BER J BUSINESS AND ECONOMICS RESEARCH JOURNAL
www.berjournal.com ISSN: 2619-9491

Business and Economics Research Journal Vol. 16, No.4, 2025 pp. 395-416 doi: 10.20409/berj.2025.474

The Relationship Between Misery Index and Stringency Index for Emerging Markets: A Wavelet Analysis

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Abstract: *This study examines whether the degree of strictness in economic and social isolation measures implemented by governments to prevent the spread of Covid-19 is related to the level of inflation and unemployment in the country. Data from Brazil, Russia, India, Mexico, South Korea, and Türkiye were used in the study. The analysis used the stringency index, misery index, and vaccination rate series of the countries. The empirical analysis covers the 24 months from January 2020 to December 2021. The causality relationship in the analysis was examined with panel data analysis, where the series were divided into frequencies using the wavelet method. According to the results obtained, it is seen that there is a bidirectional causality relationship between the stringency index and misery indices at 4-month frequencies. These results indicate that the stringency index and misery index interact with each other over four-month periods. In other words, in countries with high unemployment and inflation rates, restrictions are affected by the misery index.*

Keywords: Covid-19, Misery Index, Stringency Index, Wavelet Method, Panel Data

JEL: E24, E31, C02

Received : 23 May 2025
Revised : 23 July 2025
Accepted : 09 October 2025

Type : Research

1. Introduction

From a world perspective, the Covid-19 pandemic can be listed as one of the most important sociological events of the 21st century. Due to this pandemic, many deaths occurred between 2020-2021, and intensive care rates reached their highest levels in the world. Experts have put forward some measures to prevent the disease from spreading and infecting people. Thus, many developed and developing countries followed the recommendations of the World Health Organization (WHO) and imposed some restrictions on social life. For this reason, while social activities in the world are restricted, economic activities are also affected by this situation. One of the main problems that governments have faced during the pandemic is the need to slow down economic activity in order to reduce the spread of the disease. The risk of spreading the disease is particularly high in densely populated areas such as restaurants, markets and public transport. To minimise this risk, governments have introduced social distancing rules. The severity of the policies implemented has been determined by taking into account the daily number of infections and deaths (Sheridan et al., 2020: 20468). Because the intensive social measures taken in many countries against this disease, whose treatment method is not known enough, included a decrease in human mobility, these measures also meant a slowdown in economic life.

Cite this article as: Gürbüz, S., & Tombak, F. (2025). The relationship between misery index and stringency index for emerging markets: A wavelet analysis. *Business and Economics Research Journal, 16*(4), 395-416. http://dx.doi.org/10.20409/berj.2025.474

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Both production slowed down and demand came to a halt due to society's inability to consume. Faced with a crisis on both supply and demand sides, developed and developing countries began to print free money at the expense of inflation in order to combat unemployment. The US Federal Reserve (FED) first cut interest rates and then announced that it would purchase $700 billion worth of bonds. Similarly, the EU Central Bank announced that it would purchase €750 billion worth of public and private sector bonds (Pehlivan et al., 2021: 118). Especially since developing countries have already been struggling with high unemployment for years, with the pandemic, they would either choose to protect public health by increasing social and economic life restrictions, or they would choose to endanger public health by reducing social and economic life restrictions in order not to further increase the already high unemployment. The lockdown has been linked to a significant economic recession. The declines in output and consumption resulting from the current virus surpass those caused by the Spanish flu, even when considering conservative estimates.

A critical issue for policymakers is how to balance the trade-off between controlling the virus's spread and the intensity of the lockdown measures. Addressing this trade-off presents a substantial challenge in the context of a pandemic (Dreger & Gros, 2021: 450). Therefore, it would not be wrong to say that this dilemma is the reason why some developing countries reacted late or less than expected to quarantine measures. Supporting this, according to the research findings of Cross et al. (2020), while the number of infections decreased in countries that responded quickly to the pandemic and closed down faster, the deterioration in GDP was faster than in other countries. Another important finding of this study is that there are countries trying to support GDP by postponing restrictions or reducing quarantine strictness in order to limit the impact of Covid-19 on the economy in the short term.

The negative picture that emerged in the economy was causing some results that households would not be happy with. The most negative factors that emerged from the perspective of households are seen as inflation and unemployment. These two phenomena that negatively affect people's well-being are also called the economic discontent index or the misery index (Cohen et al., 2014: 2) The 'economic discomfort index' (EDI), also known as Okun's misery index and developed by Arthur Okun in 1970, was probably one of the first attempts to combine various macroeconomic indicators into a single statistic for tracking the overall health of the macroeconomy throughout the business cycle. In its initial form, the misery index combines two primary objectives of macroeconomic policy—unemployment and inflation—into a basic aggregate disutility function. This function assesses the level of economic discomfort as the unweighted sum of the unemployment and inflation rates (Mankiw, 2010). As unemployment and inflation rates rise, the misery index correspondingly increases, whereas a decline in these rates leads to a reduction in the index.

In empirical research on policy responses to the Covid-19 pandemic, one of the most widely used composite measures is the stringency index developed by the University of Oxford as part of the Oxford Covid-19 Government Response Tracker (OxCGRT) project (Hale et al., 2021). The stringency index is a numerical indicator (ranging from 0 to 100) that quantifies the strictness of government-imposed measures aimed at containing the spread of the virus. It provides a standardized metric to compare policy responses across countries and over time.

The index is constructed from nine policy indicators that capture the scope and intensity of containment and closure measures: School closures, workplace closures, cancellation of public events, restrictions on gatherings, public transport closures, stay-at-home requirements, restrictions on internal movement, international travel controls and public information campaigns. Each indicator is coded on an ordinal scale according to the severity of the measure (e.g., from “no measures” to “strictly enforced closures”). These ordinal values are rescaled to a 0–100 range and aggregated, with the final index representing the average of the nine rescaled scores (Hale et al., 2021). Importantly, the index is a measure of policy strictness, not policy effectiveness—it reflects the stringency of rules in place, regardless of compliance levels or actual health outcomes.

Researchers have used the stringency index extensively in cross-country panel data studies to examine the relationships between policy interventions and epidemiological, economic, or behavioral outcomes (Demir & Ersan, 2021; Sebhatu et al., 2020). For example, in an instrumental variables (IV) regression framework, the stringency index can serve either as an explanatory variable capturing policy intensity or as an instrument for related endogenous variables, provided the relevance and exogeneity conditions are met.

The utility of the stringency index lies in its comparability and temporal coverage—it is updated regularly and covers a large number of countries and regions. However, scholars caution that it may mask heterogeneity in enforcement, local-level variation, and contextual factors influencing the impact of policies (Hale et al., 2021; Ritchie et al., 2022). Thus, while it is a powerful tool for empirical analysis, it should be interpreted in conjunction with other qualitative and quantitative data sources. An increase in the stringency index, reflecting stricter government-imposed restrictions, tends to slow down economic activity. This deceleration can lead to rising unemployment, particularly in sectors reliant on face-to-face interaction, such as services. Hale et al. (2021) emphasize that while strict measures are essential in combating pandemics, they come with economic costs, especially for low- and middle-income countries, where such policies may contribute to higher unemployment. Similarly, Pak et al. (2020) demonstrate that Covid-19 measures significantly curtailed economic activity, with varying effects on unemployment and inflation across countries. Aknin et al. (2022) also highlight that while stringent restrictions are critical for public health, they may have adverse effects on individuals' psychological and economic well-being. Deb et al. (2020, IMF) find a positive relationship between strict containment measures and economic misery during the pandemic, though they suggest this impact can be mitigated by state support and fiscal interventions. Furthermore, these policies may generate supply-side shocks that can contribute to inflation. Harsh lockdowns can increase economic uncertainty and financial hardship, thereby diminishing individuals' overall well-being and potentially influencing not only the statistical but also the perceived dimension of "misery." These impacts are more acutely felt by vulnerable groups such as low-income earners, the unemployed, and informal workers (Blundell et al., 2020).

There is also a theoretical and empirical basis for the reverse relationship—namely, that the misery index (the sum of unemployment and inflation rates) can influence the stringency index. In other words, beyond strict government policies exacerbating economic hardship, economic misery itself may prompt governments to ease restrictions. This inverse relationship becomes particularly salient when examined through the lenses of political economy, social acceptance, and governance pressure. A high misery index signals widespread economic distress among citizens. In response to growing dissatisfaction and the threat of civil unrest, governments may feel compelled to relax restrictions earlier or avoid imposing new ones in order to maintain economic activity and respond to public and private sector pressure. This tendency is especially relevant in democratic regimes, where elected officials may resort to populist or pragmatic strategies to retain public support (Acemoglu & Robinson, 2006).

The effectiveness of strict measures is not only dependent on policy decisions but also on the degree of societal compliance. However, elevated levels of economic hardship can erode individuals' motivation to adhere to these restrictions, thereby undermining governments' capacity to sustain them. For low-income individuals in particular, the imperative to survive economically may make it difficult to comply with lockdowns. Governments, in turn, may be pressured to ease measures in order to accommodate these realities. Ashraf (2020) provides evidence that governments in economically fragile countries tend to adopt less restrictive policies. Gurvich and Vlasov (2021) similarly argue that governments eased pandemic restrictions due to economic distress, which was closely linked to political support. Fotiou and Lagerborg (2021) find that during the pandemic, containment policies had to be adjusted in response to economic conditions, with unemployment and inflationary pressures placing clear constraints on the extent of policy stringency.

The main purpose of the study is to investigate whether the degree of stringency of the measures when developing countries took quarantine measures during the 2020-2021 period, which was the peak period of the Covid-19 pandemic, was affected by the unemployment and inflation data of these countries. However, this study is important in ensuring that developing countries review their policies in the face of any public health threat, especially due to concerns about new virus spreads and a renewed pandemic, which have started to be discussed again recently. For example, Zumla et al. (2024) state that diseases of the upper respiratory tract, such as MERS-CoV, are particularly prevalent in Africa and pose a potential pandemic risk.

According to He and Kam (2024), avian influenza viruses have posed a potential pandemic risk ever since they were first discovered. It will provide a foresight to ensure that the social and economic life restriction measures that these countries may implement in the future will not be affected by their macroeconomic conditions. Therefore, the study is instructive in that it proves that the decisions taken by policy makers depend on the macroeconomic performance of their countries.

In this study, the BRICS countries Brazil, Russia, and India, along with the MIST countries Mexico, South Korea, and Türkiye, were examined. China and South Africa from the BRICS group and Indonesia from the MIST group were excluded due to the unavailability of relevant data. Goldman Sachs economist Jim O'Neill (2001, 2005, 2011) had earlier projected that by the mid-21st century, these economies would surpass the G7 nations in terms of economic strength (Gök & Gök, 2016: 1). Both BRICS and MIST countries are also members of the G20. The study contributes to the literature by investigating whether social and economic lockdown restrictions during the pandemic affected unemployment and inflation in countries such as Brazil, Russia, India, Mexico, South Korea, and Türkiye. Furthermore, by employing wavelet analysis to decompose the series into frequencies and applying a panel IV fixed-effects model, the study seeks to address potential endogeneity issues through the use of instrumental variables. The Okun Misery Index was chosen as the primary indicator, as the focus of the research is on inflation and unemployment. The inclusion of alternative misery indices would have complicated the analysis unnecessarily.

The study consists of five sections. The next section contains the literature review. After giving a general summary of the studies conducted on the misery index and stringency index in the literature, the contribution of the studies to the literature is explained. In the third section of the study, the data and method were discussed. Country data of the misery and stringency indexes included in the study were interpreted with graphs. In the fourth section, the findings from the empirical analysis are presented. In the last section, results and evaluations are given.

2. Literature Review

The global spread of Covid-19 has raised significant concerns regarding its impact on national economies. Several studies in the literature have investigated the impact of lockdowns on stock markets, mostly focusing on the U.S. and Chinese exchanges. Others have directly examined the effects of lockdowns on economic growth, particularly analyzing changes in GDP. Beyond these, some studies have incorporated the misery index, while others have explored the impact of lockdowns on unemployment.

Sharif et al. (2020) analyzed the effects of the rapid spread of Covid-19 and oil price shocks on stock market volatility, geographic risk, and economic policy uncertainty in the U.S. economy. Using daily data from January 21 to March 30, 2020, they conducted wavelet transform and Granger causality analyses, revealing short-term and unpredictable effects, with the impact on geographic risk found to be stronger than that on economic uncertainty. Qureshi (2021) employed a continuous wavelet transform approach to examine the relationship between the Covid-19 pandemic and economic indicators in China and the U.S., including stock returns, exchange rates, government bond yields, and CDS risk premiums. The findings indicate that contagion effects in the Chinese stock market had a more pronounced impact on domestic sectoral returns compared to those in the U.S. He et al. (2021) compared the macroeconomic performance of China and the U.S., the first two countries affected by the pandemic. Their results suggested that China's consistent policies and timely lockdown measures resulted in less severe negative outcomes than those observed in the U.S., supported by indicators such as the purchasing managers' index (PMI), the Shanghai composite index, news-based indices, and monetary aggregates. Sergi et al. (2021) analyzed the effects of the Barro misery index and the rise in Covid-19 cases and deaths on stock returns and volatility using data from 76 countries. Their findings revealed a negative relationship between the misery index and stock returns, and a positive relationship with market volatility. They further argued that incorporating changes in inflation, instead of GDP, unemployment, or interest rates, into the misery index yields more robust results, particularly in developed countries. Sakawa and Watanabel (2022) used a case study approach to investigate the impact of negative Covid-19-related news on the stock prices of Japanese maritime companies. They highlighted that the detention of the Diamond Princess cruise ship, following the Japanese government's border closure policy on February 3, 2020, had a significantly negative effect on stock market returns.

Cross et al. (2020) examined the impact of the stringency index on inflation and economic growth in China and 37 OECD countries, using data from January 1 to July 6, 2020. They found that although countries that responded quickly to the pandemic experienced fewer infections, they also suffered greater GDP declines. Additionally, some countries delayed or relaxed restrictions in an effort to mitigate short-term economic damage. The study noted that China implemented the strictest measures, while Sweden and Japan adopted more lenient approaches. Goswami et al. (2021) investigated the impact of Covid-19 on India's macroeconomic performance using panel data between April and November 2020. Their findings revealed that disruptions in employment during the pandemic led to significant economic losses, and that the nationwide lockdowns in April and May 2020 severely hindered economic activity. Siddik (2020) developed a Covid-19 economic stimulus index to assess policy responses across countries. The index was found to be statistically significant, and the study revealed that countries such as Chile, Switzerland, Croatia, Sweden, and the Netherlands implemented stricter economic measures than others, while most countries increased their economic support during this period. Coccia (2021) analyzed the effects of long-term lockdowns on GDP in six countries—Austria, Portugal, Sweden, France, Spain, and Italy—and found that extended restrictions resulted in an average GDP contraction of 21% from the second quarter of 2019 to the second quarter of 2020. However, countries with shorter lockdowns, such as Austria, Portugal, and Sweden, experienced higher infection rates compared to those with longer lockdowns. Ashraf and Goodell (2022) studied the effects of social distancing policies on GDP growth in 46 OECD countries, using data from the first quarter of 2020 to the second quarter of 2021. While they identified short-term negative impacts, these effects diminished over the longer term.

König and Winkler (2020) drew on revisions proposed by the OECD, IMF, and World Bank to examine the extent to which government policies should be implemented during the pandemic. They employed the Economist intelligence unit index to assess policy quality, the misery ındex to measure macroeconomic performance, and the stringency ındex to evaluate the severity of lockdown measures. Their findings suggested that countries with stronger economic performance were likely to experience less severe downward growth revisions, while those dependent on tourism revenues were more adversely affected. Lopez (2022) emphasized the importance of the tourism sector as a key driver of economic growth and incorporated GDP, the consumer price ındex, and international visitor numbers into the misery index. Using a structural VAR model for Mexico, the study identified a unidirectional negative causal relationship from international tourist arrivals to the misery index, with mobility data accounting for a large portion of the index in the second quarter of 2020, when Covid-19 cases peaked. Özçatal and Güven (2022) found that during the pandemic, strict measures caused severe job and income losses for women working informally, due to the vulnerability of such work to high-level quarantine restrictions. Even after restrictions eased, patterns indicated a cycle of informal employment for women, with persistent poor working conditions and gender inequality. Levent and Özen (2022) examined the impact of Covid-19 on economic growth in selected EU countries between 2005 and 2020. Their findings showed that strict pandemic measures in 2020 caused significant declines, with Spain experiencing the largest drop. They concluded that such measures can suppress economic activity and influence inflation through both supply-side disruptions and demand contractions. Tokol and Emirgil (2023) stated that the Covid-19 pandemic had a profound impact on youth, who were more adversely affected than adults, facing new inequalities in employment and education, as well as negative effects on physical and mental health. In OECD countries, despite protective measures, high stringency periods hindered young people's labor market participation and increased unemployment rates. Morris et al. (2023) examined the effect of the stringency index on unemployment in 46 countries and concluded that the index had a particularly strong effect in less developed economies. They argued that increasing the income levels of disadvantaged populations would facilitate governments' efforts in managing similar future pandemics. Finally, Li et al. (2023) investigated labor market disruptions in Guangdong, China, finding that even after the full reopening of the economy in 2020, unemployment rose by 72% and unemployment benefit claims increased by 57%, with disproportionate impacts on women, workers over 40, and migrant laborers. Kete and Karasaç (2022) highlighted that the stringency index is used for cross-country comparisons when analyzing the economic impacts of pandemic measures. They noted that higher stringency levels are associated with significant declines in economic growth and exert pressure on labor markets, production, and consumption, thereby contributing to inflationary pressures.

As observed in the literature, although many studies have focused primarily on the U.S. and China, numerous analyses have been conducted on a wide range of countries. Given that developing countries tend to suffer more severe macroeconomic consequences from external shocks such as Covid-19, this study specifically focuses on developing economies. An empirical analysis is conducted using data from both MIST and BRICS countries. As highlighted in the literature, no previous study has examined the frequency-based relationship between the misery index and the stringency index in these countries. Therefore, this study fills a critical gap and makes a meaningful contribution to the existing literature. Furthermore, it provides policy-relevant insights that may help governments formulate effective responses to potential future external shocks such as Covid-19.

3. Data and Methodology

The empirical analysis was conducted using stringency index, misery index, and vaccination rate data. The study covers the 24-month period from January 2020 to December 2021. By separating the data into frequencies using the wavelet method, D1 series covering 2-month periods, D2 covering 4-month periods, D3 covering 8-month periods, D4 covering 16-month periods, and finally A1 series, also called approximate wavelet, were created. MATLAB 2021A package program was used for frequency decomposition of the series, and STATA package program was used for econometric analysis.

3.1. Data

The misery index is an economic indicator developed by Arthur Okun (1970). This index, called the Okun misery index, is equal to the sum of unemployment and inflation. Thus, it is used to measure the macroeconomic performance of countries and the living standards of individuals. An increase in the misery index value indicates that macroeconomic deterioration is increasing in the relevant country, and a decrease in the misery index value indicates that the macroeconomic performance of the relevant country is improving (Büyüksarıkulak & Suluk, 2022: 1109). The increase in the misery index is seen as an indicator of loss of social welfare. In other words, this index reveals economic and social costs (Lopez, 2022: 2). The misery index is calculated as follows (Okun, 1970):

$$\textit{Misery Index} = \textit{Inflation Rate } (\pi) + \textit{Unemployment Rate } (\upsilon) \tag{1}$$

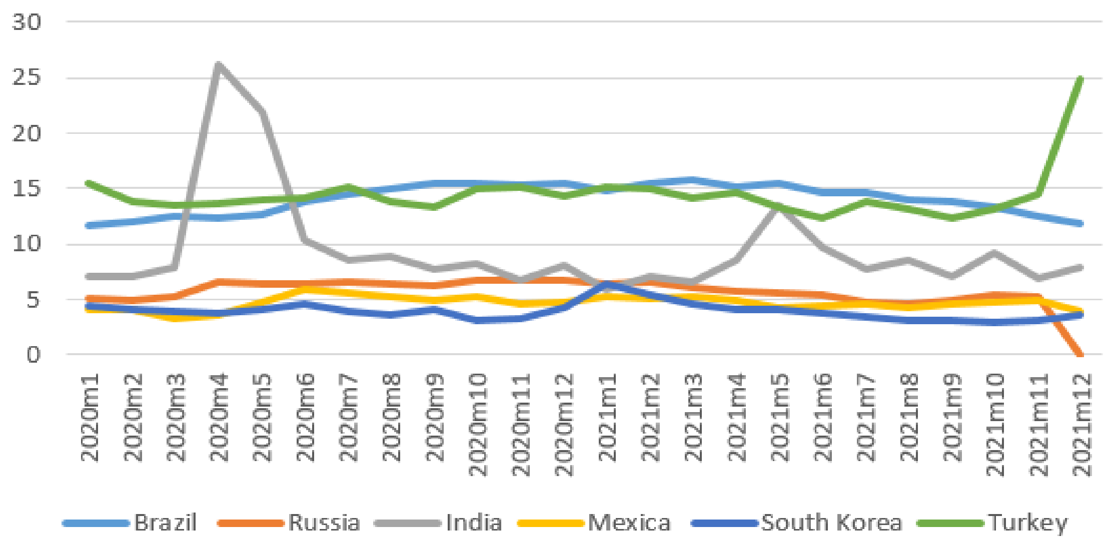
The misery index, developed by Robert Barro in 1999, was obtained by subtracting the percentage change in growth from the sum of the percentage change in inflation, unemployment rate, and long-term interest rates compared to the previous year (Barro, 1999; Işık & Öztürk Çetenak, 2018: 39):

$$\textit{Barro Misery Index} = (\Delta \textit{Inflation Rate } (\pi) + \Delta \textit{Unemployment Rate } (\upsilon) + \Delta \textit{Long-Term Interest Rate } (i)) - \Delta \textit{ Growth Rate } (y) \tag{2}$$

Misery index does not cover many important indicators such as the education system, health system, environmental pollution, and poverty. Nevertheless, it is an index used to compare the macroeconomic performance of countries (Büyüksarıkulak & Suluk, 2022: 1111). The calculation of the misery index developed by Barro requires GDP growth rates, which are only available on a quarterly basis. However, due to the limited time span covered by the data, the use of monthly data was considered more appropriate for the econometric model. The study therefore uses the misery index developed by Okun instead.

Figure 1 shows the graph obtained with the misery Indices of Brazil, Russia, India, Mexico, South Korea, and Türkiye. In the graph, the misery index is shown with monthly data for 2020 and 2021. The misery index in Figure 1 is obtained by collecting unemployment and inflation data of the countries included in the empirical analysis. Data are taken from www.globaleconomy.com.

Figure 1. Misery Index of Developing Countries During the Pandemic Period



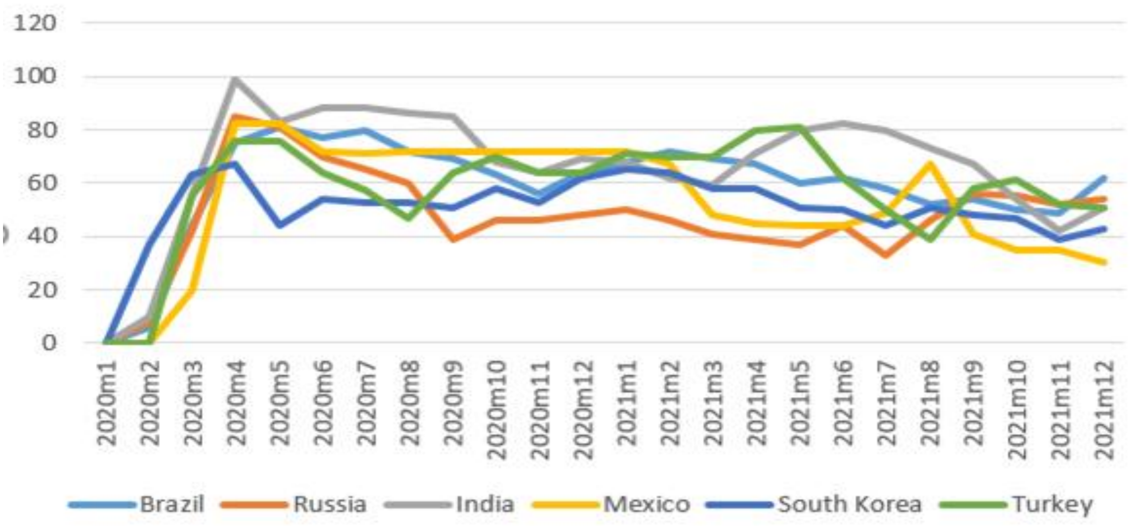
Source: The chart created by authors with data from www.globaleconomy.com

As seen in Figure 1, it is seen that the rate of increase and decrease of misery index in India, especially in the first months of the pandemic, is much higher than other countries. In addition, Türkiye and Brazil have higher misery indexes than other countries. The high unemployment rates of these two countries may have caused their misery indexes to be high. According to Figure 1, South Korea has the lowest misery index.

The stringency index is an index that measures the closure stringencies imposed by governments for the Covid-19 respiratory infection, which was declared as a pandemic by the World Health Organisation (WHO) in 2020. These closure strictures include movement restrictions such as school, workplace, national and international tourism. The stringency index is an Oxford University project that consists of nine indicators and takes a value between "0" and "100" (Hale et al., 2021). A stringency index close to "100" indicates that the country is experiencing complete closure with movement restrictions such as school, workplace and tourism. When the stringency index is close to "0", it shows that the country is moving away from complete closure only with the restrictions deemed necessary by the government (https://ourworldindata.org/coronavirus). Since the purpose of this study is to measure the reaction of the misery index to the closures experienced between 2020 and 2021, when Covid-19 was declared a pandemic by WHO, especially in developing countries, the structure of the stringency index is important. In particular, the inclusion of workplace closures and travel bans in the stringency index is an important indicator in this respect.

As seen in Figure 2, the stringency index, which measures the closure stringency of countries due to the Covid-19 pandemic, reached the highest rate in April and May 2020 in all countries included in the empirical analysis. In 2021, especially in April, May, and June, according to the stringency index, Türkiye and India had the highest closures.

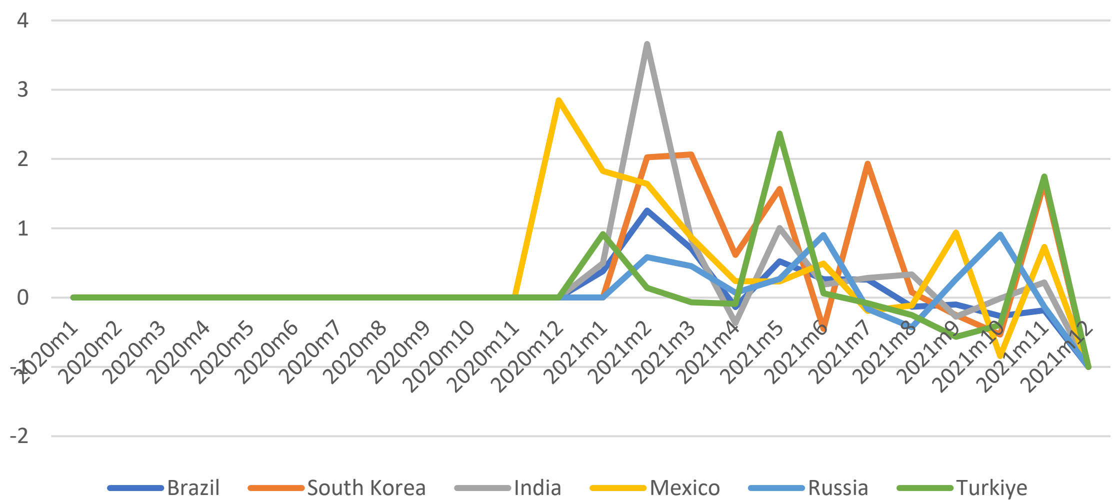
Figure 2. Stringency Index of Developing Countries During the Pandemic Period



Source: The chart created by authors with data from https://ourworldindata.org

Another variable used in the study is the vaccination rate. Like the stringency index, this rate was obtained from the database prepared by Oxford University (https://ourworldindata.org). Since there was no vaccination for 2020, this rate was zero for 2020 and started to take gradually increasing values in 2021. The reason for including this data in the study is to examine whether starting vaccination has an effect on the misery index.

Figure 3. Vaccation Rate of Developing Countries During 2021



Source: The chart created by authors with data from www.globaleconomy.com

Figure 3 shows the vaccination rates of the countries included in the analysis on a monthly basis from the beginning to the end of 2021. According to the chart, the countries with the highest increase in vaccination rates in the early days are India and Mexico. In order to eliminate the endogeneity problem that may arise in the model, policy interest rates for each country and the number of deaths due to Covid-19 are also included in the model.

3.2. Methodology

Actors in the field of economy may try to achieve different objectives with different instruments within the same time frame. In addition, the same instruments may also be used to achieve different objectives.

From this point of view, it can be said that time series related to the economy may be a combination of components at different frequencies. For this reason, frequency-based analyses of time series have become popular in recent years.

The maximal overlap discrete wavelet transform (MODWT) offers several advantages over classical econometric techniques, particularly in the context of analyzing non-stationary and multi-scale time series data. Unlike traditional time-domain models, MODWT decomposes a time series into different frequency components without losing temporal resolution, making it particularly suitable for capturing both short- and long-term dynamics in economic indicators (Percival & Walden, 2000). The economic effects of strict policies might emerge with time lags or differ across frequency domains. For example, a strict lockdown could have immediate effects on employment (short-term), while inflationary pressures may appear more gradually (medium- or long-term). MODWT can isolate these frequency bands and allow for more nuanced interpretation of such lags and spillovers.

One of the key benefits of MODWT is its ability to handle non-stationary data more flexibly than classical methods such as ARIMA or VAR models, which typically require stationarity assumptions (Gençay et al., 2002). MODWT does not rely on fixed time intervals and retains the original time series length after transformation, unlike the standard DWT (Discrete Wavelet Transform), which results in downsampled series and potential information loss. Both the misery index and the stringency index are likely to exhibit non-stationary behavior due to policy shifts, economic cycles, or external shocks (e.g., pandemics). MODWT does not require the strong stationarity assumptions of conventional models like VAR or Granger causality tests, making it more appropriate for real-world, policy-related time series.

Moreover, MODWT is robust in the presence of structural breaks and can uncover hidden patterns at multiple time horizons, offering deeper insights into economic relationships that may be missed by single-scale models (Rua & Nunes, 2009). This makes MODWT a powerful tool in macroeconomic and financial research, especially when studying phenomena such as business cycles, co-movement between variables, and long-run equilibrium relationships. The COVID-19 pandemic represents a major structural break, and conventional econometric models often struggle under such conditions. MODWT is more robust to such breaks, allowing researchers to detect shifts in comovement or causality during periods of economic upheaval.

Economic time series are often subject to both short-term shocks and long-term trends. Wavelet transforms offer a powerful tool for analyzing this multi-scale nature. The MODWT, in particular, decomposes a time series into different frequency bands, revealing the time horizon represented by each component. These components are often labeled with levels such as D1, D2, D3, and D4, each representing a specific time scale:

- D1: Very short-term fluctuations (e.g., between 2 and 4 months)
- D2: Short-term components (4 to 8 months)
- D3: Medium-term components (8 to 16 months)
- D4: Long-term trends (over 16 months)

These frequencies are not fixed numbers; they represent different time periods depending on the data frequency (monthly, quarterly, annual). For example, in monthly data, D1 reflects short-term fluctuations of approximately 2 to 4 months, while D4 reflects long-term structural trends exceeding one year.

Each D component is a version of the original time series and can therefore be included in regression analyses as either a dependent or independent variable. Because each frequency component is orthogonal (independent of each other), using these components separately in regression analyses reveals relationships across multiple frequencies in detail. This approach allows for more in-depth analysis by distinguishing between short-term and long-term effects that traditional regressions might overlook.

This method is widely used in the literature. For example, Ramsay (2010) stated that wavelet decomposition transforms time series into nearly ideal instrumental variables for variables containing measurement error or co-endogeneity. This study laid out the theoretical basis for the use of wavelet components in instrumental variable (IV) models. Similarly, Michis (2007) demonstrated that model efficiency can be increased by integrating wavelet components into a GMM framework. These studies support both the applicability and econometric validity of regression with frequency-based data. Furthermore, early studies such as Ramsay and Lampart (1998) and Schleicher (2002) demonstrated with practical examples how wavelet decomposition can be used to analyze economic relationships at different time scales. In this framework, wavelet-decomposed components provide a powerful framework that can be integrated not only into visualization but also directly into empirical modeling.

3.2.1. Wavelet Analysis

In order to analyse a time series, signal or image on a frequency basis, linear functions must be transformed into a periodic form. This process can be performed with the Fourier transform. In the Fourier transform, periodic functions formed by sines and cosines are allowed to converge to infinity by combining them. However, with the Fourier transform, only the frequency dimension of the series can be accessed and it is not possible to analyse the time dimension. As an alternative to this situation, the short-time Fourier transform (STFD) was introduced. In STFD, a moving window is applied on the data in order to detect local spectra. However, since the time-frequency window is of a fixed width, it may not have the characteristics of the data at each point (Daubechies, 1992; Mallat, 1999).

As a result of the efforts to overcome the deficiencies detected in the Fourier transform, the wavelet transform has emerged. The wavelet transform is a more suitable method for capturing details in signals with finite intervals or signals that are rapidly exhausted after a finite interval. According to this method, small window widths at high frequencies and large window widths at low frequencies are preferred and time particles of different sizes can be analysed (Mallat, 1999).

The time series analysed in wavelet theory may behave like a rising wave in a certain part of the time, while it may show a stagnation behavior in the remaining parts. For example, $a \in (-\infty,\infty)$ and $\delta(.) \in (-\infty,\infty)$ Let a function of the form be analysed. The integral of this function is expected to be zero and the integral of the square of the function is expected to be equal to one. The fact that the first integral of this function is zero causes it to take an infinite value. A function with finite range and $0<\sigma<1$. If the function is considered with an equation in the form of equation (3):

$$\int_{-\infty}^{\infty} \delta^2(a)da = 1 - \sigma \tag{3}$$

If the value of σ in equation (3) is close to zero $\delta(.)$, the function may deviate significantly from zero during the time period it is in. These deviations should be brought back closer to zero by reversing movements. This causes the signal to move in the waveform. The function defined as $\|\delta\|=1$, normalized to t=0 and located around t=0, is scaled by n from the family of frequency atoms and transformed to m to find the mother wavelet. If this situation is expressed by an equation (4):

$$\delta_{m,n}(t) = \frac{1}{\sqrt{n}}\delta(\frac{t-m)}{n} \tag{4}$$

The equation (4) expresses the wavelet transform. Continuous wavelet transform provides an advantage in the transformation of unbounded signals. For unlimited signals, coefficient estimation can be done continuously. In cases where the signal is not unlimited, it is unnecessary to calculate the coefficients. Especially since economic and financial data are within a certain time limit, continuous wavelet transform may sometimes not give meaningful results. In order to prevent this problem, discrete wavelet transform has been developed. The discrete wavelet transform is used like a short-time Fourier transform for time-frequency analysis of a bivariate function. The main purpose is to construct a series of expansion functions in which the signals of the function whose square integral is infinite can be represented by series. This situation is formulated in equation (5) as follows.

$$\delta(t) = \sum_{j,k} a_{j,k}\, 2^{\frac{j}{2}} \rho(2^j t - k) \tag{5}$$

$a_{j,k}$ two-dimensional set of coefficients $\delta(t)$ is called the discrete wavelet transform. In the equation (5), k represents the time shift coefficient on the function and j represents the scaling index. $a_{j,k}$ a more specialised form used in the calculation of the wavelet transform can be written as follows:

$$\delta(t) = \sum_{j,k} \langle \rho_{j,k}(t), \delta(t) \rangle \, \rho_{j,k}(t) \tag{6}$$

If the equation $\rho_{j,k}(t)$ has an orthonormal basis in the space of the analysed signal, the inner product is written as follows:

$$\langle \delta(t), p(t) \rangle = \int \delta^*(t)\, \rho(t)\, dt \tag{7}$$

The main purpose of extending a function or signal, $a_{j,k}$ the aim is to obtain more useful information about the signal through the expansion coefficients. Another aim is to ensure that the coefficients are mostly zero or close to zero. In this way, better results can be obtained in statistical estimation, data compression and nonlinear noise reduction (Burrus et al., 1998: 7-8).

In this study, the maximum overlapped discrete wavelet transform (MODWT) is used. In MODWT, the calculation is performed by splitting the filtered output into subsamples. During this process, the wavelet and scaling coefficients are rescaled and the variance preservation feature of the discrete wavelet transform is valid. In this way, the wavelet variance estimator of MODWT gives asymptotically better results than the estimator of DWT in time series analyses. There are some features that distinguish MODWT from DWT. For example, in MODWT, the window is shifted on the signal in integer units. This is not the case in DWT. Another feature is that in MODWT, detail and correction coefficients are processed with zero-phase filters in multiresolution analysis. In this way, the events in the original signals act similar to the features in multiresolution analyses Gençay et al. (2002).

In MODWT, the wavelet filter is denoted by $(\widetilde{x_J})$ and the scale filter by $(\widetilde{y_J})$. The expression $1 = 1 \ldots \ldots \ldots .. L$ represents the length of the filter, while j represents the level of decomposition. It is defined as $(\widetilde{x_J}) = {x_j}/{2^j}$ and $(\widetilde{y_J}) = {y_j}/{2^j}$ in this equation (Percival & Walden, 2000: 163). MODWT consists of wavelet and scale coefficients. W matrix of vectors and $\tilde{m}$ and $\tilde{n}$ matrices are created. A represents the original series. These coefficients are calculated as follows (Boubaker & Raza, 2017: 108):

$$\widetilde{m_{J,t}} = \sum_{l=0}^{L-1} \widetilde{x_{J,t}}\, A_{t-1} \;\; mod\, T, t = 0,1,2 \ldots \ldots \ldots .., T-1 \tag{8}$$

$$\widetilde{n_{J,t}} = \sum_{l=0}^{L-1} \widetilde{y_{J,t}}\, A_{t-1} \;\; mod\, T, t = 0,1,2 \ldots \ldots \ldots .., T-1 \tag{9}$$

The equation $L_j = (2^j - 1)(l - 1) + 1$ represents the length of the wavelet filter, which is related to the scale. 2^j the expression shows us how many wavelets the series will be divided into. The MODWT wavelet coefficients of each scale to be obtained from these equations will be equal to the original series A. When these operations are reversed, it is also possible to reach the original series by moving from the scale coefficients. For example, the time period examined in this study is 24 months. Based on the formula $2^j = n$, j was determined to be 4. In other words, four main wavelets and one approximation wavelet were used.

When we look at the literature, there is no definite judgement about which wavelet filter should be applied to which signals. Especially when the number of studies involving wavelet transform applied to series related to economics and finance increases, perhaps an answer to this question will be found. In this study, Daubechies wavelet is preferred as a wavelet filter. Daubechies wavelet filter can be defined as the squared gain function of a low-pass scaling filter (Gençay et al., 2002: 112).

$$\delta(t) = 2cos^L(\pi t) \sum_{l=0}^{\frac{L}{2}-1} \binom{\frac{L}{2}-1+1}{l} sin^{2l}(\pi t) \tag{10}$$

The value L in equation 10 is a positive and even integer and represents the length of the filter applied. For example, if we say L=2, when the inverse wavelet transform is applied to the function δ, the coefficients of the Haar wavelet will be found.

3.2.2. Panel Data Methods

In the study, horizontal cross-section data consisting of 6 countries and 24-month time series covering the years 2020 and 2021 were used. Thus, in the empirical analysis, N=6 and T=24. These series are constructed separately for each frequency. Panel data method is used in the study. In this section of the study, the tests used in the panel data method are briefly introduced.

3.2.2.1. Cross Sectional Dependence Test

The most commonly used tests for horizontal cross-section dependence in the literature are Breusch & Pagan LM test (1980), Pesaran et al. (2008) test and Pesaran (2004) CD test. Breusch & Pagan LM test (1980) is used to test whether there is correlation between the residuals of the cointegration or error correction model for each unit. The null hypothesis is shown below (Pesaran et al., 2006: 3):

Ho: cov($u_{it,}$ u_{jt} $)_j$=0, (i≠j for all t),

In this case, under the assumption that uit∼IIDN(0,σui2)u_{it} \sim IIDN(0,\sigma^2_{ui})uit ∼IIDN(0,σui2) and when the null hypothesis holds, the LM test is generally applicable and does not require a particular ordering of the cross-section units. The LM test is presented in Equation (11).

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}ij^2 \tag{11}$$

where $\hat{p}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals:

$$\hat{p}_{ij} = \hat{p}_{ji} = \frac{\sum_{i=1}^{T} e_{it}\, e_{jt}}{(\sum_{i=1}^{T} e^2{}_{it})^{\frac{1}{2}} (\sum_{i=1}^{T} e^2{}_{jt})^{\frac{1}{2}}} \tag{12}$$

e_{it}, is the residuals estimated by the appropriate method from each unit. X^2 distribution with N(N-1)/2 degrees of freedom (Tatoğlu, 2020: 238). Pesaran et al. (2008) adapted the Breusch and Pagan (1980) LM test—originally valid when *N* is small and *T* is sufficiently large but inappropriate as *N* approaches infinity—to the case where both *N* and *T* are large. The corresponding test statistic is given in Tatoğlu (2020: 244).

$$NLM = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T\hat{p}ij^2 - 1) \tag{13}$$

The mean of the NLM statistic is zero for all T and N (Tatoğlu, 2020: 245). In panel data analysis, the CD test proposed by Pesaran (2004) is also used to measure dependence between cross-sections. This test, which is used when N > T, is known to give better results than the Breusch and Pagan (1980) LM test (Tatoğlu, 2020: 240). The CD test uses the residuals obtained from the estimation of the ADF regression. The correlation of each unit with other units other than itself is calculated. Therefore, while N is the unit size, N*N-1 correlation is calculated. The hypotheses are as follows (Pesaran, 2004):

H_o: p_{ij}=0

H_1: p_{ij} ≠ 0

Pesaran (2004) uses the equation in the balanced panel to test the correlation between units (Tatoğlu, 2020: 105):

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}ij^2 \tag{14}$$

In the equation (14), "$\hat{p}_{ij}{}^2$" is located between the residuals of the OLS estimates of countries "i" and "j" and the correlation coefficient (Saldivia et al., 2020: 4). The main hypothesis states that there is no horizontal cross-section dependence, while the alternative hypothesis states that there is horizontal cross-section dependence. The CD test statistic is an asymptotically distributed test (Pesaran, 2004).

3.2.2.2. Testing Slope of Homogeneity

An important issue to be considered in panel data analysis is whether the slopes are the same for each horizontal cross-section. The null hypothesis to test whether the slopes are the same for each horizontal cross-section is that the slope coefficients are homogeneous, while the alternative hypothesis is that the slope coefficients are not homogeneous. The homogeneity of the slope coefficients is tested using the $\hat{\Delta}$ test developed by Pesaran and Yamagata (2008).

$$H_0 : \beta_i = \beta$$

$$H_1 : \beta_i \neq \beta_j$$

The $\hat{\Delta}$ test is shown in equation (15):

$$\hat{\Delta} = \sqrt{N}\,\frac{N^{-1}\check{S} - K}{\sqrt{2k}} \tag{15}$$

The adjusted delta test statistic is given below:

$$\hat{\Delta}\text{adj} = \sqrt{N}\,\frac{N^{-1}\check{S} - E(Zit)}{\sqrt{var(Zit)}} \tag{16}$$

When the probability value of the test statistics is less than 10%, the null hypothesis is rejected and thus the slope coefficients are accepted to be heterogeneous (Doğanay & Değer, 2017: 133).

3.2.2.3. ***Unit Root Test***

Pesaran (2007) uses the extended version of the ADF regression with lagged cross-sectional averages for unit root tests and the first difference of the regression eliminates the correlation between units. This is called "cross section generalised Dickey Fuller" (CADF). CADF regression is defined as follows (Tatoğlu, 2013: 223):

$$\Delta y_{it} = \alpha_i + pi^* Y_{it-1} + d_0 \overline{y}_{t-1} + d_1 \Delta \overline{y}_t + \varepsilon_{it} \tag{17}$$

When there is autocorrelation in the error term, the regression is regressed on Y_{it} and y_t can be extended by adding lagged first differences. With this extension, the CIPS statistic introduced by Pesaran (2004) is obtained to measure the stationarity of series with horizontal cross-section dependence. This test statistic is a second generation unit root test statistic that allows for horizontal cross-section dependence and heterogeneity. The CIPS test statistic is based on standard ADF regressions and lagged values of the adjusted horizontal cross-section means and first differences of the series (Saldivia et al., 2020: 4):

$$\text{CIPS} = \frac{1}{N}\sum_{i=1}^{N} t_i^{\sim} \tag{18}$$

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \overline{y}_{t-1} + \sum_{j=0}^{p} d_{ij} \Delta \overline{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \tag{19}$$

The null hypothesis states that the series are non-stationary and $b_i = 0$ for all "i". The alternative hypothesis states that the series are stationary.

3.2.2.4. The Instrumental Variables (IV) Regression Model

In econometric analyses, the reliable estimation of causal relationships often depends on the assumption that the explanatory variables in the model are exogenous. However, when one or more explanatory variables are correlated with the error term, the classical ordinary least squares (OLS) estimator becomes biased and inconsistent (Wooldridge, 2010). This situation, known as the endogeneity problem, makes it difficult to accurately identify causal effects. Endogeneity can arise from various sources, such as measurement error, omitted variables, or reverse causality (Greene, 2018).

One of the methods developed to address endogeneity is the Instrumental Variables (IV) regression. The IV approach relies on the use of additional variables—called instruments—that are correlated with the endogenous explanatory variable(s) but uncorrelated with the error term in the structural equation (Angrist & Pischke, 2009). These instruments must satisfy two key conditions. The first of these is relevance. The instrument must be strongly correlated with the endogenous explanatory variable(s). This is often assessed via a high first-stage F-statistic (Staiger & Stock, 1997). The second is exogeneity. The instrument must be uncorrelated with the error term of the structural equation. This assumption is crucial for the consistency of the IV estimator. In a simple linear framework, the model can be expressed as:

$$Y_i = \beta X_i + \gamma W_i + \varepsilon_i \tag{20}$$

Here, Y_i denotes the dependent variable, X_i the endogenous explanatory variable, W_i the control variables, and ε_i the error term. If $E[X_i\varepsilon_i]\neq0$, the OLS estimator is biased. In such a case, the two-stage least squares (2SLS) method is applied using instruments Z_i.

In the first stage, the endogenous variable X_i is regressed on the instruments Z_i and the control variables W_i:

$$X_i = \pi' Z_i + \theta' W_i + v_i \tag{21}$$

The predicted values from this regression ($\widehat{X_\iota}$) are then used in the second stage, where Y_i is regressed on $\widehat{X_\iota}$ and W_i :

$$Y_i = \beta \widehat{X_\iota} + \gamma W_i + u_i \tag{22}$$

This process ensures a consistent estimate of β by isolating the variation in X_i that is attributable only to the instruments (Stock & Watson, 2020; Wooldridge, 2010).

The strength of the IV approach depends critically on the choice of suitable instruments. The weak instruments problem arises when the correlation between the instrument and the endogenous variable is weak, which can severely undermine the reliability of the estimates (Andrews et al., 2019; Bound et al., 1995). Therefore, studies such as Montiel Olea and Pflueger (2013) have proposed measures like the “effective F-statistic” to assess instrument strength, particularly in the presence of heteroskedasticity.

In conclusion, the IV regression model is one of the most important tools in econometrics for overcoming endogeneity problems and ensuring the consistency of causal estimates. However, the success of the method depends on both meeting its theoretical conditions and carefully selecting instruments in empirical applications.

4. Empirical Results

In the empirical analysis, for each frequency separately, first horizontal cross-section dependence and then whether the slope coefficients are heterogeneous are examined. Since second generation unit root tests should be applied in case of the existence of horizontal cross-section in the series, horizontal cross-section dependence test should be performed. Likewise, it is also important to know whether the slope coefficients are heterogeneous or not as it will change the type and interpretation of the tests. The empirical analysis is continued by conducting unit root and panel causality tests separately for all wavelets. In this section of the paper, the results of the analyses are presented in tables.

In Table 1, Breusch Pagan (1980) LM test, Pesaran et al. (2008) LM adjusted test, and Pesaran (2004) LM CD test are performed for all frequencies. As seen in Table 1, the null hypothesis of "no horizontal cross-section dependence" is rejected in all wavelets. Thus, it is accepted that there is horizontal cross-section dependence in all wavelets. Therefore, the second generation unit root test will be used in this study.

Table 1. The Results of Cross Section Dependency Tests

Frequency	*LM Statistic*	*LM Adj Statistic*	*LM CD Statistic*
D1	152.1***	62.15***	11.54***
D2	176***	73.02***	13.07***
D3	116.7***	45.79***	10.31***
D4	70.05***	24.03***	4.825***
A1	65.5***	22.99***	5.424***

***,**,* are significant at 1%, 5%, and 10% significance levels, respectively.

In this study, the heterogeneity of the slope coefficients is tested by the delta test developed by Pesaran and Yamagata (2008). Table 2, the null hypothesis "the slope coefficient is homogeneous" is rejected for all wavelets except D2 wavelet. Thus, while the slope coefficients are heterogeneous in D1, D3, D4, and A1 wavelets, it is revealed that the slope coefficients are homogeneous in the series in D2 wavelet.

Table 2. The Results of Homogenity Test

Frequency	$\hat{\Delta}$	$\hat{\Delta}$ *Adj*
D1	2.269***	2.485***
D2	1.524	1.669
D3	3.978***	4.357***
D4	15.373***	16.841***
A1	14.717***	16.121***

***,**,* are significant at 1%, 5%, and 10% significance levels, respectively.

In this part of the empirical analysis, unit root tests were conducted to test the stationarity of the series. According to the result in Table 1, since all wavelets exhibit horizontal cross-section dependence, the CADF test of Pesaran (2007), which is the second generation unit root test, was applied for stationarity testing. The results are shown in Table 3.

Table 3. The Results of Unit Roots Test for D1

Variables	***Deterministic***	***Lags***	***Zt-bar***	***Prob.***
StringencyD1	Constant	1	-7.717	0.000
StringencyD1	Constant&Trend	1	-6.820	0.000
MiseryD1	Constant	1	-7.715	0.000
MiseryD1	Constant&Trend	1	-5.859	0.000
VacD1	Constant	1	-4.331	0.000
VacD1	Constant&Trend	1	-2.728	0.003
StringencyD2	Constant	1	-3.296	0.000
StringencyD2	Constant&Trend	1	-1.422	0.077
MiseryD2	Constant	1	-5.273	0.000
MiseryD2	Constant&Trend	1	-3.887	0.000
VacD2	Constant	1	-4.543	0.000
VacD2	Constant&Trend	1	-3.127	0.001
StringencyD3	Constant	1	-1.851	0.032
StringencyD3	Constant&Trend	1	-0.989	0.161
MiseryD3	Constant	1	-4.473	0.000
MiseryD3	Constant&Trend	1	-4.809	0.000
VacD3	Constant	1	1.152	0.875
VacD3	Constant&Trend	1	3.580	1.000
StringencyD4	Constant	1	-3.149	0.001
StringencyD4	Constant&Trend	1	-1.454	0.073
MiseryD4	Constant	1	-5.206	0.000
MiseryD4	Constant&Trend	1	-1.957	0.025
VacD4	Constant	1	0.820	0.794
VacD4	Constant&Trend	1	3.892	1.000

Table 3. The Results of Unit Roots Test for D1 (Continue)

StringencyA1	*Constant*	*1*	*-4.551*	*0.000*
StringencyA1	Constant&Trend	1	-1.624	0.052
MiseryA1	Constant	1	-5.272	0.000
MiseryA1	Constant&Trend	1	-2.830	0.002
VacA1	Constant	1	-1.886	0.030
VacA1	Constant&Trend	1	1.819	0.966

In Table 3, Pesaran (2007) CADF unit root test was performed for each series separately for the 1st lags with both constant and constant and trend. The stringency index and misery index are stationary at the level at 5% significance level at all frequencies. The vaccination rate is not stationary at the level values in the D3, D4 and A1 frequency bands.

Table 4. Summary of the IV 2SLS Analysis Results
(Stringency is the dependent variable)

	D1		D2		D3		D4		A1	
	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob
Misery	19.0406	0.338	-4.2026	0.711	17.8848	0.263	5.4552	0.089	5.4551	0.089
Vacation	0.000007	0.879	-0.0000	0.809	-0.0001	0.652	0.0000	0.138	0.0000	0.138
Diagontic Tests										
F(2,136)=		0.45		0.10		0.62		1.88		1.88
R^2(c)=		-0.68		0.5310		-2.374		0.013		0.013
Weak identification		0.875		0.823		1.159		12.384		12.384

Table 5. Summary of the IV 2SLS Analysis Results
(Stringency is the dependent variable with robust model)

	D1		D2		D3		D4		A1	
	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob
Misery	19.04	0.348	-4.2026	0.752	17.8847	0.285	5.4551	0.090	5.4551	0.090
Vacation	0.0000	0.361	0.0000	0.128	-0.0000	0.316	0.0000	0.001	0.0000	0.001
Diagontic Tests										
F(2,136)=		0.43		1.15		0.57		7.24		7.24
R^2(c)=		-6.65		-0.53		-2.37		0.013		0.013
Weak identification		0.875		0.823		1.159		12.384		12.384

Table 6. Summary of the IV 2SLS Analysis Results
(Misery is the dependent variable)

	D1		D2		D3		D4		A1	
	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob
Stringency	0.1623	0.067	0.1017	0.042	0.0550	0.010	-0.0073	0.759	-0.0073	0.759
Vacation	0.0000	0.908	0.0000	0.837	0.0000	0.627	0.0000	0.274	0.0000	0.274
Diagontic Tests										
F(2,136)=		1.66		2.04		3.36		0.76		0.76
R^2(c)=		-0.68		-0.25		0.07		-0.03		-0.03
Weak identification		4.818		7.447		27.140		17.229		17.229

Table 7. Summary of the IV 2SLS Analysis Results
(Misery is the dependent variable with robust model)

	D1		D2		D3		D4		A1	
	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob
Stringency	0.1623	0.195	0.1017	0.044	0.0550	0.002	-0.0073	0.826	-0.0073	0.826
Vacation	0.0000	0.160	-0.0000	0.301	0.0000	0.027	0.0000	0.063	0.0000	0.063
Diagontic Tests										
F(2,136)=		1.80		2		6.88		2.88		2.88
R^2(c)=		-0.68		-0.25		0.07		-0.03		-0.03
Weak identification		4.818		7.477		27.140		17.229		17.229

In the models where the stringency index was the dependent variable, the misery coefficients appeared positive (e.g., D1 = 19.04; D3 = 17.88), yet they were not statistically significant. Similarly, the vacation variable was insignificant across all models. Given that the R^2 values were generally negative or very low, the explanatory power of the models was weak. Weak identification statistics exceeded the threshold of 10 only in D4 and A1, indicating problems with instrumental variables in the other models. Based on these non-robust results, misery does not have a notable or reliable effect on stringency.

In the models where the misery index was the dependent variable, the stringency coefficients were found to be positive and statistically significant, particularly in the D2 ($p = 0.042$) and D3 ($p = 0.010$) periods. D1 was marginally significant ($p = 0.067$), while D4 and A1 were not significant. The vacation variable was largely insignificant. Weak identification tests were strong for D2, D3, and D4 (e.g., D3 = 27.14). According to the non-robust results, increases in stringency significantly raise the misery index in the short and medium term.

In the stringency-dependent models, the misery coefficients remained positive but failed to reach statistical significance even under robust estimation. Although the vacation variable was significant in D4 and A1, the effect size was very small. Due to the persistently low R^2 values, the overall explanatory power of the models was weak. Robust results confirm that misery does not exert a significant effect on stringency.

In the misery-dependent models, stringency coefficients were once again positive and statistically significant in D2 ($p = 0.044$) and especially D3 ($p = 0.002$). The marginal significance of D1 disappeared ($p = 0.195$), while D4 and A1 remained insignificant. The vacation variable gained significance in D3 ($p = 0.027$) and D4 ($p = 0.063$). Weak identification statistics were again strong for D2, D3, and D4. Robust results confirm that stringency, particularly in the medium term (D3), significantly increases the misery index.

5. Conclusion and Discussion

While the Covid-19 pandemic caused many deaths around the world, it also disrupted social and economic life. While some countries took very strict measures during the pandemic, some countries took loose measures. Restrictions in economic life have led to serious disruptions in the world supply chain and a contraction in production volume. In addition to the contraction in production volume, measures such as curfews and restrictions on collective activities also negatively affected the demand dimension of the economy. These developments on a global scale caused both the unemployment rate and the inflation rate to increase. The main motivation of this study is to observe whether economic conditions are related to the measures taken by developing countries. An answer was sought to the question of whether the high misery index affects the stringency of countries' measures. In this context, the relationship between the poverty index and the rigidity index for Brazil, Russia, India, Mexico, South Korea, and Türkiye was analyzed using wavelet analysis to decompose the series into frequencies, combined with a panel IV fixed-effects model.

In the analysis, cross-sectional dependence and homogeneity among the series were first examined. The results indicated the presence of cross-sectional dependence across all wavelets; therefore, second-generation unit root tests were employed. Initially, the stringency index was used as the dependent variable for all wavelets, and the core hypothesis of the study—"developing countries adjusted the degree of stringency in line with their inflation and unemployment rates"—was tested using both robust and non-robust estimations. Furthermore, to test the widely held assumption that the stringency index has an adverse relationship with the misery index, the models were re-specified with the misery index as the dependent variable, again under both robust and non-robust settings. To address potential endogeneity in the empirical analysis, estimations were conducted using the instrumental variables (IV) method.

When examining the models where the stringency index served as the dependent variable, the vacation variable was found to be negative and, in most cases, statistically significant. By contrast, at the D2 and D3 frequency levels, the instrumental strength was very weak, and the coefficients were not statistically significant. These findings were largely consistent in the robust estimations as well. In the d4 and a1 models, the instruments demonstrated moderate strength, and the misery coefficient was found to be marginally significant. Overall, these results indicate that the core hypothesis of the study—"developing countries adjusted the degree of stringency in line with their inflation and unemployment rates"—could not be confirmed.

In the models where the misery index was used as the dependent variable, the classical estimations highlighted the importance of the D2 and D3 frequency levels. At D2, the death variable functioned as a moderately strong instrument, with the stringency coefficient being positive and statistically significant. At D3, the instrumental strength was very high, and again, the stringency coefficient was positive and statistically significant. In contrast, while the instrument strength was weak at D1, and high at both D4 and A1, the stringency coefficient was not statistically significant in these cases. In the robust estimations, these findings were reinforced, with the D3 model emerging as the most reliable estimation due to its strong instrument power and the significant positive effects of both the stringency and vacation variables. These results demonstrate that the effects of variables differ across frequencies and that the choice of strong instruments is critical for ensuring model reliability. Moreover, the robust approach largely confirmed the tendencies observed in the classical estimations, underscoring that models with strong instruments should be prioritized for policy implications.

Within the framework of the study's findings, the results directly reflect the impact of policy restrictions on economic well-being. Accordingly, when determining the level of restrictions during pandemics or crises, changes in indicators of economic welfare should be carefully considered. The findings reveal that, at certain frequencies, restrictions significantly influence economic well-being. Therefore, instead of imposing restrictions in a prolonged and rigid manner, they should be applied with a more flexible and adaptive approach—allowing for sectoral and regional variation.

In periods when restrictions that may inevitably increase the misery index become unavoidable, economic buffer policies such as direct income support, tax deferrals, and employment incentives should be activated. Alongside short-term crisis management measures, long-term reforms are also necessary, particularly in enhancing labor market flexibility, strengthening social safety nets, and improving the resilience of healthcare systems. Such reforms would help to minimize the potential adverse economic effects of restriction policies.

These results show that individual actions of countries may not mean much in pandemic that can affect the whole world. Failure of any country to take adequate precautions against the pandemic due to inadequate economic conditions may cause the pandemic to not end even in countries with strong economies and strict measures. It is estimated that the rate of spread of the pandemic worldwide can be significantly reduced by supporting countries that are unable to implement additional measures due to economic constraints. Providing equal opportunities in all countries of the world will both slow down the spread of the pandemic and help countries in economically difficult situations to quickly solve their economic problems. The findings underscore the need for developing countries to prepare systematic economic resilience strategies. These may include mechanisms such as employment protection schemes, short-time work allowances, and supply chain supports that help absorb economic shocks in times of public health emergencies. Such mechanisms can reduce the pressure to implement extreme containment measures driven by deteriorating macroeconomic indicators. International organizations, including the World Health Organization and the International Monetary Fund, should design flexible global health frameworks that recognize the economic vulnerabilities of developing countries. Since the study reveals that the severity of containment measures is, in part, determined by inflation and unemployment levels, one-size-fits-all containment policies may not be feasible across countries with varying economic capacities.

One of the key findings from the analysis is that no relationship was identified between the stringency index or the misery index and vaccination efforts. Since vaccination only began toward the end of 2020 in the period covered by the study, it may not have been possible to observe its effects within a one-year timeframe. Furthermore, determining whether the decline in case numbers is attributable to vaccination or community immunity within such a short period remains challenging.

The fact that the data used in the research covers a short period of time can be considered as a limitation of the study. The period from the announcement of the Covid-19 pandemic to the announcement that the Covid-19 pandemic is over will yield clearer results. Also, the study focuses on six developing countries—Brazil, Russia, India, Mexico, South Korea, and Türkiye. While these countries are diverse in terms of geography and economic structure, the findings may not be generalizable to all developing economies or to low-income countries with weaker institutional capacities. The misery index, although useful as a composite indicator, only includes unemployment and inflation. Other relevant variables such as GDP growth, poverty rates, or fiscal capacity were not included, potentially omitting other critical dimensions of economic distress.

Future studies could include a longer post-pandemic period to assess how economic recovery and policy reversals affected the relationship between economic distress and containment measures. Incorporating a broader set of countries, including least developed or African nations, could enhance the external validity of the findings and allow for regional comparisons. Future research may integrate additional socio-economic indicators such as consumer confidence, government fiscal responses, mobility trends, or health system capacity to build a more holistic understanding of policy behavior.

Declarations and Disclosures

Ethical Responsibilities of Authors: The authors of this article confirm that their work complies with the principles of research and publication ethics.

Conflicts of Interest: No potential conflict of interest was reported by the authors.

Funding: The authors received no financial support for the preparation and/or publication of this article.

Author Contributions: The authors confirm contribution to the article as follows: Conceptualization and design, S. Gürbüz; data collection, F. Tombak; analysis of data and interpretation of results, F. Tombak and S. Gürbüz; writing the first draft of the manuscript, S. Gürbüz and F. Tombak; review and editing, S. Gürbüz and F. Tombak. The manuscript/article was read and approved by all the authors, and all authors accepted responsibility for their article.

Plagiarism Checking: This article was screened for potential plagiarism using a plagiarism screening program.

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