sustainability

Article

Analyzing the Impact of COVID-19 on Economic Sustainability: A Clustering Approach

Orietta Nicolis [1,2,†], Jean Paul Maidana [1,†], Fabian Contreras [3,†] and Danilo Leal [1,4,*,†]

1 Engineering Faculty, Universidad Andres Bello, Quillota 980, Viña del Mar 2520000, Chile; orietta.nicolis@unab.cl (O.N.); jean.maidana@unab.cl (J.P.M.)
2 Research Center for Integrated Disaster Risk Management (CIGIDEN), Santiago 8331150, Chile
3 School of Engineering in Expedition Management and Ecotourism, Faculty of Natural Sciences, Universidad San Sebastián, Santiago 7510157, Chile; fcontrerasa@docente.uss.cl
4 Statistical Institute, Universidad de Valparaíso, Valparaíso 2340000, Chile
* Correspondence: danilo.leal@unab.cl
† These authors contributed equally to this work.

Abstract: This work presents a comprehensive analysis of the economic impact of the COVID-19 pandemic, with a focus on OECD countries and the Chilean case. Utilizing a clustering approach, the research aims to investigate how countries can be categorized based on their pandemic mitigation strategies, economic responses, and infection rates. The methodology incorporates k-means and hierarchical clustering techniques, along with dynamic time warping, to account for the temporal variations in the pandemic's progression across different nations. The study integrates the GDP into the analysis, thereby offering a perspective on the relationship between this economic indicator and health measures. Special attention is given to the case of Chile, thus providing a detailed examination of its economic and financial indicators during the pandemic. In particular, the work addresses the following main research questions: How can the OECD countries be clustered according to some health and economical indicators? What are the impacts of mitigation measures and the pension fund withdrawals on the Chilean economy? The study identifies significant differences (p-value $< 0.05\%$) in the GDPs and infection rates between the two identified clusters that are influenced by government measures, particularly in the banking sector (55% and 60% in clusters 1 and 2, respectively). In Chile, a rebound in the IMACEC index is noted after increased liquidity, especially following partial pension fund withdrawals, thereby aligning with discrepancies between model forecasts and actual data. This study provides important insights for evidence-based public policies, thus aiding decision makers in mitigating the socioeconomic impact of global health crises and offering strategic advice for a sustainable economy.

Keywords: economic sustainability; COVID-19; dynamic time warping (DTW); k-means; hierarchical clustering

Citation: Nicolis, O.; Maidana, J.P.; Contreras, F.; Leal, D. Analyzing the Impact of COVID-19 on Economic Sustainability: A Clustering Approach. *Sustainability* **2024**, *16*, 1525. https://doi.org/10.3390/su16041525

Academic Editors: Sebastian Saniuk, Tomasz Rokicki and Dariusz Milewski

Received: 11 January 2024
Revised: 5 February 2024
Accepted: 7 February 2024
Published: 10 February 2024

1. Introduction

Originating in Wuhan in late 2019, the COVID-19 pandemic has led to the most substantial worldwide economic downturn since World War II, thereby resulting in a 5% decline in global economic activity by 2020 (according to the World Bank, June 2020, [1]). This crisis has had a profound impact on advanced economies, which witnessed a 7% decline in 2020, while emerging economies experienced their first output contraction in at least 60 years, with a decline of −2.5% [1]. In this context, the International Monetary Fund (IMF) has urged governments to consider implementing economic measures that can provide support to the population and productive sectors. The goal was to alleviate the significant economic losses and social hardships resulting from the pandemic. In response, the IMF has devised several initiatives. These include emergency financing options like the Rapid Credit Facility (RCF) and the Rapid Financing Instrument (RFI), which are specifically designed to address the financial requirements arising from health catastrophes. Additionally, the IMF established the Catastrophe Relief and Containment Trust Fund, which facilitates assistance to underprivileged and vulnerable countries through donations, with a focus on managing public health crises effectively.

The specific case of Chile, as indicated by [2] (BCCh), highlights the economic repercussions caused by the pandemic on its national economic activity. For instance, in 2020, the IMACEC (monthly index of economic activity) indicator, which measures national economic activity, showed a significant negative variation of 11.5% compared to the same month of the previous year (August 2019). Furthermore, when conducting a detailed analysis using volume figures at prices from the previous year, adjusted for seasonal changes, both the mining and nonmining IMACEC reported declines of −3.6% and −12.3%, respectively. In the same period of time, the publication of the gross domestic product by economic activity (June 2020) further confirmed the severe impact of the pandemic on various sectors, as can be seen in Figure 1. Many of them, including manufacturing (−12.5%), commerce (−16.2%), and business services (−11.2%), experienced sharp declines. However, a few sectors managed to slightly surpass positive variations, such as copper mining (+3.3%) and financial services (+0.3%). These figures underscore the significant challenges faced by Chile's economy during the pandemic and the varying degrees of resilience demonstrated by different sectors in the face of the crisis.

Amidst the pandemic crisis, the global economy has faced severe repercussions due to mobility restrictions and reduced interpersonal interactions imposed to curb the spread of the virus. As a result, it becomes of utmost importance to conduct in-depth analyses to identify and explore potential actions that can effectively minimize the economic costs borne by countries. In this context, the utilization of cluster analysis emerges as a powerful tool that enables us to delve into spatial and temporal data patterns. Through this analytical approach, valuable insights can be gleaned, thus aiding policymakers and decision makers in formulating effective economic mitigation measures. By identifying clusters of regions or countries with similar economic trends and impacts, targeted and tailored strategies can be devised to alleviate the adverse effects of the crisis on different sectors and regions.

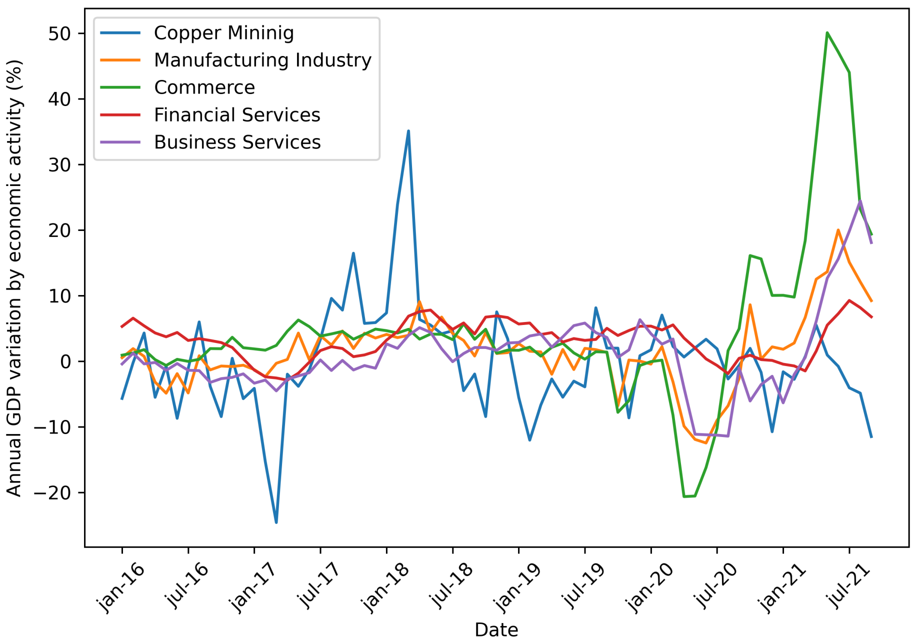

Figure 1. Annual GDP percent variation in Chile, from January 2016 to December 2021, according to most important economic sectors.

In this work we explore the economic impacts of COVID-19 on different countries, especially those in the OECD, and how different mitigation strategies and economic responses influenced the economic sustainability of those countries during the COVID-19 pandemic. The paper aims to accomplish this through advanced data analysis techniques, including clustering and time series analysis, to identify patterns and correlations between countries' pandemic responses and their economic outcomes. The use of these techniques provides a novel approach in this area of study. Additionally, the study focuses on providing insights that can assist policymakers in developing strategies to maintain economic sustainability during global health crises, with a special emphasis on the case of Chile. The work is based on the hypothesis that there are some variations in the economic impact of COVID-19 across different countries due to varying mitigation strategies, economic responses, and infection rates. Furthermore, the special case study of Chile implies a hypothesis about the specific impacts and responses in this country, thus contributing to the broader understanding of the pandemic's economic effects. In summary, this work tries to answer to the following main research questions: How can the OECD countries be clustered according to some health and economical indicators? What are the impacts of mitigation measures and the pension fund withdrawals on the Chilean economy? In this work, we will answer these questions in depth by proposing a novel methodology in order to fill the knowledge gap in this area, especially for the case of Chile.

The work is organized as follows. In Section 2, we present a literature review. Section 3 describes the methodology and how it addresses a novel way of including economic variables in our analysis. Section 4 presents the results of the analyses carried out in our study, with a particular analysis to Chile's case. Sections 5 and 6 provide a discussion of the results and some conclusions, respectively.

2. Literature Review

Studies show that health crises, including pandemics and epidemics, have significant effects on both human health and on various productive sectors. In the declared COVID-19 pandemic, the world experienced a virus capable of conditioning the economy, impacting tourism, disrupting hospitalization levels, and implementing capacity limits on social activities. Scientists and experts have highlighted a range of repercussions, thereby encompassing the detrimental effects on the productivity of several countries. This is particularly evident by the fact that various governments opted to implement sanitary measures in an effort to mitigate the risk of contagion [3,4]. Nevertheless, the implementation of these measures has been adversely affecting the economy on a global scale, thereby leading to a decline in both employment opportunities and overall economic activity [5].

Moreover, the fulfillment of the United Nations' Sustainable Development Goals (SDGs) by 2030 encountered setbacks attributed to the time delay induced by the COVID-19 pandemic [6]. Specifically, in the pursuit of SDG 8, which centers on "Decent Work and Economic Growth", it has become important to investigate strategies for alleviating the adverse impacts of poor and precarious growth that have reverberated through the world economy.

As outlined by [6], the updated target for achieving the employment rate goal should be within a span of 2–7 years, all while addressing the issue that young individuals not being in employment, education, or training (NEET) may necessitate a timeframe of 15–18 years.

Discussions and analysis of the economical impact and consequences of COVID-19 have been provided by several authors. According to the review paper of [7], the COVID-19 pandemic has affected several sectors of the world economy such as agriculture, oil and petroleum, the manufacturing industry, the finance industry, healthcare, tourism, real estate and housing, sports, information technology, media, research and development, and the food sector. The book of Vasile and Bunduchi [8] investigates how the COVID-19 pandemic has influenced the labor market and business environment within the European Union (EU), thereby placing a particular emphasis on Romania. The economic impact and consequences of COVID-19, on the global scale and for specific countries, have also been considered by [9]. Sofonov and Borshch [10] analyze the economic impact of COVID-19, thereby highlighting challenges like employment reduction and proposing recovery strategies, with an emphasis on the pandemic's uneven sector and regional effects.

Mofijur [11] primarily highlights the extensive economic impacts of the COVID-19 pandemic. The paper emphasizes the disruption of global supply chains, significant shifts in employment patterns, and the unprecedented strain on various industries. The paper also discusses the resultant financial instability and the varying impacts on different economic sectors. It provides a detailed analysis of the economic challenges faced by countries and suggests measures for recovery and resilience in the face of such global health crises.

Pak et al. [4] focus on the profound economic impacts of the COVID-19 pandemic. It discusses the significant global economic downturn, thus highlighting challenges like income reductions, unemployment, and disruptions in transportation, service, and manufacturing industries. The paper emphasizes the need for proactive international actions and preparedness to protect economic prosperity, thereby highlighting how the pandemic has underscored the inadequacy of global investment with respect to preventive measures and the importance of international cooperation in managing such crises.

The authors in [12] provide a survey on the economic consequences of the COVID-19 pandemic and governmental responses. In particular, the paper gives an overview of methodologies for measuring the spread of COVID-19 and social distancing, reviews the determinants and effectiveness of social distancing, and discusses the macroeconomic and financial impacts of the pandemic. Additionally, the paper summarizes the socioeconomic consequences of COVID-19, thereby focusing on labor, health, gender discrimination, environmental outcomes, and public policy responses.

The economic effects of COVID-19 are also examined by [13], thereby considering income declines, unemployment, and sector disruptions. This work emphasizes the global economic downturn and underscores the need for swift government responses. Finally, it advocates for preventive measures to save lives and maintain economic well-being, thus providing insights into the pandemic's far-reaching economic impacts and suggesting recovery strategies for stability.

Simak et al. [14] focus on the significant economic impacts of the pandemic. Their work provides an analytical assessment of the global and Ukrainian economies, thereby detailing the decline in GDP, increasing unemployment, and the contraction of various economic sectors. The paper emphasizes the challenges faced by small and micro enterprises, household income reductions, and the heightened economic uncertainty. It also discusses the responses of different countries to support their economies and populations, thus highlighting the varied levels of stimulus measures and their economic implications. Barua [15] focuses on the extensive economic impacts of COVID-19. The paper explores the macroeconomic shocks caused by the pandemic, thus affecting areas such as demand, supply, supply chains, trade, investment, price levels, exchange rates, financial stability, risk, economic growth, and international cooperation. The paper reviews the emerging evidence of these impacts and uses a standard macroeconomic model to analyze potential outcomes. It aims to provide a comprehensive view of the pandemic's economic consequences, thereby considering both short-term and long-term effects. Gabrilovic et al. [16] provide an in-depth analysis of the economic effects of the COVID-19 pandemic on the U.S. economy. The paper discusses the significant decline in GDP, the rise in unemployment, and disruptions in key sectors like industry and transportation. The paper highlights the U.S. government's measures to mitigate these effects and maintain economic stability. It also emphasizes the importance of proactive governmental actions to protect economic prosperity and sustain long-term economic growth. Padhan and Prabheesh [17] explore the economic effects of the pandemic and propose policy directions to mitigate these effects. Their paper emphasizes the need for coordinated monetary, macroprudential, and fiscal policies to address the pandemic's adverse economic impacts. The study suggests integrating these policy areas to effectively combat the economic challenges posed by COVID-19.

Additionally, it outlines potential directions for future research in understanding and managing the economic consequences of global health crises like COVID-19.

Shcherbakov [18] provides a comprehensive analysis of the pandemic's multidimensional effects. The paper covers the severe impact on global health, economic downturns, disruptions in global supply chains, and the challenges faced by various sectors. The study also examines social and political aspects, such as changes in work culture, increased unemployment, and social inequalities. It highlights the importance of robust healthcare systems and effective government policies in managing the crisis. The paper concludes with a discussion on the long-term implications of the pandemic and the need for resilient and adaptive strategies to mitigate future crises.

The research by [19] gives a better understanding of the impact of the pandemic in developing countries, where less preparedness in terms of infrastructure and equipment in the face of high infection rates has increased the impact, which has led to the need to prioritize virus mitigation measures.

Ahmad et al. [9] pointed out the possible impact that COVID-19 may have when compared to a similar type of virus, which affected China in 2002. Among the effects, they point out the impact of confinement on GDP levels not only for China, given the productivity levels, but also around the world due to the restrictions on tourism resulting from the outbreak. Finally, we must not overlook the positive impact of financial technology (FinTech) on the economy of several countries. Liu et al. [20] found that this association is particularly strong in countries with high internet usage, thereby indicating that the incremental impact of FinTech depends on local internet penetration. Overall, FinTech appears to play a crucial role in mitigating the economic impact of the pandemic.

Some other authors used statistical, computational, and mathematical models for explaining the impact of COVID-19 on the global economy and detecting the main correlations that caused it. König and Winkler [21] presented their study on the impact of COVID-19 on economic levels in the first three quarters of 2020, for which they performed different regressions (ordinary least squares and instrumental variable) in order to determine the impact on GDP given the confinement measures, where it was obtained that the more restrictive the measures were, the greater the negative impact on the economy, thereby causing an inverse relationship between mortality rate and GDP.

It is known that sanitary measures were taken depending on the country, and, therefore, these will depend on different factors associated with each country. Lassard et al. [22] suggested a scoring system (0–100) to assess a country's pandemic response based on factors like cases and deaths per million, mortality rate, hospitalizations, tests, vaccinations, public policy restrictions, and excess mortality. A predictive model was created by [23], who show that GDP is strongly related to the market in which each country participates, together with the sanitary measures applied. Furthermore, Fuente-Mella [24] evaluates COVID-19's economic impact on countries, thereby analyzing GDP and the Global Health Security Index (GHSI) for both OECD and non-OECD nations. Using statistical econometric models with COVID-19 rates, the GHSI, default spreads, OECD affiliation, and GDP per capita as covariates, they estimated the 2020 GDP variation. Their results underscore the substantial impact of COVID-19 on domestic economies, thereby emphasizing factors like OECD membership.

The research by [25] allows us to understand to what extent the damage caused by the pandemic is reversible. In this study, derivatives were used to put forward the idea that COVID-19 is the product of more than one variable, where the degree of impact will ultimately depend on the time of implementation of a vaccine and the effectiveness of containment.

He and Zhang [26] studied the consequences of the COVID-19 pandemic on a sample of OECD countries with regard the energy and the economy. By using the data from 2010 to 2022, they used the generalized method of moments for quantifying the relationship between these two variables and the COVID-19 pandemic.

Restrepo-Morales et al. [27] explored how innovation mitigated the economic impact of COVID-19 on Latin American small- and medium-sized enterprises (SMEs). By using a structural equation model, the study reveals that the pandemic had predominantly negative effects on SMEs' finances and sales. However, it found that these challenges spurred increased innovation, thus emphasizing the crucial role of innovation in sustaining competitiveness during crises. The study provides practical insights for SME owners and managers.

In order to group countries with similar health and economic impact, statistical clustering techniques have been proposed by some researchers.

The most often used clustering algorithms are the *K-Means* and the hierarchical cluster. In particular, *K-Means* clustering is based on the shortest distance between the data and the variable centroids [28], and the number of clusters has to be prespecified. The optimal number of clusters can be determined by using some techniques proposed by Benmahdi et al. [29]. In hierarchical clustering, one can stop at any number of clusters, which could be appropriate for interpreting the dendrogram [30]. In the context of the COVID-19 pandemic, Gohari et al. [31] applied the k-means method for clustering 216 countries affected by COVID-19 using mortality and incidence rates.

Zarikas et al. [32] analyzed the COVID-19 pandemic in several country by applying the hierarchical clustering algorithm to active cases, active cases per population, and active cases per population and per area based on Johns Hopkins epidemiological data. Rizvi et al. [33] presented a study aimed to cluster different countries using social-, economic-, health-, and environmental-related metrics affecting the disease spread in order to implement adequate policies to control the wide spread of the disease. By considering 79 countries and 18 different features, the countries were grouped into four clusters using k-means techniques.

Sadeghi et al. [34] used hierarchical clustering analysis to evaluate the COVID-19 pandemic. In particular, they clustered 180 countries into five groups using the cumulative COVID-19 fatality per day over the year and the cumulative COVID-19 cases per million population per day over the half-month period. Rahman et al. [35] proposed a dynamic clustering framework utilizing healthcare and mobility data to mitigate the economic impact of the COVID-19 pandemic. The framework, applied and validated in a Malaysian context, suggests reduced economic loss and military deployment, thus anticipating broader applications for future viral outbreaks. In order to cluster time series with temporal differences, the dynamic time warping distance measure proposed by [36] has been often used in the literature jointly with the clustering methods.

Yavuz et al. [37] implemented time series clustering with the dynamic time warping method for world countries by using all available daily confirmed cases, recovered cases, and death data after adjusting for population. Their results evidenced that European, North, and South American continents had homogeneous structures regarding the number of daily confirmed cases and relatively more heterogeneous regarding the daily number of recoveries.

The dynamic time warping distance and hierarchical cluster were also used by [38] to cluster the time series of daily new cases and deaths from different countries into four patterns. They found that geographic factors were important but not decisive for the pandemic development and that the population age may have also influenced the formation of cluster patterns. Finally, Mahmoudi et al. [39] proposed the use of fuzzy clustering for studying the distributions of the spread rate of COVID-19 in the Unites States of America, Spain, Italy, Germany, United Kingdom, France, and Iran. The results showed that COVID-19 spreading in Spain and Italy was approximately similar, but those rates were different from other countries.

To deal with the COVID-19 crisis, many countries have implemented various measures to activate the economy and to improve health conditions. These measures consist of medium–long-term recovery plans to incentivize economic growth or address economic and social impacts in order to contribute to resilience and sustainability, with the main aim of achieving the Sustainable Development Goals (SDGs) SDGs scheduled for 2030 [40]. Teresienė et al. [41] focused on the role of the pandemic emergency purchase program (PEPP) launched in March 2020 by the European Central Bank (ECB) to deal with the economic crisis of the bank sector (in particular, the credit transmission channel) caused by the COVID-19 pandemic. After analyzing the economic indicator and identifying the significant factors influencing the long-term loans that were issued, they concluded that the banks had enough funds to support sustainable economic growth, but the commercial banks were not willing to take the credit risk due to their risk tolerance. Similarly, Przybytniowski et al. [42] assume that the social, economic, and financial aspects concerning the development of Poland are related to the behavior of the financial market, which are responsible for modeling economic growth by implementing socially responsible actions both during and after the COVID-19 pandemic.

3. Methods

The methodology employed in this study is centered around the application of clustering techniques, with the main aim being to report the impact of the SARS-CoV-2 pandemic on selected OECD countries. In order to do this, we consider the gross domestic product (GDP) and the economic mitigation measures implemented by these nations. Additionally, we consider the cumulative infection rate per 100,000 inhabitants within the target population from the onset of the pandemic through the conclusion of 2021.

3.1. Data Sample

In this study, we considered global and national data. For the global analysis, we selected variables collected by 52 countries (38 OECD member countries and 14 not OECD members), represented in Table 1, during the years 2020 and 2021. The state of Venezuela was not considered in this study due to its different economic situation (the GDP was outside the ranges of the other countries at −10% according to the International Monetary Fund). In particular, for each country, we considered the following: (i) the infection rate per 100,000 inhabitants (Daily contagious $\times$ $100,000$/Country's population) for each country [43]; (ii) the variation in GDP (gross domestic product) for the period between 2020 and 2021 for each country, thereby taking the year 2019 as the basis; and (iii) the number of mitigation measures [44] that countries took into account for the years 2020 and 2021.

For the GDP variation, two folds were considered: the variation between 2019 and 2020 and between 2019 and 2021. We considered these variations by extracting data from [45] and calculating the variation over each period as follows:

$$\Delta GDP_{2019-2020} = (\mathrm{GDP}_{2020} - \mathrm{GDP}_{2019})/\mathrm{GDP}_{2019}$$

$$\Delta GDP_{2019-2021} = (\mathrm{GDP}_{2021} - \mathrm{GDP}_{2019})/\mathrm{GDP}_{2019}.$$

The database referenced herein [44] categorizes policy measures into five principal levels, with each one having a set of specific submeasures. These are detailed as follows:

1. Banking Sector: This level includes operational continuity, integrity, support for borrowers, prudential regulations, and crisis management strategies.
2. Financial Markets/Non-Bank Financial Institutions (NBFIs): This level addresses measures related to non-bank financial institutions (NBFIs), public debt management, and market functioning.
3. Insolvency Frameworks: This level encompasses enhancing tools for out-of-court debt restructuring and workouts, amending bankruptcy filing obligations, and other insolvency-related measures.
4. Liquidity/Funding Mechanisms: This level comprises policy rate adjustments, asset purchases, liquidity provisions (including foreign exchange/ELA), and other liquidity-related measures.
5. Payment Systems Infrastructure: This level includes easing regulatory requirements, promoting and ensuring the availability of digital payment mechanisms, consumer

protection measures, ensuring the availability and acceptance of cash, and other payment system-related measures.

Table 1. List of OECD member countries (with the dates of Ratification of the Convention) and some non-OECD members considered in this study.

OECD Member (with Ratification Date)	Not OECD Member
Australia—7 June 1971	Argentina
Austria—29 September 1961	Bolivia
Belgium—13 September 1961	Brazil
Canada—10 April 1961	Bulgaria
Chile—7 May 2010	China
Colombia—28 April 2020	Ecuador
Costa Rica—25 May 2021	India
Czechia —21 December 1995	Indonesia
Denmark—30 May 1961	Paraguay
Estonia—9 December 2010	Perú
Finland—28 January 1969	Romania
France—7 August 1961	Russia
Germany—27 September 1961	South Africa
Greece—27 September 1961	Uruguay
Hungary—7 May 1996	
Iceland—5 June 1961	
Ireland—17 August 1961	
Israel—7 September 2010	
Italy—29 March 1962	
Japan—28 April 1964	
Latvia—1 July 2016	
Lithuania—5 July 2018	
Luxemburg—7 December 1961	
Mexico—18 May 1994	
Netherlands —13 November 1961	
New Zealand—29 May 1973	
Norway—4 July 1961	
Poland—22 November 1996	
Portugal—4 August 1961	
Slovakia—14 December 2000	
Slovenia—21 July 2010	
South Korea—12 December 1996	
Spain—3 August 1961	
Sweden —28 September 1961	
Switzerland —28 September 1961	
Turkiye—2 August 1961	
United Kingdom—2 May 1961	
United States—12 April 1961	

Regarding the mitigation measures, while [46] utilized information up until the year 2020, in this study, the database has been updated to include data up to the year 2021. This update allows for the incorporation of all financial policy measures undertaken during this two periods. Particularly, we employ a simple count of the total measures taken by each country in both the years 2020 and 2021, thereby providing a comprehensive overview of the policy actions.

It is important to note that not all countries involved in this study have implemented each of these measures. The following analysis will leverage these measures to gain insights into the decision-making processes across the identified clusters.

In the context of the national case, we considered three time series. Firstly, we examined the Chilean daily infection rate per 100,000 inhabitants. This infection rate was calculated by multiplying the number of daily cases by 100,000 and dividing by the total Chilean population. Secondly, we investigated the closing prices of the daily Chilean stock market index, known as IPSA [47]. This index effectively tracks the performance of the largest Chilean companies. The third variable to study is the daily interest rate, which is given by the Central Bank of Chile [48]. It is important to note that the data for the IPSA and the daily interest rate were available exclusively for business days. Therefore, to ensure consistency and comparability across these variables, we calculated the percentage variation between each data, thereby facilitating meaningful comparisons into the dynamics of the data. For example, the percentage variation of IPSA ($\Delta \mathrm{IPSA}_t$) was calculated as follows:

$$\Delta \mathrm{IPSA}_t = \frac{\mathrm{IPSA}_t - \mathrm{IPSA}_{t-1}}{\mathrm{IPSA}_{t-1}} \cdot 100\%$$

3.2. Clustering

As we mentioned in the previous subsections, we used two different databases to analyze the effects of the pandemic on the economy. In order to give a detailed description of how groups of countries can gather together based on a similar course of actions, related to economical variables, we used the classical clustering techniques, i.e., k-means and hierarchical clustering.

K-means clustering is a part of a unsupervised learning technique from machine learning [28,49,50]. It begins partitioning a dataset into K distinct clusters based on data similarity. It starts by randomly selecting K initial cluster centroids and assigns each data point to the nearest centroid. The centroids are then updated iteratively as the mean of their assigned data points, thereby continuing until stabilization. To determine the appropriate value for K, three distinct methods are employed, which will be briefly described in the following subsection.

Hierarchical clustering is also a unsupervised learning technique from machine learning [51], which form clusters according on agglomerative (bottom-up) or divisive (top-down) approach. In this work, we will consider the agglomerative method, where the clustering process starts by considering each data point as an individual cluster and then iteratively merges the closest clusters into larger ones. This process continues until all data points belong to a single cluster or meet specific stopping criteria. Hierarchical clustering produces a dendrogram, a tree-like structure, which reveals the hierarchy of cluster relationships. It does not require specifying the number of clusters beforehand, thereby making it versatile for exploring data structures.

Dynamic time warping (DTW) is an algorithm employed for assessing the similarity between time sequences that may exhibit variations in both time and speed [52]. Its primary purpose is to identify patterns by measuring the temporal distance between data points in the sequence under consideration and the centroids of one or more clusters. It accomplishes this by selecting various points from these sequences at different time intervals and grouping them based on the minimal distance to the centroids of the clusters to be determined during analysis (for details, see [53]).

3.3. Number of Clusters Estimation Methods

A crucial step in cluster analysis is related to the selection of the optimal number of clusters. In this work, we used the elbow method, the silhouette method, and gap statistics. The elbow method, which can be traced back to [54], is a heuristic algorithm that analyzes the within-cluster sum of squares across various cluster numbers. The "elbow point" indicates optimal clusters where reduction slows, thereby balancing variance capture and fragmentation prevention. The silhouette method, proposed by [55], assesses clustering by cohesion and separation distances. Individual scores create averages for various cluster counts, thus revealing optimal clusters with high cohesion and separation balance. The third method, called gap statistics, is based on a statistic proposed by [56] and consists of determining clusters by comparing actual data's clustering to random data, thereby revealing optimal clusters without biases toward excessive clusters or noisy data.

3.4. IMACEC Modelling

To provide an alternative perspective on the economic impact of COVID-19 on the Chilean economy, we analyzed the monthly economic activity indicator (IMACEC) by modeling this economic indicator using additive time series decomposition [57]. The IMACEC is an estimate that summarizes the activity of the different sectors of the economy in a given month, at prices of the previous year; its year-on-year variation is an approximation of the evolution of GDP. The model is expressed as follows:

$$\mathrm{IMACEC}_t = \mathrm{T}_t + \mathrm{S}_t + \mathrm{e}_t$$

Here, T_t represents the trend component of the time series, S_t is the seasonal component, and e_t are the residuals of the model. We employed the *Statsmodels* module [58] in Python to fit the seasonal decomposition model using moving averages. Specifically, we decomposed the trend component using moving averages and fitted a simple linear regression to project IMACEC values for the period starting from 1 April 2020 (the onset of COVID-19). The seasonal component S_t was replicated for the projection period, and the residuals were modeled using a probability density function based on a Gaussian kernel. This approach was chosen because the residuals did not pass the Shapiro–Wilk normality test, thereby indicating a heavy-tailed distribution. To estimate the projected IMACEC using pre-COVID-19 data, we simulated 1000 paths from the inverse cumulative distribution of the kernel density approximation of the residuals, which were combined with the linear trend and seasonal component. The mean of these 1000 paths served as our estimate for IMACEC from April 2020, thus providing an indicator of the expected economic activity in the absence of COVID-19.

4. Results

4.1. Exploratory Data Analysis

In this section, we present some summary statistics for the global dataset, as shown in Table 2. Notably, we observed a significant standard deviation for the variables related to measures; this variability can be attributed to the inclusion of 14 countries that reported no economic mitigation measures for both years. Figure 2 represents the number of economical mitigation policy measures, related to the banking sector, liquidity/funding, financial markets, insolvency, payment systems, etc. Focusing on Chile (the bar within the red box in Figure 2), we can see that it falls below the mean value and ranks lower than several other American countries.

Table 2. Summary statistics of the variables in the global database: number of countries (N), mean (Mean), standard deviation(Std.Dev.), minimum (Min), 25th percentile (Pctl.25), 75th percentile (Pctl.75), and maximum (Max).

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Measures	52	46.096	39.825	0	0.000	79.000	134
Infected	52	10,568.8	5894.7	9.3	6539.3	14,700.5	23,961.3
$\Delta GDP_{2019-2020}$	52	−0.0416	0.0618	−0.212	−0.0822	0.00613	0.0664
$\Delta GDP_{2019-2021}$	52	0.0995	0.0801	−0.119	0.0529	0.142	0.263

Additionally, in Figure 2, the countries that took measures related to COVID-19 during both 2020 and 2021 are shown [44]. The countries that did not take any mitigation policy measures were Austria, Belgium, Denmark, Finland, Greece, Iceland, Ireland, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Sweden, and Switzerland. From this figure, we observe that the three countries with the highest number of measures, in descending order, are India, Italy, and Spain.

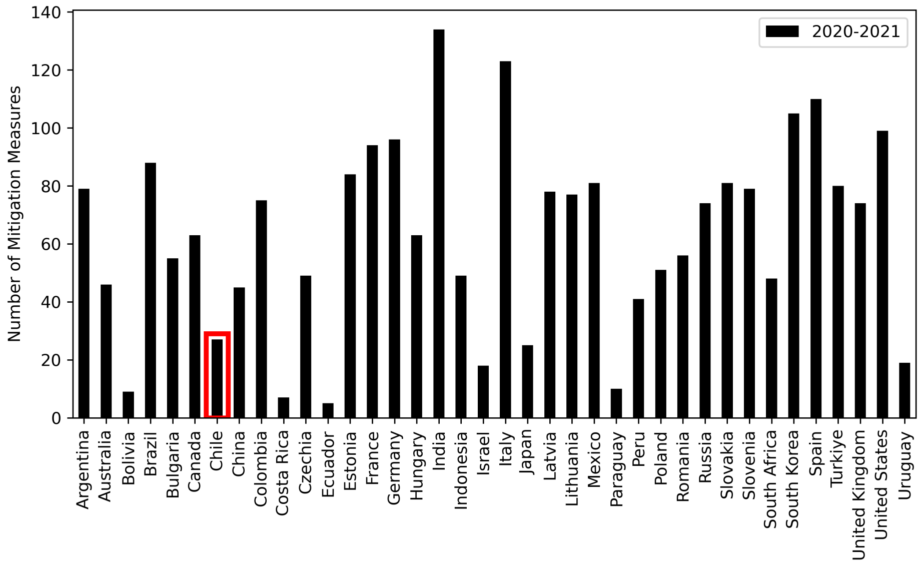

Figure 2. Number of mitigation policy measures taken by different governments during the years 2020 and 2021. The red box highlights the Chilean case.

Based on the variable infected in Table 2, which represents the accumulated infection rate until 2021 [59], we notice that the minimum value is 91, which belongs to China and is represented by the last bar on the right of Figure 3. This phenomenon can be elucidated by considering that infection rates are adjusted according to the respective population size. In this regard, China stands out as the world's most populous country, as documented in [43]. It is noteworthy that India, the second-most populous nation, significantly surpassed China's infection rate.

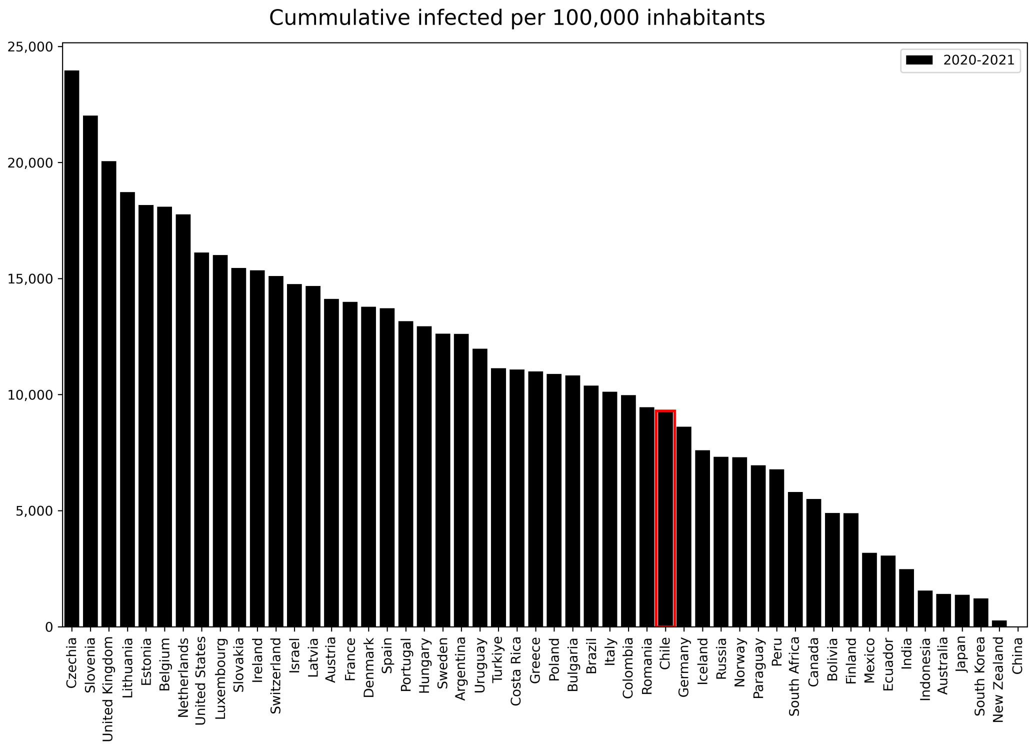

Figure 3. Number of cumulative infections per 100,000 population. The red box highlights the Chilean case.

Shifting our focus to Chile, we find that it exhibited an infection rate below the mean (9258.02), which is illustrated in Table 2. Furthermore, in Figure 3, Chile is highlighted within a red box, thus signifying its position as the thirty-third country in descending order of cumulative infections per 100,000 inhabitants. Interestingly, Chile's rate exceeds that of five other Latin American countries, namely Paraguay, Peru, Bolivia, Mexico, and Ecuador. An additional noteworthy observation arises from Figure 3, where we see that nine out of the top ten countries with the highest cumulative infections per 100,000 population belong to Europe, with the exception of the United States (eighth position).

The analysis of GDP variation for the periods 2019–2020 and 2019–2021 is represented in Table 2 by the variables $\Delta GDP_{2019-2020}$ and $\Delta GDP_{2019-2021}$, respectively. A comparative analysis of these two-year variations underscores the evident negative impact of the COVID-19 pandemic on global GDP values. The mean value for these variables was consistently negative, and the GDP values remained negative above the median and until at least the 69th percentile (-0.0002862). Notably, in 2021, there was a visible rebound reflected in the positive mean and a positive 25th percentile. A more detailed country-level analysis in Figure 4 provides valuable insights into the diverse behaviors of nations. The gray and black bars in this figure represent $\Delta GDP_{2019-2020}$ and $\Delta GDP_{2019-2021}$, respectively. Within this figure, an interesting situation becomes evident: several countries did not experience a negative GDP variation for both comparative years, with the majority of them being European nations, except for China, Israel, and New Zealand. Conversely, there is a group of countries that encountered negative GDP variations for both years, thereby encompassing nearly all Latin American countries, such as Bolivia, Brazil, Colombia, Ecuador, Peru, and Uruguay, with Japan being the exception. Notably, Chile, along with Argentina, Costa Rica, and Paraguay, stands out as the only Latin American countries that managed to rebound in 2021, thereby showing a positive trend.

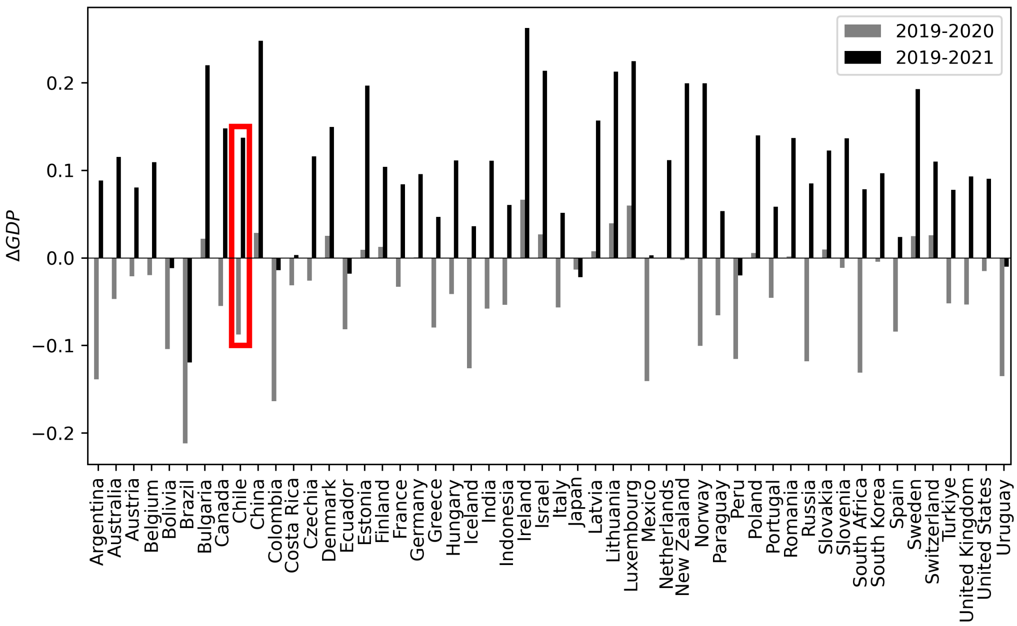

Figure 4. GDP variation for all the countries. Gray bars refer to $\Delta GDP_{2019-2020}$, while black bars refer to $\Delta GDP_{2019-2021}$. Red boxes highlight the Chilean case.

Lastly, in order to give a quantification of the relevance of the variables in this part of the study, we applied principal component analysis (PCA) to measure the contribution and squares cosine (CSC) of the observations to the first two principal components (Dim 1 and Dim 2) in Figure 5 and Table 3. In particular, the square cosine shows the importance of each variable with respect to the two principal components, and positively correlated variables are grouped together in the same quadrant. By observing Figure 5 and Table 3, we notice that the GDP variable is the one that has the greater contribution and square cosine for the first component, while for the second principal component, the variable "Measures", which quantifies the economic changes implemented by each country, exhibits the greatest contribution and squared cosine.

Table 3. Contribution (Ctr) and squares cosine of the observations to the principal components 1 (48.5%) and 2 (25.5%).

Variable	Ctr_1	Ctr_2	cos_1^2	cos_2^2
GDP 19–20	42.88	0.0848	0.8323	0.0009
GDP 19–21	40.43	0.0001	0.7849	0.0000
Infected	12.78	27.22	0.2481	0.2773
Measures	3.89	72.70	0.0755	0.7408

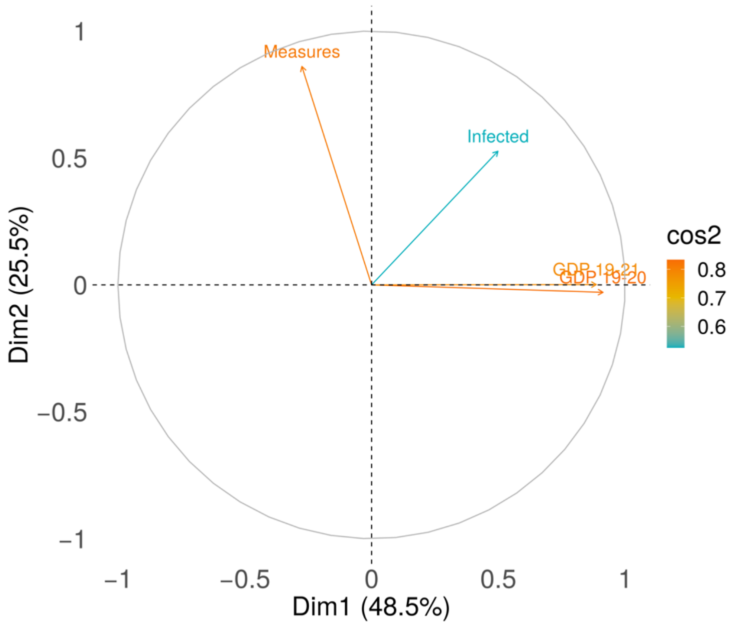

Figure 5. Square cosine of the variables to the principal components (Dim 1 and Dim 2) and the circle of correlations.

4.2. Selection of the Number of Clusters

In Figure 6, we present various methods for selecting the optimal number of clusters, which is a crucial step in our study. The decision on how many clusters to use relies on a consensus derived from the collective insights of different methodologies outlined earlier, including the elbow method (panels a and d), silhouette analysis (panels b and e), and gap statistic (panels c and f). The goal is to strike a balance in identifying a reasonable number of clusters that effectively reveal the inherent patterns within the global dataset. In our analysis, we prominently denote K = 2 with a segmented vertical red line, thus aligning with both the elbow method's weighted sum of squares (WSS) and the silhouette method. Although the gap statistic points towards an optimum at K = 1, signifying unclustered data, we chose to follow the collective recommendation of the elbow method and silhouette analysis. Both methods concur on K = 2 as the most appropriate choice for clustering countries' behaviors. This consensus-driven decision ensures that our clustering approach effectively captures the underlying dynamics of the dataset, thereby enhancing the reliability of our findings and interpretations.

The second column of Figure 6 determines the appropriate number of clusters for the global database specifically concerning the daily infected rate per 100,000 inhabitants. In this scenario, we utilized the hierarchical clustering method with dynamic time warping (DTW) as the distance metric to cluster the data from 52 countries. Again, we found an alignment among the elbow method's weighted sum of squares (WSS) and the silhouette method. K = 2 emerged as the choice across this two methodologies. This consensus on the optimal number of clusters holds substantial significance, as it underpins the comparison between two perspectives of the pandemic.

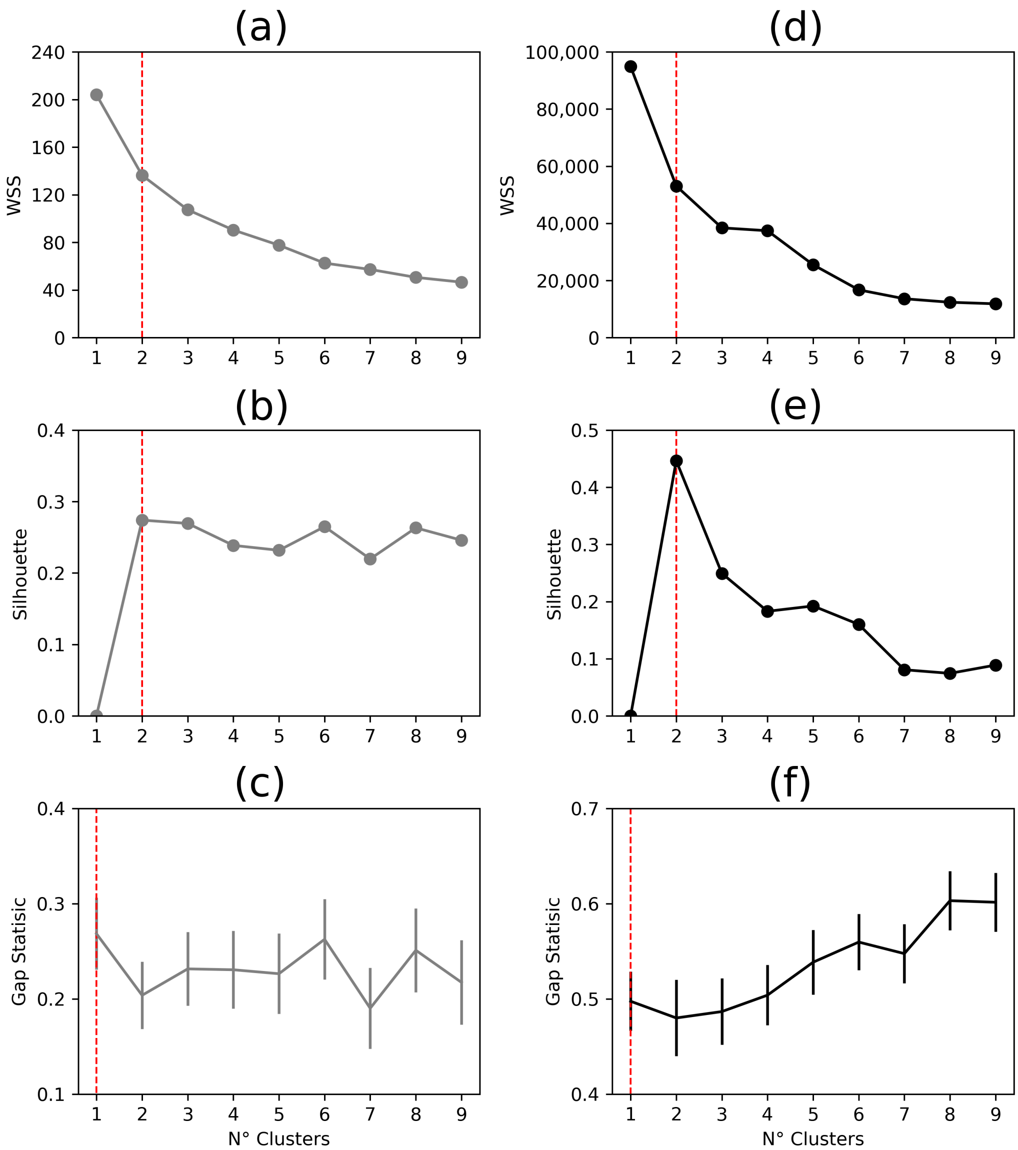

Figure 6. Selection of the number of clusters: row panels correspond to the methods we used, that is, weighted sum of squares (WSS) (**a**,**d**), sillhouette (**b**,**e**) and gap statistics (**c**,**f**); the first column of panels (**a**–**c**) indicates the application of the above methods to the database considering four variables (mitigation measures, cumulative infections per 100,000 inhabitants, and annual GDP variation for years 2019–2020 and 2019–2021), while the second column of panels (**d**–**f**), shows the selection of clusters using monthly time series with the DTW technique. In both analysis, global analysis including 52 countries has been considered. In each figure, the optimal number of clusters, as suggested by the analysis, is denoted by a dashed red vertical line.

4.3. Formation of Two Significant Clusters Using Static Data from Countries

Utilizing data related to the pandemic's development, mitigation policies, GDP variations from 2019–2020 and 2019–2021, and cumulative infection rates until the end of 2021, we constructed a comprehensive database for each country. Subsequently, we conducted two classical data clustering analyses, hierarchical and k-means, using the R Statistical

Software Version 4.3.2 [60]. Figure 7 illustrates the hierarchical clustering dendrogram, thereby revealing the formation of two prominent clusters: one consisting of 18 countries (depicted in red) and the other comprising 34 countries (represented in cyan). This analysis allowed us to group countries based on shared characteristics, thus shedding light on the dynamics of the pandemic's impact on different nations, their economic performance, and policy responses.

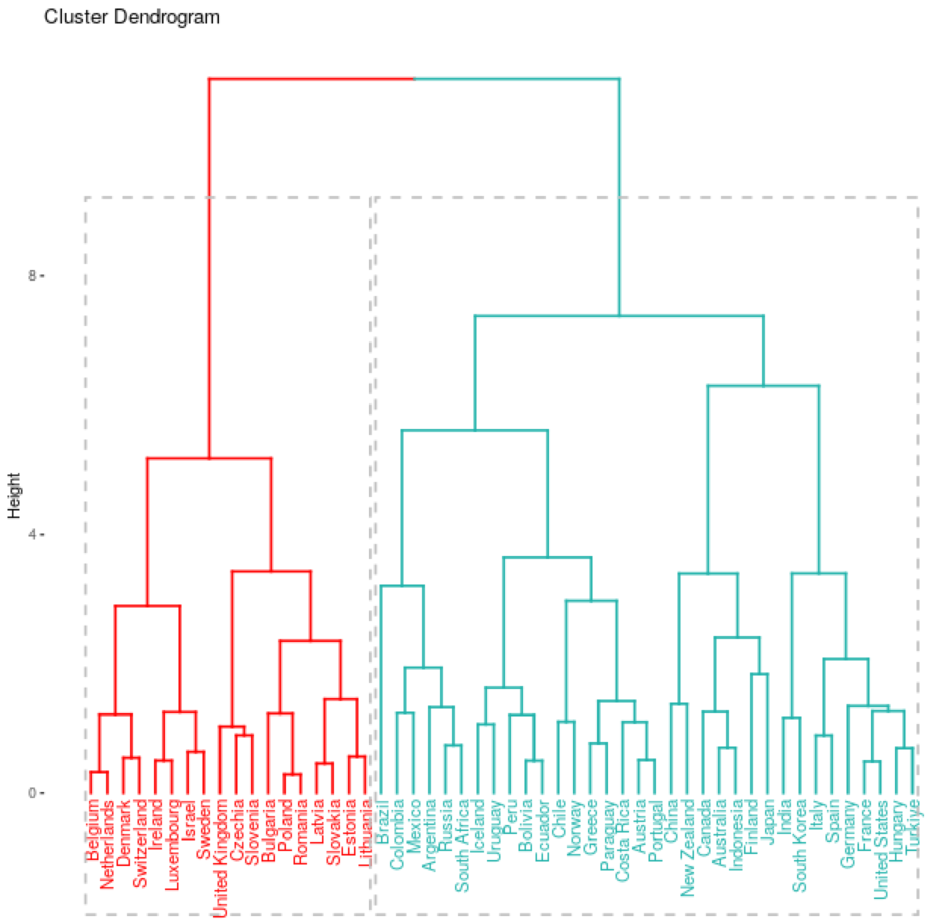

Figure 7. Hierarchical clustering of countries into two main groups. Clusters 1 and 2 are in red and cyan colors, respectively.

In Figure 7, an interesting pattern arises as we observe that all Latin American countries are clustered within the cyan group. The hierarchical cluster analysis not only shows the arrangement of countries but also offers valuable insights into the similarities among data points. Notably, the red cluster primarily encompasses European countries, with the sole exception being Israel. Furthermore, it is important to highlight that within the smaller cluster, the majority of countries belong to Central Europe (10), with the remaining four represent Western Europe.

Another pattern that emerges from Figure 7 pertains to the geographical distribution of the countries. On one side, we find all countries from Asia and Oceania within the cyan cluster. However, upon closer examination of the dendrogram, it becomes evident that if we were to partition the cyan cluster into two, it would lead to a more distinct alignment with these countries. In such a scenario, the other cluster would encompass all the Latin American countries. This potential division of the cyan cluster offers an intriguing opportunity for further investigation, thereby providing insights into the factors influencing these groupings.

When we examine the k-means clustering using principal component analysis (PCA) by projecting the countries into the first two components in Figure 8, we found that eight countries that were initially categorized in the cyan cluster in hierarchical clustering depicted on Figure 7 were reassigned to a different cluster in the k-means analysis. This finding underscores the influence of the clustering method on how countries are grouped and categorized, thereby revealing the sensitivity of the results to the chosen methodology.

Figure 8. K-means clustering of countries into two main groups.

However, it is notable that all the countries incorporated into the red cluster in Figure 8 are primarily clustered along the left boundary of the convex hull formed by the countries in this group. Importantly, the majority of the countries newly added to the red cluster are of European origin, with exceptions such as the United States, China, and New Zealand. Another noteworthy feature of this PCA projection is its capacity to reveal that all the countries belonging to the red cluster in Figure 7 are collectively positioned towards the right side of the convex hull illustrated in Figure 8. This observation highlights an interesting geographical and structural distribution within the red cluster.

The differences from the two groups are shown in Figure 9, where we see the economical variables (GDP1920, GDP1921, and Measures) and the infected rate. Based on the t-test, all the variables except for Measures showed significant difference; the p-values for GDP 2019–2020, GDP 2019–2021, and Infected rate were 5.51×10^{-9}, 6.05×10^{-8}, and 1.68×10^{-5} respectively, while Measures gave a nonsignificant p-value of 0.1857. Even when this last p-value was nonsignificant, we notice that almost all the countries that did not implement economical measures were grouped into Cluster 2.

We compared the policy measures across the two clusters by representing the proportion of measures focused on the Banking Sector, Financial Markets/NBFIs, Insolvency, Liquidity/Funding, and Payment Systems in Table 4. For both Cluster 1 and Cluster 2, the majority of the policy measures are concentrated in the Banking Sector, with Cluster 2 implementing these at a higher rate of 61.87%, compared to 53.85% in Cluster 1. Additionally, there is a significant engagement in Financial Markets/Non-Bank Financial Institutions (NBFIs) measures, with Cluster 1 and Cluster 2 allocating 15.87% and 16.2%, respectively. This indicates a notable but relatively balanced focus on this sector across both clusters.

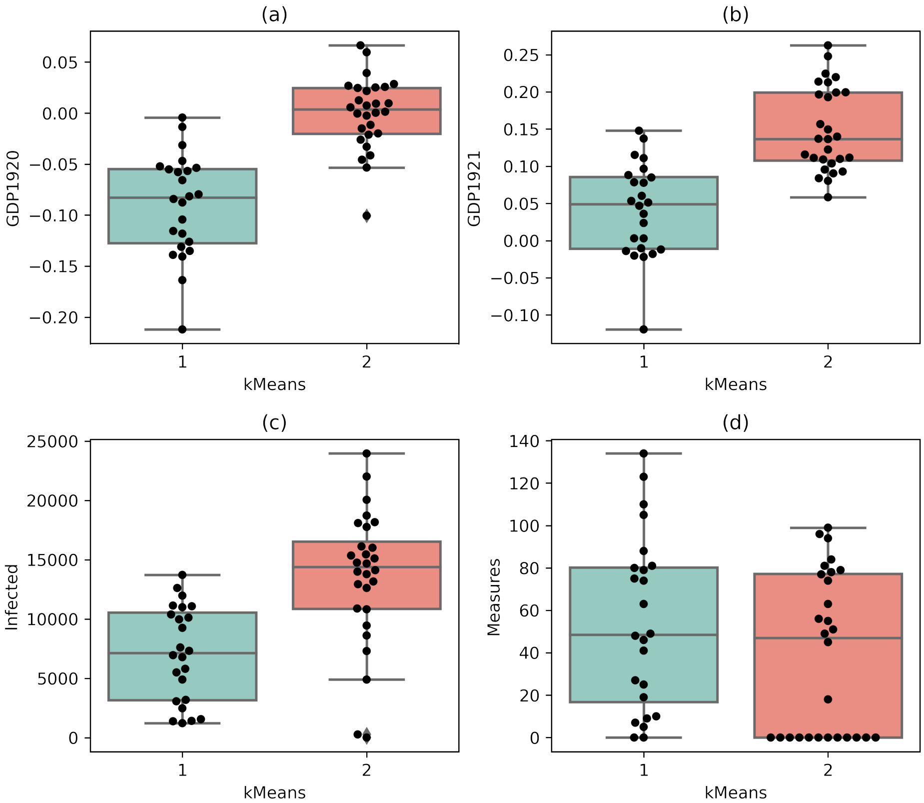

Figure 9. Boxplots of of the four variables for each cluster obtained using k-means clustering technique: GDP 2019–2020 and GDP 2019–2021 are on panel (**a**,**b**), while the infected rate and economical measures are in (**c**,**d**), respectively. Black points represent the countries included in Clusters 1 and 2. Differences between clusters where significant (p-values $< 10^{-4}$) using a t-test for all the variables except for Measures (panel **d**).

Regarding insolvency measures, both clusters exhibited lower engagement, with Cluster 2 at 1.46% and Cluster 1 slightly higher at 1.92%. This suggests a less pronounced but still present focus on insolvency policy measures. In the domain of Liquidity/Funding, Cluster 1 shows a more substantial commitment, allocating 24.57%, compared to Cluster 2, which dedicated 19.65% to these measures. This disparity highlights differing priorities in liquidity and funding policies between the clusters.

Lastly, the Payment Systems sector saw the most significant divergence between the two clusters. Cluster 1 allocated 3.76% of its measures to this area, while Cluster 2 showed a minimal focus, with only 0.08% of its measures dedicated to Payment Systems. This distinct contrast emphasizes the varied strategic priorities allocated to the enhancement of payment systems infrastructure across the identified clusters.

Table 4. Proportion of financial policy measures adopted by the countries in Clusters 1 and 2.

Measures	Cluster 1	Cluster 2
Banking sector	0.53852	0.61874
Financial Markets/NBFIs	0.15871	0.16197
Insolvency	0.01926	0.01456
Liquidity/Funding	0.24576	0.19654
Payment Systems	0.03775	0.00819

4.4. Clustering the Evolution of Infection Rates in Countries Using Dynamic Time Warping (DTW)

The global spread of COVID-19 began in China and subsequently affected countries worldwide, thereby leading to a common issue in analyzing time series data, i.e., the absence of a consistent starting point in time for each country's pandemic experience. To address this issue, the dynamic time warping (DTW) method as a distance function emerges as an ideal tool for handling the variations in the beginning of the COVID-19 outbreak in different regions. The main advantages of DTW, when compared to other distance metrics, is that we can better analyze and understand the global dynamics of the COVID-19 pandemic, thus accounting for the temporal disparities in the spread of the virus and capturing complex patterns that define its progression. In Figure 10, we employed DTW as a distance measure between the time series of infection rates for each country spanning from 2020 to 2021. We used this DTW-based approach within the context of hierarchical clustering.

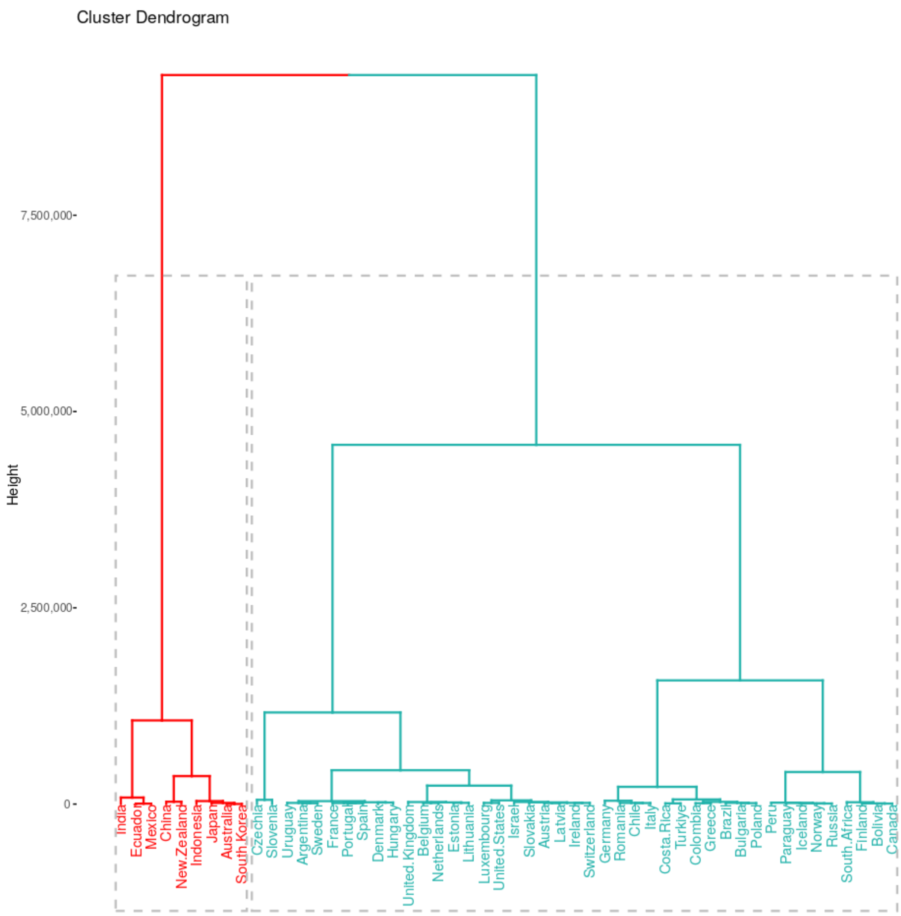

Figure 10. Hierarchical clustering applied to the time series of infection rate using DTW as distance metric.

In Figure 10, it is clear that the red cluster encompasses fewer countries compared to the initial database analyzed using both clustering methods. This reduction in the number of countries highlights a consistent pattern when comparing the composition of the red clusters in Figures 7 and 8 with those in Figure 10. Notably, the countries within this cluster align together across the two figures, thus maintaining a degree of consistence.

A noteworthy outcome of this clustering analysis is the prevalence of countries from Asia and Oceania within the red cluster. However, exceptions exist, with Mexico and Ecuador representing the Latin American countries. An intriguing observation arises when examining the dendrogram of the red cluster, thus revealing that Mexico and Ecuador share a subgroup with India, while the remaining countries form a distinct group. This finding aligns with the grouping pattern observed in Figure 7, where Latin American countries (Mexico and Ecuador) were clustered together, and countries from Asia and Oceania were grouped separately.

In order to provide an alternative view on the clustering characterization, we projected the clusters onto the first two principal components, as illustrated in Figure 11. In this visualization, the red cluster is situated on the right side of the figure. Notably, there is an overlap between the two clusters in this projection. This overlap can be addressed by further projecting our countries, thus incorporating a third principal component, as is shown in Figure 12. The projection into the first three principal components not only reveals a more accurate separation of the two groups but also provides a deeper understanding of how countries are distributed within this three-dimensional subspace. It is worth noting that this subspace encapsulates over 80% of the total explained variance. Additionally, Figure 12 also shows that the cluster belongs to the boundary of the dataset. We also notice that this cluster includes countries like China, Japan, India, and Australia, which experienced active cases within the first thirty days of the pandemic's onset.

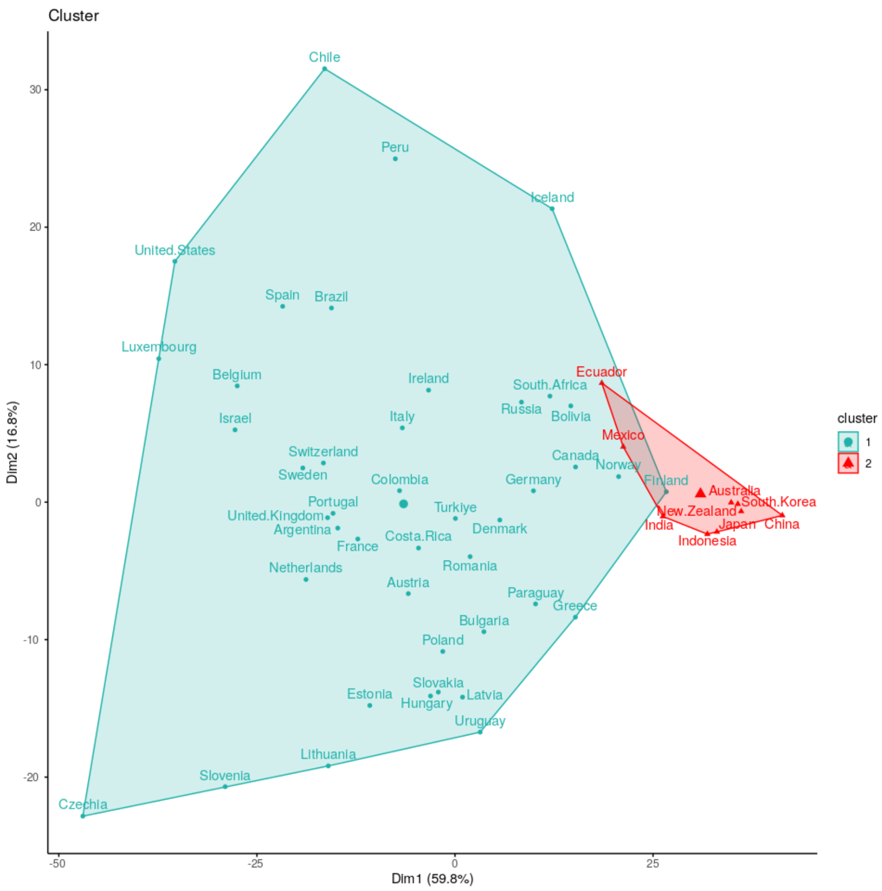

Figure 11. Hierarchical clustering projections into the first two principal components for infected rate time series using DTW as a distance.

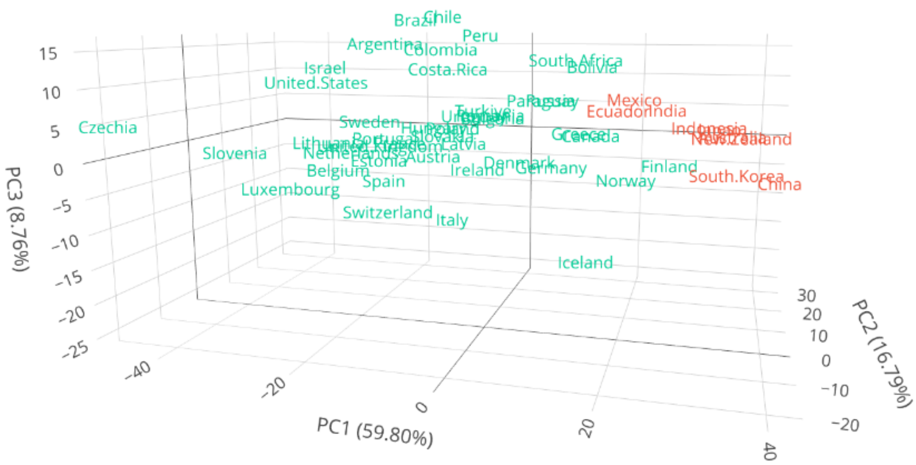

Figure 12. Hierarchical clustering projections into the first three principal components for infected rate time series using DTW as a distance.

Compared to the initial cluster analysis, the utilization of DTW in Figure 10 unveils a notable distinction. It shows that all European countries are consolidated within a single cluster, i.e., the cyan group, whereas the selection of the number of clusters in Figure 2 suggests the presence of two distinct groups; a closer examination of the dendrogram in Figure 10 may indicate the potential existence of three clusters. In this scenario, the group formation shows an interesting pattern, where seven Latin American countries are positioned on the right branch of the dendrogram, while Argentina and Uruguay find their place within the middle cluster. It is essential to note that the two countries with the highest infection rates, depicted in Figure 3, namely Czechia and Slovenia, share a common branch in the dendrogram.

4.5. Chilean Case

This section aims to analyze more deeply how COVID-19 affected certain economic variables in Chile. By having a more detailed analysis of the Chilean case, it will be possible to highlight specific actions that helped from a practical point of view to mitigate the complications caused by the pandemic, e.g., if the COVID-19 pandemic has had long-term structural effects on individual consumption behavior.

The International Federation of Pension Fund Administrators [61] published a study in which it analyzed the impact of the pandemic on employment, the number of contributors, and the collection of pension funds in different countries of the world, thereby indicating that only three countries in the world (Australia, Chile, and Peru) allowed withdrawals from mandatory pension funds. In contrast, other countries allowed withdrawals from voluntary savings accounts as a measure adopted by governments to help them cope with the crisis.

In the case of Chile, three withdrawals from mandatory pension funds were authorized (Laws: N° 21.248, N° 21.295, N° 21.330), which could be a total for those with a balance of less than 35 UF (approx. 1346 USD) or 10% with a cap of 150 UF (approx. 5767 USD), with only the second withdrawal being subject to tax for those with a monthly income of more than CL 1,500,000 (approx. 1890 USD). These withdrawals were approved by three constitutional reforms at different times. The total withdrawal amounts to 50,334 million dollars in less than 12 months, thus reaching a total of 25,527,807 withdrawals by the inhabitants of Chile.

The above-mentioned information is important to consider, since injecting a large amount of money into the Chilean economy would affect different variables such as inflation, interest rates, and the capital market. These finally have repercussions in the different measures that must be taken to balance the economy during and after having faced the pandemic. Understanding that the measures taken by different countries are not homogeneous, we can analyze certain variables that give us some guidelines on a country's economic direction. Therefore, we analyzed the interest rate, infection rate, and market profitability.

Figure 13 shows the three variables used to analyze the Chilean case, and we can see in orange the series representing the rate of COVID-19 infections, thereby showing a reasonably marked pick in the periods that most affected Chile. The the following two series, the interest rate in black and the market return represented by the IPSA stock market indicator (for details on the IPSA, see [62,63] and the references therein) in purple represent a certain degree of positive correlation, which we can see visually. In particular, the financial markets experienced strong volatility, with sharp declines in stock prices during March 2020 due to the uncertainty of the investors on the economic outlook.

Additionally, in Figure 13, the measures adopted by Chile to mitigate the impact of COVID-19 are marked with red triangles. A detailed description of these measures can be found in Table 5. The timeline of the measures' implementation (from March to August 2020), highlights the dynamic response of Chile's government and financial institutions to the evolving economic challenges posed by COVID-19. Compared to Table 4, Chile opted to target mitigation measures to the banking sector and liquidity equally.

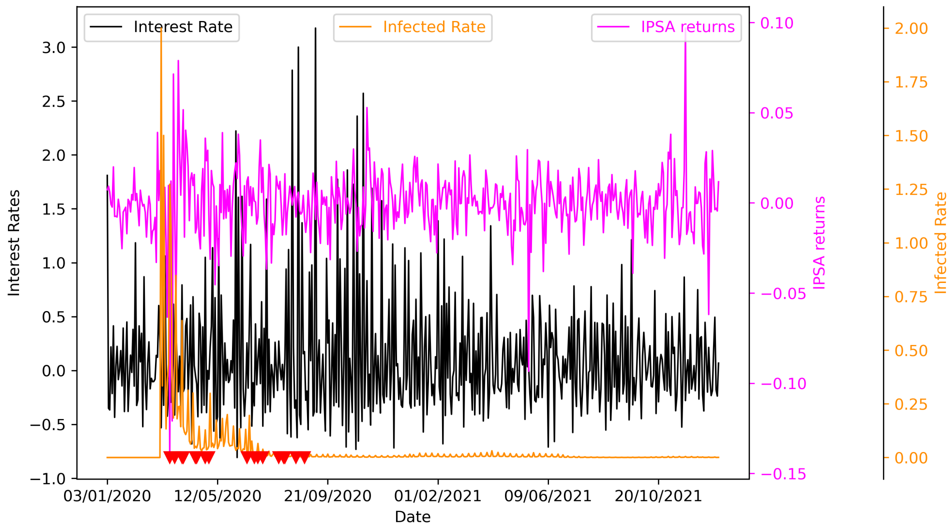

Figure 13. Daily time series variation for Chilean variable. Each time series has its one axis specified by different colors to give a comprehensive representation of the changes, because all of the three are in different ranges of values. The red triangles show the dates were Chile took mitigation policy measures.

As we can see in Figure 14 and Table 6, we analyzed the crosscorrelation to track the movements between the variables. The three time series were daily and from January 2020 to December 2021. As expected, the interest rate was correlated with the IPSA; according to economic theory, they should have a negative correlation, because when interest rates increase, companies may have less money to invest back into the company due to higher borrowing costs, which can reduce cash flow stability and put pressure on share prices. However, as we can see, this was positive in certain lags, which could occur due to the sudden increase in the purchasing power of people due to different economic aids. Specifically, for this case, we can observe a maximum lag of 54 days, which would imply a mismatch between the monetary policy decision and the reaction of the capital market. This can also be seen in the Figure 15, which contains a negative correlation.

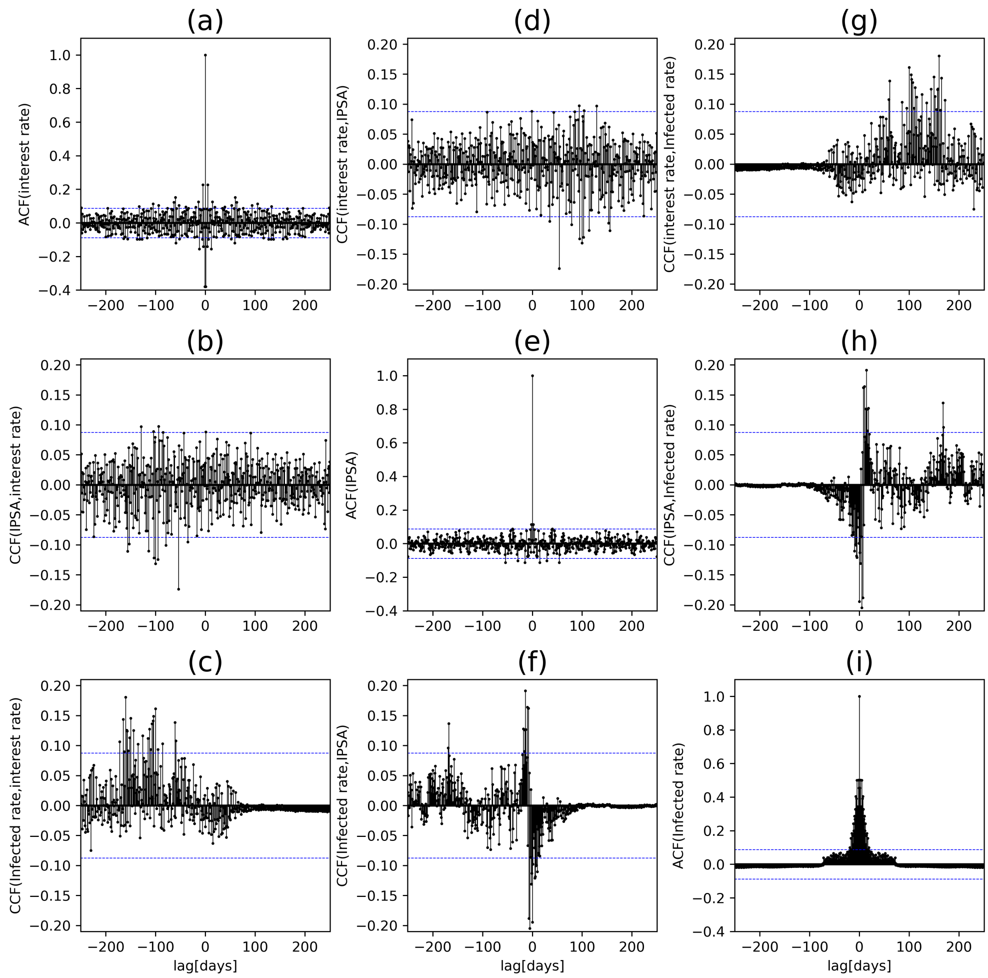

Figure 14. Autocorrelation (ACF) and cross-correlation (CCF) analyses of key economic and health-related variables in Chile, indicating their interdependencies and time-lagged relationships. Autocorrelation for the interest rate, the IPSA index, and the infection rate are displayed in panels (**a**), (**e**), and (**i**), respectively. Cross-correlations are shown in the remaining panels (**b**), (**c**), (**d**), (**f**), (**g**), and (**h**), respectively), clarifying the temporal interactions and dependencies among these variables. To delineate the statistical significance of the autocorrelation coefficients, 95% confidence bands have been added in dashed blue horizontal lines.

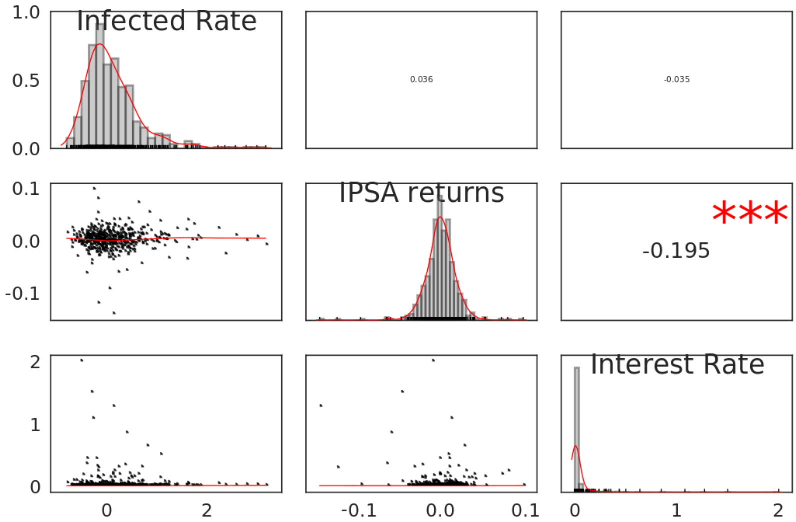

Figure 15. Pearson correlation between Chilean economical variables. Red asterisk means a significant p-value less than 0.001.

Table 5. Chronological sequence of economic measures implemented by Chile from March to August 2020 to alleviate the impact of COVID-19. The measures are categorized into two levels as in [44].

Date	Level 1 Policy Measures	Level 2 Policy Measures
16 March 2020	Liquidity/Funding	Asset purchases
16 March 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
20 March 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
16 March 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
16 March 2020	Liquidity/Funding	Policy rate
16 March 2020	Banking Sector	Support borrowers
30 March 2020	Banking Sector	Operational continuity
31 March 2020	Liquidity/Funding	Policy rate
15 April 2020	Financial Markets/NBFIs	NBFIs
27 April 2020	Banking Sector	Prudential
30 April 2020	Banking Sector	Support borrowers
30 April 2020	Banking Sector	Support borrowers
16 April 2020	Banking Sector	Support borrowers
16 June 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
24 June 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
29 June 2020	Banking Sector	Support borrowers
05 July 2020	Banking Sector	Support borrowers
05 July 2020	Banking Sector	Support borrowers
05 July 2020	Banking Sector	Support borrowers
24 July 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
24 July 2020	Financial Markets/NBFIs	NBFIs
30 July 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
30 July 2020	Liquidity/Funding	Asset purchases
30 July 2020	Liquidity/Funding	Liquidity (incl FX)/ELA
31 July 2020	Banking Sector	Prudential
13 August 2020	Liquidity/Funding	Asset purchases
24 August 2020	Banking Sector	Prudential

Table 6. Crosscorrelations (CCFs) and autocorrelations (ACFs) functions for the Chilean variables: the first column indicates the estimated function, the third and second columns represent the maximum value of the estimated CCF (or ACF) and the corresponding lag, respectively.

Function (CCF or ACF)	lag	max (CCF) or max (ACF)
ACF (Interest rate)	1	−0.37925
CCF (Interest rate, IPSA)	54	−0.17408
CCF (Interest rate, Infected rate)	160	0.18057
CCF (IPSA, Interest rate)	−54	−0.17408
ACF (IPSA)	2	0.11375
CCF (IPSA, Infected rate)	5	−0.20480
CCF (Infected rate, Interest rate)	−160	0.18057
CCF (Infected rate, IPSA)	−5	−0.20480
ACF (Infected rate)	2	0.50206

On the other hand, there was no significant correlation between the infected rate with the IPSA and the interest rate, as shown in Figure 15. However, we can evidence in Table 6 a maximum lag of 160 days between the infected rate and the interest rate and a slight maximum lag of 5 days between the infected rate and the IPSA.

To enhance our analysis, we use the monthly economic activity indicator (IMACEC) described in Section 3.4. Our primary objective was to understand how the economy would have performed if the pandemic and the economic measures provided by the Chilean government were not implemented. Thus, we projected a scenario using historical data to determine of how the IMACEC would have performed without COVID-19 and compared it with the actual behavior. Figure 16a shows the predictions with respect to the observed values. For obtaining this projection, we estimated an additive decomposition time series model until December 2019, and we predicted the IMACEC values for the months of the following years (2020–2023). In order to obtain the confidence interval of the predictions, we simulated 1000 scenarios for different values of the residuals in order to obtain the minimum and maximum values of the bands. As shown in Figure 16b, we calculated the difference between the real and projected scenarios to determine the losses incurred during the studied period. As it can be seen, the red portion represents the potential losses due to the impact of COVID-19 on the economy, thereby resulting in a decrease in economic growth in Chile. In particular, the losses increased in the first period of COVID-19, but the economical measures (especially the withdrawals of pension funds) caused a reactivation of economic activities, which produced a significant increase of the IMACEC in the last month of 2021. In particular, the most impacted sectors in Chile during the COVID-19 pandemic were commerce and services, including restaurants, hotels, transportation, and communications (from the monthly data of the IMACEC sectors in [2]). Despite this, commerce experienced its first positive variation (7.1%) in September 2020, which is attributed to increased liquidity from pension fund withdrawals, as shown in the IMACEC plot of Figure 16b, where the green inverted triangles indicates the withdrawal dates. In contrast, the services sector saw its initial positive increase (6%) in March 2021. Although in the successive months, the IMACEC underwent various changes, we can conclude that the economical measures, implemented in the pandemic period, have produced the sustainability of the Chilean economy.

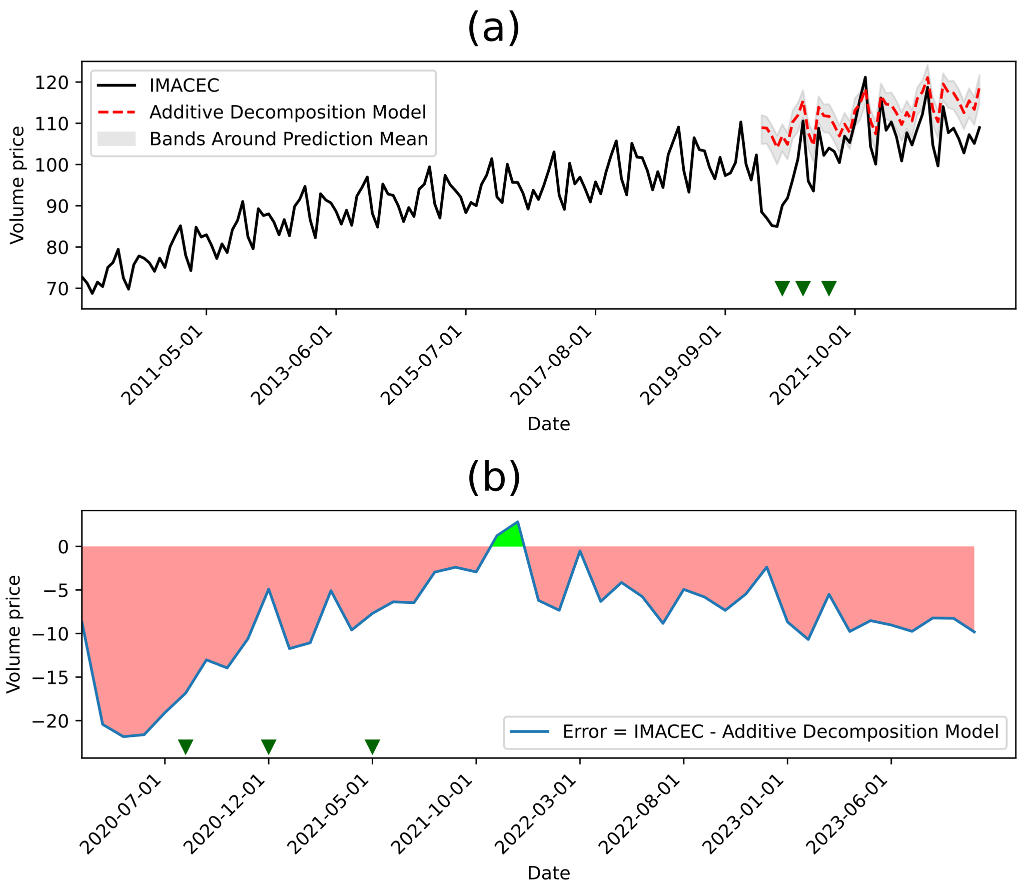

Figure 16. Monthly IMACEC time series (black line) with the projection (red dashed line) for the years 2020–2023 (without COVID-19) obtained using an additive decomposition time series model and its confidence bands (gray area). In panel (**a**) we modeled the IMACEC (black lines) using an additive decomposition model (red dashed lines). The trend (red color) is fitted by a simple linear regression model. The green area represents the confidence interval obtained by simulating 1000 scenarios for different values of the residuals in order to get the minimum and maximum values of the bands. For estimating the trend we fit a simple linear regression model. We then simulate 1000 scenarios for different values of the residuals in order to get the minimum and maximum values of the bands (gray area). The green inverted triangles correspond to the dates where the Chilean government allowed the withdrawal of a percentage (10%) of pension funds. Panel (**b**) shows the estimated difference between the observed IMACEC and the model's predictions. The red and green colors are the negative and positive differences, respectively.

5. Discussion

The impact of COVID-19 caused a significant shock to the economies of all countries in the world. In just one year, the effects could be seen in the lower projections of the different economic indicators, with values that had not been recorded for a long time [1]. The International Monetary Fund recommended adopting economic measures that could halt this slowdown, which were adopted in several countries to help people who lost their jobs and who, as time went by, found themselves increasingly submerged in debt.

The economic impact of the financial sector policies in response to COVID-19 was notable in 2021, with many economies experiencing positive changes. This was reflected in the GDP growth of various countries, as illustrated in Figure 5, thereby indicating a recovery from the challenging year of 2020. The authors in [46] observed that factors like COVID-19 spread, macrofinancial fundamentals, foreign exchange pressures, political dynamics, and fiscal and containment policies had limited influence on policy response decisions, as are also depicted in Figure 4. This figure shows that countries without mitigation policies did not necessarily have higher infection rates. The study emphasizes the importance of ongoing research into cost-effective strategies to mitigate future economic crises caused by pandemics or natural disasters, particularly in Latin American countries, which may struggle to withstand another economic downturn.

The work of Rizvi et al. [33] analyzed several metrics using k-means clustering in order to gain insights for policymakers to tailor strategies for controlling the pandemic. We found that countries were grouped together in two different clusters; on the contrary, Rizvi et al. [33] found four different clusters, but Clusters 1 and 2 partially coincide with ours. Also, it is important to notice that we analyzed the 38 countries that belong to the OECD, and we added 14 non-OECD members (mainly from America); they analyzed 79 countries but not all belonged to OECD.

The results from the second cluster analysis we performed, taking into account the daily infected rate per 100,000 inhabitants for each country, behaved similarly to what Yavuz et al. [37] found, because in both analysis European and Latin American countries were grouped together. One of the limitations is that our work only considers countries from the OECD and a few others that are not, which is different from Yavuz et al. [37], which considered all world countries until 27 June 2021. In our work, we use daily data until the end of 2021, which allowed us to better understand the effects of economical measures postpandemic.

With respect to economic sustainability, our analysis can be compared with the study of [64], where they used a machine learning model to analyze the PIB projection with and without COVID-19 for the EMDEs and AEs. Although Chile can not be included in the AEs, it showed a similar behavior in being the country with the highest nominal GDP per capita in Latin America. Like these economies, it was able to implement measures for a sustainable economy, although small losses continued in the years after the pandemic period.

The Implications for the Involved Stakeholders

The COVID-19 pandemic has caused deep effects on the global economy, thus impacting various stakeholders across different sectors. In particular, the lockdown led to a sharp contraction in worldwide economic activity such as in tourism and commerce, which were forced to close or to operate at reduced capacity. Also, the disruption of supply chains strongly affected manufacturing and distribution processes. However, the most developed countries included in Cluster 2 (such as those of Northern Europe and New Zealand, among others) managed to keep the GDP sufficiently high despite the high number of people affected by COVID-19, and lower implemented measures, which was probably due to their high flexibility to implement digital transformation initiatives.

In the case of Chile, the monthly index of economic activity (IMACEC) significantly decreased to a maximum of 15.3% on May of 2020 with respect to the previous year. This variation includes the mining IMACEC, which grew by 1.2%, while the nonmining IMACEC fell by 17.0% in the same month. The most affected activities were services and commerce, and, to a lesser extent, manufacturing and construction. Specifically in services, noteworthy reductions were observed in education, transportation, and business services, as well as in restaurants and hotels. When seasonally adjusted and compared to the preceding month, the mining IMACEC exhibited a 0.6% decrease, while the nonmining IMACEC saw a decline of 3.7% [2]. A similar situation continued in the following two months, where the result was partially offset by a slight growth in commerce, which was probably due to the first fund pension withdrawal authorized by the Chilean government. The first positive IMACEC variation (0.3%) occurred on November 2020 due to the people mobility, which influenced the stable working of manufacturing and construction plants.

Also, the pandemic strongly affected the world and Chilean financial markets, which produced a high volatility of stock prices, during the initial phases of the pandemic, due to the uncertainty of investors about the future of the economy.

6. Conclusions

This work has explored various dimensions of the COVID-19 pandemic's impact on countries worldwide. We began by investigating the economic measures taken in response to the pandemic, thus highlighting the diversity of policy responses among countries. Despite Chile's relatively low number of economic measures, we observed other countries that did not take economic measures at all. Notably, India, Italy, and Spain were at the forefront of implementing mitigation policies.

Our cluster formation analysis incorporated various static data parameters, thereby encompassing aspects related to pandemic development, mitigation policies, GDP variations, and cumulative infection rates. Through the application of hierarchical and k-means clustering methods, we were able to delineate two distinct clusters within our dataset. An interesting finding emerged, as Latin American countries exhibited a notable propensity to cluster together, thus forming a cohesive subgroup within one of the identified clusters. Similarly, Asian and Oceania countries tended to coalesce within the same cluster, thereby further emphasizing regional patterns. This study carried out significant findings by extending the analytical framework proposed by previous researchers (see, [37] for example), thus exploring not only the epidemiological component but also the economic and political implications of infectious diseases. The congruence in outcomes between the two analytical perspectives is particularly noteworthy.

We employed dynamic time warping as a distance metric in hierarchical clustering to address the temporal disparities in the pandemic's spread. This approach facilitated the alignment of infection rate time series, thereby overcoming the challenges related to varying pandemic onset dates. While the number of countries in the smaller cluster previously described decreased its size, there was consistency when comparing the countries in this cluster in the two different analyses. The projection of clusters onto the first three principal components further enhanced our understanding, thereby revealing a more precise separation of groups and providing deeper insights into country distribution within a three-dimensional space. Based on the findings from the clustering analysis, we validate the hypotheses suggesting variations in the economic impact of COVID-19 across different countries being attributable to diverse mitigation strategies, economic responses, and infection rates.

The Chilean case analysis allows us to better understand the relationship between the main economic variables and how they react to the economic measures established during the most substantial pandemic. The study of the IMACEC allowed us to detect the main affected productive sectors during pandemic. This supports the hypothesis regarding the specific impacts and responses in this country, thereby enhancing our comprehensive understanding of the economic effects of the pandemic.

On the other hand, being one of the few countries in the world that allowed the withdrawal of pension funds caused higher inflation than for other countries, which forced the central bank to take more drastic measures than even the US. Allowing withdrawals from pension funds caused many Chileans to have little or no funds to retire with in the future, which will generate a more significant burden on the state.

In conclusion, our study unveils the distinct responses of OECD countries and Chile to the COVID-19 pandemic. We discovered varying levels of economic resilience and identified the efficacy of diverse mitigation strategies. Particular findings have to be highlighted, such as the significant negative deviation in Chile's economic indicators, ranging from -20% to -5% throughout 2020 and into part of 2021, compared to the projections without COVID-19. For the OECD countries, we found a correlation between GDP, mitigation measures, and infection rates. These findings offer valuable insights for policymakers, thereby aiding in the development of effective strategies to manage the economic impacts of health crises.

For future work, it is expected to disaggregate at a smaller level the analyses carried out previously by applying the input–output model and the sequential interindustry model (SIM) like [65] to quantify the economic relationships (losses) between productive activities and regions in addition to the possibility of regionalizing the economic losses (GDP) produced by the pandemic, thereby taking into account that the numbers of infected people per region are available. It is also essential to study the expenditure (per capita) of economic aid that should be made in the present in the face of a natural disaster or a pandemic that does not imply a more significant future expenditure for governments.

Author Contributions: Conceptualization, O.N., J.P.M. and D.L.; Methodology, O.N., J.P.M. and D.L.; Software, J.P.M., F.C. and D.L.; Validation, O.N. and D.L.; Formal analysis, O.N.; Investigation, O.N., J.P.M. and F.C.; Writing—original draft, J.P.M. and D.L.; Writing—review & editing, O.N. and D.L.. All authors have read and agreed to the published version of the manuscript.

Funding: The authors thank the support of the Research Center for Integrated Disaster Risk Management (CIGIDEN) through the FONDAP project 1522A0005.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article.

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

References

1. World Bank. *Global Economic Prospects, June 2020*; World Bank: Washington, DC, USA, 2020. Available online: https://openknowledge.worldbank.org/handle/10986/33748 (accessed on 22 October 2023).
2. Banco Central de Chile, Base de Datos Estadísticos, Cuentas Nacionales. Available online: https://si3.bcentral.cl/Siete/ES/Siete/Cuadro/CAP_CCNN/MN_CCNN76/CCNN2013_P2_MD/CCNN2013_P2_MD (accessed on 22 October 2023).
3. Bloom, N.; Bunn, P.; Mizen, P.; Smietanka, P.; Thwaites, G. The Impact of COVID-19 on Productivity. *Rev. Econ. Stat.* **2023**, 1–45. [CrossRef]
4. Pak, A.; Adegboye, O.A.; Adekunle, A.I.; Rahman, K.M.; McBryde, E.S.; Eisen, D.P. Economic Consequences of the COVID-19 Outbreak: The Need for Epidemic Preparedness. *Front. Public Health* **2020**, *8*, 241. [CrossRef] [PubMed]
5. Clemente-Suárez, V.J.; Navarro-Jiménez, E.; Jimenez, M.; Hormeño-Holgado, A.; Martinez-Gonzalez, M.B.; Benitez-Agudelo, J.C.; Perez-Palencia, N.; Laborde-Cárdenas, C.C.; Tornero-Aguilera, J.F. Impact of COVID-19 Pandemic in Public Mental Health: An Extensive Narrative Review. *Sustainability* **2021**, *13*, 3221. [CrossRef]
6. Brzyska, J.; Szamrej-Baran, I. The COVID-19 Pandemic and the Implementation of Sustainable Development Goals: The EU Perspective. *Sustainability* **2023**, *15*, 13503. [CrossRef]
7. Nicola, M.; Alsafi, Z.; Sohrabi, C.; Kerwan, A.; Al-Jabir, A.; Iosifidis, C.; Agha, M.; Agha, R. The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *Int. J. Surg.* **2020**, *78*, 185–193. [CrossRef]
8. Vasile, V.; Bunduchi, E. (Eds.) *The Economic and Social Impact of the COVID-19 Pandemic*; Springer: Cham, Switzerland, 2024.
9. Ahmad, T.; Haroon, B.M.; Hui, J. Coronavirus Disease 2019 (COVID-19) Pandemic and Economic Impact. *Pak. J. Med. Sci.* **2020**, *36*, S73–S78. [CrossRef]
10. Safonov, Y.; Borshch, V. Economic consequences of COVID-19 and the concepts of their overcoming. *Ef. Ekon.* **2020**, *5*. [CrossRef]
11. Mofijur, M.; Fattah, I.R.; Alam, M.A.; Islam, A.S.; Ong, H.C.; Rahman, S.A.; Najafi, G.; Ahmed, S.F.; Uddin, M.A.; Mahlia, T.M.I. Impact of COVID-19 on the social, economic, environmental and energy domains: Lessons learnt from a global pandemic. *Sustain. Prod. Consum.* **2020**, *26*, 343–359. [CrossRef]
12. Brodeur, A.; Gray, D.; Islam, A.; Bhuiyan, S. A literature review of the economics of COVID-19. *J. Econ. Surv.* **2021**, *35*, 1007–1044. [CrossRef]
13. Mishra, N.P.; Das, S.S.; Yadav, S.; Khan, W.; Afzal, M.; Alarifi, A.; Kenawy, E.R.; Ansari, M.T.; Hasnain, M.S.; Nayak, A.K. Global impacts of pre- and post-COVID-19 pandemic: Focus on socio-economic consequences. *Sens. Int.* **2020**, *1*, 100042. [CrossRef] [PubMed]
14. Simak, S.; Davydiuk, Y.; Burdeina, N.; Budiaiev, M.; Taran, O.; Ingram, K. Comprehensive assessment of the economic consequences of the COVID-19 pandemic. *Sci. Bull. Natl. Min. Univ.* **2020**, *6*, 168–173. [CrossRef]
15. Barua, S. Understanding Coronanomics: The Economic Implications of the Coronavirus (COVID-19) Pandemic. 2020. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3566477 (accessed on 8 November 2023).
16. Gavrilovic, K.; Vucekovic, M. Impact and Consequences of the COVID-19 Virus on the Economy of the United States. *Int. Rev.* **2020**, 56–64. [CrossRef]
17. Padhan, R.; Prabheesh, K.P. The Economics of COVID-19 Pandemic: A Survey. *Econ. Anal. Pol.* **2021**, *70*, 220–237. [CrossRef]
18. Shcherbakov, G.A. The Impact and Consequences of the COVID-19 Pandemic: A Socio-Economic Dimension. *WORLD (Mod. Innov. Dev.)* **2021**, *12*, 8–22. [CrossRef]
19. Rodela, T.T.; Tasnim, S.; Mazumder, H.; Faizah, F.; Sultana, A.; Hossain, M. Economic Impacts of Coronavirus Disease (COVID-19) in Developing Countries. 2020. Available online: https://osf.io/preprints/socarxiv/wygpk (accessed on 22 October 2023).

20. Liu, W.-P.; Chu, Y.-C. FinTech, economic growth, and COVID-19: International evidence. *Asia Pac. Manag. Rev.* 2024, *in press*. [CrossRef]
21. König, M.; Winkler, A. COVID-19: Lockdowns, Fatality Rates and GDP Growth. *Intereconomics* **2021**, *56*, 32–39. [CrossRef] [PubMed]
22. Lassard Rosenthal, J.; Medina Núñez, C.; Palmero Picazo, J.; de la Parra Muñoz, B.E.; Mejía Martínez, L.L.; Rivas Morales, J.M. «SCORE-CoV-2» y su relación con el comportamiento del PIB. *Anáhuac J.* **2021**, *21*, 66–93. [CrossRef]
23. Jena, P.R.; Majhi, R.; Kalli, R.; Managi, S.; Majhi, B. Impact of COVID-19 on GDP of major economies: Application of the artificial neural network forecaster. *Econ. Anal. Policy* **2021**, *69*, 324–339. [CrossRef]
24. De la Fuente-Mella, H.; Rubilar, R.; Chahuán-Jiménez, K.; Leiva, V. Modeling COVID-19 Cases Statistically and Evaluating Their Effect on the Economy of Countries. *Mathematics* **2021**, *9*, 1558. https://doi.org/10.3390/math9131558. [CrossRef]
25. Ruiz-Estrada, M.A. COVID-19: Economic recession or depression? *Estud. Econ.* **2020**, *37*, 139–147. Available online: http://www.scielo.org.ar/scielo.php?script=sci_arttext&pid=S2525-12952020000200007&lng=es&tlng=en (accessed on 4 January 2023). [CrossRef]
26. He, Y.; Zhang, Z. Energy and Economic Effects of the COVID-19 Pandemic: Evidence from OECD Countries. *Sustainability* **2022**, *14*, 12043. [CrossRef]
27. Restrepo-Morales, J.A.; Valencia-Cárdenas, M.; García-Pérez-de-Lema, D. The role of technological innovation in the mitigation of the crisis generated by COVID-19: An empirical study of small and medium-sized businesses (SMEs) in Latin America. *Int. Stud. Manag. Organ.* **2024**. [CrossRef]
28. Wu, J. *Cluster Analysis and k-Means Clustering: An Introduction in Advances in K-Means Clustering: A Data Mining Thinking*; Springer Science & Business Media: New York, NY, USA, 2012; pp. 1–16.
29. Benmahdi, M.; Lehsaini, M. Performance evaluation of main approaches for determining optimal number of clusters in wireless sensor networks. *Int. J. Ad Hoc Ubiquitous Comput.* **2020**, *33*, 184. [CrossRef]
30. Halkidi, M. Hierarchial Clustering. In *Encyclopedia of Database Systems*; Liu, L., Özsu, M.T., Eds.; Springer: Boston, MA, USA, 2009. [CrossRef]
31. Gohari, K.; Kazemnejad, A.; Sheidaei, A.; Hajari, S. Clustering of countries according to the COVID-19 incidence and mortality rates. *BMC Public Health* **2022**, *22*, 632. [CrossRef] [PubMed]
32. Zarikas, V.; Poulopoulos, S.G.; Gareiou, Z.; Zervas, E. Clustering analysis of countries using the COVID-19 cases dataset. *Data Brief* **2020**, *31*, 105787. [CrossRef]
33. Rizvi, S.A.; Umair, M.; Cheema, M.A. Clustering of countries for COVID-19 cases based on disease prevalence, health systems and environmental indicators. *Chaos Solitons Fractals* **2021**, *151*, 111240. [CrossRef]
34. Sadeghi, B.; Cheung, R.C.Y.; Hanbury, M. Using hierarchical clustering analysis to evaluate COVID-19 pandemic preparedness and performance in 180 countries in 2020. *BMJ Open* **2021**, *11*, e049844. [CrossRef]
35. Rahman, M.A.; Zaman, N.; Asyhari, A.T.; Al-Turjman, F.; Alam, Bhuiyan, M.Z.; Zolkipli, M.F. Data-driven dynamic clustering framework for mitigating the adverse economic impact of COVID-19 lockdown practices. *Sustain. Cities Soc.* **2020**, *62*, 102372. [CrossRef]
36. Sakoe, H.; Chiba, S. Dynamic programming algorithm optimization for spoken word recognition. *IEEE Trans. Acoust. Speech Signal Process.* **1978**, *26*, 43–49. [CrossRef]
37. Yavuz, F.; Guney, Y.; Özdemir, Ş.; Tuaç, Y.; Arslan, O. The Clustering Structure of the COVID-19 Outbreak in Global Scale. *Adv. Data Sci. Adapt. Anal.* **2022**, *14*, 2250005. [CrossRef]
38. Luo, Z.; Zhang, L.; Liu, N.; Wu, Y. Time series clustering of COVID-19 pandemic-related data. *Data Sci. Manag.* **2023**, *6*, 79–87. [CrossRef]
39. Mahmoudi, M.; Baleanu, D.; ; Mansor, Z.; Tuan, B.; Kim-Hung, P. Fuzzy Clustering method to Compare the Spread Rate of Covid-19 in the High Risks Countries. *Chaos Solitons Fractals* **2020**, *140*, 110230. [CrossRef]
40. Zhou, X.; Moinuddin, M. Impacts and implications of the COVID-19 crisis and its recovery for achieving sustainable development goals in Asia A review from an SDG interlinkage perspective. In *Environmental Resilience and Transformation in Times of COVID-19*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 273–288. [CrossRef]
41. Teresiené, D.; Keliuotyté-Staniuléniené, G.; Kanapickiené, R. Sustainable Economic Growth Support through Credit Transmission Channel and Financial Stability: In the Context of the COVID-19 Pandemic. *Sustainability* **2021**, *13*, 2692. [CrossRef]
42. Przybytniowski, J.W.; Borkowski, S.; Grzebieniak, A.; Garasyim, P.; Dziekański, P.; Ciesielska, A. Social, Economic, and Financial Aspects of Modelling Sustainable Growth in the Irresponsible World during COVID-19 Pandemic. *Sustainability* **2022**, *14*, 12480. [CrossRef]
43. World Bank Open Data | Total Population Using ID: WSP.POP.TOTL. Available online: https://data.worldbank.org/ (accessed on 22 October 2023).
44. COVID-19 Finance Sector Related Policy Responses | Updated 18 January 2023. Available online: https://datacatalog.worldbank.org/search/dataset/0037999 (accessed on 22 October 2023).
45. World Bank Open Data | GDP (Current US$). Available online: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD (accessed on 22 October 2023).
46. Feyen, E.; Gispert, T.A.; Kliatskova, T.; Mare, D.S. Financial Sector Policy Response to COVID-19 in Emerging Markets and Developing Economies. *J. Bank. Financ.* **2021**, *133*, 106184. [CrossRef]

47. Chilean Stock Market Index IPSA Data from the Public Web Site. Available online: https://es.investing.com/indices/ipsa-historical-data (accessed on 22 October 2023).
48. Annual Chilean Interest Rates Percentages, Monthly Base (TIP Colocaciones de 90 Días a un Año, no Reajustable). From Mean Rate of Financial System. Available online: https://si3.bcentral.cl/Indicadoressiete/secure/IndicadoresDiarios.aspx (accessed on 22 October 2023).
49. Steinhaus, H. Sur la division des corps matériels en parties. *Bull. L'AcadÉmie Pol. Des Sci.* **1957**, *4*, 801–804. (In French)
50. MacQueen, J. Some Methods for Classification and Analysis of Multivariate Observations. In Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability, Los Angeles, CA, USA, 21 June–18 July 1965; Volume 1, pp. 281–297.
51. Nielsen, F. Hierarchical Clustering. In *Introduction to HPC with MPI for Data Science. Undergraduate Topics in Computer Science*; Springer: Cham, Switzerland, 2016. [CrossRef]
52. Berndt, D.; Clifford, J. Using Dynamic Time Warping to Find Patterns in Time Series. In Proceedings of the 3rd International Conference on Knowledge Discovery and Data Mining, Seattle, WA, USA, 31 July–1 August 1994; AAAI Press: Washington, DC, USA, 1994; pp. 359–370.
53. Li, H.; Liu, J.; Yang, Z.; Liu, R.W.; Wu, K.; Wan, Y. Adaptively constrained dynamic time warping for time series classification and clustering. *Inf. Sci.* **2020**, *534*, 97–116. [CrossRef]
54. Thorndike, R.L. Who belongs in the family? *Psychometrika* **1953**, *18*, 267–276. [CrossRef]
55. Rousseeuw, P.J. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.* **1987**, *20*, 53–65. [CrossRef]
56. Tibshirani, R.; Guenther, W.; Hastie, T. Estimating the Number of Clusters in a Data Set via the Gap Statistic. *J. R. Stat. Soc. Ser. B (Stat. Methodol.)* **2001**, *63*, 411–423. [CrossRef]
57. Brockwell, P.J.; Davis, R.A. (Eds.) *Introduction to Time Series and Forecasting*; Springer: New York, NY, USA, 2002. [CrossRef]
58. Seabold, S.; Perktold, J. Statsmodels: Econometric and statistical modeling with python. In Proceedings of the 9th Python in Science Conference, Austin, TX, USA, 28 June–3 July 2010. [CrossRef]
59. World Health Organization (WHO) Daily Cases and Deaths by Date Reported to WHO. Available online: https://covid19.who.int/WHO-COVID-19-global-data.csv (accessed on 22 October 2023).
60. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2023. Available online: https://www.R-project.org/ (accessed on 22 October 2023).
61. FIAP. Retiro de Fondos: Desnaturalizando los Sistemas de Pensiones, una Mirada a los Efectos de Esta Politica Publica. 2021. Available online: www.fiapinternacional.org (accessed on 22 October 2023).
62. Leal, D.; Jiménez, R.; Riquelme, M.; Leiva, V. Elliptical Capital Asset Pricing Models: Formulation, Diagnostics, Case Study with Chilean Data, and Economic Rationale. *Mathematics* **2023**, *11*, 1394. [CrossRef]
63. Stehlik, M.; Leal, D.; Kiseak, J.; Leers, J.; Strelec, J.; Fuders, F. Stochastic approach to heterogeneity in short-time announcement effects on the Chilean stock market indexes within 2016–2019. *Stoch. Anal. Appl.* **2023**, *42*, 1–19. [CrossRef]

64. Shuai, C.; Zhao, B.; Chen, X.; Liu, J.; Zheng, C.; Qu, S.; Zou, J.-P.; Xu, M. Quantifying the impacts of COVID-19 on Sustainable Development Goals using machine learning models. *Fundam. Res.* **2022**. [CrossRef]
65. Okuyama, Y.; Hewings, G.; Sonis, M. Sequential Interindustry Model (SIM) and Impact Analysis: Application for Measuring Economic Impact of Unscheduled Events. In Proceedings of the 47th North American Meetings of the Regional Science Association International, Chicago, IL, USA, 9–11 November 2000.