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Impact of a Pandemic and Its Management on Market Risk: Value-at-Risk Analysis

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Master in Finance

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Department of Finance

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Agradecimento

Em primeiro lugar gostaria de agradecer a todos os que me acompanharam ao longo do meu percurso académico e que permitiram que crescesse tanto a nível pessoal, como a nível profissional. Família, amigos, colegas, professores, desconhecidos que ocuparam horas nos meus ouvidos ou na minha televisão. Todos contribuíram e foram fundamentais para que estivesse o melhor preparado possível para enfrentar esta tarefa árdua e terminá-la inteiramente satisfeito com o resultado final.

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Resumo

O risco de perda num investimento torna-se uma componente chave no mercado financeiro durante períodos de grande incerteza visto que os investidores tendem a tornarem-se mais aversos ao risco. 2020 e 2021 foram marcados por uma pandemia inesperada e sem precedentes neste século, que mudou a conjuntura social, laboral e financeira. Nesta dissertação analisamos como a Pandemia COVID-19 e a gestão da mesma afetaram expectativas dos investidores e, consequentemente, o risco de mercado, em países desenvolvidos e em desenvolvimento, ao longo das suas diferentes fases. Assim, utilizamos um conjunto de análises de *Panel Data* para avaliar o impacto de diferentes indicadores que descrevem a situação pandémica no risco de mercado, estimado através da medida *Value-at-Risk*. Resultados demonstram que o risco de mercado foi severamente afetado nos momentos iniciais de 2020, tendo-se verificado um aumento exponencial dos níveis de risco nos dois grupos de países, estatisticamente explicado por indicadores pandémicos tais como a taxa de reprodução do vírus e pelo pânico à volta da situação. No entanto, o período de risco elevado foi curto visto que na segunda metade de 2020 verificou-se um declínio acentuado dos VaR que quase compensou o aumento nos momentos iniciais do ano, seguido por uma recuperação mais lenta para os seus valores usuais durante 2021. Além disso, o mercado dos países desenvolvidos foi mais rápido a reagir, enquanto nos países em desenvolvimento a situação pandémica impactou mais os índices de risco, que se mantiveram acima dos seus valores usuais durante todo o período de análise.

Palavras-chave: Risco de Mercado, COVID-19, *Value-at-Risk*, *Panel Data*

JEL Classification: G32, G41

Abstract

The downside risk of an investment becomes a key component in the financial market during periods of great uncertainty as investors tend to become more risk averse. 2020 and 2021 were marked by an unexpected and unprecedent pandemic that changed the social, labor, and financial conjuncture. In this dissertation we analyze how the COVID-19 Pandemic and its management affected investors' expectations and, consequently, the market risk, in developed and developing countries, throughout different phases. In order to assessed that, we conduct a set of Panel Data analysis to evaluate the impact of different indicators that describe the pandemic situation on the market risk, estimated through the Value-at-Risk measure. Results show that the market risk were severely affected in the initial moments of 2020, when it was verified an exponential increase in the risk level of both country groups that is statistically explained by the pandemic indicators such as the reproduction rate and the panic surrounding the situation. However, high-risk period was short since in the second half of 2020 we verified a sharp decline in the VaRs that almost compensated the increase, followed by a slow recovery to their usual levels during 2021. The market of developed countries was quick to react, while in developing countries the pandemic situation had a greater impact on its risk indices, which remained above the usual levels throughout the entire period of analysis.

Keywords: Market Risk, COVID-19, Value-at-Risk, Panel Data

JEL Classification: G32, G41

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List of Abbreviations

AR – Autoregressive Model

BLUE – Best Linear Unbiased Estimators

CAPM – Capital Asset Pricing Model

CDC – Centers of Disease Control and Prevention

CEE – Central and Eastern Europe

EVT – Extreme Value Theory

EWMA – Exponentially Weighted Moving Average

FGLS – Feasible Generalized Least Squares

GARCH - Generalized Autoregressive Conditional Heteroskedasticity

GDP – Gross Domestic Product

GLS – Generalized Least Squares

GPD – General Pareto Distribution

HDI – Human Development Index

LSDV – Least Squares Dummy Variables

NY – New York

OLS – Ordinary Least Squares

P&L – Profit and Loss

SARS - Severe Acute Respiratory Syndrome Coronavirus

UK – United Kingdom

US – United States

VaR – Value-at-Risk

VaRs – Values-at-Risk

WHO – World Health Organization

CHAPTER 1

Introduction

Over the recent decades, the topic of risk has been increasingly present in the most diverse debates on finance and investments, particularly during economic crisis periods. The uncertainty associated with these moments affects future expectations and consequently leads to changes in investors' behaviors, which tend to become more risk averse and to pay special attention to the downside risk of an investment.

The most common measure used to evaluate the downside risk of an investment is the Value-at-Risk, which represents the maximum loss that it is expected in a certain portfolio hold for a certain period, given a certain level of confidence (Alexander, 2005). This metric was first introduced by J.P. Morgan in the 90s and today is the standardized method to assess market risk, used by several financial practitioners, especially financial institutions. Its quantitative value is a highly valued feature since, being a number, it is easy to understand, to communicate and to serve as a term of comparison. Furthermore, the fact that it can be applied to any type of asset made it easily to become a universally used measure.

The period between 2020 and 2021 was marked with an unpredictable international disaster: the COVID-19 Pandemic. In addition to serious health cases, which have led to millions of deaths around the world, the economic and financial conjuncture has seriously changed. Companies and people had to adapt to new procedures by force and experienced moments of great instability due to the uncertainty lived, with countless companies being closed and innumerous people losing their jobs. Since investors' behavior changes in crisis situations as mentioned before, we expect that this uncertainty also extended to investors, causing major changes in the risk verified in the financial market. Existing studies show that, as expected, market risk increased significantly in the initial moments of the pandemic due to the panic experienced surrounding the situation. However, as far as we know, these studies are lacking in just assessing the initial impact of the pandemic. But how has the market reacted after the initial shock and throughout the different pandemic phases? Has the risk returned to its normal values yet or is the market still under COVID-19 effect? What was the role of the pandemic management on the market risk behavior? Was the impact equal in developed and developing countries? These are the questions that this study proposes to answer.

First, to estimate the market risk experienced in the two country groups during the period between January 2020 and December 2021, we use the daily Value-at-Risk of twenty stock indexes, from ten developing countries and ten developed countries. Using the Parametric Normal Model, a model that assumes a normal distribution for the assets prices' returns, and the Exponentially Weighted Moving Average (EWMA) method to estimate their volatility, which allows to assign higher sensitivity to most recent observations, we can easily capture and evaluate the current market risk conditions.

To answer the proposed research questions, we run a set of econometric analysis that make it possible to establish relationships between the risk behavior and the COVID-19 situation, in developing and developed countries. For that purpose, we use Panel Data regressions, with Values-at-Risk as the dependent variable and indicators that allow to characterize the pandemic situation as explanatory variables. Those indicators include metrics to evaluate the reproduction rate of the virus, an index that allows to measure the stringency of the countermeasures taken, a metric to evaluate the impact of vaccination, as well as indicators to assess the social response to the pandemic.

In an initial phase, to analyze the global impact of the pandemic on the market over these two years and how specific characteristics of countries and time have influenced the risk behavior, we use the Fixed Effects Model for Panel Data with all the information obtained from the twenty countries for the two years. Then, to assess the impact separately by country group and by pandemic phase, we separated the information into eight regressions: four different pandemic phases corresponding to each semester of 2020 and 2021, in each period a regression for developing countries and another for developed countries.

Results show that the market risk increased with the pandemic, moving from an average VaR of 2% in 2019 to 3.58% in 2020 and then recovering to values around 2.10% in 2021. The market risk behavior during these two years was quite similar in the two country groups: an exponential increase at the beginning of the pandemic, a quick reaction of the market with huge risk decreases in the second phase, followed by a gradual recovery to its usual values during 2021. However, there is a particularity that differentiates the two markets. While during the period of analysis the market of developing countries always maintained an average VaR above the one observed in the pre-pandemic, the average VaR of developed countries recovered its usual values right in the first half of 2021, having even reached values below those of 2019. This shows that the market of developing countries was slower to recover after this unexpected huge increase in risk.

The initial phase of the pandemic (first half of 2020) was critical for the elevated levels of risk verified on the financial market. In both developed and developing countries, the rates of infection were found statistically significant to explain the VaRs observed, as well as the panic and the sentiment surrounding the news about the pandemic situation. Thus, as the pandemic situation worsens and the news gained presence and preponderance in the media, investors' behavior became more unstable, generating greater uncertainty in the market. In addition, restrictive measures also contributed statistically to the increase of risk in developed countries during this phase.

In the following phases, the pandemic situation and its management lost significance to explain the VaRs observed in the market of both groups, demonstrating that the market quickly adapted to the new conjuncture and stopped reacting to it. However, the intensive vaccination that took place in the first half of 2021 statistically contributed to decrease the risk level during this period, both in developed and developing countries. The appearance and predominance of new variants in the last semester of 2021 also statistically affected the risk levels. Finally, developing countries were affected for a longer time by the evolution of the pandemic and the news and sentiment surrounding the situation, which once again demonstrates the greater difficulty of this market to react and adapt to new realities.

This dissertation follows the following structure: in section 2, the existing literature that can contribute to the study is confronted and analyzed. The next section includes a timeline with the most important moments of the pandemic and the justification for dividing it into four phases. Then the methodology used in the study is presented, both in terms of market risk estimation and of econometric analyzes to be used and, in section 5, the way in which this methodology is implemented. Finally, the results obtained are analyzed in section 6 and the main conclusions are presented in the following section.

CHAPTER 2

Literature Review

Past events help to predict the results of future events with similar characteristics and thus the existing literature on the economic and financial impact of other crises is fundamental in this study.

In 2003, Fan concluded that the economic short-term impact of SARS viral respiratory disease in Asia was enormous and that the long-term impact depended on the speed and effectiveness of government measures to counteract the virus. She estimated that if the virus circulated for one quarter of the year, Asia would face GDP losses of 0.9%, but if it remained for two quarters, the potential losses could ascend to 2.4%, equivalent to twenty-eight billion dollars. Lee and McKibbin (2004) verified those estimates when they concluded that after 5,327 cases in China, its GDP faced losses of 1.05%. Moreover, the impact also spread besides the virus country of origin, since countries such as Japan, South Korea, the US or Australia suffered global GDP losses between 0.07% and 0.10%, despite low case numbers. Later, between 2014 and 2016, the Ebola propagation in West African countries also impacted economies and the financial market worldwide, leading to abnormal negative returns and high volatility in stock prices during this period. Places with more geographical proximity to the country of origin of the virus were more affected but it also impacted countries with direct and indirect relations to such markets and countries exposed to heavy information dissemination and intense media coverage of such event (Ichev & Marinč, 2018).

With these events in mind, we can deduce that a virus outbreak can shrink the global economy and change the financial market due not only to the evident costs of such situation but also to changes in investors' expectations and behavior. Furthermore, the internationalization of financial markets leads to the global and quick spread of consequences. This vision is in line with the statements of Baker and Wurgler (2007) and Fang and Peress (2009), that affirm that during periods of recession, characterized by anxiety and uncertainty, investors' attitude toward risk become more risk averse and hypersensitive to analyst forecasts. Therefore the downside risk becomes their main concern and a key component for the risk management and the decision-making processes.

Value-at-Risk, introduced by J.P. Morgan in the 1990s, is one of the most used measures to evaluate the downside risk of an investment, especially in financial institutions, since it allows investors to understand, in present value terms, the losses that will not be exceeded with a certain level of confidence (Alexander, 2005). Obtained through the lower percentile of profit and losses (P&L) or returns distributions and the mapping of investment positions to risk factors, it gives the investor a single number that can be applied to all activities and markets and that it is easy to communicate, disaggregate and compare. The literature on Value-at-Risk models is vast and diverse for different needs, but the models' structure tends to be similar: estimation of parameters that allow to generate assumptions about data and risk factors' behavior, choice of the most suitable P&L distribution and then the help of a quantile on the left-tail of such distribution to estimate the maximum absolute loss expected. The most used models in practice are Parametric Models that assume well-known distributions for the assets and risk factors such as the Normal and Student-T distributions, Historical Models that use historical data to estimate empirical distributions and Monte Carlo Models that simulate asset and risk factor returns through stochastic processes (Alexander, 2005).

Being a forward-looking measure, VaR performance depends on the appropriate choice of mapping instruments and estimation techniques, especially during crisis (Marshall & Siegel, 1997). Most standard Value-at-Risk Models underestimate the risk of losses, that is, the maximum losses estimated end up being smaller than the losses that happen, generally due to changes in the returns' distribution. Mirjana Miletic and Sinisa Miletic (2015) analyzed the behavior of CEE countries' VaR and Gaio et al. (2015) the Brazilian VaR during the global financial crisis of 2008 and both concluded that in such periods, the normality of the returns' distribution is usually rejected. On the other hand, models that use heavy-tails distributions as the student-t or the general pareto distribution based on the extreme value theory provide more efficient fits to estimate the market risk since return series become asymmetric. Furthermore, the first authors affirm that the use of GARCH-type methods are more precise to forecast the volatility in such periods.

These conclusions are in line with those of Gençay and Selçuk (2004) that studied the VaR of Asian countries during the Asian crisis of 1998 using 6 different models and concluded that for moderate levels of significance all models are quite efficient, while for stricter levels of significance, the GPD VaR model based on the extreme value theory (EVT) outperforms all the remaining models. However, it is important to refer that the EVT is not usual in practice since the Basel II agreement does not allow institutions to use this model for capital requirements as they believe that their suggested models with high confidence levels and longer time horizons are sufficient to decrease the underestimations and the number of VaR violations (Kourouma et al., 2011).

To evaluate the impact of a crisis in the market risk, most of the studies tend to focus on volatility and standard Value-at-Risk models. As expected, they conclude that financial markets are highly affected by economic and structural changes that take place during periods of recessions, verifying an increase in the market risk. In 2015, Grout and Zalewska analyzed if specific characteristics of periods of recession could explain changes in beta coefficients of Famma-French and CAPM models for the G12 countries' indexes between 1996 and 2014. They verified that coefficients for industrial and banking sectors increased significantly during the financial crisis and that the more severe the crisis, the higher the increase, that is, the greater the risk. Another study (Soultanaeva & Strömqvist, 2009) identified an increase in the Swedish short-term money market risk between 2006 and 2009, demonstrating greater demand of investors towards the risk during the Global Crisis. Orlowski (2012) monitored the market risk of 8 countries through GARCH volatility models for stocks, interest rates and exchange rates. He concluded that large and unpredictable shocks that result from global crisis led to volatility outbursts in most of the countries and that the weaker the macroeconomic policy discipline of the country, the more vulnerable its market risk to global financial crisis was. However, when analyzing the S&P500 behavior between 1982 and 2010, Schwert (2011) concluded that the market does not expect prolonged periods of high volatility. In the period of analysis the S&P500 returns' volatility only deviated from its usual values for longer during the Great Depression, while in other recessions as the 1987 Market Crash or the 2008 Global Financial Crisis, the stock market faced historical high levels of volatility but that did not remain high for long.

The COVID-19 pandemic crisis has already surpassed by a considerable amount the quantity of people and countries affected in others recent public health crisis, and it is now the biggest pandemic of the century. Therefore, we can only expect this event to have a financial impact never seen before. This was confirmed by Das and Rout when they verified that between January and May 2020, the market risk level of countries such as the US, Germany and France surpassed the levels observed during crisis as the 1992 US recession or even the Global Financial Crisis of 2007-2008. In the US the consequences of the pandemic start were so severe that 90% stocks of the S&P500 index showed negative returns during March 2020, reaching losses of 60% and volatilities of 20% in just one day (Mazur et al., 2021). Moreover, Al-Awadhi (2020) concluded that the number of cases and deaths due to the virus influenced the returns of Chinese stock indexes between January and March 2020, since the higher the number of cases and deaths, the more negative the returns. The authors also found that the negative impact increases with the sector market capitalization, which matches the findings of Li et al. (2021), that identifies a sharp increase on market risk exposure in China, especially in large-cap industries. However, the situation was different in countries such as the US and the UK, as they faced higher risk than China and the companies more affected were mid cap in the US, and small cap in the UK.

Many studies show that despite China being the source of the outbreak, it was outside this country that COVID-19 had major consequences on risk. While the market volatility in China stabilized upon February, indexes of other big economies such as the US, the UK, Germany, and South Korea, as well as most European indexes, faced constant increases of volatility and negative returns in a later stage and for longer (Alam, 2020). Through an analysis of the financial market volatility index (VIX), Albulescu (2020) reported that despite being the country with the highest volatility level in February, China had the lowest volatility in the very next month, while in US the volatility quadrupled from February to March (Zhang et al., 2020). Moreover, only new cases announcements outside China led to high VIX values between January and March 2020, meaning that markets were more sensitive to what was happening in the rest of the world.

Different market reactions can be related to the effectiveness or failure in containing the virus, as well as different investors' behaviors and expectations or even country specific characteristics such as fiscal policies or information structures. Evidence reveals that least developed countries and emerging markets suffered more during the pandemic, facing higher market risk and abnormal negative returns when compared to developed countries (McKibbin and Fernando, 2020; Harjoto et. al, 2020). Additionally, Erdem (2020) concluded that the impact decreases with the level of freedom as freer countries faced smaller return decreases and volatility due to COVID-19 cases and death announcements, meaning that investors of less freedom countries are more sensitive to local and global information. Information had a significant role in investors' panic around the pandemic situation and were one of the main sources of market changes. Aggarwal et al. (2021) affirm that panic had negative effect on stock returns through the Market Risk Premium Channel, while lockdown effects impacted positively, which means that investors became more risk-averse demanding high premiums immediately after the initial boom, but less risk-averse as increasingly secure they felt. On the other hand, considering that only the lockdown affected negatively returns through the Growth Channel (expected future cash flows) while panic did not affect, investors' expectations were not influenced by fear emotions but by uncertainty around the consequences of restrictive measures in business. Consequences on stock market are highly correlated to investors' fear and their reactions to the news, and therefore it is fundamental that competent entities strive for regulate the market and prevent unprecedent stock crashes (Liu et al, 2022).

We can conclude that existing studies show that the market risk increased, especially in developing countries, due to changes in investors' behavior and expectations as a result of the pandemic conjuncture, its management, social and media reactions. However, as far as we know, these studies are lacking in only looking to the initial moments of the pandemic, a specific and short timeframe that may not translate the actual impact of such situation. Thus, in this dissertation we focus our analysis on a longer period that allows us to properly analyze the impact of the pandemic in the overall scope of the market.

CHAPTER 3

Contextualization: COVID-19 Phases

This study attempts to analyze the market risk behavior throughout the COVID-19 pandemic situation and how the market reacted in its separate phases. For that purpose, we elaborate a timeline, based on reports from the World Health Organization (WHO), the Centers of Disease Control and Prevention (CDC), as well as a news piece from the NY Times (2021), to clearly identify and framework the different moments lived between 2020 and 2021.

The start of the pandemic goes back to December 2019, when in China several people were affected by symptoms of shortness of breath and fever, in what seemed to be cases of pneumonia with no known explanation. Although Chinese health authorities implemented protocols such as flight controls, travel bans or entire cities lockdowns to sustain the outbreak, the virus, later known as a new type of the coronavirus, quickly spread throughout the country. On January 11, China reported the first death due to the disease. It did not take long for WHO to declare the outbreak as a Public Health Emergency of International Concern as the first cases were confirmed outside its epicenter, in countries such as Japan, South Korea, Thailand and the US. Travels to and from China were suspended and controls in travels between countries were tightened, however efforts remained insufficient to contain the proportions that the outbreak would have. In February, the situation worsened in Asia but also outside this continent. In addition to the number of cases that increased exponentially and completely unexpectedly, Asia already faced a number of 1,500 deaths, while the first deaths were confirmed in Europe, the US, and some South American countries. During this month, Italy became the center of infections outside China, which forced extraordinary measures such as shutdowns of schools and other public spaces, besides the restrictions on travels that were already implemented.

March was marked by the declaration of the COVID-19 outbreak as a pandemic and the worldwide panic and efforts to contain the situation. All around the world, schools, restaurants, and other public institutions were shutdown, sporting, cultural and public events were canceled, people were required to use mask in public, to avoid big groups of people, to maintain social distance, companies had to cease activity, some people went into layoff, others lost their job and the pandemic numbers continued to rise. In April 2020, more than 1 million of infections were already faced amongst 171 countries and in that month the death toll surpassed 200 thousand people.

Despite the numbers, economies needed to open again, otherwise, as mentioned by the World Bank, the Global Economy would fall to the worst recession since World War II. As such, between June and July there were defined specific frameworks with details to reopen safely the countries, to lift restrictions, and to help financially the most affected nations. However, after that, new waves appeared, new measures were taken, and the cycle repeated until the end of 2020. During this period of ups and downs, major international pharmaceutical organizations worked to manufacture a vaccine against the COVID-19 virus. In December 2020, the first vaccines were approved, and the global vaccination agenda started with health care professionals and residents of long-term care facilities.

In January 2021, the world surpassed the mark of 100 million COVID-19 cases. Due to special efforts from WHO, who created a program to accelerate and ensure safe, quick, and equitable access to the vaccination agenda for all countries around the world, the administration of the vaccine protocol was intensified. Between this month and April 2021, more than thirty-eight million doses were delivered, and some restrictive measures were lifted. The rest of 2021 was marked by advances and setbacks in counter the pandemic situation, due to the emergence and predominance of new cases of the Delta variant after June and the Omicron variant in November. Furthermore, new vaccination protocols were implemented that included the administration of booster doses.

Based on this timeline, we propose the division of the COVID-19 period into four phases, corresponding to each semester of 2020 and 2021. The first phase, between January and June 2020, is characterized by the start of the virus outbreak, the worldwide spread, the panic generated by this unpredictable event and the first countermeasures taken. In the second half of 2020, there was an attempt to return to the normal life conditions, with the opening and lifting of restrictions and the appearance of new waves of infections that led to constant progress and regressions in the pandemic situation. Finally, the first half of 2021, corresponding to phase three, was marked by the global agenda of vaccination, while the second semester, phase four, was characterized by the appearance of new variants and the intensification of the vaccination through the administration of booster doses.

CHAPTER 4

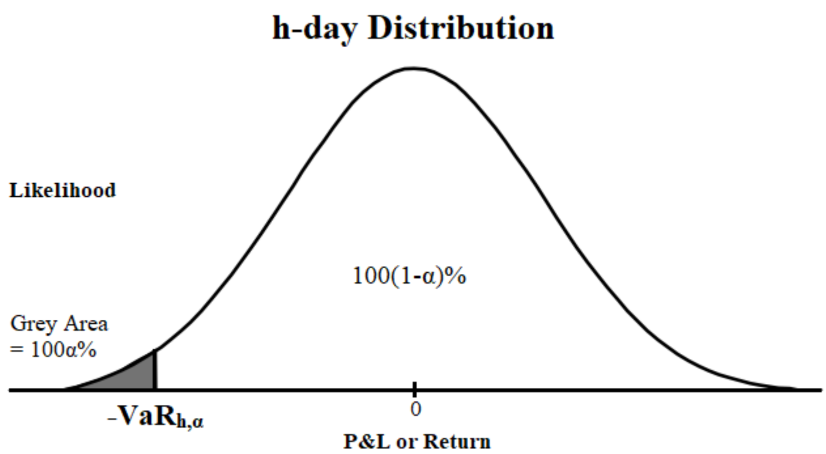
Methodology

4.1. Value-at-Risk

Value-at-Risk is currently the widely used measure to evaluate market risk. VaR estimates the loss, in present value terms, that a portfolio will not exceed during a certain period of time h, with a confidence level of 100(1-α)%. Therefore, this metric relies on a model of changes in the asset prices, represented by return distributions and the probability of such losses.

Figure 1. Value-at-Risk Representation

Source: ISCTE Risk Management course



The 100α% h-day VaR (VaR$_{h,\alpha}$) can be mathematically defined as minus the α quantile of h-day discounted distribution:

$$VaR_{h,\alpha} = -F^{-1}(\alpha) \tag{1}$$

where F^{-1} is the inverse distribution function, h the time horizon and α (significance level) the probability of losses below the estimated VaR:

$$\alpha = P(X < -VaR_{h,\alpha}) \tag{2}$$

Therefore, since the VaR relies on return distributions, it represents the maximum percentual loss expected, with a certain confidence level, in the date t portfolio if we hold it for the next h trading days. In this study, we consider the significance level set by the Basel Accord $(\alpha = 1\%)$ and a risk horizon of one day $(h = 1d)$.

Summarizing, to evaluate the market risk of a country, we compute the $VaR_{1d,1\%}$ of its stock index, that estimates the maximum percentual loss of such portfolio (composed equally by the set of stocks included in such index) in a trading day, for a confidence level of 99%.

4.1.1. Parametric Normal VaR

Over the years, several VaR Models have been developed to suit different data characteristics and different market conditions. In this study, we use the Parametric Normal Model purposed by J.P Morgan/Reuters in the Risk Metrics™ – Technical Document (1996). This model is widely used in practice due to its minimal computation time and simple processes that can produce appropriate results to capture market risk.

The model delivers analytical formulas for VaR that relates to easy to estimate parameters such as the mean and the standard deviation of the returns and, as the name implies, it assumes that the h-day portfolio returns follow a normal distribution, i.e.:

$$X_h \sim N(\mu_h, \sigma_h^2) \tag{3}$$

where μ_h is the returns' mean and σ_h^2 the variance.

Recalling the formula (1) and denoting the α quantile of the normal distribution as $\Phi_{\mu_h,\sigma_h}^{-1}(\alpha)$, the formula for the Parametric Normal VaR is:

$$VaR_{h,\alpha} = -\,\Phi_{\mu_h,\sigma_h}^{-1}(\alpha) \tag{4}$$

which can be presented as:

$$VaR_{h,\alpha} = \Phi^{-1}(1-\alpha) \times \sigma_h - \mu_h \tag{5}$$

where Φ^{-1} represents the inverse of the standard normal cumulative distribution (with mean zero and standard deviation one) and σ_h represents the returns' standard deviation.

Furthermore, since the risk horizon considered is only one trading day ($h = 1d$), the daily returns will always be very close to zero and consequently we can assume that their expected value is zero ($\mu_h = 0$). , With this assumption, the Parametric Normal VaR formula simplifies to:

$$VaR_{h,\alpha} = \Phi^{-1}(1-\alpha) \times \sigma_h \tag{6}$$

and therefore, we only need to compute the inverse of the standard normal cumulative distribution with a probability of 99% (as $\alpha = 1\%$) and multiply it by the daily standard deviation of the country stock index' returns to obtain its daily Value-at-Risk.

4.1.2. Standard Deviation Estimation

Considering that the objective is to capture the information about market risk adjusted to current market conditions, we use the exponential weighted moving average (EWMA) model to estimate returns' volatility. As the name implies, this model assigns exponentially decaying weights to older observations, increasing the sensitivity of the estimation to most recent observations, without renouncing completely the sensitivity to the oldest ones. Therefore, recent observations will have bigger impact in reflecting more precisely what is happening in the market in the moment of the estimation.

EWMA Model uses the following formula to estimate the variance of returns (σ_t^2):

$$\hat{\sigma}_t^2 = (1-\lambda) r_{t-1}^2 + \lambda \hat{\sigma}_{t-1}^2 \tag{7}$$

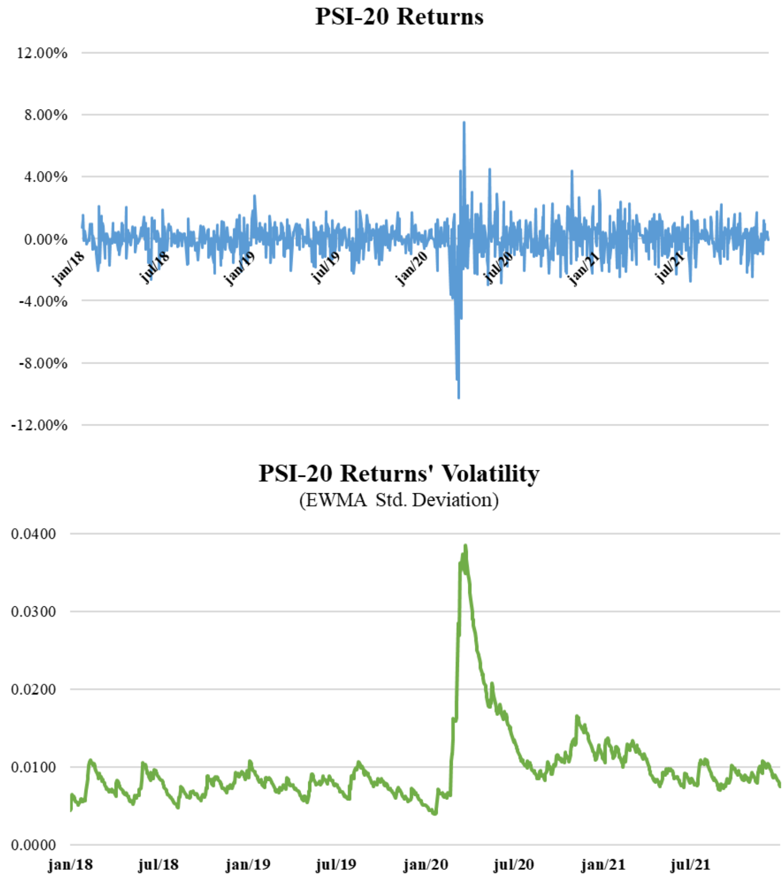
and consequently, their volatility is represented by the respective standard errors:

$$\hat{\sigma}_t = \sqrt{\hat{\sigma}_t^2} \tag{8}$$

Through the smoothing factor λ $(0 < \lambda < 1)$, we can control the weight assigned to different observations. The portion assigned to the most recent observation will be 100(1- λ)% and consequently, the smaller the smoothing factor, the higher the sensitivity to the newest market conditions. In this study we use the smoothing factor purposed by the Risk MetricsTM – Technical Document ($\lambda = 0.94$), which means that 6% of the total weight is given to the most recent observation and as time recedes the weight given to each observation decreases exponentially. As referred before, since the variance estimated at time t ($\hat{\sigma}_t^2$) depends on the variance of the immediate previous estimation ($\hat{\sigma}_{t-1}^2$), old observations are not completely discarded, only lose relevance as we advance in time and adapt new estimations to capture new conditions.

To demonstrate that the EWMA model represents realistically what happens in the market, we present the graphs below that show the returns of PSI-20 and their volatility (through the EWMA standard deviations) in the period between 2018 and 2021.

Figure 2. PSI-20 Returns and Return Volatility (2018-2021)



Focusing on the returns graph, we can identify that the initial period of 2020 was the most turbulent period in the market, marked by constant changes in prices that reflect in returns ranging from -10.27% to 7.53%. As a result, we expect high volatilities during this period and from the volatilities graph, we realize that the EWMA model easily captures this information from the market. We observe that volatility estimations increase exponentially in the first semester of 2020 and reach their highest peak during this period, in line with what is observed in the returns. Additionally, after this period of great turbulence, the EWMA volatilities quickly decrease, adjusting again to the new market conditions where there is more stability in prices and returns. We can then conclude that this model is able to produce a quite reliable representation of what is really happening in the market at each estimation moment.

4.2. Panel Data

Panel data or longitudinal data is a multi-dimensional method of data organization that results from a combination of two other methods: cross-sectional data and time series. The first one refers to a set of observations from different subjects (individuals, groups, countries, states, etc.), at a specific point-in-time or period, usually used to compare those subjects at that specific time. Time series is a sequence of data points indexed in chronological order over an interval of time, collected on a single subject to track changes between the observed data points. Combining these two models, Panel Data provides a pool of observations captured from different entities across time, allowing to analyze simultaneously different individuals over different time periods (Wooldridge, 2013).

Therefore, to understand different behaviors of a dependent variable in different individuals at different periods and to analyze what can explain changes in such behaviors, we use linear regression models for Panel Data that follow this general formula:

$$y_{it} = \alpha_i + \lambda_t + x'_{it}\beta' + \varepsilon_{it} \tag{9}$$

The individual-specific effects are represented by α_i, while λ_t is the time-specific effects and can be a result of fixed effects or random effects, as we present later. x_{it} represents the observation of K explanatory variables for the individual *i* (*i* = 1, …, N) at time *t* (*t* = 1, …, T) and β the K × 1 vector of the estimated coefficients. y_{it} is the *i*th observation of the dependent variable and ε_{it} the error term.

4.2.1 Advantages of Panel Data

Combining cross-section and time series allows to pool information from different individuals, guaranteeing complete data for the study (Gujarati, 2004). Therefore, Panel Data approach allows not only to improve the efficiency to capture, describe and compare different behaviors through different periods, but also to predict an individual's behavior based on the behavior of others with similar characteristics. Furthermore, by providing data with more degrees of freedom than unidimensional models, it allows to infer and test more complex hypotheses.

Hsiao (2006) and Verbeek (2004) state that Panel Data analysis can correct or reduce 3 problems that usually occur in other methodologies: the existence of omitted variables, the collinearity between variables and the measurement error.

The omission of variables can be a problem in estimations since when variables that can impact the dependent variable or that can be correlated to the considered explanatory variables are not included in the model, it can lead to misleading inferences of the effects of explanatory variables on the dependent. Since Panel Data models include information about specific dynamics of individuals (α_i) and different time dimensions (λ_t), this methodology is robust to omitted variables. In other words, it allows to control and reduce the impact of variables that are not know, that are difficult to measure or that are simply omitted on the statistic inference.

In statistics, multicollinearity corresponds to the existence of correlation between explanatory variables. Since one major objective of regression analysis is to understand the impact of explanatory variables in the dependent one in isolation, when there are strongly correlated explanatory variables, the model loses accuracy in estimating these individual predictors, affecting the statistical power of the regression. However, Panel Data has available bigger samples with higher degrees of freedom that allow to observe inter-individual differences and intra-individual dynamics and to reduce the collinearity amongst explanatory variables.

Finally, the measurement error is the difference between the estimated inference and its true value, caused by random effects (unpredictable sources affecting different measurements) or systematic effects (bias in the estimation that affects all measurements). This problem can lead to inconsistency or less reliability in the estimations' inference. However, by providing a large scale of data for different individuals at a given time-point, Panel Data allows to apply transformations to the explanatory variables to reduce the measurement error without any need of external instruments.

4.2.2 Fixed Effects Model

In the Fixed Effects Model, individual-specific effects (α_i) are assumed as fixed and constant, i.e., they do not vary with time (Verbeek, 2004). These individual effects are usually represented through dummy variables, variables that take value of 1 when we observe the presence of some condition in the individual i or the value of 0 when we observe the absence of that condition. Moreover, despite being a model that focus especially on the study of individuals' differences, the analyzes of specific temporal effects are not entirely ruled out, since we can also create dummy variables to characterize time.

Recalling the formula (9), these fixed constant variables that represent specific effects only affect the intercept term of the model and therefore there is no problem if they are correlated or uncorrelated with the others explanatory variables (X_{it}). Including dummy variables to identify fixed specific effects in the model, we use a so-called Least Squares Dummy Variables (LSDV) estimator, where the regression formula becomes:

$$y_{it} = \sum_{j=1}^{N} \alpha_j d_{ij} + \beta x'_{it} + \varepsilon_{it}, \varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2) \tag{10}$$

In this case we have two types of explanatory variables: N dummy variables represented by the d_{ij} that assume the value 1 if $i = j$ and 0 if $i \neq j$, and K input explanatory variables (x_{it}).

To analyze the impact of such variables on the dependent variable, we must estimate their parameters α_j ($N \times 1$ vector) and β ($1 \times K$ vector). Assuming that the explanatory variables X_{it} are non-stochastic, the LSDV estimator inferred through the OLS method are linear, efficient, unbiased and consistent, but it becomes computationally intensive and sometimes impractical to estimate $N + K$ parameters. Therefore, we can clean individual effects through the within transformation by subtracting the group mean from each individual observation. In this case, the regression becomes:

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \tag{11}$$

Using this transformation, we use a so-called within estimator ($\hat{\beta}_{WE}$) to estimate the parameters β, which obeys the following formula:

$$\hat{\beta}_{WE} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)' \tag{12}$$

and using the formula:

$$\hat{\alpha}_i = \bar{y}_i - \hat{\beta}_{WE} \bar{x}'_i \tag{13}$$

we estimate the parameter alpha.

4.2.3 Random Effects Model

The Random Effects Model assumes that differences across entities have random causes and, unlike the Fixed Effects Model, the unobservable individual-specific effects are not correlated with the explanatory variables, i.e., $cov(\alpha_i, x_{it}) = 0$. Since assumed as random, the constant individual-specific effects (α_i) are included the error term along with within-entity error (ε_{it}) forming the random error term ($\alpha_i + \varepsilon_{it}$), where both components are independently and identically distributed over individuals (Verbeek, 2004). Therefore, the regression formula for the Random Effect Model is:

$$y_{it} = \beta_0 + \beta x'_{it} + \alpha_i + \varepsilon_{it},\ \ \alpha_{it} \sim IID(0, \sigma_\alpha^2)\ \varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2) \tag{14}$$

The OLS method can produce consistent estimators for the parameters β_0 and β by minimizing the difference between the actual and the predicted value of the outcome variable (sum of square errors), i.e.:

$$\hat{\beta}_{OLS} = \arg\min_{\beta} \sum_{i=1}^{n} \left| Y_i - (\hat{\beta}_0 + \hat{\beta} X_{it}) \right|^2 \tag{15}$$

However, if we verify the existence of autocorrelation in the random error term, it could lead to bias in the estimation of the standard errors, ceasing the OLS to provide the Best Linear Unbiased Estimators (BLUE). In that case, we must use more robust estimators to clean the bias in the estimation as the GLS method, where:

$$\hat{\beta}_{GLS} = W\hat{\beta}_B + (I_k - W)\hat{\beta}_{FE} \tag{16}$$

By combining the within estimator (*12*) with the between estimator $\hat{\beta}_b$:(*18*)

$$\hat{\beta}_{WE} = \left(\sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})' \right)^{-1} \left(\sum_{i=1}^{N} (x_i - \bar{x})(y_{it} - \bar{y}) \right) \tag{17}$$

and assigning different weights to the estimators through the weighting matrix (W) and the identity matrix (I_k), the GLS Model can produce efficient estimators for the Random Effects Model (Verbeek, 2004).

4.2.4 BLUE Consistent Estimations

Although the fixed effects model is mainly based on the OLS method to estimate the parameters of the regressions while the same is not true for the random effects model, we can assess the consistency of the models using the same tests, as the data can be applied to both of them.

The Gauss-Markov Theorem states that the OLS estimator is considered BLUE when compared to all the other linear regression models, it produces unbiased (centered on the actual population) estimations that follow the distribution with the smallest variance possible, i.e, for any other unbiased estimator $\tilde{\beta}$:

$$Var(\tilde{\beta}|X) \geq Var(\hat{\beta}_{OLS}|X) \tag{18}$$

If the estimator is not BLUE, the estimation is does not cease to be valid, but the model used is not the most efficient one to fit to the sample, leading to misleading calculation of the standard errors and, consequently, and incorrect interpretation of the tests of significance.

The two main properties that we must verify to consider that the OLS provides BLUE consistent estimations are the homoskedasticity and no autocorrelation.

The first condition refers to the existence of constant and equal variance (σ^2) in the error term (ε_{it}), i.e.:

$$Var(\varepsilon_{it}|X) = E(\varepsilon_{it}^2|X) = \sigma^2 \tag{19}$$

If this condition does not apply, there is heteroskedasticity in the error term and consequently the estimators are no longer BLUE. To detect the existence of heteroskedasticity in Panel Data we use the Breusch-Pagan Test associated with the Lagrange multiplier:

$$\sigma_i^2 = \sigma^2 h(z_{it}'\alpha) \tag{20}$$

and we test:

$$H_0: \alpha = 0 \; ; \; H_1: \alpha \neq 0 \tag{21}$$

where z_{it} represents K variables that can affect heteroskedasticity, *h* the unknown continuously differentiable function and H_0 and H_1 the null and alternative hypothesis respectively. If we do not reject H_0, the homoskedasticity property is verified and the OLS estimator is BLUE, otherwise there is heteroskedasticity in the model and the model is not providing the most efficient estimations.

The second property (no autocorrelation) assumes that lagged versions of the error term are linearly independent and not correlated, i.e.:

$$Cov(\varepsilon_i, \varepsilon_j) = 0, for\ i, j = 1, 2, \dots, n \tag{22}$$

Through the Durbin-Watson test, by applying in the AR(1) lag process we can detect the existence of errors' first order autocorrelation:

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + \upsilon_{it} \tag{23}$$

where $\rho \in (0,1)$ and υ_{it} follows a normal distribution with mean 0 and variance σ_{υ}^2. In this case, the null hypothesis ($H_0: \rho = 0$) must not be rejected so that there is no autocorrelation. Otherwise, there is first order autocorrelation in the error term and the OLS estimators are no longer BLUE.

The main sources of heteroskedasticity and autocorrelation are the omission of variables, the use of incorrect transformations or functional forms in the model, the existence of measurement error or misspecification error and particular characteristics of some explanatory variables (v.g. presence of skewness and big range of values). Recalling, if heteroskedasticity or/and autocorrelation is detected, the OLS method is still unbiased but does not provide the most fitting estimators possible since it is not BLUE. To bypass this problem, we can use models that are robust are robust with heteroskedasticity and autocorrelation to get the most efficient model possible to estimate and evaluate the impact of explanatory variables in a dependent variable

CHAPTER 5

Implementation

The overall scope of this study is to understand the impact of the pandemic and its management in the market risk of developing and developed countries and at different phases of the pandemic evolution.

The first step is to differentiate developing countries and developed countries. For that purpose, we use the Human Development Index (HDI) that is "a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and have a decent standard of living" (Human Development Reports, n.d.). This index ranges from 0 to 1 but since it is an index that compiles many factors, some of them subjective to the eyes of different institutions, there is no standard minimum value for a country to be considered developed. However, according to many portals such as the Investopedia and the WorldData, most developed countries have HDI equal or above 0.80 and therefore this is our point of differentiation.

To assess market risk, we compute the daily $\text{VaR}_{1d,1\%}$ (i.e., Value-at-Risk of 1 trading day with 1% significance level) from the different groups in a sample period of 5 years (2016 to 2021) to guarantee a sufficiently large comparison window. For that purpose, we first collect from the Investing.com website the daily close prices of 20 stock indexes from different countries (10 developing countries and 10 developed countries) from 2014 to 2021 (see Appendix A). After collecting such time series of prices, we compute their daily logarithmic returns and estimate the volatility of such returns using the EWMA model (7). Finally, we evaluate the market risk of those 20 stock indexes through their daily Parametric Normal $\text{VaR}_{1d,1\%}$ (7).

The characterization of the pandemic situation is carried out through 5 different measures and indexes collected from the OurWorldInData portal:

1. $reproduction\_rate$: "represents the average number of new infections caused by a single infected individual. If the rate is greater than 1, the infection is able to spread in the population. If it is below 1, the number of cases occurring in the population will gradually decrease to zero."

2. $stringency\_index$: "composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest)."
3. $delta\_share$: "Share of SARS-CoV-2 sequences that are the delta variant"
4. $omicron\_share$: "Share of SARS-CoV-2 sequences that are the omicron variant"
5. $people\_fully\_vaccinated$: "Total number of people who received all doses prescribed by the initial vaccination protocol, divided by the total population of the country"

and 3 from the RavenPack's Coronavirus Media Monitor to characterize media and social response:

1. $panic\_index$: "Measures the level of news chatter that makes reference to panic or hysteria alongside the Coronavirus", where "the higher the index value, the more references to panic found in the media."
2. $media\_hype\_index$: "measures the percentage of news talking about the novel Coronavirus."
3. $sentiment\_index$: "measures the level of sentiment across all entities mentioned in the news alongside the Coronavirus. The index ranges between -100 and 100 where a value of 100 is the most positive sentiment, -100 is the most negative, and 0 is neutral."

These indicators are collected for the whole period between the beginning of 2020 and the end of 2021 and for the 20 countries in consideration. In case of not having available data on a specific date, we use interpolation to estimate those missing points and complete the data to have balanced panels, i.e., complete datasets to each individual i and each time-point t.

Finally, to evaluate the effects of the pandemic and its management in the market risk, we use Panel Data regression models with the VaR as dependent variable and different COVID-19 monitoring indicators as explanatory variables, in 5 different periods: the overall period and the 4 specific sub-periods (called PHASES), each one corresponding to each semester of 2020 and 2021.

5.1. Overall Period

The overall period comprises data from all existing business days between 2020 and 2021. When the number of time-points (T) is sufficiently large, the choice between the use of fixed effects model or random effects model for Panel Data just depends on the user's intention to analyze the data since their estimators become very close or even the same (Hsiao, 2003, as cited in Borges, 2020). Since our intention for the overall period is to analyze the importance of specific characteristics of each country group in their VaR behavior and the dynamics throughout different periods of time, i.e., infer the existence of fixed and constant individual-specific effects and time-specific effects, we use the Fixed Effects Model using the LSDV estimator (10).

For that purpose, we create 6 dummy variables: $d_{Developing\ Country,i}$ that assumes value 1 if the individual i is considered a developing country and 0 otherwise, $d_{Developed\ Country,i}$ that assumes value 1 if the individual i is considered a developed country and 0 otherwise, and $d_{Phase\ I,t}$, $d_{Phase\ II,t}$, $d_{Phase\ III,t}$ and $d_{Phase\ IV,t}$ that assume value 1 if the time-point t is included in the period corresponding to PHASE I, II, III or IV respectively, and 0 otherwise.

After having all the necessary information available, we run two regressions using the Fixed Effects model with the LSDV estimator (10), one to analyze individual-specific effects and other to analyze time-specific effects. The VaR estimated for the twenty countries is the dependent variable and as for explanatory variables, we use 6 COVID-19 indicators combined with dummy variables according to the objective (dummy variables of country groups to control individual-specific effects and dummy variables of phases to control time-specific effects). Note that we do not include indicators correspondent to delta and omicron variants in the study for the overall period since they are only observable during one specific sub-period (PHASE IV).

5.2. Specific Periods

The analyzes that we want to do for each specific period is different from the one for the overall period. While in the overall period we want to understand if the specific characteristics of the countries and specific characteristics of time can explain the risk observed in the market, in the sub-periods we want to compare the significance of the different measures in the market risk of each country group. In other words, we want to reach conclusions about two populations, developing countries and developed countries, based on the sample of 10 countries from each group. Therefore, we must use the Random Effects Model (14) and estimate two regressions in each PHASE: one with the VaR of the 10 developing countries as the dependent variable and the COVID-19 monitoring indicators of the same 10 developing countries as explanatory variables and another regression with the VaR of the 10 developed countries as the dependent variable and their corresponding COVID-19 indicators as explanatory variables.

5.2.1 PHASE I and PHASE II

PHASE I and PHASE II comprise the first and the second semester of 2020 respectively. The first period corresponds to the start of the pandemic and its global spread, followed by the first government responses and social panic around the unpredictable situation that impacted immediately millions of people and companies. The second one corresponds to the post-initial shock, after several different measures were tested, taken, and lifted, with greater knowledge and global perception of the conjuncture and how to deal with it.

In both phases we study and compare the impact of the pandemic evolution (through the $reproduction\_rate$ indicator), the measures taken (through the $stringency\_index$) and the social and media response (through the $panic\_index$, $media\_hype\_index$ and $sentiment\_index$ indicators) in the market risk of each group of countries.

5.2.2 PHASE III

The period between January 2021 and June 2021 is characterized by the implementation of the global COVID-19 vaccination agenda. Therefore, to the indicators used as explanatory variables in PHASE I and PHASE II, we add an explanatory variable corresponding to the percentage of people fully vaccinated ($people\_fully\_vaccinated$). Moreover, since a year with the pandemic has passed until this phase, the $panic\_index$ variable is not relevant anymore and therefore is excluded from the model.

5.2.3 PHASE IV

During the last half of 2021, the delta and omicron variants predominated the number of confirmed COVID-19 cases, almost reaching 100% of the cases in many countries when combined. Thereby, instead of using the $reproduction\_rate$ indicator, we resort to the $delta\_share$ and $omicron\_share$ indicators to characterize the pandemic evolution. Apart from this change, the same indicators that were considered as explanatory variables in the analyzes of PHASE III are considered also in PHASE IV.

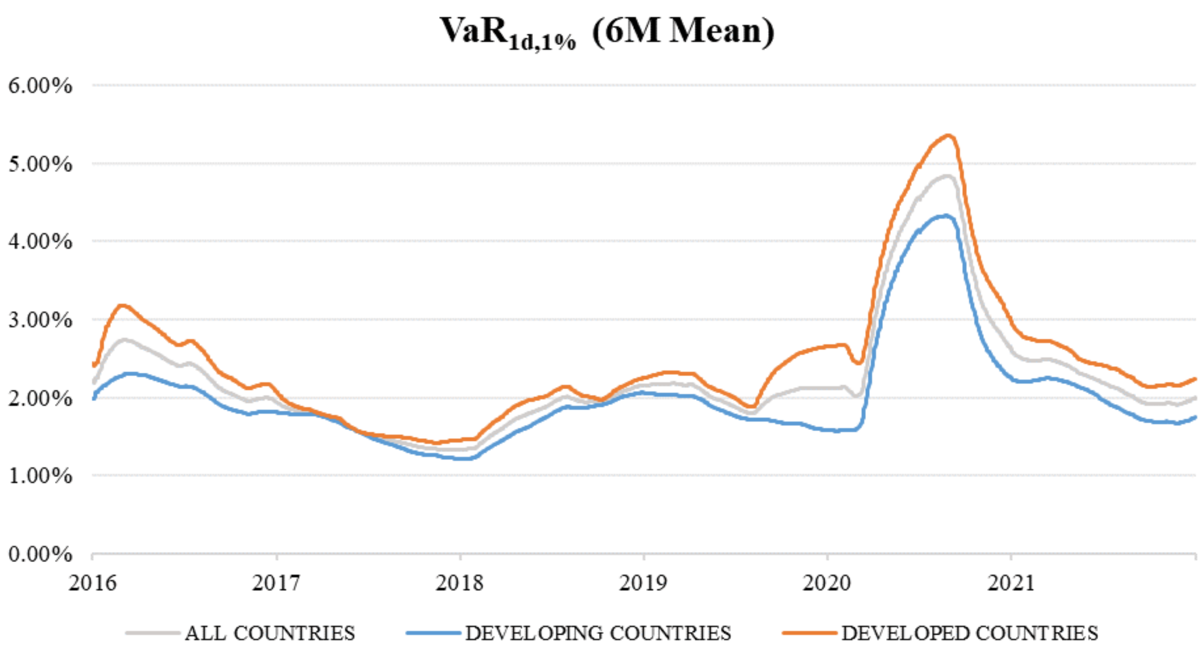
CHAPTER 6

Results

This completely unexpected and unprecedent event in the 21st century changed the entire social and labor situation from one day to the other. Expectations and prospects of people and companies are expected to be severally affected during this period, and naturally the financial market will react. Prices of assets and liabilities will go through turbulent phases of great changes and uncertainty, affecting volatility and market risk, that we expect to increase. However, it is also expected that as measures are taken and efforts are made to control and reduce the consequences of this situation, the risk verified in the market will also return to its usual values or at least adapt to the new reality.

These hypotheses are confirmed in the graph and table below. We can see a huge increase in the 6-month average of the daily Values-at-Risk in both developing and developed countries in the beginning of 2020, when most of the countries reached their maximum risk peak since 2016. Moreover, we find that as we progress in time towards the end of 2020 and 2021, VaRs decrease in both groups of countries, indicating the adaptation to the new reality and the return to usual market conditions and risk indices.

Figure 3. 6M Average Value-at-Risk – Developing vs Developed Countries (2016-2021)



Description: *The 6M Average Value-at-Risk is the average over a rolling sample of 6 months of the daily VaRs*

During the pre-covid period (2016-2019) the average VaR of all countries under consideration was 1.91%, while the VaR average in the overall pandemic period (2020-2021) was 2.84%. This increase in risk was seen both in developing and developed countries, demonstrating the worldwide transformation that happened in the market in the last two years. However, it is important to understand its behavior throughout different phases and the differences between each country group.

Table 1. Value-at-Risk Mean and the Absolute Change per year, period, and PHASE

PERIOD	Mean			Absolute Change		
	ALL	DEVELOPING	DEVELOPED	ALL	DEVELOPING	DEVELOPED
Before COVID	1.91%	1.74%	2.09%			
During COVID	2.84%	2.52%	3.15%	0.84%	0.85%	0.83%
2016	2.18%	1.98%	2.39%	-	-	-
2017	1.43%	1.37%	1.50%	-0.75%	-0.61%	-0.89%
2018	2.03%	1.92%	2.15%	0.60%	0.55%	0.65%
2019	2.00%	1.68%	2.32%	-0.03%	-0.24%	0.18%
2020	3.58%	3.19%	3.97%	1.58%	1.51%	1.65%
2021	2.09%	1.85%	2.32%	-1.49%	-1.34%	-1.65%
1st Semester 2019	1.89%	1.77%	2.00%	-	-	-
2nd Semester 2019	2.11%	1.58%	2.64%	0.22%	-0.19%	0.64%
PHASE I	4.56%	4.14%	4.98%	2.45%	2.56%	2.34%
PHASE II	2.62%	2.25%	2.98%	-1.94%	-1.89%	-1.99%
PHASE III	2.19%	1.96%	2.41%	-0.43%	-0.29%	-0.57%
PHASE IV	1.99%	1.75%	2.24%	-0.19%	-0.22%	-0.17%

Description: *Mean in each period represents the average of the daily VaRs of the dates corresponding to such period. Absolute Change is the VaR Mean of the period of calculation minus the VaR Mean of the previous period. For example, the absolute Change in 2019 is the difference between the 2019 VaR Mean and the 2018 VaR Mean, and the Absolute Change in PHASE I is the PHASE I VaR Mean minus the 2nd Semester 2019 VaR Mean.*

The first year of the pandemic was critical to set new high levels of risk, while the second was characterized by great recovery, where in many cases the risk returned or approximated to its usual values. Considering all countries in the study, the VaR average in 2019 was almost 2%. In 2020, the risk exploded with the pandemic, increasing to an average of 3.58%. However, in 2021 market risk returned to values close to 2%, which may indicate the effectiveness of the measures taken and the effort to control the pandemic and, consequently, to reduce panic and uncertainty in people, companies, and in the market.

The initial shock of the pandemic and the panic around the situation were enormous and caused tremendous changes in the market. Apart from Bosnia and Argentina, all remaining countries had their peak risk since 2016 in March 2020, the month in which the pandemic exploded and spread globally (see Appendix B). From the last semester of 2019 to the first of 2020 (PHASE I) there was a 2.45% increase in risk indices. At this stage, VaRs reached an average value of 4.56%, more than double the values observed in all pre-COVID periods.

However, measures taken to control the panic around this unexpected event seem to have contributed to reduce the risk, since VaR averages continuously decreased in all following phases, with special emphasis on PHASE II. In PHASE IV, risk indices were already close or even below the levels verified in the last pre-COVID semester.

Furthermore, in all periods considered, market risk was always higher in the developed countries considered than in the developing countries. Nonetheless, this difference shortened after this event, given that its impact was higher in the last group of countries. While in developed countries we verify that an absolute increase of 1.65% in their VaRs from 2019 to 2020 was offset by an almost equal reduction around 1.65% in 2021, the VaRs of developing countries increased 1.51% in 2020 and decreased only 1.34%, demonstrating a greater difficulty of this group to recover and adapt to the new reality. In fact, when considering the last semester of 2021 as baseline, the risk of developed countries recovered to its usual level during PHASE III, when in May 2021 the 6-month average of the daily VaRs was lower than the value in the last semester before the pandemic. On the other hand, developing countries have not yet returned to normal as they continue to face greater risk than they did in the period between July and December 2019.

6.1. Overall Period

6.1.1. Country Group Specific Effects

Table 2. Fixed-Effects Model: LSDV Estimator with Individual-Specific Effects

R^2 = 0.7386	Explanatory Variables	Estimate	Std. Error	t-value	Pr(>|t|)	Sign
COVID-19 Indicators	reproduction_rate	6.52E-03	4.72E-04	13.827	2.00E-16	***
	stringency_index	5.56E-05	9.54E-06	5.823	5.95E-09	***
	people_fully_vaccinated	-1.51E-02	8.70E-04	-17.296	2.00E-16	***
	panic_index	1.20E-05	3.11E-05	0.386	6.99E-01	
	media_hype_index	2.11E-04	1.38E-05	15.315	2.00E-16	***
	sentiment_index	-2.16E-04	1.12E-05	-19.338	2.00E-16	***
Individual-Specific Effects	dummy_Developed_Countries	1.34E-02	5.73E-04	2.34E+01	2.00E-16	***
	dummy_Developing_Countries	5.56E-03	5.71E-04	9.73E+00	2.00E-16	***

Description: *Output of the regression produced by the Rstudio that include, by order of column, the estimated coefficient for the respective explanatory variable, the standard error of the coefficient, the t-test statistic value, the p-value for the t-test and the significance code. The significance code is '***', '**', '*' or '.' When the null is rejected for a significance level of 0, 0.001, 0.01 or 0.05, respectively.*

In view of the LSDV estimations obtained for the Fixed Effects model, we conclude that the pandemic and its management had impact on the risk values verified in the market during the overall period of 2020-2021. The R-Square of the model tell us that 73.86% of the market risk verified in the countries in study is explained by the explanatory variables considered. All COVID-19 indicators, except the $panic\_index$, and both dummy variables are statistically significant, which means that the COVID-19 indicators and country-specific effects have contributed in general to explain the VaR behavior during the overall period. However, it is important to understand which variables contributed to increase and which ones contributed to decrease the risk.

As the pandemic progresses and the contagion rate worsens, the economic uncertainty increases. Doubts around individuals' jobs, savings and the future, firms' needs of changes in work processes and uncertainty around their revenues start to appear. The uncertainty that resulted from the pandemic situation and its evolution is reflected in the increase of the market risk during the overall period, since the $reproduction\_rate$ indicator is statistically significant and has positive coefficient in the regression.

Considering that both $media\_hype\_index$ and $sentiment\_index$ indicators are statistically significant, we can also conclude that the regular presence and predominance of news about COVID-19 in the media is also significant to explain the level of risk verified between 2020 and 2021. Since the coefficient of the first indicator is positive and the coefficient of the second is negative, as more news about the novel Coronavirus was present in the media, the greater the risk verified in the market but as the more positive (negative) the sentiment surrounding this news, the lower (higher) the risk.

In addition, the vaccination agenda played a role to the adaption to this “new normality” since, as a countermeasure to the pandemic, it helped to rise again companies and investors’ expectations, consequently contributing to reduce the uncertainty and the risk in the market.

Furthermore, we can answer the question about the impact that restrictions such as the closure of schools and public services, mandatory lockdowns and telecommuting, amongst others, could have on the market risk. On one hand, these measures could be seen as a response to control the pandemic, contributing to decrease the uncertainty around the situation and to reduce the market risk. On the other hand, these measures have caused major changes in companies, both in the organizational level, forcing adjustments to work processes and even layoffs, and in the results level due to less production, productivity, and market transactions, which can thus contribute to the increase of market risk. Considering the results obtained, the last premise seems to prevail, since the $stringency\_index$ was a statistically significant variable that contributed with a positive coefficient to the market risk between 2020 and 2021.

6.1.2. Time-Specific Effects

Table 3. Fixed-Effects Model: LSDV Estimator with Time-Specific Effects

R^2 = 0.8331	Explanatory Variables	Estimate	Std. Error	t-value	Pr(>|t|)	Sign
COVID-19 Indicators	reproduction_rate	1.24E-02	3.84E-04	32.332	<2e-16	***
	stringency_index	2.06E-04	7.89E-06	26.081	<2e-16	***
	people_fully_vaccinated	1.18E-02	1.09E-03	10.79	<2e-16	***
	panic_index	-3.30E-06	2.49E-05	-0.133	8.94E-01	
	media_hype_index	9.55E-05	1.12E-05	8.559	<2e-16	***
	sentiment_index	-1.25E-04	9.07E-06	-13.787	<2e-16	***
Time-Specific Effects	dummy_Phase_I	2.14E-02	4.59E-04	46.562000	<2e-16	***
	dummy_Phase_II	-5.80E-03	5.49E-04	-1.06E+01	<2e-16	***
	dummy_Phase_III	-9.28E-03	5.25E-04	-1.77E+01	<2e-16	***
	dummy_Phase_IV	-1.39E-02	6.79E-04	-2.04E+01	<2e-16	***

Description: *Output of the regression produced by the Rstudio that include, by order of column, the estimated coefficient for the respective explanatory variable, the standard error of the coefficient, the t-test statistic value, the p-value for the t-test and the significance code. The significance code is '***', '**', '*' or '.' When the null is rejected for a significance level of 0, 0.001, 0.01 or 0.05, respectively.*

In the model with dummy variables to capture time-specific effects, we find again that only the $panic\_index$ is not statistically significant. However, the remaining COVID-19 indicators kept statistically significant as well as the dummy variables correspondent to each phase, which means that the specific characteristics of each phase and the response to the pandemic situation were relevant to explain the values observed in the market risk. Considering that the statistically significant COVID-19 indicators maintain the same coefficient signal of the previous estimation, the conclusions drawn in relation to these variables remain.

Focusing on the dummy variables, we see that the sign of the coefficient for PHASE I is positive, while for PHASE II, III and IV is negative. This demonstrates that it was during the first period from January to June 2020 that time-specific effects contributed to increase the VaRs, while the following phases are characterized as phases of recovering the usual levels. Moreover, the coefficients decrease as we progress in time and advance through the phases, which indicates that the further away from the initial moments of the pandemic, the more time-specific characteristics contribute to reduce the market risk.

6.2. PHASE I

Table 4. Random-Effects Model: PHASE I

DEVELOPING COUNTRIES				R^2 = 0.54562	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	1.59E-02	3.47E-03	4.5889	4.46E-06	***
reproduction_rate	1.96E-02	1.30E-03	15.1191	2.20E-16	***
stringency_index	-2.20E-05	3.36E-05	-0.6561	5.12E-01	
panic_index	4.45E-04	1.14E-04	3.9011	9.57E-05	***
media_hype_index	9.61E-05	4.70E-05	2.0461	4.07E-02	*
sentiment_index	-4.28E-04	3.87E-05	-11.0412	2.20E-16	***

DEVELOPED COUNTRIES				R^2 = 0.65311	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	1.60E-02	2.17E-03	7.3539	1.93E-13	***
reproduction_rate	1.11E-02	7.75E-04	14.3216	2.20E-16	***
stringency_index	2.71E-04	3.13E-05	8.6725	2.20E-16	***
panic_index	3.61E-04	1.41E-04	2.5659	1.03E-02	*
media_hype_index	2.43E-04	4.90E-05	4.9579	7.12E-07	***
sentiment_index	-1.35E-04	3.12E-05	-4.3361	1.45E-05	***

Description**: Output of the regressions produced by the Rstudio that include, by order of column, the estimated coefficient for the respective explanatory variable, the standard error of the coefficient, the t-test statistic value, the p-value for the t-test and the significance code. The significance code is '', '**', '*' or '.' When the null is rejected for a significance level of 0, 0.001, 0.01 or 0.05, respectively.*

Although in the overall period the $panic\_index$ does not have a statistically significant contribution to explain the VaRs, at an early stage of the pandemics it was highly correlated to the large increase verified in market risk, both in developed and developing countries, even though it was in the last group that it impacted more. The $reproduction\_rate$ is also proved to be statistically significant and positive in both groups, demonstrating that the evolution of the pandemic was impactful and contributed to the new risk levels verified in both country groups.

On the other hand, while developing countries were not significantly affected by the restrictions immediately imposed, they contributed to increase the uncertainty in the market of developed countries.

Regarding the importance of news about the Coronavirus in the VaR levels, as they had an increasing (lower) presence and predominance in the media, the higher (lower) the risk level, but as they were more favorable (unfavorable), the lower (higher) the risk. Furthermore, the coefficient for the $media\_hype\_index$ variable is larger in developed countries while the coefficient for $sentiment\_index$ is larger in developing countries. This shows that the presence of news about the pandemic situation was more impactful to the risk levels in developed countries than in developing countries, but their impact is less dependent on the social perception.

Summing up, considering these points presented and the high R-Squares of both regressions, we conclude that during the initial phase, the indicators chosen to characterize the pandemic situation are highly associated with the Values-at-Risk verified in the market of developing and developed countries.

6.3. PHASE II

Table 5. Random-Effects Model: PHASE II

DEVELOPING COUNTRIES				R^2 = 0.078078	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	9.88E-03	2.07E-03	4.7624	1.91E-06	***
reproduction_rate	5.13E-03	8.04E-04	6.3774	1.80E-10	***
stringency_index	1.02E-04	1.21E-05	8.4471	2.20E-16	***
panic_index	2.03E-05	1.45E-05	1.3968	1.62E-01	
media_hype_index	8.85E-06	1.02E-05	0.8648	3.87E-01	
sentiment_index	-1.93E-05	1.09E-05	-1.7725	7.63E-02	.

DEVELOPED COUNTRIES				R^2 = 0.041787	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	2.26E-02	3.73E-03	6.0654	1.32E-09	***
reproduction_rate	2.91E-03	7.98E-04	3.6416	2.71E-04	***
stringency_index	2.82E-05	2.42E-05	1.1658	2.44E-01	
panic_index	8.45E-06	4.17E-05	0.2027	8.39E-01	
media_hype_index	3.66E-05	2.01E-05	1.8212	6.86E-02	.
sentiment_index	-5.91E-05	1.20E-05	-4.9281	8.30E-07	***

Description: *Output of the regressions produced by the Rstudio that include, by order of column, the estimated coefficient for the respective explanatory variable, the standard error of the coefficient, the t-test statistic value, the p-value for the t-test and the significance code. The significance code is '***', '**', '*' or '.' When the null is rejected for a significance level of 0, 0.001, 0.01 or 0.05, respectively.*

In view of the R-Squares obtained in the estimated regressions for PHASE II and comparing with those of PHASE I, we find that the considered indicators had little impact in the market risk during this period, explaining only 7.80% of the VaRs of developing countries and 4.18% of the VaRs of developed countries.

Society and investors seem to have already understood the new reality, adapted to new market conditions and stopped reacting to the news since social and media indicators such as the $panic\_index$, the $media\_hype\_index$ and the $sentiment\_index$ in some cases cease to be statistically significant in comparison to the previous phase.

Nonetheless, despite having lower influence, the pandemic evolution continues to impact the risk levels verified during this period since in both groups of countries the $reproduction\_rate$ continues to be statistically significant and to have a positive coefficient.

6.4. PHASE III

Table 6. Random-Effects Model: PHASE III

DEVELOPING COUNTRIES				*R^2* = 0.16984	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	2.76E-02	2.31E-03	11.9652	2.20E-16	***
reproduction_rate	1.45E-03	5.73E-04	2.5231	1.16E-02	*
stringency_index	-1.45E-04	1.82E-05	-7.9529	1.82E-15	***
people_fully_vaccinated	-5.84E-02	3.89E-03	-15.014	2.20E-16	***
media_hype_index	2.17E-05	9.00E-06	2.4072	1.61E-02	*
sentiment_index	-6.54E-06	1.14E-05	-0.5724	5.67E-01	

DEVELOPED COUNTRIES				*R^2* = 0.13607	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	-4.19E+00	1.14E-01	-36.8088	2.20E-16	***
reproduction_rate	-4.90E-02	2.78E-02	-1.7607	7.83E-02	.
stringency_index	6.00E-03	8.04E-04	7.4589	8.73E-14	***
people_fully_vaccinated	-1.29E-02	1.41E-03	-9.1513	2.20E-16	***
media_hype_index	-6.80E-03	1.48E-02	-0.4592	6.46E-01	
sentiment_index	3.77E-04	3.85E-04	0.9789	3.28E-01	

Description: *Output of the regressions produced by the Rstudio that include, by order of column, the estimated coefficient for the respective explanatory variable, the standard error of the coefficient, the t-test statistic value, the p-value for the t-test and the significance code. The significance code is '***', '**', '*' or '.' When the null is rejected for a significance level of 0, 0.001, 0.01 or 0.05, respectively.*

In the phase marked by mass vaccination, this factor was considered influent to explain the VaR behavior during the period between January and June 2021, as the vaccination agenda was a fundamental measure to reduce the uncertainty surrounding the pandemic situation and the future of people and companies, consequently contributing to reduce the market risk. Despite having been statistically significant in both developed and developing countries, it was in the latter group that it proved to be more decisive in its contribute to the risk, as it has a higher coefficient.

Furthermore, during this phase the market risk of developing countries is still being affected by the situation and evolution of the pandemic, since the $reproduction\_rate$ variable is still positive and statistically significant, contrary to what happens in developed countries. The same is verified for the $media\_hype\_index$ variable.

There is also another interesting output: the $stringency\_index$ is statistically significant in both groups, but their coefficients show opposite signs. Since for developing countries it is negative and for developed countries it is positive, while in developed countries the decision to lift (impose) restrictions contributed to reduce (increase) the market risk, in developing countries it generated more (less) uncertainty amongst investors.

6.5. PHASE IV

Table 7. Random-Effects Model: PHASE IV

DEVELOPING COUNTRIES				*R^2* = 0.086181	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	1.25E-02	1.97E-03	6.3508	2.14E-10	***
delta_share	6.63E-03	6.23E-04	10.6407	2.20E-16	***
omicron_share	6.71E-03	8.91E-04	7.533	4.96E-14	***
stringency_index	-1.82E-03	2.56E-03	-0.7107	4.77E-01	
people_fully_vaccinated	-2.13E-03	6.77E-03	-0.3139	7.54E-01	
media_hype_index	2.24E-05	7.84E-06	2.8524	4.34E-03	**
sentiment_index	-2.03E-05	1.05E-05	-1.931	5.35E-02	.

DEVELOPED COUNTRIES				*R^2* = 0.21809	
Explanatory Variables	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**	**Sign**
(Intercept)	1.49E-02	1.42E-03	10.4661	<2e-16	***
delta_share	8.52E-03	6.40E-04	13.3115	<2e-16	***
omicron_share	2.01E-02	1.31E-03	15.3133	<2e-16	***
stringency_index	-6.57E-04	1.38E-03	-0.4778	6.33E-01	
people_fully_vaccinated	5.90E-03	1.23E-02	0.4808	6.31E-01	
media_hype_index	-6.52E-06	1.41E-05	-0.4629	6.43E-01	
sentiment_index	2.38E-07	9.63E-06	0.0247	9.80E-01	

Description: *Output of the regressions produced by the Rstudio that include, by order of column, the estimated coefficient for the respective explanatory variable, the standard error of the coefficient, the t-test statistic value, the p-value for the t-test and the significance code. The significance code is '***', '**', '*' or '.' When the null is rejected for a significance level of 0, 0.001, 0.01 or 0.05, respectively.*

The last pandemic phase considered was marked by the predominance of cases of the delta and omicron variants and the continuation of the global vaccination agenda.

As can be seen, both in developing and developed countries, the evolution of the pandemic trough the spread of new variants had influence in their respective risk levels as the $delta\_share$ and $omicron\_share$ variables are statistically significant and have positive coefficient in both groups.

However, contrary to what could be expected, the vaccination does not have statistical significance to explain the VaRs between July and December 2021. The combination of lifting restrictions with the emergence and predominance of new variants that led to the start of a new vaccination protocol, with the introduction of booster doses, may explain the loss of relevance of the $people\_fully\_vaccinated$ variable to influence the market behavior during this phase.

Finally, it is verified once again the higher sensitivity of investors in developing countries to the news about the pandemic situation, as the *media_hype_index* is still statistically significant, contrary to what happens in developed countries.

It is also important to refer that, as happened in PHASE II and PHASE III, the R-Squares of the regressions for PHASE IV are low, which means that despite having influence in some way, the contribution of the COVID-19 pandemic situation and the measures taken were not very impactful to the risk values verified during these phases.

6.6. Robust Model

To evaluate the efficiency of the models to provide the best linear unbiased estimations, we run the Breusch-Pagan and the Durbin-Watson tests for Panel Data to check the assumptions of homoscedasticity (existence of constant and equal variance in the error-term) and no autocorrelation (linearly independence between lagged versions of the error-term), respectively. Based on the results obtained we reject both assumptions in all phases and in both developing and developed countries groups, which means that the models are not the most efficient and are not fitting the sample properly. To deal with the heteroscedasticity and the autocorrelation verified in the models, we performed the robust standard errors estimation to obtain more reliable estimations for the t-test and the outputs are resumed in the table below.

Table 8. Robust Model

ROBUST MODEL	Explanatory Variables	PHASE I	PHASE II	PHASE III	PHASE IV
DEVELOPING COUNTRIES	reproduction_rate	0.01964			---
	stringency_index		0.00010		
	panic_index	0.00044		---	---
	media_hype_index				
	sentiment_index	-0.00043			
	people_fully_vaccinated	---	---	-0.05842	
	delta_share	---	---	---	
	omicron_share	---	---	---	0.00671
DEVELOPED COUNTRIES	reproduction_rate	0.01110			---
	stringency_index	0.00027		0.00600	
	panic_index			---	---
	media_hype_index				
	sentiment_index				
	people_fully_vaccinated	---	---		
	delta_share	---	---	---	0.00852
	omicron_share	---	---	---	0.02009

Description: *Summary table of the output produced by the Rstudio for the Robust Model, where only the coefficients of the statistically significant variables are presented. The sign '---' means that the variables in question were not used in the regression for that period.*

We can conclude that in the PHASE I, the evolution of the pandemic situation was significant to explain the risk levels of both developing and developed countries as the $reproduction\_rate$ remains explanatory for the VaRs in the Robust Model. Furthermore, when compared to the previous model, the media and social response indicators are no longer statistically significant in developed countries while in developing they are still relevant, highlighting once again the greater sensitivity of investors in these countries to the news and the panic surrounding the situation.

In PHASE II and PHASE III, the contribution of the pandemic situation to the risk levels dropped significantly as the $reproduction\_rate$ and the media indicators were not sufficiently contributory to explain the VaRs verified in these periods for both groups. Only the tightening or lifting of restrictions were statistically significant to affect the risk levels of developing countries during PHASE II and to affect the risk levels of developed countries during PHASE III. Moreover, contrary to what happened in the previous models, the Robust Model found that the vaccination only contributed to reduce the market risk of developing countries.

Finally, the appearance and predominance of new variants seems to have contributed to explain in a statistically significant way the VaRs of both groups of countries since $delta\_share$ has a significant positive coefficient in developed countries and $omicron\_share$ variable in developed and developing countries.

CHAPTER 7

Conclusions

The main goal of this dissertation is to evaluate the impact of the pandemic and its management on market risk and how that impact evolved through the different pandemic situations. Furthermore, we want to understand how the markets of developing countries and developed countries reacted to the situation to identify possible differences in the characteristics of the two markets in moments of crisis.

Through a set of analyzes of the daily VaR behavior of 20 stock indexes, 10 from developing countries and 10 from developed countries, we conclude that the pandemic and its management affected the financial market, leading to an overall increase of the risk levels. This behavior is characterized by an exponential increase in the first moments of the pandemic, a quick reaction after this moment with an almost equivalent decrease, and a slow recovery to the usual risk levels afterwards. From 2019 to 2020, the first year of the pandemic, the average VaR increased 1.58%. While in the first semester of the pandemic the market of developed countries suffered the highest increase in the average VaR, in the following year they recovered their usual levels, reaching values very close or even below the ones of 2019. On the other hand, the market of developing countries had greater difficulty in recovering, remaining above this benchmark for the entire period of analysis. Thus, considering that before the pandemic (2016-2019) the risk of developed countries was always greater than of developing countries, the pandemic contributed to an approximation of the two markets after these couple years.

As referred, the market has immediately reacted negatively to this unexpected and unprecedent situation, as the average VaR of the 20 countries increased 2.45% from the second half of 2019 to the first half of 2020 (PHASE I), when it reached values of 4.56%. The pandemic situation highly contributed to this exponential increase during this phase. When the reproduction rate of the virus increased, the media focused more and more on the pandemic and the panic and sentiment around the situation became more negative, the risk increased even more. The impact of these factors was more severe in the market risk of developing countries. However, the implementation (lifting) of restrictive measures only contributed to higher (lower) risk levels in developed countries during this period.

After the large increase in risk observed in the first half of 2020, the very next semester (PHASE II) was crucial to restore the usual risk levels. We verified a decrease of 1.89% in the average VaR of developing and of 1.99% in the average of developed countries and the pandemic indicators lost relevance to influence the market behavior, demonstrating that the market quickly started to react less to the pandemic situation. This is in line with other existing studies that report that periods of high volatility are usually short, and the market tends to quickly adapt and recover from these situations (Schwert, 2011).

PHASE III and PHASE IV, corresponding to the year of 2021, presented similar behavior: a decrease in the risk levels of both groups, although in a much lower degree than the one verified in the second half of 2020. This indicates that after the big crash in the market that raised exponentially the risk and the accentuated decline after that, the following moments are characterized by a gradual and slow recovery of the usual levels. During the first phase, the vaccination agenda and the return to usual social and work procedures contributed to the reduction of risk as it helped to restore investors' expectations and behavior.

In the first semester of 2021, the average VaR of developed countries reached values below the levels verified in the second half of 2019, the last pre-pandemic period. On the other hand, the reductions in the risk of developing countries during 2021 were constant but smaller, causing this group to fail in recovering their usual values. Moreover, this market always reacted more, and for longer, to the evolution, the news and social perception of the pandemic situation. Therefore, we can conclude that this group of countries is slower to recover after an unexpected situation that severely affects the risk.

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Appendix

A. Countries and Stock Indexes used in the study and respective HDI

	Countries	Stock Index (Investing.com)	HDI 2022 (Hdr.undp.org)
Developing Countries	Bosnia and Herzegovina	BIRS (BIRS1)	0.78
	Brazil	Bovespa (BVSP)	0.765
	Colombia	COLCAP (COLCAP)	0.767
	India	BSE Sensex 30 (BSESN)	0.654
	Indonesia	IDX Composite (JKSE)	0.718
	Mexico	S&P/BMV IPC (MXX)	0.779
	Morocco	Moroccan All Shares (MASI)	0.686
	South Africa	South Africa Top 40 (JTOPI)	0.709
	Tunisia	Tunindex (TUNINDEX)	0.74
	Thailand	SET Index (SETI)	0.777
Developed Countries	Argentina	S&P Merval (MERV)	0.845
	Australia	S&P/ASX 200 (AXJO)	0.944
	Canada	S&P/TX (GSPTSE)	0.929
	Chile	S&P CLX IPSA (SPIPSA)	0.851
	Germany	DAX (GDAXI)	0.947
	Japan	Nikkei 225 (N225)	0.919
	New Zealand	NZX 50 (NZ50)	0.931
	Portugal	PSI (PSI20)	0.864
	South Korea	KOSPI 50 (KS50)	0.916
	United States	S&P 500 (SPX)	0.926

B. Maximum daily Value-at-Risk between 2016 and 2021

	Countries	Stock Index	Maximum VaR1d,1%	Date
Developing Countries	Bosnia and Herzegovina	BIRS (BIRS1)	5.3344%	22/02/2019
	Brazil	Bovespa (BVSP)	17.2272%	18/03/2020
	Colombia	COLCAP (COLCAP)	13.9610%	26/03/2020
	India	BSE Sensex 30 (BSESN)	11.4853%	25/03/2020
	Indonesia	IDX Composite (JKSE)	7.8581%	27/03/2020
	Mexico	S&P/BMV IPC (MXX)	6.8544%	27/03/2020
	Morocco	Moroccan All Shares (MASI)	7.8668%	16/03/2020
	South Africa	South Africa Top 40 (JTOPI)	10.9803%	27/03/2020
	Tunisia	Tunindex (TUNINDEX)	3.7804%	17/03/2020
	Thailand	SET Index (SETI)	10.6074%	23/03/2020
Developed Countries	Argentina	S&P Merval (MERV)	27.7670%	12/08/2019
	Australia	S&P/ASX 200 (AXJO)	10.3764%	30/03/2020
	Canada	S&P/TX (GSPTSE)	13.4022%	24/03/2020
	Chile	S&P CLX IPSA (SPIPSA)	12.3642%	19/03/2020
	Germany	DAX (GDAXI)	10.5513%	24/03/2020
	Japan	Nikkei 225 (N225)	7.9387%	27/03/2020
	New Zealand	NZX 50 (NZ50)	7.5970%	24/03/2020
	Portugal	PSI (PSI20)	8.9710%	24/03/2020
	South Korea	KOSPI 50 (KS50)	9.6735%	25/03/2020
	United States	S&P 500 (SPX)	12.4290%	24/03/2020

C. Fixed Effects Model with Country-Specific Characteristics (2020-2021)

```
Call:
lm(formula = VaR ~ reproduction_rate + stringency_index + people_fully_vaccinated
   +
    panic_index + media_hype_index + sentiment_index + factor(Country_Group) -
    1, data = Panel_Data)

Residuals:
      Min        1Q    Median        3Q       Max
-0.046741 -0.010860 -0.003304  0.005620  0.127986

Coefficients:
                                            Estimate Std. Error t value Pr(>|t|)
reproduction_rate                          6.520e-03  4.716e-04  13.827  < 2e-16
   ***
stringency_index                           5.557e-05  9.543e-06   5.823 5.95e-09
   ***
people_fully_vaccinated                   -1.505e-02  8.703e-04 -17.296  < 2e-16
   ***
panic_index                                1.202e-05  3.111e-05   0.386    0.699
media_hype_index                           2.105e-04  1.375e-05  15.315  < 2e-16
   ***
sentiment_index                           -2.159e-04  1.116e-05 -19.338  < 2e-16
   ***
factor(Country_Group)Developed Countries   1.343e-02  5.733e-04  23.420  < 2e-16
   ***
factor(Country_Group)Developing Countries  5.561e-03  5.714e-04   9.732  < 2e-16
   ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01786 on 10452 degrees of freedom
Multiple R-squared:  0.7386,	Adjusted R-squared:  0.7384
F-statistic:  3692 on 8 and 10452 DF,  p-value: < 2.2e-16
```

D. Fixed Effects Model with Time-Specific Characteristics (2020-2021)

```
Call:
lm(formula = VaR ~ reproduction_rate + stringency_index + people_fully_vaccinated
   +
    panic_index + media_hype_index + sentiment_index + factor(Phase) -
    1, data = Panel_Data)

Residuals:
      Min        1Q    Median        3Q       Max
-0.089495 -0.008107 -0.001118  0.005768  0.113843

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
reproduction_rate        1.241e-02  3.838e-04  32.332   <2e-16 ***
stringency_index         2.057e-04  7.887e-06  26.081   <2e-16 ***
people_fully_vaccinated  1.176e-02  1.090e-03  10.790   <2e-16 ***
panic_index             -3.302e-06  2.488e-05  -0.133    0.894
media_hype_index         9.547e-05  1.115e-05   8.559   <2e-16 ***
sentiment_index         -1.251e-04  9.073e-06 -13.787   <2e-16 ***
factor(Phase)Phase I     2.137e-02  4.589e-04  46.562   <2e-16 ***
factor(Phase)Phase II   -5.804e-03  5.489e-04 -10.573   <2e-16 ***
factor(Phase)Phase III  -9.276e-03  5.247e-04 -17.678   <2e-16 ***
factor(Phase)Phase IV   -1.385e-02  6.793e-04 -20.393   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01427 on 10450 degrees of freedom
Multiple R-squared:  0.8331,	Adjusted R-squared:  0.833
F-statistic:  5217 on 10 and 10450 DF,  p-value: < 2.2e-16
```

E. Random Effects Model for Developed Countries

E.1. PHASE I (January 2020 – June 2020)

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = VaR ~ reproduction_rate + stringency_index + panic_index +
    media_hype_index + sentiment_index, data = Panel_Data, model =
"random")

Balanced Panel: n = 10, T = 130, N = 1300

Effects:
                   var   std.dev share
idiosyncratic 2.672e-04 1.635e-02 0.876
individual    3.791e-05 6.157e-03 0.124
theta: 0.7732

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.0791635 -0.0106417 -0.0015722  0.0071777  0.0799952

Coefficients:
                    Estimate  Std. Error z-value  Pr(>|z|)
(Intercept)        1.5987e-02  2.1740e-03  7.3539 1.925e-13 ***
reproduction_rate  1.1102e-02  7.7519e-04 14.3216 < 2.2e-16 ***
stringency_index   2.7127e-04  3.1279e-05  8.6725 < 2.2e-16 ***
panic_index        3.6087e-04  1.4064e-04  2.5659   0.01029 *
media_hype_index   2.4308e-04  4.9028e-05  4.9579 7.124e-07 ***
sentiment_index   -1.3527e-04  3.1197e-05 -4.3361 1.451e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1.0141
Residual Sum of Squares: 0.35179
R-Squared:      0.65311
Adj. R-Squared: 0.65177
Chisq: 2436.3 on 5 DF, p-value: < 2.22e-16
```

Durbin-Watson test for serial correlation in panel models

```
data:   VaR ~ reproduction_rate + stringency_index + panic_index +
media_hype_index +  ...
DW = 0.12272, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic error
```

Breusch-Pagan test

```
data:   VaR ~ reproduction_rate + stringency_index + panic_index +
media_hype_index +     sentiment_index
BP = 226.45, df = 5, p-value < 2.2e-16
```

Robust Model - t test of coefficients:

```
                    Estimate  Std. Error t value  Pr(>|t|)
(Intercept)        1.5987e-02  4.6362e-03  3.4483 0.0005822 ***
reproduction_rate  1.1102e-02  4.1795e-03  2.6563 0.0079975 **
stringency_index   2.7127e-04  1.0577e-04  2.5647 0.0104378 *
panic_index        3.6087e-04  2.0656e-04  1.7471 0.0808542 .
```

```
media_hype_index   2.4308e-04  1.5207e-04  1.5984 0.1101871
sentiment_index   -1.3527e-04  8.6724e-05 -1.5598 0.1190509
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

E.2. PHASE II (July 2020 – December 2020)

Oneway (individual) effect Random Effect Model
(Swamy-Arora's transformation)

```
Call:
plm(formula = VaR ~ reproduction_rate + stringency_index + panic_index +
    media_hype_index + sentiment_index, data = Panel_Data, model =
"random")

Balanced Panel: n = 10, T = 132, N = 1320

Effects:
                    var   std.dev share
idiosyncratic 3.542e-05 5.952e-03  0.25
individual    1.065e-04 1.032e-02  0.75
theta: 0.9499

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.01740522 -0.00389506 -0.00068894  0.00314792  0.03202084

Coefficients:
                     Estimate  Std. Error z-value  Pr(>|z|)
(Intercept)        2.2649e-02  3.7342e-03  6.0654 1.316e-09 ***
reproduction_rate  2.9062e-03  7.9807e-04  3.6416  0.000271 ***
stringency_index   2.8236e-05  2.4220e-05  1.1658  0.243702
panic_index        8.4496e-06  4.1695e-05  0.2027  0.839405
media_hype_index   3.6561e-05  2.0075e-05  1.8212  0.068572 .
sentiment_index   -5.9067e-05  1.1986e-05 -4.9281 8.301e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.04862
Residual Sum of Squares: 0.046589
R-Squared:      0.041787
Adj. R-Squared: 0.038141
Chisq: 57.3025 on 5 DF, p-value: 4.3806e-11
```

Durbin-Watson test for serial correlation in panel models

```
data:   VaR  ~  reproduction_rate  +  stringency_index  +  panic_index  +
media_hype_index +  ...
DW = 0.13026, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Breusch-Pagan test

```
data:   VaR  ~  reproduction_rate  +  stringency_index  +  panic_index  +
media_hype_index +     sentiment_index
BP = 371.04, df = 5, p-value < 2.2e-16
```

Robust Model - t test of coefficients:

```
                     Estimate  Std. Error t value  Pr(>|t|)
(Intercept)        2.2649e-02  3.9809e-03  5.6895 1.569e-08 ***
```

```
reproduction_rate  2.9062e-03  2.2983e-03  1.2645   0.20628
stringency_index   2.8236e-05  7.5435e-05  0.3743   0.70824
panic_index        8.4496e-06  2.6427e-05  0.3197   0.74922
media_hype_index   3.6561e-05  2.5613e-05  1.4275   0.15368
sentiment_index   -5.9067e-05  3.4805e-05 -1.6971   0.08992 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

E.3. PHASE III (January 2021 – June 2021)

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = VaR ~ reproduction_rate + stringency_index + people_fully_vaccinated +
    media_hype_index + sentiment_index, data = Panel_Data, model = "random")

Balanced Panel: n = 10, T = 130, N = 1300

Effects:
                  var std.dev share
idiosyncratic 0.03336 0.18266 0.258
individual    0.09586 0.30961 0.742
theta: 0.9483

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.466896 -0.126982 -0.012054  0.128972  0.765167

Coefficients:
                           Estimate  Std. Error  z-value  Pr(>|z|)
(Intercept)             -4.18587497  0.11371928 -36.8088 < 2.2e-16 ***
reproduction_rate       -0.04903140  0.02784744  -1.7607   0.07829 .
stringency_index         0.00599921  0.00080430   7.4589 8.726e-14 ***
people_fully_vaccinated -0.01287710  0.00140713  -9.1513 < 2.2e-16 ***
media_hype_index        -0.00679771  0.01480233  -0.4592   0.64607
sentiment_index          0.00037671  0.00038482   0.9789   0.32761
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    49.91
Residual Sum of Squares: 43.119
R-Squared:      0.13607
Adj. R-Squared: 0.13274
Chisq: 203.812 on 5 DF, p-value: < 2.22e-16

Durbin-Watson test for serial correlation in panel models

data:  VaR ~ reproduction_rate + stringency_index + people_fully_vaccinated + ...
DW = 0.10045, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors

Breusch-Pagan test

data:  VaR ~ reproduction_rate + stringency_index + media_hype_index + people_fully_vaccinated + sentiment_index
BP = 93.65, df = 5, p-value < 2.2e-16
```

Robust Model - t test of coefficients:

```
                          Estimate  Std. Error  t value Pr(>|t|)    
(Intercept)             -4.18587497  0.17579891 -23.8106  < 2e-16 ***
reproduction_rate       -0.04903140  0.06398087  -0.7663  0.44361    
stringency_index         0.00599921  0.00283758   2.1142  0.03469 *  
people_fully_vaccinated -0.01287710  0.00788508  -1.6331  0.10269    
media_hype_index        -0.00679771  0.00373721  -1.8189  0.06915 .  
sentiment_index          0.00037671  0.00068054   0.5536  0.57998    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

E.4. PHASE IV (July 2021 – December 2021)

Oneway (individual) effect Random Effect Model
(Swamy-Arora's transformation)

```
Call:
plm(formula = VaR ~ delta_share + omicron_share + stringency_index + 
    people_fully_vaccinated + media_hype_index + sentiment_index, 
    data = Panel_Data, model = "random")

Balanced Panel: n = 10, T = 132, N = 1320

Effects:
                    var   std.dev share
idiosyncratic 2.252e-05 4.746e-03 0.634
individual    1.299e-05 3.604e-03 0.366
theta: 0.8861

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max. 
-0.01109849 -0.00286218 -0.00073778  0.00204742  0.02836500 

Coefficients:
                          Estimate  Std. Error z-value Pr(>|z|)    
(Intercept)              1.4886e-02  1.4223e-03 10.4661   <2e-16 ***
delta_share              8.5150e-03  6.3967e-04 13.3115   <2e-16 ***
omicron_share            2.0090e-02  1.3120e-03 15.3133   <2e-16 ***
stringency_index        -6.5721e-04  1.3756e-03 -0.4778   0.6328    
people_fully_vaccinated  5.9015e-03  1.2274e-02  0.4808   0.6306    
media_hype_index        -6.5246e-06  1.4095e-05 -0.4629   0.6434    
sentiment_index          2.3828e-07  9.6332e-06  0.0247   0.9803    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.040174
Residual Sum of Squares: 0.031413
R-Squared:      0.21809
Adj. R-Squared: 0.21451
Chisq: 366.213 on 6 DF, p-value: < 2.22e-16
```

Durbin-Watson test for serial correlation in panel models

```
data:  VaR ~ delta_share + omicron_share + stringency_index + 
people_fully_vaccinated + ...
DW = 0.11212, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Breusch-Pagan test

```
data:    VaR  ~  delta_share  +  omicron_share  +  stringency_index  +
people_fully_vaccinated +    media_hype_index + sentiment_index
BP = 185.75, df = 6, p-value < 2.2e-16
```

Robust Model - t test of coefficients:

```
                          Estimate  Std. Error t value  Pr(>|t|)
(Intercept)             1.4886e-02  2.3353e-03  6.3743 2.539e-10 ***
delta_share             8.5150e-03  3.0384e-03  2.8024 0.0051465 **
omicron_share           2.0090e-02  5.6400e-03  3.5621 0.0003811 ***
stringency_index       -6.5721e-04  5.1531e-04 -1.2754 0.2024063
people_fully_vaccinated  5.9015e-03  2.2060e-02  0.2675 0.7891106
media_hype_index       -6.5246e-06  1.4621e-05 -0.4462 0.6554916
sentiment_index         2.3828e-07  1.1529e-05  0.0207 0.9835139
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

F. Random Effects Model for Developing Countries

F.1. PHASE I

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = VaR ~ reproduction_rate + stringency_index + panic_index +
    media_hype_index + sentiment_index, data = Panel_Data, model =
"random")

Balanced Panel: n = 10, T = 130, N = 1300

Effects:
                    var   std.dev share
idiosyncratic 0.0003269 0.0180791 0.746
individual    0.0001112 0.0105458 0.254
theta: 0.8513

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.0436519 -0.0115075 -0.0025485  0.0062062  0.1014706

Coefficients:
                     Estimate  Std. Error  z-value  Pr(>|z|)
(Intercept)        1.5936e-02  3.4726e-03   4.5889 4.455e-06 ***
reproduction_rate  1.9636e-02  1.2987e-03  15.1191 < 2.2e-16 ***
stringency_index  -2.2025e-05  3.3570e-05  -0.6561   0.51175
panic_index        4.4456e-04  1.1396e-04   3.9011 9.574e-05 ***
media_hype_index   9.6065e-05  4.6950e-05   2.0461   0.04074 *
sentiment_index   -4.2757e-04  3.8725e-05 -11.0412 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.93184
Residual Sum of Squares: 0.42341
R-Squared:      0.54562
Adj. R-Squared: 0.54386
Chisq: 1553.82 on 5 DF, p-value: < 2.22e-16
```

Durbin-Watson test for serial correlation in panel models

```
data:   VaR  ~  reproduction_rate  +  stringency_index  +  panic_index  +
media_hype_index +  ...
DW = 0.13337, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Breusch-Pagan test

```
data:   VaR  ~  reproduction_rate  +  stringency_index  +  panic_index  +
media_hype_index +     sentiment_index
BP = 269.4, df = 5, p-value < 2.2e-16
```

Robust Model - t test of coefficients:

```
                     Estimate  Std. Error t value  Pr(>|t|)
(Intercept)        1.5936e-02  2.6415e-03  6.0328 2.100e-09 ***
reproduction_rate  1.9636e-02  6.9720e-03  2.8163  0.004931 **
stringency_index  -2.2025e-05  7.3938e-05 -0.2979  0.765833
panic_index        4.4456e-04  1.6414e-04  2.7085  0.006848 **
```

```
media_hype_index   9.6065e-05  1.3789e-04  0.6967  0.486117
sentiment_index   -4.2757e-04  1.0202e-04 -4.1909 2.967e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

F.2. PHASE II (July 2020 – December 2020)

Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)

```
Call:
plm(formula = VaR ~ reproduction_rate + stringency_index + panic_index +
    media_hype_index  +  sentiment_index,  data  =  Panel_Data,  model  =
"random")

Balanced Panel: n = 10, T = 132, N = 1320

Effects:
                    var   std.dev share
idiosyncratic 1.898e-05 4.357e-03 0.421
individual    2.610e-05 5.109e-03 0.579
theta: 0.926

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.00958480 -0.00315045 -0.00067791  0.00243081  0.02010754

Coefficients:
                     Estimate  Std. Error z-value  Pr(>|z|)
(Intercept)        9.8810e-03  2.0748e-03  4.7624 1.913e-06 ***
reproduction_rate  5.1271e-03  8.0395e-04  6.3774 1.801e-10 ***
stringency_index   1.0225e-04  1.2105e-05  8.4471 < 2.2e-16 ***
panic_index        2.0315e-05  1.4543e-05  1.3968   0.16246
media_hype_index   8.8513e-06  1.0235e-05  0.8648   0.38715
sentiment_index   -1.9270e-05  1.0872e-05 -1.7725   0.07632 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.027206
Residual Sum of Squares: 0.025082
R-Squared:      0.078078
Adj. R-Squared: 0.07457
Chisq: 111.283 on 5 DF, p-value: < 2.22e-16
```

Durbin-Watson test for serial correlation in panel models

```
data:   VaR  ~  reproduction_rate  +  stringency_index  +  panic_index  +
media_hype_index +  ...
DW = 0.12698, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Breusch-Pagan test

```
data:   VaR  ~  reproduction_rate  +  stringency_index  +  panic_index  +
media_hype_index +     sentiment_index
BP = 39.728, df = 5, p-value = 1.694e-07
```

Robust Model - t test of coefficients:

```
                     Estimate  Std. Error t value  Pr(>|t|)
(Intercept)        9.8810e-03  4.1662e-03  2.3717 0.0178498 *
```

```
reproduction_rate  5.1271e-03  3.1316e-03  1.6372 0.1018271
stringency_index   1.0225e-04  2.7267e-05  3.7499 0.0001846 ***
panic_index        2.0315e-05  3.2118e-05  0.6325 0.5271673
media_hype_index   8.8513e-06  2.6595e-05  0.3328 0.7393295
sentiment_index   -1.9270e-05  1.6227e-05 -1.1875 0.2352447
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

F.3. PHASE III (January 2021 – June 2021)

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = VaR ~ reproduction_rate + stringency_index + people_fully_vaccinated +
    media_hype_index + sentiment_index, data = Panel_Data, model = "random")

Balanced Panel: n = 10, T = 130, N = 1300

Effects:
                    var   std.dev share
idiosyncratic 1.946e-05 4.411e-03  0.36
individual    3.453e-05 5.876e-03  0.64
theta: 0.9343

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.00960254 -0.00297630 -0.00060973  0.00216937  0.01752988

Coefficients:
                           Estimate  Std. Error  z-value  Pr(>|z|)
(Intercept)              2.7598e-02  2.3066e-03  11.9652 < 2.2e-16 ***
reproduction_rate        1.4458e-03  5.7301e-04   2.5231   0.01163 *
stringency_index        -1.4460e-04  1.8182e-05  -7.9529 1.821e-15 ***
people_fully_vaccinated -5.8421e-02  3.8911e-03 -15.0140 < 2.2e-16 ***
media_hype_index         2.1655e-05  8.9961e-06   2.4072   0.01608 *
sentiment_index         -6.5406e-06  1.1428e-05  -0.5724   0.56708
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.030404
Residual Sum of Squares: 0.02524
R-Squared:      0.16984
Adj. R-Squared: 0.16663
Chisq: 264.731 on 5 DF, p-value: < 2.22e-16

Durbin-Watson test for serial correlation in panel models

data:  VaR ~ reproduction_rate + stringency_index + people_fully_vaccinated + ...
DW = 0.10396, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors

Breusch-Pagan test

data:  VaR ~ reproduction_rate + stringency_index + media_hype_index + people_fully_vaccinated + sentiment_index
BP = 41.844, df = 5, p-value = 6.335e-08
```

Robust Model - t test of coefficients:

```
                           Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)               2.7598e-02  7.2986e-03  3.7813 0.0001631 ***
reproduction_rate         1.4458e-03  2.0135e-03  0.7180 0.4728594    
stringency_index         -1.4460e-04  1.0076e-04 -1.4351 0.1515101    
people_fully_vaccinated -5.8421e-02  1.7712e-02 -3.2984 0.0009989 ***
media_hype_index          2.1655e-05  1.7482e-05  1.2387 0.2156800    
sentiment_index          -6.5406e-06  2.8839e-05 -0.2268 0.8206179    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

F.4. PHASE IV (July 2021 – December 2021)

Oneway (individual) effect Random Effect Model
(Swamy-Arora's transformation)

```
Call:
plm(formula = VaR ~ delta_share + omicron_share + stringency_index + 
    people_fully_vaccinated + media_hype_index + sentiment_index, 
    data = Panel_Data, model = "random")

Balanced Panel: n = 10, T = 132, N = 1320

Effects:
                   var   std.dev share
idiosyncratic 1.418e-05 3.766e-03 0.282
individual    3.613e-05 6.011e-03 0.718
theta: 0.9456

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max. 
-0.00918434 -0.00223050 -0.00041207  0.00190030  0.02373961 

Coefficients:
                           Estimate  Std. Error z-value  Pr(>|z|)    
(Intercept)               1.2507e-02  1.9694e-03  6.3508 2.142e-10 ***
delta_share               6.6263e-03  6.2274e-04 10.6407 < 2.2e-16 ***
omicron_share             6.7095e-03  8.9068e-04  7.5330 4.960e-14 ***
stringency_index         -1.8176e-03  2.5575e-03 -0.7107  0.477267    
people_fully_vaccinated -2.1263e-03  6.7732e-03 -0.3139  0.753581    
media_hype_index          2.2371e-05  7.8430e-06  2.8524  0.004339 ** 
sentiment_index          -2.0329e-05  1.0528e-05 -1.9310  0.053482 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.020355
Residual Sum of Squares: 0.018601
R-Squared:      0.086181
Adj. R-Squared: 0.082005
Chisq: 123.827 on 6 DF, p-value: < 2.22e-16
```

Durbin-Watson test for serial correlation in panel models

```
data:  VaR ~ delta_share + omicron_share + stringency_index + 
people_fully_vaccinated + ...
DW = 0.15745, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Breusch-Pagan test

```
data:    VaR  ~  delta_share  +  omicron_share  +  stringency_index  +
people_fully_vaccinated +     media_hype_index + sentiment_index
BP = 24.384, df = 6, p-value = 0.0004438
```

Robust Model - t test of coefficients:

```
                           Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)              1.2507e-02  2.0641e-03  6.0592 1.784e-09 ***
delta_share              6.6263e-03  3.7730e-03  1.7563   0.07928 .  
omicron_share            6.7095e-03  2.8923e-03  2.3198   0.02051 *  
stringency_index        -1.8176e-03  1.9522e-03 -0.9311   0.35199    
people_fully_vaccinated -2.1263e-03  1.8534e-02 -0.1147   0.90868    
media_hype_index         2.2371e-05  2.1239e-05  1.0533   0.29239    
sentiment_index         -2.0329e-05  3.0389e-05 -0.6690   0.50364    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```