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Impact of COVID-19-Related Lockdown Measures on Economic and Social Outcomes in Lithuania

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Abstract: The current world crisis caused by the COVID-19 pandemic has transformed into an economic crisis, becoming a problem and a challenge not only for individual national economies but also for the world economy as a whole. The first global lockdown, which started in mid-March of 2020 and lasted for three months in Lithuania, affected the movement and behavior of the population, and had an impact on the economy. This research presents results on the impact of lockdown measures on the economy using nonparametric methods in combination with parametric ones. The impact on unemployment and salary inequality was estimated. To assess the impact of lockdown on the labor market, the analysis of the dynamics of the unemployment rate was performed using the results of the cluster analysis. The Lithuanian data were analyzed in the context of other countries, where the dynamics of the spread of the virus were similar. The salary inequality was measured by the Gini coefficient and analyzed using change point analysis, functional data analysis and linear regression. The study found that the greatest impact of the closure restrictions on socio-economic indicators was recorded in 2020, with a lower impact in 2021. The proposed multi-step approach could be applied to other countries and to various types of shocks and interventions, not only the COVID-19 crisis, in order to avoid adverse economic and social outcomes.

Keywords: COVID-19; nonparametric analysis; Gini index; unemployment; cluster analysis; panel data; change point detection; functional data; multidimensional data; lockdown consequences

MSC: 62G10; 62F03; 62R10; 62J05

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Citation: Markevičiūtė, J.; Bernatavičienė, J.; Levulienė, R.; Medvedev, V.; Treigys, P.; Venskus, J. Impact of COVID-19-Related Lockdown Measures on Economic and Social Outcomes in Lithuania. *Mathematics* **2022**, *10*, 2734. https://doi.org/10.3390/math10152734

Academic Editors: Stefano Bonnini and Gheorghe Săvoiu

Received: 21 June 2022
Accepted: 28 July 2022
Published: 2 August 2022

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1. Introduction

The current world crisis caused by the coronavirus pandemic has transformed into an economic crisis, becoming a problem and a challenge not only for individual national economies but also for the world economy as a whole. The COVID-19 crisis has highlighted the vulnerability of individual societies and economies, individuals in particular, requiring a review of how economic and social activities are organized. The pandemic is not merely a health crisis; it is a social and economic crisis, as well as one that has affected individuals, families, communities, businesses, local communities and entire societies. The pandemic and its consequences have revealed weaknesses within and between countries and in measures and decisions taken to address the crisis. The current global situation has impacted individual health and healthcare systems, as well as economic ecosystems, as many countries have applied policies of lockdown. The results of studies indicate that countries with less prepared health systems have applied more restrictive measures, which are associated with greater negative socio-economic consequences [1]. Although there are

many similarities between countries in terms of the specifics of the virus and the features of its spread, there are also differences that exist between regions and even within countries.

The first global lockdown, which began in mid-March of 2020 and lasted for three months in Lithuania, affected both the movement and behavior of the population, and the economy. For this reason, it is important to conduct research on the consequences of the COVID-19 epidemic to identify trends in the epidemic and to assess the socio-economic consequences of the epidemic in the context of Lithuania and other countries. The consequences of lockdown should be considered as a lesson that can be useful in the future.

The main purpose of this paper is to assess the effects of lockdown measures on the economy and social indicators. Therefore, two very sensitive indicators, i.e., the unemployment rate and earnings inequality, were chosen to analyze how the lockdown during the COVID-19 crisis affected these indicators. Nonparametric statistical methods as well as parametric methods were used to achieve this goal. Nonparametric methods are suitable for this analysis, where assumptions on distribution would be very sensitive, while parametric methods are used when a straightforward interpretation of the results is needed.

To measure the impact of lockdown on the labor market, the analysis of the dynamics of the unemployment rate was performed using the results of the cluster analysis, which demonstrates the trend of the virus and makes it possible to consider the measures adopted to stop the spread of the virus in the countries identified as one cluster, and to assess the impact and effectiveness of these measures on the growth of new confirmed cases. Based on the results of the cluster analysis, it is possible to assess the socio-economic indicators in the individual groups formed by relating the intensity of the spread of the virus.

Additionally, an analysis of the labor income inequality was conducted to estimate the response to lockdown measures. The earnings inequality might arise due to unemployment (see [2–4]).

The rest of the paper is organized as follows. Section 2 provides a brief overview of the socio-economic impact of the COVID-19 pandemic. Section 3 presents the data and methods used to explore the impact of lockdown measures on the economy and to assess the impact on unemployment and wage inequality. Section 4 presents the results obtained to assess the impact of lockdown measures on the economy using nonparametric and parametric methods, analyzing Lithuania in the context of other countries where the dynamics of the virus are similar, as well as assessing the impact on unemployment and wage inequality. The results of this study, as well as some findings and observations, are included in Section 5.

2. Overview of the Socio-Economic Impact

The COVID-19 pandemic had an extremely negative impact on global health, economic and social systems [5]. In an effort to understand the impact of the shocks on the economy, various studies have been conducted in order to summarize the impact of COVID-19 and related lockdowns on certain aspects of the world economy as well as various industries and sectors. The authors in [6] conclude that medium- and long-term planning is necessary to rebalance and revitalize the economy after the crisis. The pandemic affected the economy in the following ways (see [7–9]): reduced employment, increased international transaction costs, decreased travel rates, reduced demand for services requiring proximity among people and changed customer preferences. The COVID-19 pandemic has led to an unprecedented decline in global activity. For example, in the second quarter of 2020, the global GDP had contracted by 4.9 percent due to economic turmoil (see [8,10]).

As a result of the COVID-19 outbreak in 2020, all EU member states faced an unpredictable public health crisis, forcing national governments to take special measures and actions to resolve ongoing problems. In the face of uncertainty, policy makers decided to apply containment with various levels of severity [1]. The restrictive measures introduced to control the spread of the COVID-19 pandemic led to a reduction in the underlying number of cases in most countries or territories. However, these measures have had a significant

impact on people's daily activities, work and education, social interaction, as well as physical activity (see [11]). This pandemic and the measures taken to reduce the spread of the virus have affected all sectors of society. The measures taken have affected particularly the social groups that are particularly vulnerable: the elderly and young people. The social crisis caused by the COVID-19 pandemic may also exacerbate inequalities, discrimination and unemployment if not adequately addressed (see [12]).

Eksi et al. in [13] investigated the dynamic effects of uncertainty shocks on unemployment and concluded that policy makers should take into account the particular effect of uncertainty on unemployment. Another important factor is that during the COVID-19 pandemic, there was a significant increase in uncertainty. In addition, COVID-19 pandemic policies, such as the closure of non-core businesses, significantly increased unemployment, as argued in [14].

As noted in [15], socio-economic factors have a significant role in the prevalence and mortality of COVID-19. Numerous studies are currently being conducted to assess the economic and social impact of COVID-19. The impact of political interventions on inequality indicators such as the Gini index has been investigated for various European countries, e.g., [16–20]. Due to the high number of business closures, in low-income countries in particular, the economy is expected to shrink, leading to a significant increase in unemployment as well as social inequalities [21]. In [22], the authors provide data on the impact of socio-economic inequalities on COVID-19 mortality, hospitalization and morbidity in France. The results show that a 1% increase in the Gini coefficient in one department is associated with a 0.1% increase in deaths or hospital admissions, which indicates that in departments where income inequality is higher, there are more deaths and seriously ill patients.

In addition to the GDP contraction, the lockdown measures taken to contain the spread of COVID-19 have caused important labor market effects. Palomino et al. [16] estimated for 29 European countries an average increase in the per capita poverty index of around 5 percentage points during the first two months of the lockdown. The findings show that the COVID-19 crisis will result in increased poverty and wage inequality all over Europe, and the Gini coefficient is expected to increase by 2.2% in Europe. Large-scale lockdowns impose costs, lower productivity and higher unemployment (see [23]).

Esseau-Thomas et al. in [20] analyzed a theoretical model predicting that epidemics and pandemics increase income inequality. They also examined the effect on the Gini coefficient of a dummy variable indicating the occurrence of an epidemic in a country in a particular year and deaths per 100,000 population. The emergence of a pandemic (or epidemic), as reflected by the dummy variable, causes policy responses that can affect income inequality. The use of a three-step least squares estimation method demonstrates the statistically significantly positive effect of the variable number of deaths per 100,000 population on the Gini coefficient.

Furceri et al. in [24] investigated the impact of major epidemics that have occurred in recent decades on income distribution. Using an unbalanced panel database of 175 countries, the authors of the study found that similar past events led to an increase in the Gini coefficient and a decrease in the employment-to-population ratio for individuals with primary education as compared to those with higher education. Furthermore, the article argues that the effects of COVID-19 may be more significant than those of previous pandemics.

Clark et al. in [18] used panel data from the COME-HERE survey to find out how income inequality changed in certain countries (France, Germany, Italy, Spain) during COVID-19 from January 2020 to January 2021. The dynamics of relative inequality were found to rise mostly from January to May 2020, and in September 2020, it returned to below the level that existed before COVID-19. It was found that the decrease in relative inequality has been slower in France than in other countries. The authors of the article [18] showed that some households lost more as a result of the pandemic than others, with the self-employed suffering the most. In [25], it was demonstrated that lockdown had significant welfare costs, which must be taken into account in calculating welfare when determining

pandemic policy. These costs are also unevenly distributed, e.g., the welfare of females is more severely affected. Welfare is known to predict patterns of behavior; thus, policies relating to a pandemic may have not only a short-term impact, but also an impact on future economic, social and political consequences.

In a study [26], the authors explored the impact of COVID-19 on income inequality in 295 cities in China. The results confirm that policies of social distancing have considerable economic implications and can reinforce regional income inequalities. Findings indicate that the strict nationwide policy of social distancing that China has adopted is effective, as the country's economy has recovered quickly after curbing coronavirus transmission. If a country can flatten the curve in a short time, such as a few weeks, then economic losses can be limited. However, a prolonged policy of severe social distancing may exacerbate regional income inequalities. A distributional dynamics approach is used in the study to estimate the effects on the distribution of income. The effects of a pandemic are usually studied using econometric methods, but it should be noted that regression on its own is unable to provide detailed information about changes in the distribution over time. The study [26] used the nonparametric method of stochastic kernels.

Persistent income inequality, the weakness of social security systems and the economic impact of COVID-19 have increased attention to measures to ensure a basic income (see [27]). The authors of the article [27] have therefore provided a systematic review of the available methods and areas of evaluation that have been used to evaluate basic income interventions. The study showed that most research articles used some form of multivariate statistical modeling in their analysis. The two most used statistical models were economic modeling and simple regressions. Other popular statistical methods that have been used are the method of difference-in-differences, principal component analysis and time series modeling.

The authors of the article [28] found that measures of lockdown imposed during COVID-19 in the UK had different effects on income and individual well-being depending on gender, education level and ethnicity. The extent to which COVID-19 and the measures induced by COVID-19, and the speed at which this impact developed, were found to vary between social groups with different types of vulnerability. The authors applied fixed-effects linear regressions to predict outcomes. By interacting the month index with sex, BAME group (see [28]) and level of education, it was examined how changes in income and well-being varied among people from three different socio-demographic groups during different periods of the pandemic.

In [29], the impact of COVID-19 on gender inequality is examined using survey data from six countries in different geographical regions and income levels. The results show that although there are no gender differences in the impact of COVID-19 on temporary job loss, females are 24% more likely to lose their jobs permanently than males. Females also expect their income to drop by 50% more than males and are therefore likely to reduce their current consumption and increase their savings. The results of the study also point to the heterogeneity of these gender differences across countries. Moreover, Rivera and Castro's [30] findings show that males lost fewer work positions and returned to the labor market more quickly than females. Meanwhile, Katris [31] established that the cumulative impact on unemployment was lower in Greece than in EU27, but for females and youth, it was higher than for the general unemployment in Greece.

König and Winkler in [32] analyzed the impact of mandatory social distancing imposed by lockdown policies on GDP growth in the first nine months of 2020 for 42 countries. Findings suggest that variations in the strictness of lockdown measures are an important factor in GDP change over time, and that more restrictive measures cause GDP growth to decline in the same quarter.

In the article [33], the authors refer to basic socio-economic indicators applicable to any country, which include population, density, average age, GDP and nominal GDP (per capita), the Gini coefficient of wealth distribution, the human development index (HDI) and the wealth distribution index (poverty headcount index). The analysis conducted in [33]

shows that government response policies such as testing methodology, individual tracking and social distancing measures can largely explain the diversity of coronavirus outcomes across countries. Beyond these factors, few additional socio-economic determinants can reliably explain the magnitude of the coronavirus pandemic. Population density and international tourist arrivals are strong determinants of reported coronavirus cases per million population. More densely populated countries have higher numbers of infections, while countries with higher numbers of international tourist arrivals are less affected by the negative impact of the COVID-19 virus.

The COVID-19 pandemic has slowed down economic activity and, consequently, the labor market. It has had an obvious negative impact on employment, affecting the number of unemployed. Because of the COVID-19 pandemic, with the introduction of lockdown restrictions in many countries, companies have had to suspend operations and employers have had to lay off some workers. The major changes in domestic and global markets during a pandemic are related to falling employment rates, higher unemployment, falling incomes and loss of jobs and income for individual employers. These conditions give rise to many challenges in the system of social and labor relations, which have some negative socio-economic implications (see [34]).

3. Data and Methods

As noted earlier, the first global lockdown, which started in mid-March 2020 and lasted for three months in Lithuania, had an impact on the movement and behavior of the population and also had an impact on the economy. In this work, a study was performed to evaluate the economic impact of lockdown measures, evaluating the consequences on unemployment and wage inequality. The data and methods used to achieve this objective are presented in the following section.

3.1. Data

The Gini coefficient is estimated on the basis of data from the State Social Insurance Fund Board under the Ministry of Social Security and Labor (https://atvira.sodra.lt/lt-eur/ (accessed on 21 June 2022)) on working persons who have worked at least 30 days per month, distributed by income, age and gender. In fact, we have data on how many employed persons were in different monthly salary intervals. The monthly data are available from 2010 to 2021. There is also a breakdown available by gender and different age groups.

For the cluster analysis, 36 European countries were selected: 27 EU countries, the United Kingdom, 4 EFTA countries and 4 candidate countries for membership in the EU. Sources of data on the spread of COVID-19 in Lithuania and the other countries considered are described in more detail in [35]. The following daily non-cumulative relative data (per 100,000 people) for the considered month were used: identified, deaths, recovery cases and population density.

Monthly unemployment rates in Lithuania and the other countries under consideration were extracted from the EUROSTAT database of indicators (https://ec.europa.eu/eurostat/data/database (accessed on 21 June 2022)) and these data were used to investigate the trend of unemployment before and during the COVID-19 pandemic. EUROSTAT publishes initial data as well as seasonally adjusted indicators. The data are based on the European Labor Force Survey (EU-LFS) (https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey (accessed on 21 June 2022)). The labor force is the overall number of employed and unemployed. The unemployment rate, as a percentage of the labor force, has been studied.

3.2. Wage Inequality Analysis

Analyzing wage inequality and COVID-19 lockdown effects for inequality, a multi-step approach was used. At first, we compute the salary inequality using the histogram-based Gini estimator (Section 3.2.1) for monthly data from January 2010 to December 2021.

The Gini index is calculated in various cross-sections by age group and gender. Next, we perform the exploratory data analysis and compare the distributions in different age groups by gender with the nonparametric Wilcoxon test. Further, using the obtained time series, we analyze the monthly growth rates

$$r_t = \frac{y_t - y_{t-1}}{y_{t-1}}, \tag{1}$$

where y_t denotes the Gini index at time moment t.

To analyze the effects of the COVID-19 lockdown more precisely, we use a change point analysis for our observations. Two types of analysis are performed. First, we apply nonparametric change point tests to capture the possible change points during the period of the analysis (see Section 3.2.2). Nevertheless, due to the variability of the Gini index from 2010 to 2021, we also use the functional data analysis approach. In this case, we smooth the monthly data to the annual functional observations and check the change points using the modified band depth method and changes in the functional form: magnitude, amplitude and shape (see Section 3.2.2).

In the final step, we conduct a linear regression model to evaluate the impact of unemployment on wage inequality. In this case, we choose a parametric method for a simpler interpretation.

3.2.1. Histogram-Based Gini Estimator

Since we use grouped data, we estimate the Gini index for earnings inequality using the nonparametric histogram-based method for group data, proposed by Tillé and Langel [36]:

$$\widehat{G} = \frac{1}{2\bar{x}} \sum_{j=1}^{j} \sum_{k=1}^{j} f_j f_k |x_j^{(C)} - x_k^{(C)}| + \frac{1}{\bar{x}} \sum_{j=1}^{J} \frac{f_j^2 \ell_j}{6}, \tag{2}$$

where

- J is the number of classes, and n is the sample size;
- x_j^- and x_j^+ are the lower and upper bounds of the class $j = 1, \ldots, J$;
- $x_j^{(C)} = \left(x_j^- + x_j^+\right)/2$ is the center of class $j = 1, \ldots, J$;
- $f_j = n_j/n$ is the relative frequency and n_j is the frequency of class $j = 1, \ldots, J$;
- $\ell_j = x_j^+ - x_j^-$ is the length of class $j = 1, \ldots, J$;
- $\bar{x} = \sum_{j=1}^{J} f_j x_j^{(C)}$ is the mean of grouped data.

In our application, the lower bound for the first class is set to 0, and the upper bound for the last group is set to 15,000. The bounds of the income intervals vary from year to year because of the currency change from Litas (LTL) to Euros (EUR) in 2015 in Lithuania and changing minimal salaries through the years. However, this does not affect the final results, since we compute the monthly Gini index of earnings inequality for every month separately.

The computed Gini index is investigated as a numerical monthly time series and as annual functional time series.

3.2.2. Change Point Detection

To understand whether the COVID-19 lockdown affected wage inequality, we use change point detection methods. First, we start with hierarchical divisive (e.divisive) and hierarchical agglomerative (e.agglo) change point methods. The e.divisive method evaluates multiple change points by locating one change point iteratively. At each iteration, a new change point location splits the existing segment. The process of this method can therefore be represented as a binary tree (for more details, see [37,38]). E.agglo requires an initial segmentation of the data or that each observation is assigned to a separate segment. This approach can incorporate prior knowledge of possible locations of change points. Then, adjacent segments are merged sequentially to maximize the goodness-of-fit statistic

(see [37]). The other two methods that we employ are e.cp3o and ks.cp3o (see [39]). These methods include the pruning approach for approximate nonparametric multiple change point estimation and applying a pruning procedure within a dynamic program to reduce the computational cost as well as search space. Energy statistics and Kolmogorov–Smirnov statistics are used as goodness-of-fit measures.

As mentioned above, because of the high variability from 2010 to 2021, the detection of the change points in the distribution of time series might be inaccurate. Thus, we turn to a functional data approach to see if the years 2020 and 2021 are change points. Functional data analysis (FDA) is a component of statistics that analyzes observations of a functional form.

We smooth the monthly observations to the annual curves by using the nonparametric approach—a local linear regression estimator based on a Gaussian kernel. Using a functional data approach, we have 12 observations $(X_i(t), t \in [0,1], i = 2010, \ldots, 2021)$, where t is a continuous time through a year, 0 denotes the beginning of the year and 1 denotes the end of the year and i denotes the year from 2010 to 2021. The smoothing allows us to reduce the noise that appears because of the estimation errors. Further, we use these observations to detect the change points in amplitude, magnitude and shape (see [40]). The latter methods are of a parametric type, so, as an alternative method, we use the modified band depth nonparametric method for the change point detection in functional data (see [41]).

3.2.3. Linear Regression

Finally, we perform linear regression for time series data to detect the relationship between wage inequality and unemployment:

$$y_t = \beta_0 + \sum_{j=1}^{p} \beta_j x_j + u_t, \quad t = 1, \ldots T,$$

where x_j are independent variables, T is the number of time moments, β_0, β_j are parameters, u_t is an error, p is the number of variables used in regression. Parameters are estimated using the ordinary least squares method (OLS).

3.3. Cluster Analysis

In order to investigate trends in unemployment rates in Lithuania in the context of Europe, to assess whether pre- and post-lockdown rates differ significantly, and for panel data analysis, it is necessary to identify specific countries using data clustering and visualization techniques. The data to be analyzed are quite often highly complex, described by many parameters or attributes (see [42]). These kinds of data are referred to as multidimensional data, and the main objective of analysis is to obtain a visual representation of the data set under study. Understanding such data and finding hidden information in them is a challenging task. In our case, the countries in which the trend of the COVID-19 virus spread is being analyzed are interpreted as multidimensional data. Each country is characterized by several parameters. Thirty-six European countries were chosen for the analysis: 27 European Union countries, the UK, 4 EFTA countries and 4 EU candidate countries. The data used are daily, non-cumulative relative values (per 100,000 population) for the month of the study: number of new confirmed cases, number of deaths, number of recovered cases and population density. The observation period of the last 35 days is considered. The data and the process by which the data were obtained are described in more detail in [35]. Thus, this section considers multidimensional data described by 106 features.

Markeviciute et al. in [35] describe a machine learning approach for the special registration of data and further analysis that uses data from identified countries, specially selected based on some similarity criterion, to validate forecasts for COVID-19 trend prediction and risk assessment. In our case, the proposed selection of the European

Union countries is performed by integrating the results obtained using data clustering and dimensionality reduction methods: self-organizing neural network (SOM), t-distributed stochastic neighborhood embedding (t-SNE) and multidimensional scaling (MDS). It should be noted that we refer to the data as the countries in which we analyze trends in the spread of the virus.

The analyzed multidimensional data were first clustered using the SOM neural network and then visualized on a plane for further decision making to show visually the location of different countries in relation to each other, to identify the clusters to which these countries belong. This is intended to visually identify the most similar countries to Lithuania in terms of COVID-19 spreading trends. Dimensionality reduction techniques, such as MDS and t-SNE, can be applied to represent the data in a two-dimensional space.

To cluster multidimensional data, the SOM method (see [43–45]), based on a neural network that is trained using unsupervised learning, is used. SOM is a specific set of interconnected neurons based on a certain topology—for example, a rectangular one. After training the SOM network, the data are presented to SOM, and for each input signal, a winner neuron can be identified that has the shortest Euclidean distance of the input vector. Thus, after the training process, the analyzed data are distributed over the SOM network, grouping similar data together, resulting in clusters of data.

t-SNE (see [46]) is a non-linear dimensionality reduction method for data visualization that is able to preserve the local data structure while revealing some important global structures (such as clusters at different scales). The method minimizes the discrepancy of two distributions: the distribution that measures the pairwise similarity between high-dimensional objects, and the distribution measuring the pairwise similarity between the corresponding low-dimensional objects in the embedding. Another visualization method, as an alternative, which can be used to reduce the dimensionality of the analyzed data, is MDS (see [47]). The MDS method can also be used to find the coordinates of points in an initially defined space of lower dimensionality, in which each point corresponds to one of the objects in the multidimensional space, and the distances between the corresponding pairs of points correspond to the original dissimilarities between pairs of objects as much as possible (see [48,49]).

3.4. Panel Data Models

Panel data consist of two dimensions: cross-sectional and time series. Panel data are called balanced if the same objects are observed at each time moment; otherwise, they are called unbalanced panel data. In the case of the linear dynamic panel model (see [50]), the lags of the dependent variable could be included in the model:

$$y_{i,t} = \phi_0 + \sum_{j=1}^{p} \phi_j y_{i,t-j} + \boldsymbol{\beta}' \boldsymbol{x}_{i,t} + u_{i,t}, \quad t = 1, \cdots, T, \; i = 1, \cdots, N,$$

where T and N are the number of time moments and individuals, respectively; $\phi_0, \phi_j, \boldsymbol{\beta}$ are parameters, $\boldsymbol{x}$ denotes a vector of covariates, u_{it} is an error. Parameters are estimated (see [50]) using the generalized method of moments (GMM).

4. Results

4.1. Salary Inequality and Relation with Unemployment

We computed the Gini coefficient for wage data in different age groups (total, up to 24, 25–34, 35–44, 45–54, 55–64, 65 and more) as well as for males, females and the total population. From the initial analysis, we may conclude that the first lockdown had a strong impact on wage inequality. Indeed, in 2020, the income inequality was lowest in January and February compared to previous years in most cases. Then, the inequality increased in March and April. For example, for young persons up to 24 years, the inequality increased for males by 5.7% and for females by 11.8%. Other age groups suffered the same changes, but changes were smaller. In all cases, females suffered higher jumps in wage

inequality than males. Another increase in 2020 was in November and December, when the second strict lockdown started. Although, at the beginning of 2021, the second lockdown continued, there were no high jumps. Nevertheless, the trends differ from the trends in earlier years. The reason for this may be that the economy has adapted to lockdown rules and companies could operate with less interference, but they were still affected by COVID-19 regulations. Figures 1 and 2 illustrate the changes in the Gini coefficient for males of age 35–44 and females of age 25–34.

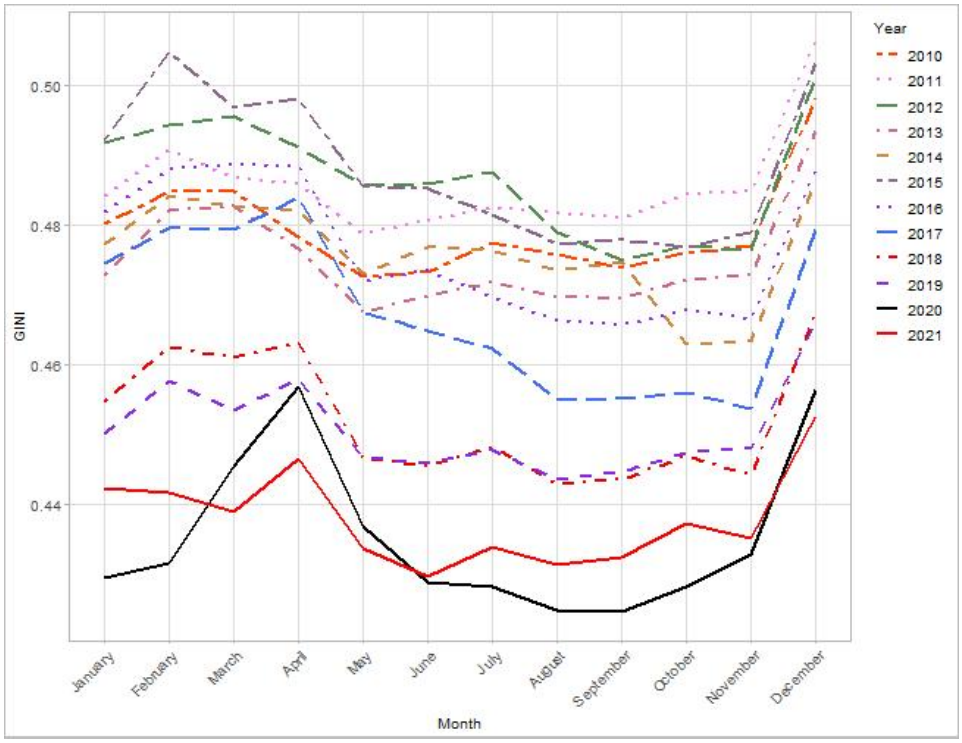


Figure 1. Gini index: males, age group 35–44.

The analysis of the statistical differences in the distribution for males and females shows that, in all age groups, we detect statistically significant differences using the Wilcoxon test (see Table 1); thus, we may conclude that wage inequality differs for both genders. Note that females have lower wage inequality compared to males, and the *t*-test shows that means of salary inequality for males and females differ statistically significantly.

Table A1 shows the monthly growth rates. We can see that for all age groups, the growth rates in 2020 are completely different, but in 2021, they are already similar to the tendencies of the previous years. Indeed, the median of growth rates from 2010 to 2019 in March, April and May is negative, while it becomes positive in 2020. Similar results are noted in November, while in December, the growth rates are always positive, but in 2020, the growth rate is higher than in previous years.

The next step is to check if there is a change point in the time series. The results are given in Table A2. We may see that the e.aglo and e.cp3o methods are more liberal and detect more change points than other methods. Nevertheless, in many cases, we may see that March, May, November and December in 2020 are detected as change points. In addition, April and May appear a few times as change points in 2021. This is related to the end of the strict lockdown regulations.

Further, Table A3 shows the change points from the functional data point of view. The results show that 2020, in many situations, is a shape outlier, but the modified band depth method does not show any outliers, except for females up to 24 years.

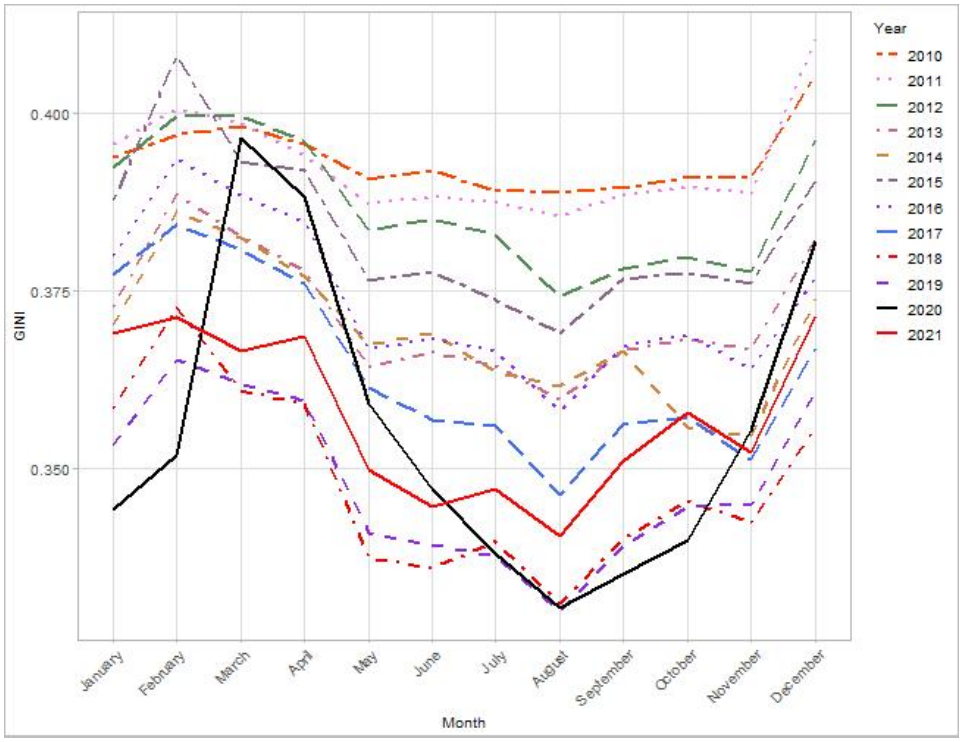


Figure 2. Gini index: females, age group 25–34.

Table 1. Summary statistics of the Gini coefficient.

Age Group	Gender	Mean	SD	Median	MAD	*p*-Value for *t*-Test	*p*-Value for Wilcoxon Statistic
Total	Male	0.434	0.019	0.435	0.024	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$
	Female	0.389	0.013	0.390	0.014		
Up to 24	Male	0.346	0.017	0.345	0.022	1.84×10^{-9}	1.12×10^{-9}
	Female	0.339	0.017	0.340	0.017		
25–34	Male	0.417	0.026	0.418	0.034	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$
	Female	0.371	0.019	0.370	0.022		
35–44	Male	0.468	0.020	0.473	0.018	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$
	Female	0.400	0.013	0.400	0.011		
45–54	Male	0.422	0.017	0.424	0.019	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$
	Female	0.379	0.013	0.380	0.014		
55–64	Male	0.406	0.025	0.411	0.031	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$
	Female	0.380	0.016	0.379	0.021		

The final step of our analysis is linear regression, which is used to detect if there is a relationship between wage inequality and unemployment. Besides the unemployment variable, we include gender and months as dummy variables. Months are included, since seasonal tendencies might be observed in monthly data. Table 2 shows the results of regression, where total unemployment and the Gini index of all age groups are included. We noticed that unemployment is a statistically significant variable and the positive signs of the coefficient show that an increase in unemployment by 1% increases the Gini index by 0.2772. Other variables show the expected results: males tend to have higher wage inequality and a significant increase in wage inequality is observed in February, March, April and December.

Table 2. Linear regression of Gini coefficient for all age groups.

Variable	Estimate	Std. Error	Statistics	*p*-Value
Intercept	0.3606	0.0016	220.086	$<2.2 \times 10^{-16}$
Gender (Male)	0.0373	0.0013	29.045	$<2.2 \times 10^{-16}$
Unemployment	0.2772	0.0157	17.637	$<2.2 \times 10^{-16}$
February	0.0100	0.002218	4.512	9.45×10^{-6}
March	0.0088	0.0022	3.947	1×10^{-4}
April	0.0095	0.0022	4.306	2.29×10^{-5}
December	0.0192	0.0022	8.687	3.12×10^{-16}

The first linear regression (see Table 2) has a quite high coefficient of determination $R^2 = 0.8648$, and the ANOVA test shows that the regression is significant (p-value $< 2 \times 10^{-16}$). According to VIF statistics, there is no multicollinearity between the independent variables; the p-value for the White test for heteroscedasticity is 0.139, which indicates that the homoscedasticity assumption is satisfied. The normality assumption is not satisfied with the 5% significance level; the p-value for the Shapiro–Wilk normality test is 0.048.

The initial analysis results presented at the beginning of this section show that young persons up to 24 years are the distinctive group; therefore, we performed a linear regression for this group separately. We included the same variables as in the previous regression (see Table 2), taking the unemployment rate for 15–24 years and Gini for persons up to 24 years. The results are given in Table 3.

Table 3. Linear regression of the Gini coefficient for the age group up to 24 years.

Variable	Estimate	Std. Error	Statistics	*p*-Value
Intercept	0.3317	0.0023	141.410	$<2.2 \times 10^{-16}$
Gender(Male)	0.0051	0.0017	3.107	0.0021
Unemployment	0.0701	0.0099	7.079	1.19×10^{-11}
May	−0.0071	0.0031	−2.318	0.0212
June	−0.0135	0.0031	−4.386	1.64×10^{-5}
July	−0.0176	0.0031	−5.723	2.70×10^{-8}
August	−0.0227	0.0031	−7.351	2.21×10^{-12}
September	−0.0089	0.0031	−2.872	0.0044
November	−0.0068	0.0031	−2.199	0.0287
December	0.0076	0.0031	2.468	0.0142

The second linear regression (see Table 3) has a significantly lower coefficient of determination $R^2 = 0.373$, but the ANOVA test shows that the regression is significant (p-value $< 2 \times 10^{-16}$). According to VIF statistics, there is no multicollinearity between the independent variables; the p-value for the White test for heteroscedasticity is 0.208, which indicates that the homoscedasticity assumption is satisfied. The normality assumption is satisfied with the 5% significance level; the p-value for the Shapiro–Wilk normality test is 0.839.

The results in Table 3 are similar to the previous regression (see Table 2). Unemployment has a positive impact on wage inequality, males have higher salary inequality, and there is a trend toward lower wage inequality in the summer months, which may be due to seasonal jobs.

To finalize, it can be concluded that wage inequality was affected by lockdown regulations, and the main effect is detected in 2020. Furthermore, it was found that there is

a relationship between wage inequality and unemployment, which might be explained by the unemployment trends. The following section analyzes unemployment trends in Lithuania in the European context.

4.2. Unemployment Trends

At the beginning of the COVID-19 pandemic, when many countries introduced the lockdown restrictions, companies were forced to suspend their activities and some sectors, such as tourism, services and small businesses, incurred heavy losses. Employers had to fire their workers, and therefore public spending increased. To assess the impact of lockdown on the labor market, the analysis of the dynamics of the unemployment rate was performed using the results of the cluster analysis. Analyzing Lithuania in the context of other countries where the dynamics of the spread of the virus is similar, we can assess the impact of the measures applied by the governments of these countries.

In most European countries, the lockdown started in 2020; however, a significant impact on unemployment was detected only after some time. Therefore, the data of April and May were used to select countries similar to Lithuania according to the trends of the spread of the virus using cluster analysis.

The analysis consisted of two steps:

1. Selection of countries with a similar COVID-19 virus spreading trend as Lithuania, using data mining and machine learning techniques (see Section 4.2.1);
2. Analysis of trends of the unemployment rate using panel data models (see Section 3.4).

Each step is described in more detail in the subsections below.

4.2.1. Machine Learning-Based Clustering

The methodology described in Section 3.3 was used to rank countries according to their proximity and similarity to the spread of the virus in Lithuania. The analyzed countries were first clustered using SOM and then visualized for further decision making. As the analyzed data have several attributes (features) and are multidimensional, the Euclidean distance in multidimensional space between the point that characterizes Lithuania and the points that characterize other European countries was estimated. Thus, based on Euclidean distances in multidimensional space, the clustered countries nearest to Lithuania were selected. To summarize, eleven countries closest to Lithuania were identified each day according to the trend and similarity of the virus spread (see Section 3.3).

During the experiments, it was observed that the results obtained using t-SNE are more informative and comprehensible when visualizing the data compared to the results obtained with MDS, and the resulting clusters better reflect the similarity of the analyzed countries. As an example, Figure 3 illustrates the visualization of the data analyzed for the period 1 April–5 May 2020, obtained using the t-SNE method. In the data visualization, one color is assigned to the countries of one cluster obtained using the SOM network.

The results of the cluster analysis (see Section 3.3) using the data of April and May 2020 demonstrate that similar trends in the spread of the virus as in Lithuania are also observed in several other countries analyzed: Bulgaria, Croatia, Estonia, Finland, Greece, Ireland, Latvia, Montenegro, Norway, Romania and Sweden. Moreover, in April–August 2020, the list of countries with a similar trend in the spread of the virus as in Lithuania was the same, with only a slight change in proximity to Lithuania.

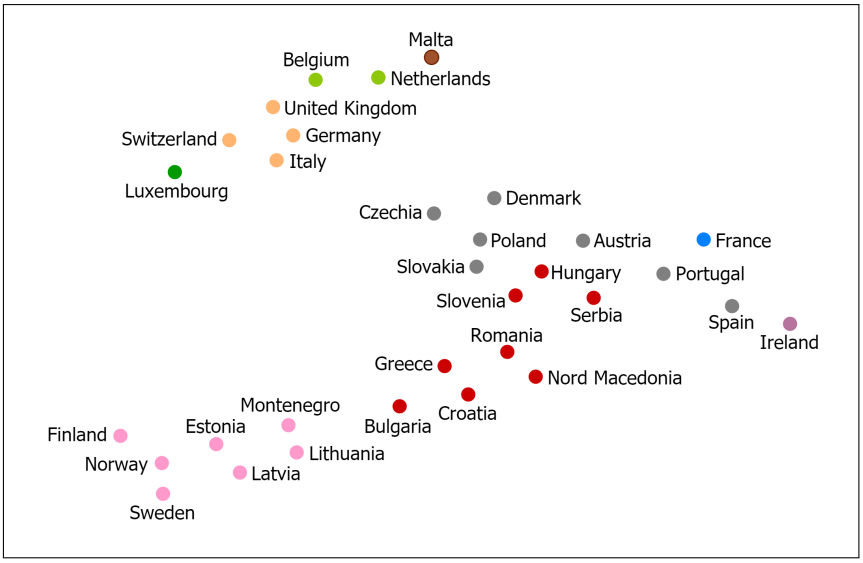


Figure 3. Visualization results of the analyzed data from 1 April to 5 May 2020, obtained using the t-SNE method. Countries labeled by the same color represent the same cluster obtained with SOM, which means a similar spread of COVID-19.

4.2.2. Panel Data Analysis

The countries selected as described in Section 4.2.1 were considered and trends of unemployment rates were investigated to assess if rates differed significantly before and after lockdown. Monthly data for Montenegro were not available; thus, this country was eliminated from the analysis.

From the analysis of the dynamics of the unemployment rate since 2000 (see Figure 4), it could be concluded that the unemployment rate varied considerably and an increase in the unemployment rate due to the 2008 crisis is observed. As the goal was to determine the effects of lockdown, which started in 2020, the data from the period of 2017–2021 were analyzed, as strong heterogeneity was observed in the previous periods due to country specifics.

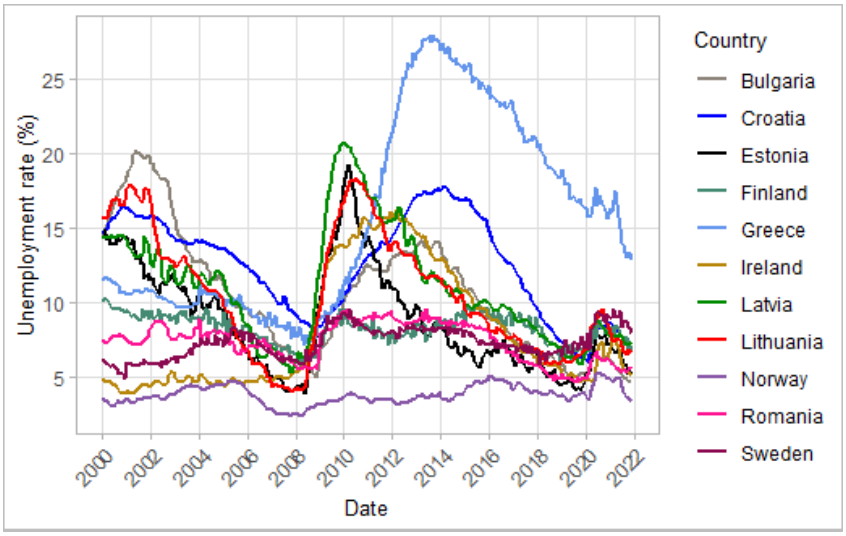


Figure 4. Comparison of the trends of the unemployment rate (seasonally adjusted data).

Having analyzed the unemployment rate in Lithuania in the context of other countries where the dynamics of the spread of the virus was similar, it can be noted that an increase was observed in all the countries (see Figure 5; Greece (where the rate of unemployment is higher compared to the other countries) was excluded from this graph for

better visualization). However, the rate of the increase differs. In the first quarter of 2020, the unemployment rate in Lithuania was similar to that of Finland, Latvia and Sweden; however, in the second quarter, the most significant increase was observed in Lithuania. The rate began to decrease starting from the third quarter of 2020. Similar dynamics was observed for all the countries in the group under consideration: the increase was temporary; however, fluctuations were noted during the period of the COVID-19 pandemic (see Figure 5).

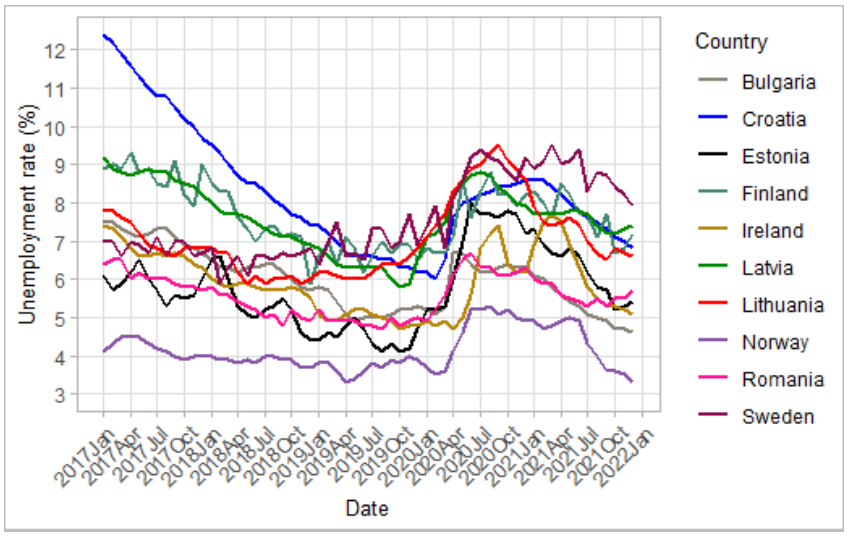


Figure 5. Trend of unemployment rate (seasonally adjusted data) before and during the COVID-19 pandemic.

The dynamic panel model was constructed (see Section 3.4) to determine if a significant change in the unemployment rate was detected during different periods of the COVID-19 pandemic compared to the rate before the pandemic. The first-order lag (higher-order lags were insignificant) of the unemployment rate and the variable indicating the time periods (I: January 2017–March 2020 (the period before COVID-19 and the beginning of the pandemic); II: April–December 2020 (lockdown and restrictions); III: January–August 2021 (vaccination started; period of lower restrictions); IV: September–December 2021 (most of the restrictions were lifted)) was included in the dynamic panel model. The parameters were estimated by the generalized method of moments (GMM; see [50]). The p-value of the Sargan test was 0.221, i.e., the instrumental variables were selected appropriately. The covariate indicating time periods was statistically significant (see Table 4): the unemployment rate was significantly higher in the period when the first lockdown started; however, the rate stabilized in September 2020 (Period III and Period IV did not significantly differ from Period I), showing the short-term impact of the lockdown on the unemployment rate.

Table 4. Panel data analysis. Estimates of parameters (Period I, January 2017–March 2020, was used as the reference category).

Period	Estimate	Std. Error	Statistic	p-Value
II: April–December, 2020	0.2309	0.0374	6.18	<0.0001
III: January–August, 2021	−0.0536	0.0388	−1.38	0.1682
IV: September–December, 2021	−0.0877	0.0529	−1.66	0.0979

5. Discussion

The Gini coefficient analysis showed the reaction of working people to the first lockdown. Overall, males had higher wage inequality, but their response to the closure was weaker than that of females, suggesting that females were more affected by the pandemic's

regulation of the economy. Because of the restrictions on business activities, the rise in income, wage and social inequality was also noted in other studies (see [16,21,26]). Clark et al. [18] noted a rise in relative inequality for France, Germany, Italy and Spain in the first half of 2020, which is similar to the Lithuanian result, with the exception that a second increase in inequality in Lithuania was observed at the end of 2020.

Further, a positive relationship was established between salary inequality and unemployment in Lithuania, indicating a correlation between these two socio-economic indicators. Some studies also confirm the gender-biased reaction to unemployment caused by lockdown measures ([23,29,30,51–54]). The findings on wage inequality also show that different age groups reacted differently to the lockdown, which is also noticed for unemployment in [31]. Younger and older persons reacted more sensitively than middle-aged persons.

The research on the unemployment rate in Lithuania, in the context of other countries where the dynamics of the spread of the virus was similar, showed that the increase was observed in all countries; however, the rate of the increase differed. The increase was temporary and shortly returned to regular figures; thus, it could be concluded that businesses adapted to the restrictions imposed due to COVID-19, and the impact on the unemployment rate increase was not long-lasting. Similarly, Pinilla et. al. [55] found that measures taken in Spain to control the pandemic were the cause of the economic downturn and a sharp increase in unemployment in 2020.

The results of the cluster analysis show trends in the spread of the virus. It allows a review of the interventions that have been used in the countries of one cluster to stop the spread of the virus and, where possible, the assessment of the effects and effectiveness of existing interventions on the increase in the number of new confirmed cases. Based on the results of the cluster analysis, it is possible to evaluate socio-economic indicators in relation to the intensity of virus spread in individual groups.

Finally, the analysis shows that the most significant impact of lockdown restrictions on socio-economic indicators was detected in 2020, whereas the effect was lower in 2021. The reason for this might be an adaptation to the lockdown rules. The proposed multi-step approach used to analyze data from Lithuania could be applied to other countries as well as to different types of shocks and interventions to avoid negative economic and social consequences.

The main limitation of this paper is the use of binned data to compute the Gini index for wage inequality; more precise results could be obtained if the information were available about each working person. Nevertheless, the analysis successfully reveals the trends in wage inequality. For future research, an analysis of tendencies in wage inequality in the context of the economic crisis and other shocks could be possible, analyzing gender and age factors in more detail. Moreover, the relationship between unemployment and wage inequality could be explored in more detail if data on unemployment were available for the same age groups as data on salary inequality.

Author Contributions: Conceptualization, J.M., J.B., R.L. and V.M.; methodology, J.M., P.T. and R.L.; validation, R.L, P.T. and V.M.; formal analysis, V.M., P.T. and J.V.; investigation, J.M., J.B, R.L., V.M., P.T. and J.V.; resources, J.V. and J.M.; data curation, P.T., R.L., J.B. and V.M.; writing—original draft preparation, J.M., J.B., V.M., R.L., P.T. and J.V.; writing—review and editing, J.M., J.B., V.M., R.L., P.T. and J.V.; visualization, J.B., V.M. and P.T.; supervision: J.M. All authors have read and agreed to the published version of the manuscript.

Funding: This project has received funding from the Research Council of Lithuania (LMTLT), agreement No. S-COV-20-4.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors are thankful for the high-performance computing resources provided by the Information Technology Open Access Center at the Faculty of Mathematics and Informatics of Vilnius University Information Technology Research Center.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Growth rates of Gini index compared to the previous months.

Growth Rate	March		April		May		November		December	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Age group: Total										
Median growth rate in 2010–2019 (%)	−0.67	−0.80	−0.29	−0.46	−2.17	−2.23	−0.02	0.37	5.45	4.22
Growth rate in 2020 (%)	2.58	5.73	3.24	1.88	−4.40	−4.95	1.75	4.76	6.18	6.16
Growth rate in 2021 (%)	−0.53	−1.03	1.66	0.51	−2.78	−2.77	−0.03	0.33	4.41	4.93
Age group: up to 24										
Median growth rate in 2010–2019 (%)	−0.92	−1.59	−0.44	−0.05	−1.31	−2.05	−0.72	0.002	5.02	3.25
Growth rate in 2020 (%)	2.78	7.51	2.85	3.99	−5.07	−8.27	2.10	5.03	7.59	6.56
Growth rate in 2021 (%)	−1.73	−4.74	1.34	0.21	−2.62	−4.17	−0.36	−0.54	5.03	2.54
Age group: 25–34										
Median growth rate in 2010–2019 (%)	−0.55	−0.93	−0.91	−0.95	−2.89	−3.78	−0.52	−0.38	6.51	4.34
Growth rate in 2020 (%)	4.63	12.18	3.01	−2.11	−5.92	−7.51	1.24	4.61	7.80	7.48
Growth rate in 2021 (%)	−0.29	−1.28	1.82	0.57	−3.93	−5.13	−0.71	−1.59	5.75	5.48
Age group: 35–44										
Median growth rate in 2010–2019 (%)	−0.18	−0.60	−0.08	−0.58	−2.17	−2.53	0.09	0.27	4.78	4.23
Growth rate in 2020 (%)	3.22	9.00	2.53	−0.58	−4.38	−6.23	1.10	3.99	5.44	5.38
Growth rate in 2021 (%)	−0.61	−0.68	1.74	0.37	−2.89	−3.87	−0.51	−0.81	4.06	4.82
Age group: 45–54										
Median growth rate in 2010–2019 (%)	−1.01	−0.65	−0.05	−0.27	−1.81	−1.68	0.29	0.54	5.71	4.30
Growth rate in 2020 (%)	1.73	2.97	3.88	3.82	−3.79	−3.91	2.24	5.59	5.93	6.59
Growth rate in 2021 (%)	−0.53	−1.11	1.80	0.82	−1.82	−1.87	0.53	1.24	4.32	5.33
Age group: 55–64										
Median growth rate in 2010–2019 (%)	−1.25	−0.94	−0.22	−0.19	−1.57	−1.07	0.25	0.87	5.75	4.50
Growth rate in 2020 (%)	1.09	1.97	4.56	4.00	−3.92	−2.59	3.58	6.02	6.36	6.61
Growth rate in 2021 (%)	−0.88	−0.97	1.43	0.59	−2.41	−0.92	1.09	1.76	4.91	5.69

Table A2. Nonparametric multiple change point detection in time series.

Age Group	Gender	e.divisive	e.agglo	e.cp3o	ks.cp3o
Up to 24	Total	3/0	12/(May 2020, December 2020, May 2021)	12/(March 2020, June 2020, September 2020, December 2020, March 2021, June 2021, October 2021)	12/0
25–34	Total	4/0	2/0	11/(March 2020, June 2020, November 2020, February 2021, May 2021, October 2021)	3/0
35–44	Total	8/(June 2020, December 2020)	29/(March 2020, May 2020, December 2020, May 2021)	10/(January 2021, May 2021, October 2021)	3/0
45–54	Total	4/0	2/0	4/(October 2020)	11/(May 2020, November 2020, April 2021)
55–64	Total	4/0	0/0	11/(August 2020, November 2020, April 2021, July 2021, October 2021)	10/(June 2020, November 2020)
Total	Total	5/0	2/0	14/(June 2020, November 2020, April 2021, July 2021, October 2021)	9/0
Up to 24	Male	7/(June 2020)	3/0	3/0	10/0
25–34	Male	8/(June 2020, December 2020)	1/0	13/(March 2020, June 2020, November 2020, February 2021, May 2021, October 2021)	5/0
35–44	Male	7/0	1/0	10/0	3/0
45–54	Male	5/0	0/0	7/0	15/(April 2020, July 2020, October 2020, May 2021, October 2021)
55–64	Male	4/0	1/0	14/(June 2020, November 2020, February 2021, May 2021, October 2021)	4/0
Total	Male	8/(June 2020, November 2020)	2/0	7/0	3/0
Up to 24	Female	3/0	39/(March 2020, May 2020, August 2020, September 2020, December 2020, January 2021, June 2021, September 2021)	16/(March 2020, June 2020, September 2020, May 2021, October2021)	4/0
25–34	Female	17/(March 2020, June 2020, December 2020, May 2021)	26/(March 2020, May 2020, December 2020, May 2021)	5/0	15/0
35–44	Female	2/0	37/(March 2020, May 2020, December 2020, May 2021, December 2021)	11/(March 2020, June 2020, September 2020, December 2020, April 2021, July 2021, October 2021)	8/0
45–54	Female	5/(November 2020)	2/0	12/(August 2020, November 2020, February 2021, July 2021, October 2021)	14/(March 2020, June 2020, November 2020, May 2021, October 2021)
55–64	Female	5/(November2020)	2/0	11/(August 2020, November 2020, February 2021, June 2021, October 2021)	13/0
Total	Female	6/(November 2020, May 2021)	11/(March 2020, May 2020, December 2020, May 2021)	11/(March 2020, June 2020, September 2020, December 2020, May 2021, October 2021)	2/0

Notation a/0 shows that change points are detected, but 0 from March 2020. Notation a/(M YYYY, M YYYY) shows that change points are detected and there are change points from March 2020, so the dates of the change point in the COVID-19 period are given.

Table A3. Functional data methods for outlier detection.

Age Group	Gender	Magnitude Type Outlier	Amplitude Type Outlier	Shape Type Outlier	MBD Depth Method	Optimal Bandwidth h
Up to 24	Total	x	x	2014, 2020	2014	2.72
25–34	Total	x	x	2020	x	4.07
35–44	Total	x	x	x	x	4.07
45–54	Total	x	x	2014, 2020	x	4.07
55–64	Total	x	x	2014	x	4.07
Total	Total	x	x	2014, 2020	x	4.07
Up to 24	Male	2014	2014	2014	x	4.07
25–34	Male	x	x	2020	x	4.07
35–44	Male	x	x	x	x	4.07
45–54	Male	2014	2014	2014	x	4.07
55–64	Male	x	2014	2014, 2020	x	4.07
Total	Male	x	x	2014, 2020	x	4.07
Up to 24	Female	x	x	2020	2013, 2014, 2020	2.72
25–34	Female	x	x	2020	x	4.07
35–44	Female	x	x	x	x	4.07
45–54	Female	x	x	2014	x	4.07
55–64	Female	x	x	2014	x	4.07
Total	Female	x	x	2014	x	4.07

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