Norway Oman Pakistan Panama	150001 55,001 55,001 55,001 55,001 55,012 4,010 51,000 17,007 15,072 5,070 5,000 17,007 15,072 5,010 50,001 50,071 50,070	1 56,6358 56,8365 5' 9 48,3616 49,4904 4' 9 53,6777 49,6838 5' 1 39,3887 37,3812 3' 3 38,1941 37,1851 3' 7 48,4489 50,2625 4' 0 38,8101 39,0823 3' 1 49,2655 50,2611 5' 5 51,2688 50,613 5' 5 51,2688 50,2613 5' 5 51,2688 5'
Nigenia Norway Oman Pakistan Pansma Pensuna Penu	150001 55,001 55,001 55,001 55,001 55,012 4,010 51,000 17,007 15,072 5,070 5,000 17,007 15,072 5,010 50,001 50,071 50,070	1 56,6358 56,8365 5' 9 48,3616 49,4904 4' 9 53,6777 49,6838 5' 1 39,3887 37,3812 3' 3 38,1941 37,1851 3' 7 48,4489 50,2625 4' 0 38,8101 39,0823 3' 1 49,2655 50,2611 5' 5 51,2688 50,613 5' 5 51,2688 50,2613 5' 5 51,2688 5'
Nigeria Noeway Oman Pakistan Panama Peru Philippines	15,000 15,001 55,001 55,001 55,010 51,000 17,007 15,072 5,072 5,070 51,007 15,072 5,070 51,070 15,070 15,070 51,07	1 56,6358 56,8368 57 9 48,3616 49,4904 42 9 35,6777 49,6338 57 1 39,3887 37,3812 37 9 38,1941 37,1851 37 9 38,1941 37,1851 37 9 48,4489 59,2625 44 9 38,8101 39,0823 39 1 49,2655 59,2613 54 5 42,5682 43,2133 44 9 53,3793 54,1810 5 34,9914 56,0220 57
Nigeria Norway Oman Pakistan Panama Peru Philippines Philippines	150001 55001 55001 55001 55001 5501 550	1 56,6358 56,8365 57 9 48,3616 49,4904 44 9 53,6777 49,6338 57 1 39,3887 37,3812 37 9 38,1941 37,1851 37 9 38,1941 37,1851 37 9 38,1941 39,0823 33 1 49,2655 59,2611 57 5 51,2655 59,2611 57 5 51,2655 59,2611 35 9 42,8682 43,2133 44 9 53,3793 54,1810 55 3 49,9144 50,0200 57 3 49,2144 50,0200 57 3 72,549 31 353 37
Nigeria Norway Oman Pakistan Panama Peru Philippines Philippines	150001 55001 55001 55001 55001 5501 550	1 56,6358 56,8365 57 9 48,3616 49,4904 44 9 53,6777 49,6338 57 1 39,3887 37,3812 37 9 38,1941 37,1851 37 9 38,1941 37,1851 37 9 38,1941 39,0823 33 1 49,2655 59,2611 57 5 51,2655 59,2611 57 5 51,2655 59,2611 35 9 42,8682 43,2133 44 9 53,3793 54,1810 55 3 49,9144 50,0200 57 3 49,2144 50,0200 57 3 72,549 31 353 37
Nigeria Noeway Omen Pakistan Parama Pera Philippines Poland Portugal Qatar	150001 55,4405 55,345 55,445 55,345 45,000 1200 13,257 55,27 24,049 55,070 13,517 34,071 55,071 55,071 54,010 13,029 15,020 54,000 13,020 15,020 15,020 54,000 13,020 15,0	I 56,6338 56,8386 55 948,3616 49,4904 44 9 53,6777 49,6838 51 139,3887 37,3812 37 938,1941 37,1881 37 7 45,4489 59,2625 44 938,8101 39,0823 39 49,2655 59,2611 55 5 51,2688 59,6133 54 49,2655 59,2611 55 5 31,2688 59,6133 54 49,2655 59,2611 55 5 31,2688 59,2133 44 0 53,3793 54,1810 5 3 49,9144 59,0200 55 3 7,7449 37,3523 37 7 42,4628 42,2111 4 5 7,3870 67,3423 57,423 5
Nigeria Norway Omen Pakistan Panama Pena Philippines Poland Portugal Quar Resublic of Korea	150001 53010 53010 53010 53010 53010 53010 5300 7307 1307 24040 5070 43017 51070 74010 50100 5020 74000 92010 54010 10200 92010 5400 5000 9000 9000 9000 9000 9000 900	1 56,053 56,346 5 4 56,3616 49,4904 5 53,6777 49,633 5 39,3857 37,3812 3 9,81,941 37,1851 3 7 48,4489 59,2625 4 9,81,941 39,823 5 5 51,2688 50,613 5 5 51,2688 50,613 5 5 42,668 42,1810 5 5 37,7489 37,2523 5 3 4,9214 50,0200 5 5 37,7489 37,2523 5 3 7,7489 37,2523 5 3 7,7489 37,2523 5 3 7,7489 37,2523 5 3 7,7489 37,2523 5 5 37,7489 37,2523 5 5 37,259 30 5 5 37,259 5
Nigeria Norway Omen Pakistan Panama Pena Philippines Poland Portugal Quar Resublic of Korea	150001 53010 53010 53010 53010 53010 53010 5300 7307 1307 24040 5070 43017 51070 74010 50100 5020 74000 92010 54010 10200 92010 5400 5000 9000 9000 9000 9000 9000 900	1 56,053 56,346 5 4 56,3616 49,4904 5 53,6777 49,633 5 39,3857 37,3812 3 9,81,941 37,1851 3 7 48,4489 59,2625 4 9,81,941 39,823 5 5 51,2688 50,613 5 5 51,2688 50,613 5 5 42,668 42,1810 5 5 37,7489 37,2523 5 3 4,9214 50,0200 5 5 37,7489 37,2523 5 3 7,7489 37,2523 5 3 7,7489 37,2523 5 3 7,7489 37,2523 5 3 7,7489 37,2523 5 5 37,7489 37,2523 5 5 37,259 30 5 5 37,259 5
Nigeria Norway Omen Pakistan Panama Pena Philippines Poland Portugal Quar Resublic of Korea	15000 15001 5500 5500 5500 5500 5500 5700 5100 51	$\begin{array}{c} 1 & 6_{0.538} & 5_{0.3665} & 7_{0.081} \\ 8_{0.5616} & 4_{0.094} & 4_{0.081} \\ 8_{0.5616} & 4_{0.081} & 7_{0.081} & 3_{0.081} \\ 3_{0.0817} & 7_{0.0812} & 3_{0.081} \\ 3_{0.0817} & 7_{0.0812} & 3_{0.0813} & 3_{0.0813} \\ 3_{0.0818} & 3_{0.0813} & 3_{0.0813} & 3_{0.0813} \\ 4_{0.0816} & 3_{0.0813} & 3_{0.0813} \\ 4_{0.0816} & 4_{0.0822} & 4_{0.0133} & 5_{0.0813} \\ 5_{0.0816} & 4_{0.0822} & 4_{0.0133} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0822} & 4_{0.0133} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0812} & 4_{0.0100} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0812} & 4_{0.0100} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0812} & 4_{0.0100} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0816} & 4_{0.0100} & 5_{0.010} \\ 5_{0.0816} & 4_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.010$
Nigeria Noeway Owan Pakistan Pariu Pariu Pariu Portugal Qutar Republic of Korea Republic of Korea Republic of Korea Republic of Korea	15000 15001 5500 5500 5500 5500 5500 5700 5100 51	$\begin{array}{c} 1 & 6_{0.538} & 5_{0.3665} & 7_{0.081} \\ 8_{0.5616} & 4_{0.094} & 4_{0.081} \\ 8_{0.5616} & 4_{0.081} & 7_{0.081} & 3_{0.081} \\ 3_{0.0817} & 7_{0.0812} & 3_{0.081} \\ 3_{0.0817} & 7_{0.0812} & 3_{0.0813} & 3_{0.0813} \\ 3_{0.0818} & 3_{0.0813} & 3_{0.0813} & 3_{0.0813} \\ 4_{0.0816} & 3_{0.0813} & 3_{0.0813} \\ 4_{0.0816} & 4_{0.0822} & 4_{0.0133} & 5_{0.0813} \\ 5_{0.0816} & 4_{0.0822} & 4_{0.0133} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0822} & 4_{0.0133} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0812} & 4_{0.0100} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0812} & 4_{0.0100} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0812} & 4_{0.0100} & 5_{0.013} \\ 5_{0.0816} & 4_{0.0816} & 4_{0.0100} & 5_{0.010} \\ 5_{0.0816} & 4_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} & 5_{0.0100} \\ 5_{0.0100} & 5_{0.010$
Nigeria Norway Oman Pakidan Parama Pera Pera Poland Portugal Quar Republic of Korea Republic of Korea Republic of Korea Republic of Korea Republic of Korea	15000 15001 5500 5500 5500 5500 5500 55	$1 \le 6.33 \le 5.3465 \le 7.4845$ $4 \le 3.5616 49.4904 49$ $5 \le 3.5616 49.4904 49$ $5 \le 3.5616 49.4904 49$ $5 \le 3.5617 49.63185 32$ $1 \le 9.3887 53.73812 32$ $1 \le 9.3887 53.8212 39.8323 32$ $4 \le 9.2655 50.2611 52$ $5 \le 1.2688 50.6313 51$ $5 \le 42.5682 42.2133 44$ $5 \le 7.7489 37.3523 53$ $4 \ge 2.3875 44.22111 44$ $5 \le 7.370 57.9423 52$ $4 \ge 4.3875 64 42.9023 44$ $2 \le 4.3875 64 42.9023 44$ $2 \le 4.3875 64 43.9023 44$ $2 \le 4.3875 64 43.9023 44$ $2 \le 4.3875 64 43.9023 44$ $2 \le 3.857 64 43.9023 44$
Nigeria Norway Omen Pakistan Panya Panya Patand Potngal Qatar Ogatar Republic of Korea Republic of Korea Republic of Korea Republic of Korea Republic of Korea Republic of Korea	15000 15001 5500 5500 5500 5500 5500 55	$1 \le 6.33 \le 5.3465 \le 7.4845$ $4 \le 3.5616 49.4904 49$ $5 \le 3.5616 49.4904 49$ $5 \le 3.5616 49.4904 49$ $5 \le 3.5617 49.63185 32$ $1 \le 9.3887 53.73812 32$ $1 \le 9.3887 53.8212 39.8323 32$ $4 \le 9.2655 50.2611 52$ $5 \le 1.2688 50.6313 51$ $5 \le 42.5682 42.2133 44$ $5 \le 7.7489 37.3523 53$ $4 \ge 2.3875 44.22111 44$ $5 \le 7.370 57.9423 52$ $4 \ge 4.3875 64 42.9023 44$ $2 \le 4.3875 64 42.9023 44$ $2 \le 4.3875 64 43.9023 44$ $2 \le 4.3875 64 43.9023 44$ $2 \le 4.3875 64 43.9023 44$ $2 \le 3.857 64 43.9023 44$
Nigeria Nooway Omen Pakistan Pama Pena Pena Poland Portugal Quar Republic of Korea Republic of Korea Republic of Korea Results of Korea Sangapore	15,000 15	$\begin{array}{r} 1 & 6_{0.538} & 5_{0.3065} & 0\\ 8_{0.5616} & 4_{0.4094} & 4\\ 9 & 3_{0.6717} & 4_{0.6385} & 3\\ 9 & 3_{0.5717} & 4_{0.6385} & 3\\ 3 & 3_{0.1944} & 3_{0.3857} & 3_{0.73812} & 3\\ 3 & 3_{0.1944} & 3_{0.3857} & 3\\ 4 & 4_{0.2655} & 5_{0.2625} & 4\\ 4 & 4_{0.2655} & 5_{0.2621} & 3\\ 4 & 4_{0.2655} & 5_{0.2621} & 3\\ 4 & 4_{0.2655} & 5_{0.2621} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2655} & 4_{0.2112} & 4\\ 4 & 3_{0.2756} & 4_{0.2012} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4_{0.2022} & 4\\ 4 & 3_{0.2756} & 4\\ 4 & 4\\ 4 & 4 & 4\\ 4 & 4\\ 4 & 4 & 4$
Nigeria Norway Oman Pakitan Pansma Pena Pena Potand Potngal Qatar Republic of Korea Republic of Korea Resultic of Korea Resultic of Korea Resultic of Korea Resultic of Korea Resultic of Korea Resultic of Korea Storokia	15000 15201 5201 5201 5201 5201 5201 520	$\begin{array}{r} 56,6358,56,366,57\\ 84,5616,49,4094,49\\ 53,677,49,6385,57\\ 39,9387,37,3812,37\\ 39,9387,37,3812,37\\ 39,9387,37,3812,37\\ 39,9387,37,3812,37\\ 39,9387,37,3812,37\\ 39,9387,39,2625,44\\ 49,055,59,2625,44\\ 49,055,59,2625,44\\ 49,055,59,2625,42\\ 49,055,59,262,42\\ 49,055,59,262,52,52\\ 49,02,42,42,562,52,52\\ 49,02,42,42,562,52,52\\ 49,02,42,42,562,52,52\\ 49,02,42,42,562,52,52\\ 49,02,42,42,562,52,52\\ 49,02,42,42,562,52,52\\ 49,02,52,52,52,52\\ 49,02,52,52,52,52,52,52\\ 49,02,52,52,52,52,52,52\\ 49,02,52,52,52,52,52,52,52\\ 49,02,52,52,52,52,52,52,52,52,52\\ 49,02,52,52,52,52,52,52,52,52,52,52,52,52,52$
Nigeria Noeway Oman Pakistan Panama Pena Polikpines Politad Portugal Quia Republic of Korea Republic of Korea Republic of Koledova Romania Russian Federation Sanegal Singapore Skovakia Skoveria	15000 15001 5500 5500 5500 5500 5500 55	$\begin{array}{r} 1 & 6_{0.538} & 5_{0.5065} & 0\\ 8_{0.5616} & 4_{0.4094} & 4\\ 9 & 3_{0.6717} & 4_{0.6385} & 3\\ 9 & 3_{0.5717} & 4_{0.6385} & 3\\ 3 & 3_{0.1944} & 3_{0.5857} & 3_{0.73812} & 3\\ 3 & 3_{0.1944} & 3_{0.5857} & 3_{0.52625} & 4\\ 3 & 3_{0.510} & 3_{0.011} & 3_{0.022} & 3\\ 4 & 4_{0.2655} & 5_{0.2621} & 3\\ 5 & 5_{0.1268} & 5_{0.0133} & 4\\ 4 & 4_{0.2655} & 5_{0.2611} & 3\\ 4 & 4_{0.2658} & 5_{0.0133} & 4\\ 4 & 4_{0.2658} & 5_{0.0133} & 4\\ 4 & 4_{0.2658} & 4_{0.2113} & 4\\ 4 & 4_{0.2658} & 4_{0.2113} & 4\\ 4 & 4_{0.5618} & 4_{0.2113} & 4\\ 4 & 4_{0.5618} & 4_{0.2113} & 4\\ 4 & 4_{0.5618} & 4_{0.2113} & 4\\ 4 & 4_{0.5618} & 4_{0.2113} & 4\\ 4 & 4_{0.5618} & 4_{0.2113} & 4\\ 4 & 4_{0.5618} & 4_{0.2114} & 4\\ 4 & 4_{0.5619} & 3_{0.0327} & 4\\ 4 & 4 & 3_{0.576} & 4\\ 4 & 4 & 3_{0.576} & 4\\ 4 & 4 & 3_{0.576} & 4\\ 4 & 4 & 3_{0.576} & 4\\ 4 & 4 & 3_{0.576} & 4\\ 4 & 4 & 3_{0.576} & 4\\ 3 & 4 & 4 & 4\\ 4 & 4 & 5_{0.670} & 3\\ 5 & 3 & 5 & 3_{0.556} & 3\\ 5 & 3 & 5 & 3_{0.556} & 3\\ 5 & 3 & 3 & 3_{0.556} & 3\\ 5 & 3 & 3 & 3_{0.556} & 3\\ 4 & 3 & 4 & 4\\ 4 & 3 & 4 & 3 & 4\\ 4 & 3 & 4 & 3 & 4\\ 4 & 3 & 3 & 3 & 3\\ 4 & 4 & 4 & 3 & 4\\ 4 & 4 & 3 & 5 & 4\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 4 & 5\\ 4 & 4 & 4 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 5 & 6\\ 4 & 4 & 3 & 4 & 5\\ 4 & 4 & 5 & 6\\ 4 & 5 & 6 & 6\\ 4 & 5 & 6 & 6\\ 4 & 5 & 6 & 6\\ 5 & 6 & 6 & 6\\ 5 & 6 & 6 & 6\\ 5 & 6 &$
Nigeris Norway Omm Pakistan Panuma Panuma Panga	150001 55001 <t< td=""><td>$\begin{array}{r} 8 \\ 5 \\ 6 \\ 6 \\ 5 \\ 8 \\ 7 \\ 7 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8$</td></t<>	$\begin{array}{r} 8 \\ 5 \\ 6 \\ 6 \\ 5 \\ 8 \\ 7 \\ 7 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8$
Ngeria Norony Oman Pakistan Pana Pakistan Portugal Quin Portugal Quin Republic of Korea Republic of Korea Republic of Madava Republic of Madava Salveria Salveria Salveria	15000 15001 5500 5500 5500 5500 5500 55	$\begin{array}{c} 3 = 6, 6, 53 = 5, 5, 0, 84 \le 5, \\ 4 = 8, 5616 = 49, 4094 = 49 \\ 5 = 3, 6777 = 49, 5618 \le 5 \\ 3 = 9, 9, 3887 = 37, 7381 = 23 \\ 3 = 8, 1944 = 37, 1581 = 33 \\ 3 = 8, 1944 = 37, 1581 = 34 \\ 4 = 9, 2655 = 50, 2625 = 44 \\ 4 = 9, 2655 = 50, 2625 = 54 \\ 4 = 9, 2655 = 50, 2625 = 54 \\ 5 = 1, 2638 = 50, 2625 = 54 \\ 5 = 1, 2638 = 50, 2625 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 54, 2638 = 54 \\ 5 = 1, 2638 = 1, 2638 = 1, 2638 = 54 \\ 5 = 1, 2638 = 1$
Nigeria Nicowy Omm Pakistan Parama Pakistan Parama Palikaj Quar Portugal Quar Republic of Modowa Ropathic of Modowa Ropathic of Modowa Ropathic of Modowa Ropathic of Modowa Singaporta Singaporta South Africa South Africa South Africa	15000 15001 5500 5500 5500 5500 5500 55	$\begin{array}{c} 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 $
Nigeria Nicowy Omm Pakistan Parama Pakistan Parama Palikaj Quar Portugal Quar Republic of Modowa Ropathic of Modowa Ropathic of Modowa Ropathic of Modowa Ropathic of Modowa Singaporta Singaporta South Africa South Africa South Africa	15000 15001 5500 5500 5500 5500 5500 55	$\begin{array}{c} 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 8 $
Nigeria Nicrowy Oman Pakistan Patistan Petany Palitopiros Palitopi	 Martia Martin Salahi Sal	5.6,633 5,6346 5; 5.6,616 4,9,040 4; 5.1,677 4,943 5; 3.1,614 4,940 4; 3.1,677 4,943 5; 3.1,144 7,943 5; 3.1,144 7,943 5; 3.1,144 7,943 5; 3.1,144 7,943 5; 3.1,144 7,945 7; 3.1,145 7; 3.1
Ngeria Norony Otana Padatan Peng Peng Peng Peng Peng Peng Peng Pen	 Martia Martin Salahi Sal	5.6,633 5,6346 5; 5.6,616 4,9,040 4; 5.1,677 4,943 5; 3.1,614 4,940 4; 3.1,677 4,943 5; 3.1,144 7,943 5; 3.1,144 7,943 5; 3.1,144 7,943 5; 3.1,144 7,943 5; 3.1,144 7,945 7; 3.1,145 7; 3.1
Nigeria Niceway Olam ak Marina Para Palipipotes Poling Pol	150001 550001<	5 46,253 56,346 57 4 5,616 49,0404 5 5 10,777 49,4383 5 10,337 17,3423 1 10,337 17,3423 1 10,337 17,342 1 10,337 17,343 1 10,342 1 10,337 14,342 1 10,342 1 10,342 1 11,342
Nigeria Niceway Olam ak Marina Para Palipipotes Poling Pol	150001 550001<	5 46,253 56,346 57 4 5,616 49,0404 5 5 10,777 49,4383 5 10,337 17,3423 1 10,337 17,3423 1 10,337 17,342 1 10,337 17,343 1 10,342 1 10,337 14,342 1 10,342 1 10,342 1 11,342
Nipris Nicrosy Otem Para Para Peligipines Poling Po	 Martin Agurta Salari Salari Salari Salari Lange Target Target Agues Kannel Salari Salar	5 46,035 9,634,06 5 5 46,036 9,64,040 5 5 3,077 9,64,035 5 5 3,077 9,64,035 5 5 3,077 9,64,035 5 5 3,077 9,64,035 5 4 4,045 5,04,05 5 4 4,045 5,04,01 5 4 4,045 5,04,01 5 5 3,748 5,04,01 5 5 3,978 5,04,01 5 5 3,9
Nigeris Nicenaya Adatama Patam	State State <th< td=""><td>5 46,035 9,63,046 5 5 46,075 9,63,046 5 5 36,777 44,0435 5 5 36,777 44,0435 5 4 36,007 9,740 4 4 4,645 9,50,757 4 4 ,646 9,50,758 4 4 ,954 9,50,758 4 4 ,957 4 ,950 5 4 ,955 7 4 ,950 5 4 ,955 7 4 ,950 5 4 ,955 7 4 ,950 5 4 ,155 4 ,950 6 4 ,155 6 ,950 6 4 ,155 6 ,950 6 4 ,155 6 ,950 6 4 ,155</td></th<>	5 46,035 9,63,046 5 5 46,075 9,63,046 5 5 36,777 44,0435 5 5 36,777 44,0435 5 4 36,007 9,740 4 4 4,645 9,50,757 4 4 ,646 9,50,758 4 4 ,954 9,50,758 4 4 ,957 4 ,950 5 4 ,955 7 4 ,950 5 4 ,955 7 4 ,950 5 4 ,955 7 4 ,950 5 4 ,155 4 ,950 6 4 ,155 6 ,950 6 4 ,155 6 ,950 6 4 ,155 6 ,950 6 4 ,155
Ngersi Ngersi Ngersi Patsana Para Para Para Para Para Para Para P	 Martia M, J. W. M. K. M. S. M. M.	5 46,253 56,346 57 5 46,354 67,494 48 5 3,077 7 49,435 51 5 3,074 7 51,557 51 4 2,625 53,011 59,525 52 5 3,024 59,541 51 5 3,024 59,542 51 5 3,024 59,
Ngersi Ngersi Ngersi Pakatan Para Para Para Para Para Para Para Pa	 Marcia A., Jack S. 19, Marcia S. 19, Marcia S. 1997. 3, Marcia S. 2019. 3, Marcia S. 2019. 1, Marcia S. 2019. 3, M	5.46,253 5.46,245 5.46,245 5.47,245 5.4
Ngersi Ngersi Ngersi Pakatan Para Para Para Para Para Para Para Pa	 Marcia A., Jack S. 19, Marcia S. 19, Marcia S. 1997. 3, Marcia S. 2019. 3, Marcia S. 2019. 1, Marcia S. 2019. 3, M	5.46,253 5.46,245 5.46,245 5.47,245 5.4
Ngersi Ngersi Ngersi Pakatan Para Para Para Para Para Para Para Pa	Store Store <th< td=""><td>$\begin{array}{c} 5 < 5$</td></th<>	$\begin{array}{c} 5 < 5 < 5 < 5 < 5 < 5 < 5 < 5 < 5 < 5 $
Ngersi Ngersi Ngersi Pakatan Patatan Para Para Para Para Para Para Para Pa	Store Store <th< td=""><td>$\begin{array}{c} 5 < 5$</td></th<>	$\begin{array}{c} 5 < 5 < 5 < 5 < 5 < 5 < 5 < 5 < 5 < 5 $
Ngersi Ngersi Ngersi Pakisan Pana Pana Pana Pana Pana Pana Pana P	150001 550001	5 46,025 9,634,05 5 5 46,025 9,634,05 5 10 3,034 9,746,04 1 10 3,037 7,7381 1 10 3,041 7,7381 1 10 3,041 7,7381 1 10 3,041 7,7381 1 10 3,041 9,7381 1 10 3,041 9,738 1 10 4,041 9,458 1 10 4,0
Nigeris Nicewa ma Oktober Patama Para Para Para Para Para Para Para P	15000 55200 <td< td=""><td>5 46,253 56,2346 57 5 46,254 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,245 77 10,245 77 10,255 77 10,255 77</td></td<>	5 46,253 56,2346 57 5 46,254 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,235 77,248 27 10,245 77 10,245 77 10,255 77 10,255 77
Nigeris Nigeris Nigeris Patistan Para Para Para Para Para Para Para Pa	150001 53.001	5.46,253 9.42,846 5; 5.46,254 9.42,946 5; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 5.1268 5,4214 4; 5.1268 5,4214 4; 5.12
Nigeris Nicewa ma Oktober Patama Para Para Para Para Para Para Para P	15000 55200 <td< td=""><td>5.46,253 9.42,846 5; 5.46,254 9.42,946 5; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 5.1268 5,4214 4; 5.1268 5,4214 4; 5.12</td></td<>	5.46,253 9.42,846 5; 5.46,254 9.42,946 5; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 9.3847 5,7348 2; 5.1268 5,4214 4; 5.1268 5,4214 4; 5.12

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