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ABSTRACT

Refugees are more vulnerable to COVID-19 due to factors such as low standard of living, accommodation in crowded households, difficulty in receiving health care due to high treatment costs in some countries, and inability to access public health and social services. The increasing income inequalities, anxiety about providing minimum living conditions, and fear of being unemployed compel refugees to continue their jobs, and this affects the number of cases and case-related deaths. The aim of the study is to analyze the impact of refugees and income inequality on COVID-19 cases and deaths in 95 countries for the year 2021 using Poisson regression, Negative Binomial Regression, and Machine Learning methods. According to the estimation results, refugees and income inequalities increase both COVID-19 cases and deaths. On the other hand, the impact of income inequality on COVID-19 cases and deaths is stronger than on refugees.

KEYWORDS

COVID-19; income inequality; refugees; machine learning; negative binomial regression

Introduction

The COVID-19 epidemic, which emerged in Wuhan, China in December 2019 and is called SARS-CoV-2, has affected many indicators such as health, socio-economic well-being, supply chain, foreign trade, unemployment, economic instability, poverty, high inflation, and income inequality and immigrants or refugees (Ajibo, 2020; Bayraktar et al., 2021; Ecer, 2020; Isik et al., 2022; Lambovska, Sardinha, & Belas, 2021; Ozyilmaz et al., 2022; Recepoğlu, 2021).

It can be said that COVID-19 affects low socio-economic groups and minorities more. For example, in Stockholm, Sweden, the infection rate in some socioeconomically disadvantaged settlements is 3–4 times higher than the regional average (Burström and Tao, 2020). Similarly, in another study on Israel, COVID-19 cases, incidence, and deaths were found to be twice as high in Arab settlements with higher unemployment, lower household income, and economically disadvantaged settlements than in Jewish settlements (Saban, Myers, Peretz, Avni, & Wilf-Miron, 2021). One of the main reasons for this is that, in addition to poverty and racism, these households had limited access to the health system before the epidemic. The conditions of these individuals, who are mostly excluded from the system, have become more controversial with COVID-19 (Yaya, Yeboah, Charles, Otu, & Labonte, 2020)

In this study, the impact of income inequality and refugees on COVID-19 cases and deaths are analyzed in 95 countries for the year 2021. There is a large literature investigating the impact of COVID-19 on refugees and income inequalities. However, the literature examining the impact of income inequalities on COVID-19 is limited, and studies investigating the impact of refugees on COVID-19 are much more limited. The study is expected to contribute to the literature in this context.

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This article has been corrected with minor changes that do not affect the academic content.

The second contribution of the study to the literature is the relative effects of refugees and income inequalities on the epidemic. The hypothesis of the study is that both income inequalities and refugees have an impact on COVID-19, but the relative effects of both parameters are another problem that the study focuses on. Therefore, in the study, both parameters were used in the same models. According to the findings, income inequality, and refugees increase COVID-19 cases and deaths. When comparing the effect of income inequality and refugees on COVID-19 deaths and cases, it can be said that the effect of income inequality is stronger. On the other hand, income inequality affects COVID-19 deaths more than COVID-19 cases in all models. However, refugees affect COVID-19 cases more strongly than COVID-19 deaths in most models.

The remainder of this paper is structured as follows. In section 2 following the introduction, the interaction between COVID-19 and refugees are presented. In section 3, the relationship between COVID-19 and income inequality is discussed. In section 4, the literature on the impact of both refugees and income inequalities on COVID-19 has been presented. The econometric method; and empirical findings are given in sections 5 and 6.

COVID-19 and refugees

One of the groups where the social effects of COVID-19 are discussed is refugees, who are mostly disadvantaged in social life. In general, refugees who experience discrimination in their countries of residence may face accusations such as spreading disease. Combined with the widespread rise of populism and anti-immigrant/anti-refugee sentiment, the pandemic is expected to exacerbate the hostile view toward these individuals. Therefore, COVID-19 can lead refugees and other immigrant groups to face inhumane treatment on the pretext of the pandemic (Truelove, Abrahim, Altare, Azman, & Spiegel, 2020).

The current situation of the refugee camps is important in deepening the impact of the epidemic. Because poor air quality, ventilation, and the prevalence of respiratory infections in refugee camps are straining the immunological capacity to fight COVID-19 (Gilman, Mahroof-Shaffi, Harkensee, & Chamberlain, 2020; ICMHD, 2020). In addition, refugees are more likely to have underlying health problems such as acute and malnutrition (Volkin, 2020). And also, factors such as the difficulty of self-isolation and social distancing to prevent the spread of the virus in refugee camps (Betts, Easton-Calabria, & Pincock, 2020), poor drinking water supplies (Kassem & Jaafar, 2020), and lack of hygiene and sanitation, make refugees one of the most vulnerable groups in a pandemic. On the other hand, malnutrition and the problem of access to health services can cause the pandemic to become more widespread among refugees (Shammi, Robi, & Tareq, 2020). For example, tens of thousands of people live in refugee camps around the Mediterranean. They are often operated far above capacity and in suboptimal conditions, including a lack of basic infrastructure or hygiene, making them individuals at high risk for the spread of coronavirus. On the other hand, although refugees increase the number of cases among themselves in the camps, they are less likely to spread the virus outside because their contact with the local population is limited (Hargreaves, Kumar, McKee, Jones, & Veizis, 2020). Kakuma refugee camp in Kenya, one of the prominent camps in the World has a population density of about 1,000 times the host Turkana community (SFD, 2020; United Nations, 2020). In Bangladesh, the population density per kilometer in Rohingya camps is 40 times higher than the average density (Islam, Inan, & Islam, 2020). According to the study by Gilman, Mahroof-Shaffi, Harkensee, and Chamberlain (2020), refugees have limited access to water, toilet, shower, or electricity in Moria camp, which is the largest refugee camp in Europe and on the Greek island of Lesbos. According to the simulation method, these conditions are effective COVID-19 cases.

One of the transmission channels in the refugee pandemic relationship is the mobility of the refugee population. In some studies, the spread of epidemic diseases that affect societies through migration has been examined and infectious diseases can increase the rate of transmission in a population through migration (Ginsburg et al., 2018). In this context, the high mobility of the immigrant population may lead to the spread of the epidemic to wider geography (Fan, Cai, Gai, & Wu, 2020).

Stigma is one of the factors that can be decisive in the relationship between COVID-19 and refugees. Fear of stigma or discrimination negatively impacts immigrants' access to healthcare. The effort to keep the disease secret for fear of stigma contributes to the further spread of COVID-19 among the refugee population, where isolation is already difficult. Therefore, stigma can affect COVID-19 cases (IFRC, 2020).

The increasing number of cases among refugees is not limited to refugees only. Considering that these people live in many countries with local people, it is expected that the pandemic will spread more throughout the country through refugees. Therefore, refugees who often live in precarious conditions and face barriers to accessing to public health and social services in their host countries can make difficult COVID-19 outbreak control (Hargreaves, Kumar, McKee, Jones, & Veizis, 2020) . . . In addition, the direction of the pandemic is not only from COVID-19 to refugees or from refugees to the pandemic but also from refugees to the whole society.

Due to the limited number of beds required for treatment despite the high population density, the difficulty of isolation through hospitalization, and the impossibility of social distance, governments focus on developing surveillance and tests in refugee camps instead of social isolation. For example, in Kenya, the UN High Commissioner for Refugees prefers to notify immigrants via text message to encourage them to report their COVID-19 symptoms (Dahab et al., 2020; Hargreaves, Kumar, McKee, Jones, & Veizis, 2020; Truelove, Abrahim, Altare, Azman, & Spiegel, 2020).

Access to accurate information is undoubtedly important in controlling the pandemic. Considering that COVID-19 causes more panic among refugees than the local population, the importance of correct information is better understood. For example, according to those who live in Rohingya refugee camps, the authorities have to kill the infected people, otherwise, their survival will lead to the transmission of the virus to other people. According to another rumor in the camp, those infected are taken to hospital but if recovery is impossible, they are killed by injection (ACAPS, 2020). There is a large information pollution among refugees that does not rely on reliable sources, and this causes further panic among refugees (Betts, Easton-Calabria, & Pincock, 2020). Adding to this the fear of stigmatization of refugees, the importance of information pollution about COVID-19 is better understood.

In fact, it is difficult to reach COVID-19 cases in the camps due to the refugees fear of deportation and the inadequacy of test kits (Kassem, 2020). Studies on this subject support this hypothesis. For example, in Norway, 31% of COVID-19 cases are foreign-born, which is almost twice the share of foreign-born people in the population. In Denmark, the number of infected immigrants from low-income countries and their native-born children is 18% of the population, which is twice the share of immigrants in the population. In Sweden, which showed a similar trend, 32% of COVID-19 cases were immigrants. (although their share in the population is 19%). In Lisbon, the capital of Portugal, the share of immigrants in the population was 11%, but 24% of COVID-19 cases belonged to immigrants. In summary, although immigrants are younger on average, they are more disadvantaged against COVID-19 with a higher risk of infection and higher mortality (Guttmann et al., 2020; OECD, 2020). According to a similar study, Fielding-Miller, Sundaram, and Brouwer (2020) found higher mortality rates among farmworkers (75% of whom are immigrants) in the United States. According to a survey carried out by Relief International (2020) on Syrian refugees in Turkey, 87% of households of the participants stated that at least one lost his/her job due to the pandemic. 71% of participants stated that they had difficulties accessing health services. Despite being one of the countries with the most humane policies toward immigrants/refugees, Turkey also has relatively higher adverse conditions comparing the local people. Therefore, in the world in general, conditions can be predicted to be much more unfavorable to refugees.

In the measures against COVID-19, the living conditions of the refugees should be taken into account, and the policies to be implemented within this framework should be more comprehensive (Martinez-Juarez, Sedas, Orcutt, & Bhopal, 2020). In the framework of policy recommendations, Favas et al. (2020) stated that the contact of those in the high-risk group with other individuals in the camps should be minimized, and in this context, risky people should be grouped in certain areas (Green

Areas) within the camp. However, given that the pandemic has deeply affected national economies and the refugees are mostly clustered in the least developed and developing countries, it is clear that the measures to be taken by governments may be insufficient and international assistance is required. For example, in Bangladesh, which hosts nearly one million Rohingya refugees, there are only 2000 ventilators (Reuters, 2020). For this reason, countries with a high refugee population need to be supported by international aid organizations and donor countries in controlling the pandemic.

In case the necessary assistance cannot be provided or the economy of the country cannot cover the health costs of the refugee population, at least, taking some measures that do not create a big burden for the national economy facilitates the control of the pandemic. For example, medical equipment such as gloves, masks, and disinfectants must be provided primarily to all refugees, but in the case of stock shortages, primarily for the elderly and risky groups. In addition, some of the measures that can be taken in the camps are to isolate and protect especially the elderly in a different areas to place handwashing disinfectants at many points of the camps; and to have health consultants provide accurate and reliable information about outbreaks in the camp.

COVID-19 and income inequality

One of the socioeconomic factors that pandemic diseases interact with is income inequality. The relationship between income inequality and health was one of the topics of discussion before COVID-19 (Karlsson, Lyttkens, Nilson, & Leeson, 2008; Kim, 2019; Lynch et al., 1998; Wilkinson, 1992; Wilkinson & Pickett, 2008) and this topic has started to be discussed again with the pandemic. In this context, there is a large literature dealing with the relationship between income inequality and COVID-19 (Brown & Ravallion, 2020; Elgar, Stefaniak, & Wohl, 2020; Frempong, Novignon, & Stadelmann, 2021, Benita and Gasca-Sanchez, 2021; Vilandre, 2021).

The pandemic, which has an impact on income inequality (Bonacini, Gallo, & Scicchitano, 2020), is also directly affected by inequalities (Eligon, Burch, & Searcey, 2020). Therefore, the pandemic and income inequality are processes that feed each other. For example, in the USA, especially the uninsured poor who are caught by COVID-19 continue to work due to high bills and fear of dismissal (Hoadley, Fuchs, & Lucia, 2020) and this causes the pandemic to spread to more people, and, in case of treatment, and causes these individuals to become more impoverished through both unemployment and cost channels, and this can affect income inequality. Fisher and Bubola (2020) explain the vicious circle between pandemic, and inequality as follows: With the onset of a health crisis, the whole society is affected, the economic contractions caused by the pandemic can trigger chronic diseases, this process that affects productivity in all aspects increases health care costs and deepens poverty, this also can brings with it more disease.

The impact of income inequalities on health emerges mainly through two channels. These are the absolute effect and the contextual effect. According to the absolute effect, small changes in the income of the poorest individuals lead to significant changes in health outcomes, but changes in the income of the rich individuals do not lead to a large change in health standards. In the contextual effect, the negative effects of the current conditions of people living in unequal societies come to the fore. For example, individuals at the bottom of the income distribution living in areas with high levels of pollution, poor public structures such as health, safety, sanitation, and urban planning are more at risk for health. These conditions, which more severely affect the poorest individuals, are an important parameter in explaining why COVID-19 case and death rates are higher in more unequal states (Demenech, Dumith, Vieira, & Neiva-Silva, 2020; Kawachi & Subramanian, 2014).

Many parameters are decisive in the relationship between income inequality and COVID-19. The most important of these indicators are poverty caused by income inequality and health indicators of the poor. For example, a study for the United Kingdom suggested that the health indicators of low-income individuals make these individuals more vulnerable to COVID-19. According to the study, individuals in the lowest segment of the income distribution are more likely to face high-risk diseases. It has also been revealed that mental health problems are more common among low-income individuals. Given that the poorest populations are more likely to have chronic conditions, this may make them more susceptible to COVID-19. This is a parameter that directly increases both the number of cases and the number of deaths (Ahmed, Ahmed, Pissarides, & Stiglitz, 2020; Blundell, Costa Dias, Joyce, & Xu, 2020). As a matter of fact, the prominent view in the literature on the income inequality-epidemic relationship is that the increase in cases and deaths is mostly due to the effects of poverty. Therefore, higher inequalities can lead to more COVID-19 cases and deaths. Because unequal income distribution creates a large population without access to basic services and health facilities. At this point, as the density of the population that receives the least share of income increases, it may be possible for the virus to spread to a wider population. In fact, all these factors support the argument of Fisher and Bubola (2020) that "Inequalities can be the multiplier of the coronavirus."

One of the determinants of income inequality to deepen the effects of the epidemic is social distance. Poor individuals often live in crowded regions and households where it is difficult to implement the necessary measures for the pandemic, including social distancing. These living conditions, where social distance is difficult, directly affect the number of cases. In addition, low-income individuals generally work in jobs where they may be more exposed to COVID-19, and they often do not have the opportunity to work from home. Therefore, these conditions can affect COVID-19 cases. For example, in the USA, states with a higher Gini index have experienced more deaths due to COVID-19 (Oronce, Scannell, Kawachi, & Tsugawa, 2020)

Literature review

There is a large literature focusing on the migration relationship in the spread of diseases (Ginsburg et al., 2018; Hâncean, Perc, & Lerner, 2020), but the literature dealing with the refugee- COVID-19 relationship is quite limited. In addition, studies on the refugee- COVID-19 relationship have mostly discussed the effect of COVID-19 on refugees (Bohnet & Rüegger, 2021; Grais & Baron, 2022; Litzkow, 2021; Navarro-Román & Román, 2022). In recent studies, the impact of immigrants on COVID-19 cases and deaths Jung, Ahn, and Bommarito (2022) reviewed for US. According to the study, total immigrants negatively affect both the number of COVID-19 cases and deaths. However, when the immigrants are examined in groups, the findings differ. For example, Hispanic American and Asian Americans reduce COVID-19 cases and increase the death toll, but African American increases both the number of COVID-19 cases and the death toll. But the literature investigating the impact of refugees on COVID-19 cases and deaths is very limited. In this context, Salom et al. (2021) discuss the impact of refugees on the number of COVID-19 cases in 118 countries. According to the study, there is no clear evidence that the number of refugees is increasing the spread of COVID-19. Thus, the findings indicate that refugees are not a primary concern in pandemics.

When the literature discussing the relationship between COVID-19 and income inequality is examined, it is seen that the studies are mostly focused on the USA, and there are many studies that deal with this relationship at the state level in the USA. Tan, Hinman, Magid, Nelson, and Odden (2021) found that there is a positive relationship between income inequality and COVID-19 cases and deaths in the USA. Accordingly, US Counties with high-income inequality have more COVID-19 cases and deaths.

Brown and Ravallion (2020) found that US Counties with higher income inequality have higher COVID-19 cases. Vilandre (2021) examined the role of past inequalities in the risk of infection and death in the context of COVID-19 in US Counties. Accordingly, income inequality increases the negative effects of COVID-19 on health. Yu et al. (2021) discussed the impact of racial and ethnic settlement and income inequality on COVID-19 during the COVID-19 epidemic in large USA cities. Accordingly, racial inequalities and income inequality lead to conditions that negatively affect health and this increases COVID-19 deaths. Tan, Hinman, Magid, Nelson, and Odden (2021), Liao and De Maio (2021), and Karmakar, Lantz, and Tipirneni (2021) found that income inequality increases the number of COVID-19 cases and the number of deaths in US counties. Mukherji (2020) found that income inequality increases both the number of cases and the death toll in US counties. Oronce, Scannell, Kawachi, and Tsugawa (2020) revealed that COVID-19 causes more deaths in US states with higher income inequality. According to the study, income inequality is one of the parameters that explains why some US counties are more affected by COVID-19.

Looking at the literature investigating the relationship between income inequality and COVID-19, Davies (2021) discussed the effect of pre-pandemic inequalities on the number of COVID-19 cases and deaths in 141 countries. According to the study, there is a strong and positive relationship between Gini and COVID-19 mortality rate. Sepulveda and Brooker (2021) examined the relationship between income inequality and COVID-19 deaths in 22 OECD countries. Accordingly, there is a positive relationship between income inequality and COVID-19 deaths. Frempong, Novignon, and Stadelmann (2021) investigated the effects of education, gender, income, and political inequalities on COVID-19 in Sub-Saharan Africa. According to the study, income inequalities increase both the number of COVID-19 cases and deaths. Lindström (2020) examined 84 countries and found that countries with high-income inequality have higher COVID-19 death rates. Bolaño-Ortiz et al. (2020) concluded that there is a positive relationship between income inequality and the number of COVID-19 cases in the Latin America and Caribbean (LAC) region. Benita and Gasca-Sanchez (2021) found a positive relationship between income inequality and the number of COVID-19 cases and deaths in Mexico. Veloso, Ziviani, and Dong (2022) calculated the determining factors on the COVID-19 rate in Belgium, Brazil, France, Germany, Italy, Sweden, UK, and USA. According to the study, the COVID-19 death velocity is higher in countries with high-income inequality. In this context, income inequality is an important factor that increases the COVID-19 death velocity during the epidemic in Brazil and the USA, where income inequalities are high. Arbel, Fialkoff, Kerner, and Kerner (2022) found a positive correlation between income inequality and predicted infection rates in Israel. Amate-Fortes and Guarnido-Rueda (2022) investigated the impact of income inequalities on COVID-19 incidence and mortality rates in Spain. According to the study, inequalities have a decisive role in the COVID-19 incidence rate, but not for the mortality rate. In addition, focusing on a larger sample of countries, Sánchez-Páez (2022) found that income inequality increases the number of COVID-19 infections and deaths in European countries.

When the literature investigating the effect of income inequalities on COVID-19 is examined, the general trend is that inequalities increase the number of COVID-19 cases and deaths. However, since the literature examining the impact of refugees is quite limited and the current study does not reach a clear finding, it can be said that there is an important gap in the literature on this topic.

Data and methods

In this study, the effect of refugees and income inequality on COVID-19 cases and deaths were discussed for 95 countries in 2021. Model I indicates the impact of income inequality and refugees on COVID-19 cases, Model II indicates the impact of these variables on COVID-19 deaths. The cross-section equations for the models are shown below.

Model I

$$Case = \beta_0 + \beta_1 lnRef + \beta_2 Gini + \beta_3 Pop65 + \beta_4 lnurban + \beta_5 Democracy + u \quad (1)$$

Model II

$$Deaths = \beta_0 + \beta_1 lnRef + \beta_2 Gini + \beta_3 Pop65 + \beta_4 LnDiabetes + \beta_5 LifeEx + u \quad (2)$$

Variables and data sources are presented in Table 1. Some variables do not have 2021 data. For this reason, the last data of the variables were used. These years are 2019 for some variables and 2020 or 2021 for others.

Table 1. Data description.

Variables	Description	Data Source
Case	Number of Confirmed COVID-19	Our World in Data
Death	Number of Death COVID-19	Our World in Data
Pop65	Population ages 65 and above (% of the total population)	World Bank Open Data
Gini	Household Income Inequality Index	Our World in Data
lnRef	Refugee population by country or territory of asylum	World Bank Open Data
lnUrban	Urban population (% of total population)	World Bank Open Data
Democracy	Global Freedom Score (0–100)	Freedom House
LnDiabetes	Diabetes prevalence (percentage of people ages 20–79)	Our World in Data
LifeEx	Life expectancy at birth, total (years)	World Bank Open Data

Ln indicates the natural logarithm of the variables.

For model estimation, Poisson regression, Negative Binomial regression, and Machine learning methods were used. The Poisson Regression method was preferred for model estimation because the dependent variables show the events that occurred in a certain time interval and express the counting numbers. The method in question is based on the Poisson distribution. The Poisson distribution is used when the dependent variable is a non-negative and integer (Cameron & Trivedi, 2005). Poisson probability function is as in equation 6 (Hadi, Aruldhas, Chow, & Wattleworth, 1995; Hilbe, 2011);

$$f(y;\mu) = \frac{e^{-\mu}{\mu_i}^{y_i}}{y_i!} y = 0, 1, 2, \ldots, \mu > 0 \tag{3}$$

The Poisson distribution is customized with only one parameter. This parameter (μ) defines the distribution of mean and variance (Coxe, West, & Aiken, 2009).

$$\mu_i = \exp(x'\beta) = \exp(\beta_1 + \beta_2 x_2 + \ldots + \beta_k x_k) \tag{4}$$

$E[y_i|x_i] = \mu_i = \exp(x'\beta)$ (Cameron & Trivedi, 2005; Coxe, West, & Aiken, 2009). This equality ensures that μ >0 for all combinations of explanatory variables and parameters (Winkelmann, 2008). The probability of the Poisson regression model for a single observation is expressed as follows (Cameron & Trivedi, 2005).

$$f(y|x,\beta) = \frac{e^{-\exp(x'\beta)} \exp{(x'\beta)}^y}{y!} \tag{5}$$

The assumption that the mean and variance of Poisson regression are equal is generally rejected. In case of overdispersion in the model, the Negative Binomial method can be used (Hadi, Aruldhas, Chow, & Wattleworth, 1995). The most commonly used model of negative binomial regression is NB2. In this model, the mean μ and the NB2 variance function are defined as $\mu + a\mu^2$. It has a density (Cameron & Trivedi, 2005):

$$f(y|\mu, a) = \frac{\Gamma(y + a^{-1})}{\Gamma(y+1).\Gamma(a^{-1})} \left(\frac{a^{-1}}{a^{-1} + \mu}\right)^{a^{-1}} \left(\frac{\mu}{a^{-1} + \mu}\right)^{y} \quad a \geq 0, \quad y = 0, 1, 2, \ldots\ldots \tag{6}$$

In Poisson regression, there is the assumption that the mean is equal to the variance. α indicates the overdispersion parameter in the negative binomial. If α = 0, there is no overdispersion and in this case Poisson regression can be used. However, if α > 0, there is overdispersion (Coxe, West, & Aiken, 2009). In case of overdispersion problem, Negative Binomial Regression method can be used instead of Poisson method. Negative Binomial Regression allows variance to be different from the mean (Hadi, Aruldhas, Chow, & Wattleworth, 1995). Denklem (6)'de $a = 0$ ise Poisson regresyon denklemine ulaşılır (Cameron & Trivedi, 2005).

In addition the Poisson regression model, the machine learning model was also used to determine the variable importance. Machine learning is widely used in a number of fields to handle complicated problems that are difficult to solve using traditional computer approaches

(Demet Sahin et al., 2021; Isik, 2020; Mehmet Bilal, Esme, & Isik, 2021). The variable importance measurements based on regression ensembles of tree models have become popular in a variety of fields, including species distribution for future climate scenarios (Cutler & Stevens, 2006; Garzon et al., 2006; Svetnik et al., 2003), predicting chemical properties such as reactivity and biological activity from molecular structure (Gupta, Matthew, Abreu, & Aires-De-Sousa, 2006; Sakiyama et al., 2008; Svetnik et al., 2005), chemometrics data (Zhang, Xu, Daeyaert, Lewi, & Massart, 2005) and microarray and DNA sequence data (Cummings & Segal, 2004). Ensembles of tree models are black box models that cannot be immediately interpreted, despite the fact that they provide a powerful framework for capturing nonlinear interactions between variables. Tree ensemble approaches, on the other hand, can be used to construct variable importance measures, which provide a ranking indicator of the relative significance of input variables to the classification or regression task in question (Díaz-Uriarte & Alvarez de Andrés, 2006; Pang et al., 2006). To date, only a few research have looked into the study of these variable significance measures.

A decision tree is a statistical model that performs classification or regression tasks using data from a specific training set. Breiman and colleagues proposed the CART algorithm for learning classification and regression trees in 1984 (Breiman, Friedman, Olshen, Stone, & Breiman, 1984). The CART method iteratively splits the input space to create a tree predictor (with $y_\eta{}'$ the predicted response for sample X_η) given a training sample L with N samples, M predictor variables Xi (i = 1,. . .,M) as the input space X and a response variable y:

$$y_\eta{}' = T_L\left(X_\eta\right) \tag{7}$$

Both bagged samples and random splits are now shown by the random vector, ϕ. In terms of bagging, the majority vote or average over all trees (where K is the size of the ensemble indexed by k = 1,. . .,K) is the final predictor $y_\eta{}'$ for a sample X_η:

$$y_\eta{}' = \frac{1}{K}\sum_{k=1}^{K} T_{L(\phi_k)}\left(X_\eta\right)_1^K \tag{8}$$

The inclusion of so-called out-of-bag (OOB) samples for each tree in random forests is a beneficial feature: LOOB,k. A number of observations are not used in training for each tree because bagging is used to generate a new training set for each tree. Out-of-bag samples are what they're called. OOB samples can be used to get a precise estimate of misclassification error.

Permuting the values of the predictor variables one at a time and determining the loss in model accuracy for each variable is one method of assessing the importance of each variable in a tree ensemble to the final prediction. A variable's association with the response is destroyed when it is permuted. If the new model's prediction accuracy is much lower than the prior model's, it means that the relationship between predictor and response is weak. The out of bag samples for random forests $\omega_i(T_L)$can be permuted without having to train fresh forests, Eq.(9) (where a is the model's accuracy and $L^i_{OBB}(\theta)$ s the OOB learning sample with variable i permuted) is used to calculate the variable importance measure based on permutation $\omega_i(T_L)$:

$$\omega_i(T_L) = a\left(T_{L(\theta)}\right) - a\left(T_{L^i_{OBB}(\theta)}\right) \tag{9}$$

By averaging individual tree significance ratings, these variable important metrics can be extended to ensembles of trees:

$$\omega_i = \frac{1}{K}\sum\nolimits_{k=1}^{K} \omega_i\left(T_{L(\theta_k)}\right) \tag{10}$$

Previous research have highlighted certain intriguing aspects of random forest and conditional inference forest variable importance measures, which will be considered in this investigation. The compatibility of these qualities with variable significance measures derived from boosted trees will be examined as well (Auret & Aldrich, 2011). The Root Mean Square Error (RMSE) gives an absolute result of how much the predicted results differ from the true number. R^2 is a statistical measure of how close the data are to the fitted regression line. The estimation performances of the developed models were calculated using RMSE and R^2 scores.

Empirical results

In this study, the effect of refugees and income inequality on COVID-19 cases and deaths were analyzed in 95 countries using poisson regression, negative binomial regression and tree ensemble method and findings are presented in Table 2.

α, indicates whether there is overdispersion or not. According to the negative binomial regression results for case and death models, the α value indicates that the basic hypothesis, which states that there is overdispersion at the 1% significance level, should be rejected. Therefore, it has been observed that there is a problem of overdispersion in the case and death models. In this case, Negative Binomial regression estimation results are more effective than Poisson regression.

According to the negative binomial regression results, the Gini index positively affects COVID-19 cases at the 10% significance level. The Gini estimation coefficient is 0.037. This value is equal to $e^{0.037}$, so 1.037. In this framework, one unit increase in the Gini index increases the confirmed of cases by % 3.76. Similarly, the Gini index has a statistically significant and positive effect on COVID-19 deaths at the 1% significance level. The Gini estimation coefficient is 0.066 for deaths model. This value is equal to $e^{0.066}$, so 1.068. One unit increase in the Gini index increases the number of deaths by % 6.82. The number of refugees has a statistically significant and positive effect on the number of COVID-19 cases and deaths at the 1% significance level. The LnRef coefficients for the case and death models are 0.224 and 0.172. The coefficients are not exponential because LnRef is included in the model logarithmically. Accordingly, one unit increase in the number of refugees increases the number of cases by %0.224 and deaths by %0.172. Results from poisson regression and tree ensemble method are similar to Negative Binomial results, but coefficients are different.

Table 2. Estimation results.

Variables	Poisson Reg.	Negative Binomial Reg.	Tree Ensemble Method
COVID-19 Cases Model			
Gini	0.091*** (0.027)	0.037* (0.019)	0.587* (0.007)
Pop65	0.097*** (0.034)	0.062* (0.032)	0.203* (0.011)
LnRef	0.310*** (0.082)	0.224*** (0.046)	0.200*** (0.017)
LnUrban	1.951*** (0.558)	1.348*** (0.366)	0.472*** (0.042)
Democracy	−0.040 (0.106)	−0.032 (0.106)	0.151** (0.029)
Cons.	−1.250 (3.442)	4.669*** (1.453)	-
α (overdispersion coefficient)		1.244 (0.155)	
Log-Pseudolikelihood		−1437.92	
COVID-19 Deaths Model			
LnDiabetes	0.864** (0.400)	1.108*** (0.417)	0.589** (0.183)
LnRefugee	0.214*** (0.051)	0.177*** (0.060)	0.308*** (0.21)
Gini	0.105*** (0.026)	0.066*** (0.020)	0.892*** (0.242)
LifeEx	0.051 (0.045)	0.032 (0.053)	0.200* (0.056)
Pop65	0.088** (0.040)	0.083* (0.044)	1.237* (0.035)
Constant	−2.177 (4.094)	0.724 (3.342)	-
α (overdispersion coefficient)		1.641 (0.200)	
Log-Pseudolikelihood		−1065.31	

Notes: The numbers in parentheses robust standard errors. ***,** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Considering the findings of other control variables, in COVID-19 cases model, according to the results of the negative binomial regression case model, pop65 and lnurban were found to be statistically significant, but the democracy variable did not have a statistically significant effect on COVID-19 cases. A one-unit increase in pop65 increases COVID-19 cases by %6.39 and A one-unit increase in LnUrban increases COVID-19 cases by %1.34. The results obtained from the poisson regression and tree ensemble method support the negative binomial results however, unlike other models democracy is statistically significant and positive on COVID-19 cases in Tree ensemble method.

In COVID-19 deaths model, according to the results of the negative binomial regression, pop65 and diabetes were found to be statistically significant, but the life expectancy is not statistically significant on COVID-19 deaths. According to, a one-unit increase in pop65 increases COVID-19 deaths by %8.65. If diabetes prevalence increases by 1 unit, COVID-19 deaths increases by %1.108 units. The results obtained from the Poisson regression and tree ensemble method support the negative binomial results but life expectancy is statistically significant and positive on COVID-19 deaths in tree ensemble method.

Conclusion

The impact of COVID-19, which causes the death of many people in the world and affects socio-economic life, on relatively disadvantaged individuals such as low-income households, minorities and refugees is one of the important topics of discussion. The general view in the literature is that the inadequacy and cost of the health system, the impossibility of social distance and isolation in refugee camps, the limited remote working conditions of refugees or local people with low socio-economic conditions. The increasing number of cases among these groups causes the pandemic to spread to a wider geography. Therefore, the poverty that emerges as a result of refugees and income distribution injustice is both the driving force and the result of COVID-19 and all these bring along the spiral that feeds each other.

The key mechanism here is the power of high inequalities to affect the lives of refugees and poor and wealthy people. One of the important parameters in this regard is that only high-income households can access health services, especially in countries where healthcare costs are high. Another important transmission channel is that very poor households and refugees have limited opportunities to working from home despite the increasing number of cases and they have to work despite the health risk. In addition, the fact that the socio-economic conditions of refugees and poor households do not allow isolation and that they mostly use public transport is one of the parameters that increase the risk of transmission.

In this context, in this study, the impact of refugees and income inequality on COVID-19 cases and deaths were analyzed in 95 countries. Since the dependent variables in the model are non-negative discrete values, the Poisson Regression method, which is frequently used in model estimation and counting data analysis, was preferred. However, the assumption of the Poisson regression is mean equal to variance was tested with the overdispersion coefficient (α). Therefore, also Negative Binomial Regression method was used in the study. In addition, Tree Ensembles model is also included in the study for coefficient estimation. Tree Ensembles models are used to provide a powerful framework for capturing nonlinear interactions between variables. According to the all models findings, both refugees and income inequality increase COVID-19 cases and deaths. The impact of income inequality on COVID-19 cases and deaths is stronger than refugees. In all COVID-19 cases model, urbanization, Population ages 65 and above have a significant and positive effect on COVID-19 cases but Democracy is not statistically significant in other models except tree ensembles model. In all COVID-19 deaths models, diabetes and population ages 65 and above have a significant and positive effect on COVID-19 deaths. Life expectancy at birth is statistically significant and positive only in tree ensembles model.

During the pandemic period, it has become more difficult for refugees and poor individuals, who have the lowest share of the society in income distribution, to access health services due to reasons such as the insufficiency or cost of the health system. In this context, both as a requirement of the humanitarian approach and in order to control the pandemic, protective measures for refugees and disadvantaged individuals in income distribution have a very important place in minimizing the social impact of the pandemic.

In addition, measures for public health need to be revised and implemented urgently to cover the whole society. Additionally, financing low-income households during bottlenecks, such as pandemics, is important in combating the pandemic.

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