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COVID-19 restrictions effect on volatility

How did government interventions affect global stock market volatility?

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NORWEGIAN SCHOOL OF ECONOMICS

Abstract

Our thesis seeks to investigate whether or not government lockdowns attempting to stop the spread of COVID-19 affected volatility in global stock markets. To investigate this relationship, we utilize a sample of 64 countries of developed, emerging, and frontier markets along with the Oxford Containment & Health index, a measure of government closure and containment, health, and economic policies. Our findings suggest that government interventions affected volatility between 1. Jan 2020 and 12. Apr 2022, with the relationship net being consistent across segments of markets or time. For the market segments investigated, developed, emerging, and frontier markets, changes in government policy had a significant and positive effect on volatility. However, when investigating all countries in different periods, we show that the effect is not consistent over time but rather stronger in 2020 than 2021. Overall, this study contributes to policymakers and market participants in understanding the effect of the interventions over time, and across segments of markets.

Acknowledgments

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We would like to thank our lecturers along with our fellow students, for making our stay at NHH truly great. A special thanks to our advisor working with this thesis, Svein-Arne Persson, for feedback and guidance throughout our work this spring.

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1 Introduction

In early 2020, governments worldwide introduced severe COVID-19 restrictions to halt the spread of the virus, sending economies into recession and causing spikes in volatility similar to earlier financial crises (Sharif et al., 2020). Shanaev et al. (2020) argue that these government interventions are the most significant driver of global market negative shocks, as businesses are forced to close and customers are heavily restricted. With Baker et al. (2020) arguing that COVID-19 has affected the stock market more forcefully than any previous disease outbreak, we look to analyze if the COVID-19 interventions from governments affected volatility in the stock market, and if they did, to which extent. The goal is to make policymakers, together with market participants, aware of the economic impact of the government measures employed to fight the spread of the virus.

This study contributes to existing literature with a *extended timeframe* and *new variables* on policies, such as health policies and economic policies. We operate with a time period of approximately two and a half years, from 1. Jan 2020 to 12. Apr 2022. We seek to capture government interventions' effect on volatility over time and account for variables not broadly studied yet. To achieve this, we gather stock market data from *64 countries* globally, utilized to calculate volatility with a *GARCH* model & *30d rolling* volatility model. We employ the *Containment & Health index* and sub-indicators from the University of Oxford and Blavatnik School of Government to represent government interventions in response to COVID-19 (Hale et al., 2021). With multiple regression analysis using panel data, we explore the effect of government-imposed restrictions on volatility, both across segments of markets and across time periods during the span of the COVID-19 virus spread across the world.

2 Background

2.1 COVID-19 outbreak

In late December 2019, the first case of COVID-19 was discovered in Wuhan, China (WHO, 2020). In the upcoming months, the virus spread to every continent, and as of March 2020, most countries experienced a surge in positive cases. WHO characterized COVID-19 as a global pandemic on March 11, 2020.

In an attempt to contain the virus, many governments worldwide decided to employ restrictions on their populations (WHO, 2020). These restrictions included workplace closure, school closure, travel bans, and restrictions on gatherings, both public and private. Several countries also provided income support to those who partially or entirely lost their income due to the restrictions. As countries worldwide closed down, uncertainty in the markets increased. Many stock markets experienced severe falls (Ashraf, 2020). From February 12 to March 23, the MSCI World Index fell 34,2%. The Index is displayed in **figure 1** below.

Figure 1: MSCI World Index. Data collected from Investing.com.

The stock markets recovered in the months to follow. On August 26, 2020, the MSCI World Index hit a new all-time high of 2446.05 points.

The main task of this study will be to assess what impact government containment measurements have had on global stock market volatility. We will investigate this relationship in the long run across different countries. In addition, we will examine how the impact has changed over time.

2.2 Defining Volatility

Volatility is a term often used as a measure of risk in a financial context. It is an estimate of the fluctuations in returns for a security or market index. A higher volatility means greater variance in the returns, and conversely, lower volatility means more stable returns (Poon, 2005, p. 12). Volatility in the markets can be driven by many different factors, such as political and economic factors, industry factors, or investors' behavior (Mittnik et al., 2015).

The findings of Easterling (2022) at the Crestmont Research show that high volatility often corresponds to declining markets, and low volatility corresponds to a better-performing market. Participants in the financial markets utilize volatility in different ways, to evaluate portfolio risk, pricing of options, and to predict how the market will move in the future. Thus, volatility is of great interest to participants in financial markets.

Volatility is mainly measured in two ways. Using historical prices to get the realized volatility or predicting the future volatility which yields the implied volatility (Glantz & Kissel, 2014).

The first way to measure volatility is by using the historical price movements. The past volatility is most commonly measured as the standard deviation between returns in the security or market index over a period of time (Poon, 2005, p. 1). However, the standard deviation is only a measure of the spread of the sample and tells nothing about the shape. There have been developed models to better capture the different characteristics of volatility.

A characteristic of volatility is that high volatility is often followed by high volatility, leading to volatility clustering, which means that volatility is serially correlated (Natenberg, 2014, pp. 387-388). Further, volatility tends to be mean reverting, which implies that there is a greater likelihood that the volatility moves towards the mean rather than away from it. Volatility will therefore not diverge into infinity. Another characteristic of volatility is that negative shocks at time *t-1* seem to have a more considerable impact on volatility at time *t* than positive shocks, meaning negative changes in stock prices are correlated with volatility. This volatility asymmetry is referred to as the “leverage effect” and may be important to consider to gain a robust measure of volatility in stock markets (Bollerslev et al., 1993, p. 5). We will further comment on the specifics of this effect in **5.1.3.**

Secondly, implied volatility is a prediction of how volatile the asset or market will be going forward. However, it only predicts how large the movements will be, not in what direction. This forward-looking metric is used to price options contracts. Higher implied volatility on the underlying asset leads to a higher premium on the options contract and vice versa. The projection can be made by using a pricing formula like the Black-Scholes model or the binomial model; these models will, however, not be described any further in this thesis. An example of utilizing volatility is the VIX index, determined by options prices listed on the S&P 500, and predicts 30-day expected volatility (CBOE, 2022). This forward-looking indicator is one of the most recognized measurements of market volatility and indicates the level of uncertainty and fear in the market. Thus, research on volatility, and metrics that affect it, may be of importance to various stakeholders in the market.

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3 Literature

3.1 Literature Review

Studies on the behavior of volatility in previous crises will put the COVID-19 crisis in perspective. Goswami et al. (2020) investigate local and global crisis impact on volatility in advanced equity markets, finding that market volatility strongly increases during global crises. The study by Antonakakis & Scharler (2009) shows similar results, where the S&P 500 is examined from 1928 to 2009. The study found that volatility increases both before and after a market crash. The volatility also remains in a high state for a considerable period after the crash.

There are several previous studies on the topic of volatility in the COVID-19 crisis. Chaudhary et al. (2020) investigate the influence of COVID-19 on volatility in the top 10 countries based on GDP. Results clearly show a positive impact on volatility in the COVID-19 period, using a timeframe from January 2019 to June 2020. Further, Engelhardt et al. (2020) found that the volatility from January to July 2020 is significantly higher in low-trust countries than in high-trust countries. The sample consists of stock market indexes from 47 countries, and the paper argues that higher trust in fellow citizens and government reduces uncertainty among investors.

In a study conducted by Harjoto et al. (2021), it was found that volatility increased with increasing cases and deaths during the rising infection period (January to March). However, when splitting the countries into groups of 53 emerging and 23 developed markets, there was a difference in how the new cases and mortality rate affected volatility. The new confirmed cases significantly increased volatility, but the daily deaths only significantly affected volatility in the emerging markets. Further, in the stabilization period (April to August), the stock markets are less affected by the new cases and deaths. The findings of Dutillo et al. (2021) show similar results. In a sample of 16 indexes from the euro area, they found that the stock markets respond differently to the COVID-19 pandemic over time. The first wave (January to July) had a significant impact in the countries with middle-large financial centers, while the second wave (August to December) only had a significant impact on Belgium. Thus all the euro area countries show a weakening of the impact of COVID-19 on volatility as the crisis evolved. These findings support the arguments of Phan & Narayan (2020), who propose that the markets overreact during the rising infection period.

Baker et al. (2020) found that no earlier disease outbreak has had a bigger impact on volatility in the US equity market. That includes the Spanish flu, swine flu, SARS, Ebola, and MERS. When comparing earlier pandemics to the COVID-19 pandemic, the results show that the virus's lethality can not explain the stock market reaction. They find more good explanations in the restrictions imposed by the governments.

As follows, several studies examined more closely how the specific restrictions imposed by the governments have affected volatility in the markets. One of the earliest studies on the topic was a study by Zaremba et al. (2020). They examined how the social restrictions from the government impacted the stock market volatility in a sample of 67 countries, using a timeframe from January to April 2020. They found that the government interventions led to an increase in stock volatility. Further, when investigating the specific policy measures, it proved to be the information campaigns and public event cancellations that contributed the most to the increased volatility. However, pointing out the study's limitations with a narrow research sample.

Bakry et al. (2021) also examined how COVID-19 announcements affected stock market volatility, now with a time period from January 2020 to February 2021. In addition to the restrictions, the change in covid cases and deaths were included. By selecting a sample of developed and emerging markets, they could investigate the similarities and differences between the markets. The findings showed that the level of new confirmed covid cases led to a significant increase in volatility. The confirmed covid deaths also increased volatility, but only in the emerging markets. Further, they found significant differences between the emerging and developed markets. In the emerging markets, there was a positive relationship between the stringency measures and volatility; however, in the developed markets, there was a negative relationship. They argued that the findings could indicate a higher degree of vulnerability to poor economic outcomes in the emerging markets and a lower level of trust in the governments’ actions.

When the previous studies have examined the measures taken by the governments, the stringency response measures have been in focus. In addition to these measures, we want to extend the research by exploring the impact of government containment and health measures and financial support policy on volatility across market segments and time. In addition, we want to extend the timeframe to gain a larger research sample.

3.2 Hypothesis

The COVID-19 outbreak has affected economic growth negatively. Due to *government restrictions*, the production and supply chain on the supply side is disrupted (Jackson, 2021). Congressional research service estimated that the global economic growth was reduced by 3.2% and global trade by 5.3% in 2020. However, the economic decline was not as severe as firstly estimated, probably due to the fiscal and monetary policies many governments adopted. Further, the global economic growth was projected to recover by 5.9% in 2021. Based on the disruption in the real economic activities due to the lockdown, we can form our first hypothesis:

H1:
H0: Government responses to COVID-19 *did not* affect volatility in global stock markets over a two year timeframe
Ha: Government responses to COVID-19 *did* affect volatility in global stock markets over a two year timeframe

Furthermore, we wish to investigate differences in developed, emerging and frontier market segments, in the relationship between government interventions and volatility. Girard & Biswas (2007) suggests that, compared to developed markets, emerging markets show a greater response to information shocks. The COVID-19 period from 2020-2022 was filled with announcements, such as reported cases, deaths, public information campaigns, news on vaccines, and closures (Hale et al., 2021), to which market segments may react differently to. A study by Kohers et al. (2006) implies that emerging markets have a higher risk associated, measured by the standard deviation of returns, than developed markets. Thus, volatility reactions to government interventions in response to COVID-19 may be different across market segments, which forms the basis for our second hypothesis:

H2:
H0: Government responses to COVID-19 *did not* affect volatility differently in developed, emerging or frontier markets over a two year timeframe
Ha: Government responses to COVID-19 *did* affect volatility differently in developed, emerging or frontier markets over a two year timeframe

In a study by De Bondt & Thaler (1985), they find results that suggest that the market tends to overreact, especially to negative shocks. Phan & Narayan (2020), as mentioned earlier, find results that support this theory. This is called the overreaction hypothesis, which forms the basis for our third hypothesis. We hypothesize that the government responses to COVID-19 affect volatility differently during the two and a half year period. Therefore, we construct the hypothesis:

H3:
H0: Government responses to COVID-19 *did not* affect volatility differently in different periods over the span of two and a half years
Ha: Government responses to COVID-19 *did* affect volatility differently in different periods over the span of two and a half years

4 Data

4.1 Stock Indexes

The study's goal is to establish the effect of government containment measures on global markets. Market data from countries on all continents are gathered to investigate this relationship. Thus, to make the dataset, the main-stock indexes of 64 countries were extracted from http://www.investing.com. The selected period of the data is 1. Jan 2016, up until 12. Apr 2022. This pre-COVID-19 time-period yields the possibility of computing volatility based on historical data, such as GARCH-volatility. Each index contains daily observations on the price, opening-, and closing price of the index, giving the possibility to compute returns to calculate volatility. Non-trading days are dropped from the dataset, as these dates do not carry information. The countries included are selected based on the Morgan Stanley Capital International (MSCI) market classification for 2021 and the possibility of obtaining the stock indexes for these countries with complete data.

In the dataset, 23 countries are classified as developed markets, 24 as emerging markets, and 17 as frontier markets. The classification is described in section **4.2**. The major stock indexes for the 64 countries are selected, if available. In **table 1** below, the countries with the associated index are listed.

Table 1: Stock indexes by MCSI Classification of developed, emerging, and frontier markets

Developed Markets			Emerging Markets			Frontier Markets		
Nr	**Country**	**Index**	**Nr**	**Country**	**Index**	**Nr**	**Country**	**Index**
1	Australia	S&P/ASX 200	1	Argentina*	S&P Merval	1	Bahrain	Bahrain All Share
2	Austria	ATX	2	Chile	S&P CLX IPSA	2	Bangladesh	DSE 30
3	Belgium	BEL 20	3	China	CSI 1000	3	Croatia	CROBEX
4	Canada	S&P/TSX	4	Colombia	COLCAP	4	Iceland	ICEX Main
5	Denmark	OMX Copenhagen	5	Czech Republic	PX	5	Jordan	Amman SE General
6	Finland	OMX Helsinki	6	Egypt	EGX 30	6	Kazakhstan	KASE
7	France	CAC 40	7	Greece	Athens Composite	7	Kenya	Kenya NSE 20
8	Germany	DAX	8	Hungary	Budapest SE	8	Mauritius	Semdex
9	Hong Kong	Hang Seng	9	India	BSE Sensex	9	Morocco	Moroccan All Shares
10	Ireland	ISEQ Overall	10	Indonesia	IDX Composite	10	Nigera	NSE 30
11	Israel	TA 125	11	Mexico	S&P/BMV IPC	11	Oman	MSM 30
12	Italy	ITA 40	12	Pakistan**	KMI All Shares	12	Romania	BET
13	Japan	Nikkei 225	13	Peru	S&P Lima General	13	Serbia	Belex 15
14	Netherlands	AEX	14	Philippines	PSEi Composite	14	Slovenia	Blue-Chip SBITOP
15	New Zealand	NZX All	15	Poland	WIG20	15	Sri Lanka	CSE All-Share
16	Norway	OSE Benchmark	16	Qatar	QE General	16	Tunisia	Tunindex
17	Portugal	PSI 20	17	Russia***	MOEX	17	Vietnam	VNI
18	Singapore	MSCI Singapore	18	Saudia Arabia	MSCI TADAWUL 30			
19	Spain	IXEX 35	19	South Africa	South Africa Top 40			
20	Sweden	OMX Stockholm	20	South Korea	KOSPI			
21	Switzerland	SMI	21	Taiwan	TPEx 50			
22	United Kingdom	UK 100	22	Thailand	SET			
23	United States	S&P 500	23	Turkey	BIST 100			
			24	UAE	DFM General			

*Argentina reclassified to standalone in November 2021
**Pakistan reclassified to standalone in November 2021
***Russia reclassified to standalone in March 2022

4.2 Market Classification

The MSCI market classification framework is a framework by MSCI where equity markets are evaluated for countries worldwide before classifying the countries as developed, emerging, frontier, or standalone markets. The market classification review is announced annually, most recently in June 2021 (MSCI, 2022).

The framework has three criteria based on which it evaluates: economic development, size, liquidity requirements, and market accessibility (MSCI, 2022). The developed markets are often more economically developed and liquid than the other markets and have a very high level of accessibility. Emerging markets are, in most cases, less economically developed than developed markets. To be categorized as an emerging market, there are also fewer size, liquidity, and accessibility requirements. Frontier markets are markets that are considered less mature than emerging markets. That is due to the size and liquidity requirements and some market accessibility criteria. There are, for instance, no requirements related to openness to foreign ownership. Sorting the countries based on the framework will provide the opportunity to establish potential differences in how the different markets react. For specifics on how each country is assigned to a market segment, see **appendix: table 10**.

4.3 Government Response Trackers

University of Oxford and Blavatnik School of Government has, throughout the COVID-19 pandemic, collected systematic information on policy measures taken by governments in response to the spread of the virus. The policy measures collected are coded into 23 indicators such as workplace closures, school closures, travel bans, restrictions on gatherings, both public and private, and more (Hale et al., 2021). These indicators cover more than 180 countries and are, in the case of this study, assessed against the volatility of stock indexes in selected countries. The data collection dates back to the 1. Jan 2020, and are still being recorded as of May 2022.

Table 2: Containment & Health index and Sub-indicators (Hale et al., 2021)

ID	Variable	Max Value	Description
dif_conhel	Containment and Health index	100 (1-100)	Change in Containment & Health index for county i between time t and time t-1
c1	School Closing	3 (0,1,2,3)	Level of restrictions on school closing for country i at time t
c2	Workplace Closing	3 (0,1,2,3)	Level of restrictions on workplace closing for country i at time t
c3	Cancel Public Events	2 (0,1,2)	Level of restrictions on public events for country i at time t
c4	Restrictions on Gatherings	4 (0,1,2,3,4)	Level of restrictions on gatherings for country i at time t
c5	Close Public Transport	2 (0,1,2)	Level of restrictions on public transport for country i at time t
c6	Stay at Home Requirements	3 (0,1,2,3)	Level of restrictions on stay at home requirements for country i at time t
c7	Restrictions on Internal Moven	2 (0,1,2)	Level of restrictions on internal movement for country i at time t
c8	International Travel Controls	4 (0,1,2,3,4)	Level of restrictions on international travel for country i at time t
e1	Income Support	2 (0,1,2)	Level of income support for country i at time t
h1	Public Information Campagins	2 (0,1,2)	Level of public information campagins for country i at time t
h2	Testing Policy	3 (0,1,2,3)	Level of COVID-19 testing avaliable for country i at time t
h3	Contact Tracing	2 (0,1,2)	Level of contact tracing for country i at time t
h6	Facial Coverings	4 (0,1,2,3,4)	Level of facial covering requirements for country i at time t
h7	Vaccination Policy	5 (0,1,2,3,4,5)	Level of COVID-19 vaccination avaliable for country i at time t

As shown in **table 2** above, the indicators *c1-c8*, *h1-h3*, *h6*, *h7*, and *e1* each respond to government policies and are recorded on a scale to reflect government action. The sub-indicators make up the *Oxford Containment & Health* index, a measure of the severity of restrictions in a particular country (Hale et al., 2021). The Containment & Health index takes values from 0 (no containment or health policies in place) up to a maximum of 100. We utilize the Containment & Health index, calculated as the change between day *t* and day *t-1 (dif_conhel)*. The sub-indicators included in calculating the Containment & Health index are categorized into *containment and closure policies*, *health system policies,* and *economic policies*.

The indicators *c1-c8* are containment and closure policy indicators, referring to "lockdown"-like measures like school closure or movement restrictions. Higher values apply to a higher degree of severity in each policy, with 0 referring to no policy. The variables *h1, h2, h3, h6,* and *h7* refer to health system policies and function in a similar matter. As an example, the *h1* indicator records the presence of public information campaigns, with 0 referring to no COVID-19 public information campaigns, 1 referring to public officials urging caution about the virus, and 2 referring to coordinated public information campaigns, for example, across social media channels (Hale et al., 2021). For in-depth information about what each level of the sub-indicators attains to, see **appendix: table 11**.

Oxford University also collects information on economic policies. Included in the Containment & Health index utilized in this study is *e1*, a variable that corresponds to the sectoral scope of income support. The indicator records if governments provide cash payments to those who cannot work or lost their jobs because of the restrictions. The indicator takes a value of 1 if 50% of lost income is replaced, 2 if more than 50% is replaced, and 0 if no policy is in place.

These sub-indicators, along with the Oxford Containment & Health index, act as the main variables of interest in this study.

4.4 Control Variables

Along with the main variables of interest, variables on registered COVID-19 *cases*, *deaths*, and *vaccinations* are included in the dataset. These variables are collected from Our World in Data by the University of Oxford in collaboration with Oxford Martin School (Ritchie et al., 2020). The dataset contains information on registered COVID-19 cases, COVID-19 deaths, and vaccinations with approved COVID-19 vaccines and is collected by official reports (i.e.). All variables are reported in raw format, meaning the official numbers from governments, and *smoothed* numbers, with missing values being *7-day smoothed*. These variables mainly act as control variables to separate the news about cases and deaths from government interventions.

5 Methodology

5.1 Estimating Volatility

Volatility is typically calculated as the conditional standard deviation of daily returns. A rolling window standard deviation model is an example of such a model, discussed in **5.1.1**. In this thesis, we have estimated the volatility using this model. In addition, we have estimated volatility with the GJR-GARCH model. This model is a modified version of the GARCH model, one of the most widely used volatility models, laid out in detail in section **5.1.3**.

5.1.1 30-day rolling volatility

A simple way to calculate volatility is using a rolling window of return observations. In our case, we estimated volatility with a 30-day window of observations, using the standard deviation of returns from day *t* to day *t-29*. This standard deviation represents the volatility of a specific day, which is useful for understanding the spread of asset returns (Poon, 2005, p. 1). The formula for standard deviation is given as:

$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(r_t - \mu\right)^2} \tag{1}$$

Where r_t is the return of the stock index on day *t*, and μ is the average return of the *T*-day period.

Although the standard deviation method is commonly used, it is not a perfect way of estimating volatility. The volatility for day *t*, is modeled as the standard deviation of the last 30 observations and may not draw a perfect picture of the current market, as the model operates with a non-declining weighing pattern. An Exponential Weighted Moving Average approach may result more accurately, as we then consider the largest influence played by closer prices as opposed to more distant prices (D’Ecclesia & Clementi, 2021). However, we employ this method for its simplicity, as it yields a good benchmark for more advanced models.

5.1.2 Standard GARCH

The generalized autoregressive conditional heteroskedasticity (GARCH) is a model developed by Bollerslev (1986) to estimate and forecast volatility. The GARCH model uses weighted past returns and past volatility to forecast volatility. Hence, large shocks tend to be followed by large shocks. Therefore named autoregressive, as the past influences the future.

The general GARCH (p,q) model is given by:

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon^2_{t-1} + \sum_{i=1}^{q} {}_i\, \sigma^2_{t-1} \quad (2)$$

The model includes three parameters: α_0 α_i and β_i, where $\alpha_0 > 0$, $\alpha_i >= 0$, and $\beta_i >= 0$.

From the equation we see that the predicted variance is calculated with the sum of the weighted average of past squared returns ($\alpha_i \epsilon^2_{t-1}$). Where the weights are declining, but never reaching zero completely. The p refers to the number of autoregressive lags (Bollerslev, 1986). With the last term in the formula, the sum of the weighted volatility from the earlier periods is added (${}_i\, \sigma^2_{t-1}$). The q is the number of moving average lags that are included. As follows, the model includes the fact that volatility is serially correlated. Therefore named "conditional heteroskedasticity", which means that the variance of the error term is serially correlated.

A disadvantage with the GARCH model is that it is a symmetric model; it assumes that positive and negative returns have the same relationship to volatility. Thus, it does not capture the "leverage effect", commented in **2.2**. The "leverage effect" refers to the relationship between stock returns and volatility in the market. When the stock prices fall, the volatility increases more compared to what would be the case with an increase in the stock prices of the same degree. An explanation is that a decrease in the market valuation of a firm's equity increases the leverage in its capital structure, increasing its financial risk. Models have been developed to capture this effect. In the next section, we will present one such model.

5.1.3 GJR-GARCH

A modification of the GARCH model is the GJR-GARCH model, developed by Glosten, Jagannathan, and Runkle (1993). This model has the same features as the standard GARCH model, but with the addition that it captures the “leverage effect". Thus, this is an asymmetric volatility model (Glosten, et al., 1993).

The GJR-GARCH(p, q) model:

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{p} {}_i\, \sigma^2_{t-1} + \sum_{i=1}^{q} \left(\alpha_i + \gamma_i\, I_{t-1}\right) \epsilon^2_{t-1} \tag{3}$$

The same parameter constraints are imposed in this model: $\alpha_0 > 0$, $\alpha_i >= 0$, and $\beta_i >= 0$. From equation X.2, we find that the new term now added is $\gamma_i I_{t-1}$. The I_{t-1} is an indicator that equals 1 when $\epsilon_{t-1} < 0$, and 0 when $\epsilon_{t-1} \geq 0$. And γ_i being a new parameter with constraint $\gamma_i \geq 0$ (Poon, 2005, pp. 41-44). As follows, a negative return (ϵ_{t-1}) will result in a larger impact on σ^2_t, then a positive return.

In this thesis, we have estimated the volatility using a one-step GJR-GARCH(1,1) model, which is given by equation:

$$\sigma^2_t = \alpha_0 + {}_i\, \sigma^2_{t-1} + \alpha_i\, \epsilon^2_{t-1} + \gamma_i\, I_{t-1}\, \epsilon^2_{t-1} \tag{4}$$

Using this model, we get the same benefits as with the standard GARCH, as well as capture the “leverage effect” in the time-series. Utilizing the leverage effect as the GJR-GARCH, has been shown to perform better than standard GARCH for stock indexes (Brailsford & Faff, 1996).

Computing the stock returns, we use the natural log. The equation can be expressed as:

$$\epsilon_t = r_t = \ln \frac{P_t}{P_{t-1}}, \tag{5}$$

where: r_t = return at time t; P_t = price at time t; P_{t-1} = price at time t-1.

We use daily data extending from 1. January 2016 to 12. April 2022 to be able to estimate the GJR-GARCH volatility with a historical basis. Further, the parameters in the model are estimated using the maximum likelihood method to fit the data in our dataset.

To provide a better perspective on the order of magnitude, we annualize the two volatility measures estimated. This is done with the following formula for conversion between daily and yearly volatility (Natenberg, 2014, pp. 78-79):

$$Volatility_{annual} = Volatility_{daily} * \sqrt{250} \tag{6}$$

Due to volatility being proportional to the square root of time, we multiply the daily volatility with the square root of trading days in a year. We make the assumption of 250 trading days a year, even though this number may vary.

5.2 Panel Data

A panel data or longitudinal data is a set of data with observations of multiple entities (countries), where the entity *(i)* is observed at two or more points in time *(t)*. In our case, we have *N=64* entities, observed at *T=459* to *T=691* points in time, with most entities with about *T=550*. Y_i then denotes the variable Y for the i^{th} entity in the panel data set, and $Y_{i,t}$ denotes the variable Y observed for the i^{th} of n entities observed in the t^{th} of T periods. This is summarized as:

$$(X_{i,t}, Y_{i,t}),\ i = 1,..., n\ and\ t = 1,..., T$$

A balanced panel has all observations available for all entities (i) across all points in time (t). When the time period of the observations are not perfectly identical for all entities, we deal with an *unbalanced* panel, as is the case for the data in this study (Stock & Watson, 2020, pp. 361-363). The reasoning for using panel data is its advantages over cross-sectional or time-series data. Panel data yields a large number of data points, increasing degrees of freedom and reducing collinearity between independent variables (Hsiao, 2007). Thus, it is a tool for improved efficiency of economic modeling.

5.3 Hausman Test

It is crucial to choose the most consistent and unbiased model when dealing with panel data. For the data in this study, the choice between a random-effects model and a fixed-effects model needed to be established. Hausman (1978), established a way to test whenever the random effects model would be without misspecification and have an asymptomatic normal and efficient estimator, which acts as the null hypothesis. Under the alternative hypothesis, the estimator would be biased and inconsistent. This test, called the Hausman test, is often applied in testing between random and fixed effects models in panel data literature. When performing the test, we obtain a statistical assessment of whether or not the unobserved individual effect is correlated with the conditioning regressors in the model (Amini et al., 2012).

The model choice is essential to gain an unbiased and consistent estimate of the relationship of interest. If there exists a relationship between the unobserved individual effect and regressors, the random-effects model does not address endogeneity (no correlation between the error term and regressors). We then may obtain a biased estimate.

To perform the test, we estimate our regression model with a fixed-effects model with individual-effects, and a random-effects model. The null hypothesis states that the random-effects model is consistent, while the alternative hypothesis states that the fixed effects model is consistent. Failing to reject the exogeneity of the unobserved individual effect, which serves as the null hypothesis, means a random-effects model is supported. At the same time, a rejection favors the fixed effects model (Amini et al., 2012). After summarizing our regressions and performing the Hausman test, we obtained a p-value outside the 5% level of significance. Therefore, we rejected the null hypothesis and gained support for a fixed-effects model.

5.4 Fixed Effects Model

The usefulness of panel data comes from controlling for factors that vary across entities but not across time; or across time but not across entities. If not controlled for, these could cause an omitted variable bias, but they are unobserved or unmeasurable, therefore can not be included in a standard multiple regression. If there is an omitted variable that does not change over time, any change in *y* (dependent) over time is not caused by this variable. The fixed effects regression model yields n different intercepts, one for each entity (country) in the data set. For our purpose we would estimate entity fixed effects regression, given as:

$$y_{i,t} = \alpha_i + \beta_1 x_{i,t} +\ldots \beta_N x_{i,t} + u_{i,t} \qquad (7)$$

where α_i is called the "entity fixed effect", and can be looked at as the effect of being in entity i.

Variation in α_i (entity fixed effects) comes from omitted variables, which implies variables that change across entities but not over time. The advantage of the model then is to control for these potential omitted variables (Stock & Watson, 2020, pp. 367-371).

5.5 Fixed Effects Assumptions

The first assumption (LS.1) states that $u_{i,t}$ has a mean of zero, given the entity fixed effect and the history of x for that entity in question. Mathematically this would mean that: $E(u_{i,t}|x_{i,1},..., x_{i,T}, \alpha_i) = 0$. In the case of this study, if a country has a high volatility one day, it would most likely not change its covid policy based on that; hence the assumption holds. The second assumption (LS.2) suggests entities are randomly sampled from their population. For example, if a country has a high degree of lockdown today is certainly correlated with the degree of lockdown tomorrow. Assumption LS.3 suggests $(x_{i,t}, u_{i,t})$ large outliers are unlikely, and LS.4 suggests there shall be no perfect multicollinearity, which is commented in **5.6**, and

5.7 (Stock & Watson, 2020, pp. 374-376). The model limitations imply that variation in explanatory variables x across time is needed, together with the need of robust clustered standard errors to correct for autocorrelation in $u_{i,t}$ which will be further commented on in **5.8**.

5.6 Correlation Matrices

The problem of multicollinearity can occur when independent variables are heavily correlated. The goal of the regression is to estimate a dependency between our main dependent variable and the independent variables. However, if we encounter a multicollinearity problem with our independent variables, we may have biased estimators. The problem can be visualized through a correlation matrix between the independent variables. When the correlation between variables approaches a singularity, either -1 or 1, we have an interdependence among our explanatory variables. With a high enough correlation, the model will have problems setting the effect of the correlated explanatory variables apart, leading to a bias. Multicollinearity can become problematic when simple correlations between explanatory variables are higher(lower) than 0.9(-0.9) (Farrar & Glauber, 1967).

To ensure no multicollinearity concerns exist in the dataset, we compute correlation matrices between all explanatory variables used in the regression model. Figure X below shows the correlation matrix between all sub-indicators used in the Containment & Health index by Oxford University. The dots and the shading of the color represent the severity of the correlation between variables, with “bubbles” getting more extensive and colors darker as the correlation approaches -1 or 1. The correlations of individual countries have also been established, with no signs of high correlation, which implies no multicollinearity concern in the model.

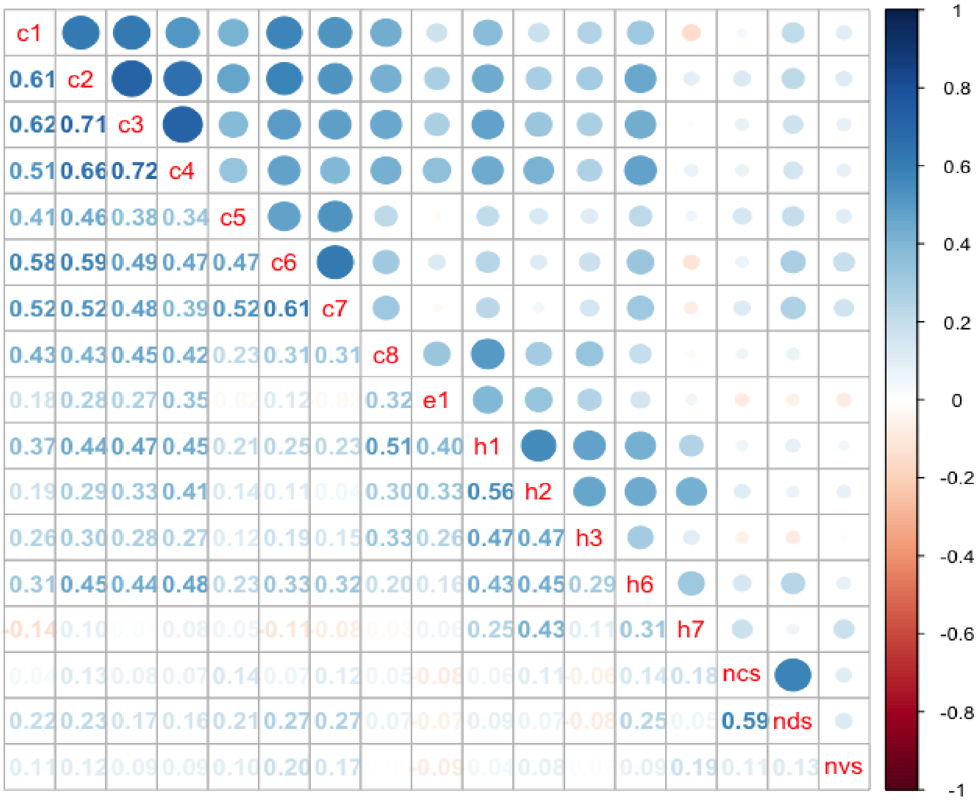

Figure 2: Correlation Matrix

5.7 Variance Inflation Factor

Another way of detecting multicollinearity in regression models is the variance inflation factor (VIF). The factor measures the correlation and strength of correlation between explanatory variables in the model and are given by (Stine, 1995):

$$VIF_J = \frac{1}{1-R_j^2} \tag{8}$$

This VIF-factor measures by how much multicollinearity has increased the variance of a slope estimate. VIF equals 1 ($R_j^2 = 0$) when the vector X_j is orthogonal (independent) to each column of the design matrix for the regression of Xj on the other covariates. When the VIF value grows, the relationship between the explanatory variable in question and other explanatory variables becomes stronger (Thompson et al., 2017). The values (VIF) are computed for all explanatory variables in the regression model. To compute our VIF-factors for the explanatory variables in all models, we estimate the models with pooled regression (OLS), since the factor does not take into consideration which regression model is chosen. Unfortunately, there is no universally established threshold as to what is a too high VIF-value; however, above 10 can indicate a major problem, while beneath 5 usually is no concern for multicollinearity (Chatterjee & Hadi, 2006, pp. 288-289, Thompson et. al, 2017).

When operating with a maximum allowed VIF-value of 5, our models are still within the threshold, and we, therefore, conclude there is no severe danger of multicollinearity. In **figure 3** below, one of the VIF-values for *developed countries* is displayed (Specifically chosen to display due to having the largest values). Note; more VIF-values in appendix.

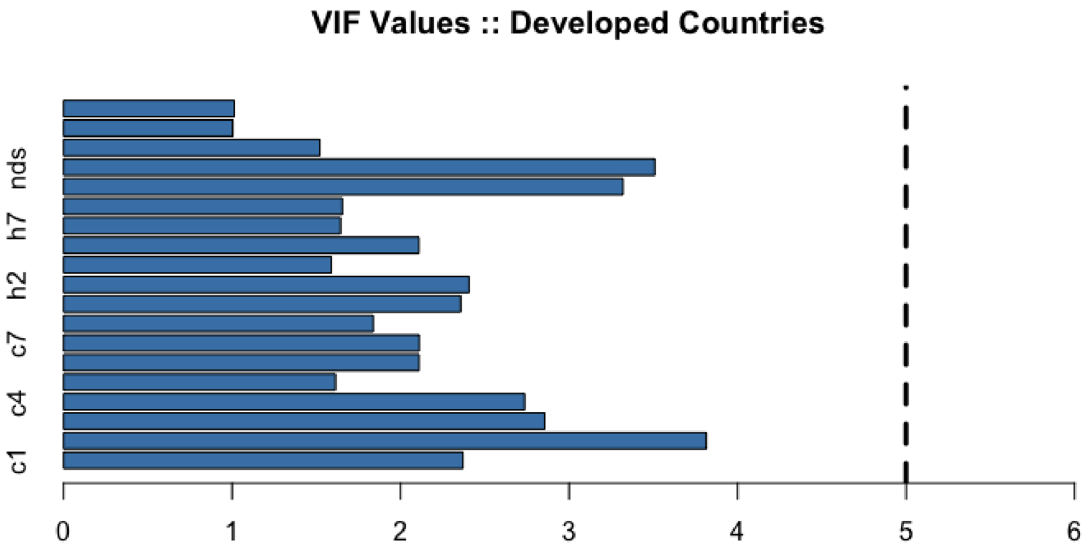

Figure 3: VIF-values for model (2, Table 6)

5.8 Robust Clustered Standard Errors

So far the discussion has been about getting unbiased and consistent estimates with the optimal model. However, it is just as important to gain accurate statistical inference, where the standard errors are the fundamental component. In panel data, as we operate with, model errors in different periods for a given entity (country) may be correlated. In contrast, the model assumes errors for separate entities are uncorrelated. Our standard errors may be misleadingly small, t-statistics high, and p-values low if not controlled for. This comes from the fact that the standard errors are computed from an assumption of *homoscedasticity* and *no serial correlation*, making the errors invalid, if errors are heteroskedastic or autocorrelated

(Stock & Watson, 2020, p. 376). Hence, standard errors need to be corrected to gain the correct significance levels for the estimates (Cameron & Miller, 2015). If the original errors are potentially heteroscedastic and potentially autocorrelated, valid standard errors are referred to as *heteroskedastic and autocorrelation robust* (HAR) *standard errors*. The type of errors used in panel data is called *clustered standard errors* (Stock & Watson, 2020, p. 376). These clustered standard errors allow for autocorrelation within entities and are robust to heteroskedasticity within and across entities. The name clustered comes from the errors having an arbitrary correlation within clusters (entities; countries), but the assumption is that the errors are uncorrelated across different groups.

The most popular method for correcting the issue of misleading standard errors is first to estimate the regression model of choice and then compute robust clustered standard errors proposed by Arellano (1987) for the fixed effects estimator in linear panel models (Cameron & Miller, 2015). This is our method of obtaining the robust clustered standard errors. Hence, we seek to eliminate the threat of misleading significance levels and t-statistics.

6 Descriptive Statistics

6.1 Graphs

In this section, we display various graphs of the data acquired to gain a general overview of the containments of the dataset. Different countries are included to diversify the presentation. Most countries have somewhat similar characteristics in the variables displayed. Thus a handful is shown in the figures in the following part, while we include more countries in **appendix: figures 14** to **28**. Note that the two variables for comparison are scaled for visualization purposes for all graphs.

6.1.1 Containment & Health Index vs. Stock index

The graphs below display the Containment & Health index acquired from the Oxford University database and the stock index for the countries selected (Mexico & Norway). For most countries, including the two shown below, the stock indexes experienced significant declines at the same point as major COVID-19 restrictions were put in place by their respective governments. However, after the immediate shock of COVID-19 spread and containment restrictions, the relationship between stock market returns and regulations becomes more unclear. The relationship between stock market volatility and containment restrictions will be analyzed further.

Figure 4: Mexico, Containment & Health index, and stock market index

Figure 5: Norway, Containment & Health index, and stock market index

6.1.2 Returns & GJR-GARCH Volatility

As expected, volatility spiked during March 2020, as this was the period COVID-19 restrictions were put in place. The graphs below observe *daily stock market returns* for the selected countries (USA & France), plotted against the *GJR-GARCH volatility estimation*. Returns fluctuated severely during the beginning of 2020, but seemingly stabilized in later 2020 and 2021. The GJR-GARCH volatility estimation substantiates this relation, as volatility for these two countries is lower after the initial shock. This relation is somewhat similar for most countries included in the dataset.

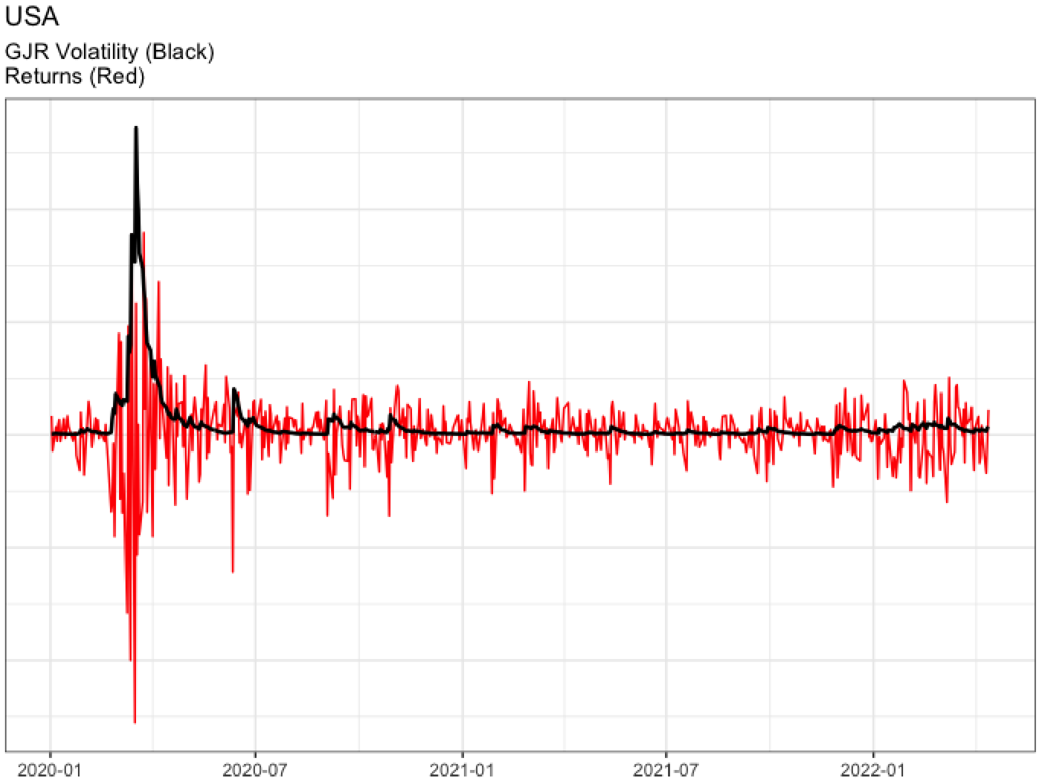

Figure 6: USA, Volatility and stock market returns

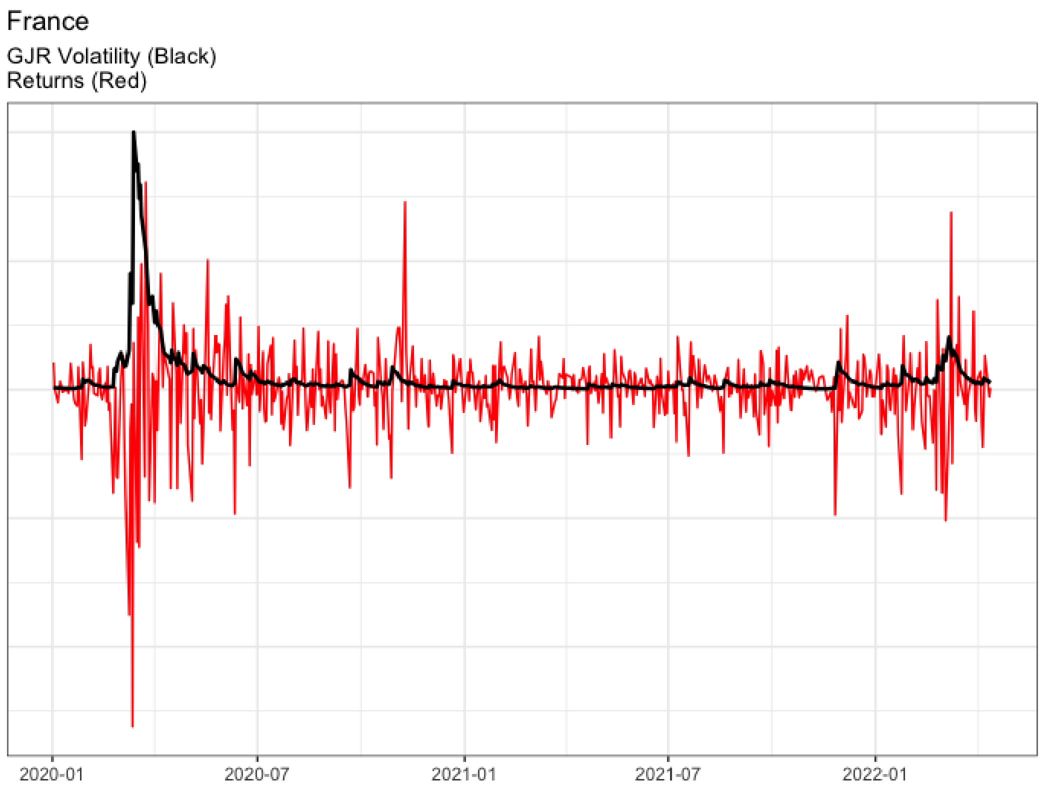

Figure 7: France, volatility and stock market returns

6.1.3 Cases & Deaths

In this section, we have plotted *COVID-19 cases* and *COVID-19 deaths* in two countries below (Sweden and Portugal). Movements in volatility, COVID-19 restrictions, and stock index act somewhat similar for most countries. However, the number of deaths and when surges in cases happened do vary among the countries in the data set. One similarity is that most countries have more significant amounts of COVID-19 cases towards the end of the period 2020-2022, which may be due to more intense testing of the population. Surges in COVID-19 deaths are, however, more unequally distributed within the countries we assess in this study. These variables are not the primary focus of this study as we seek the relationship between containment measures and volatility but could still yield additional knowledge.

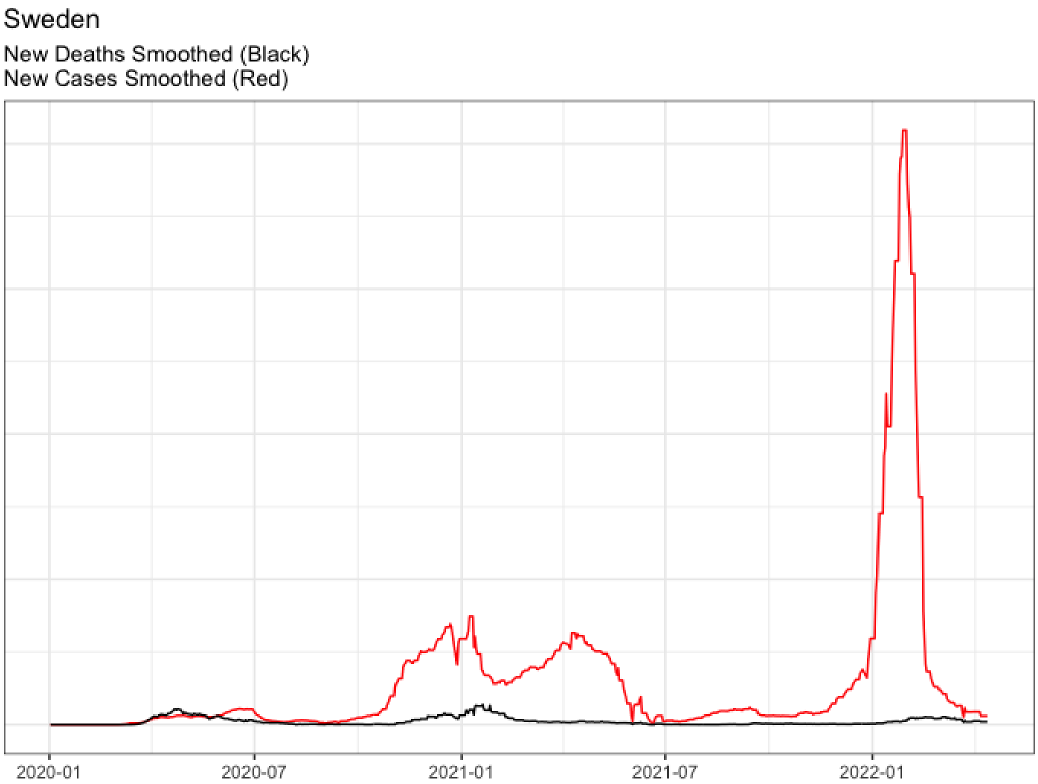

Figure 8: Sweden (*Note: Deaths scaled by x10 for visibility*)

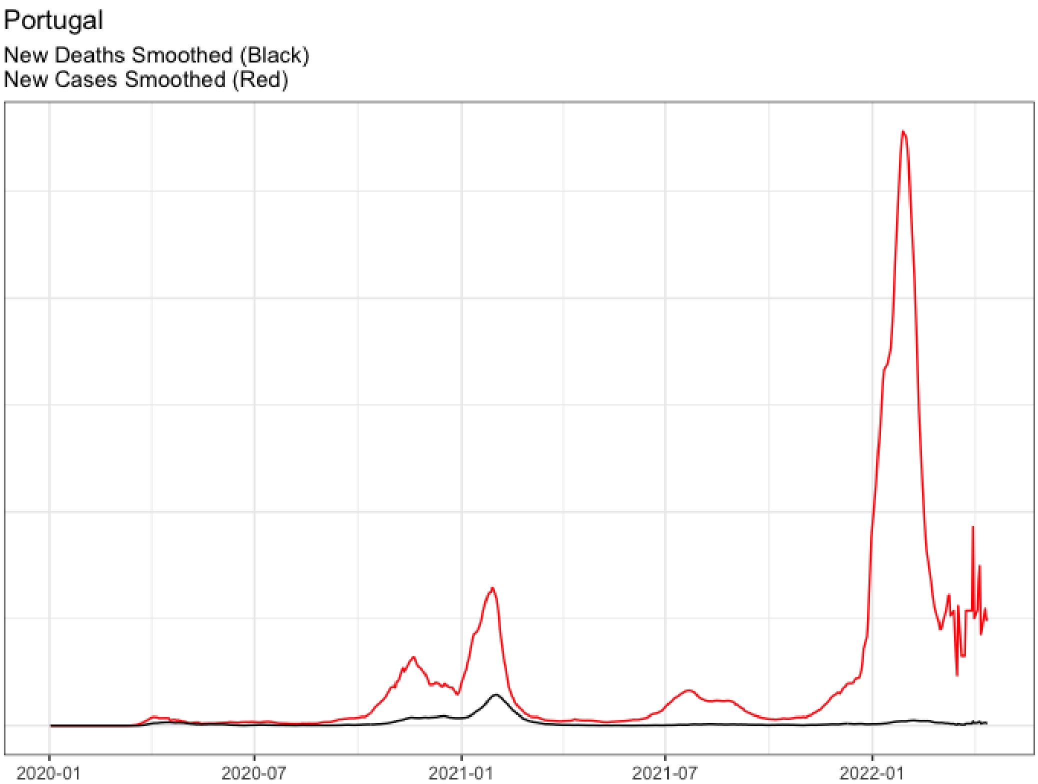

Figure 9: Portugal (*Note: Deaths scaled by x10 for visibility*)

6.1.4 GJR-GARCH & 30d Rolling Volatility

In the visual representation of the *GJR-GARCH volatility* and *30d rolling window volatility*, we observe quite similar movements. However, as we would expect, the GJR-GARCH volatility yields greater spikes in cases of rapidly increasing volatility, known as the "leverage effect" discussed in **5.1.3**. The 30d rolling window volatility does not have this leverage effect and is simply a measure of volatility from day *t-29*, to day *t*. In the analysis of the government restrictions, both volatility measurements are employed.

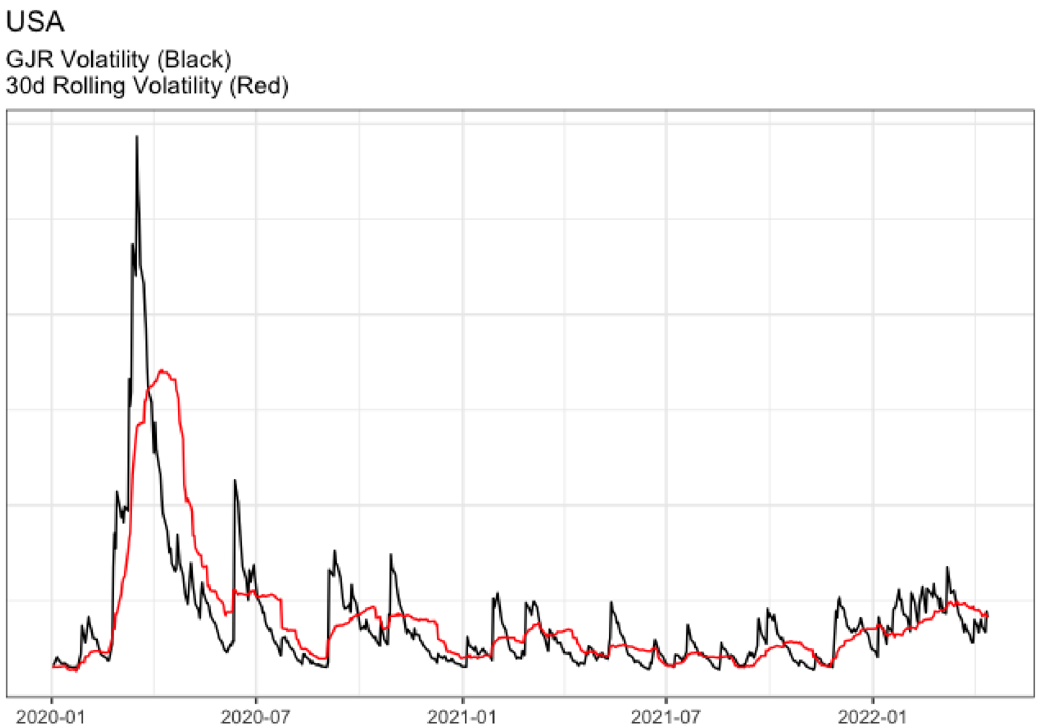

Figure 10: USA, GJR-GARCH and 30d rolling volatility

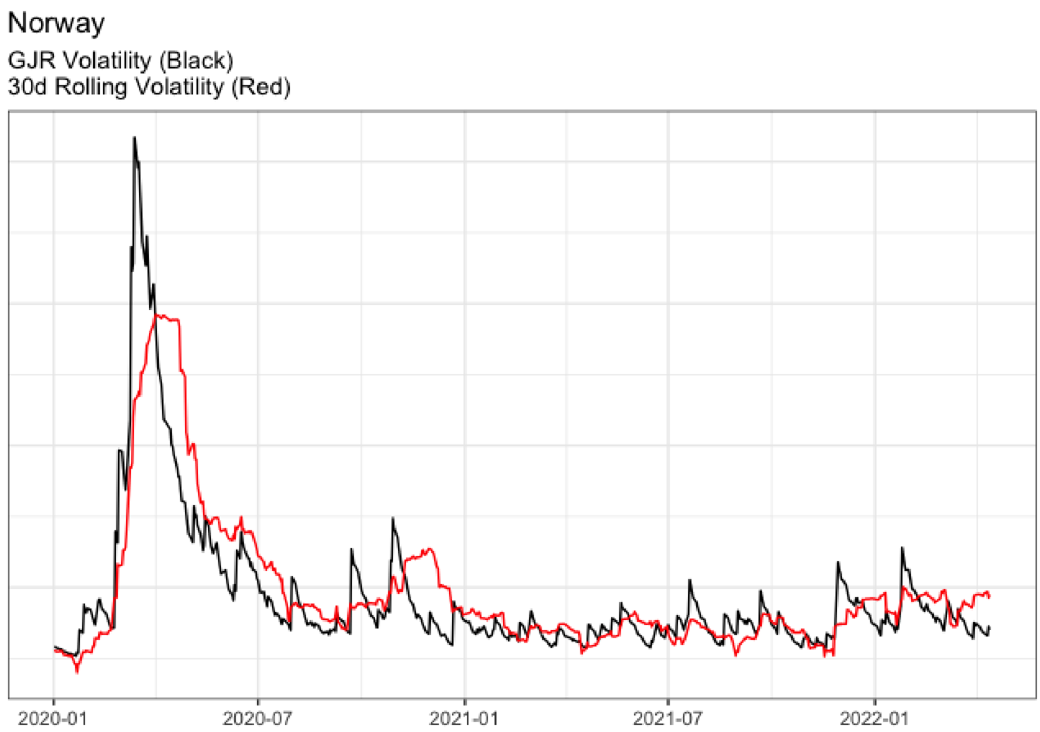

Figure 11: Norway, GJR-GARCH and 30d rolling volatility

6.2 Averages and Standard Deviation

In the following section, averages, standard deviations, and maximum and minimum observations are reported for *developed*, *emerging,* and *frontier* markets, along with all countries in which the dataset's period is divided into five. The periods *1-4* refer to half a year, first 2020 (1-2) and 2021 (3-4), while Period *5* refers to the 1. Jan to 12. Apr 2022.

6.2.1 Markets

Table 4 below displays the number of observations, mean values, standard deviation, and maximum and minimum values of all variables of interest in this study. Variables are classified in developed, emerging, and frontier markets to expose differences between the categories of markets. The 30d rolling volatility (annualized) mean observations are 0.2 for developed countries, 0.21 for emerging, and 0.13 for frontier; the GJR-GARCH delivers very similar mean values with 0.19, 0.21, and 0.13 for the same market segments. The maximum and minimum observations imply that all countries experienced fluctuations in their stock markets regardless of categorization. It is worth noting that the GJR-GARCH volatility has quite higher maximum observations compared to the 30d rolling window, however standard deviations are similar. The Containment & Health index has similar mean values for all markets and ranges from 0 to 90 or above (100 being the strictest possible). This suggests all markets experienced severe restrictions, while the standard deviation implies changes in restrictions were common throughout the period investigated in this study. For at least one country in each category of markets, every sub-indicator reached its maximum level, suggesting all variables of interest are measurements employed by governments regardless of the market. Based on this data, it is impossible to draw any concluding remarks on differences between the markets, and the markets will be further analyzed with panel data regression.

Table 4: Means, standard deviation, min & max observations for emerging, developed, and frontier markets during the complete period

	Developed					**Emerging**					**Frontier**				
Statistic	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max
vol_30d	13,423	0.20	0.12	0.04	0.88	13,487	0.22	0.14	0.04	1.41	9,524	0.13	0.09	0.02	0.63
vol_gjr_garch	13,423	0.19	0.13	0.05	1.47	13,487	0.21	0.14	0.07	2.26	9,524	0.13	0.09	0.04	1.09
conhel_index	13,423	55.47	18.68	0	93	13,487	57.72	19.25	0	92	9,524	54.31	19.48	0	90
c1	13,423	1.45	0.96	0	3	13,487	1.79	1.07	0	3	9,524	1.51	1.09	0	3
c2	13,423	1.66	0.92	0	3	13,487	1.64	0.88	0	3	9,524	1.36	0.91	0	3
c3	13,423	1.45	0.76	0	2	13,487	1.52	0.71	0	2	9,524	1.39	0.75	0	2
c4	13,423	2.78	1.55	0	4	13,487	2.73	1.48	0	4	9,524	2.75	1.44	0	4
c5	13,423	0.45	0.56	0	2	13,487	0.76	0.74	0	2	9,524	0.57	0.74	0	2
c6	13,423	0.83	0.79	0	3	13,487	1.18	1.00	0	3	9,524	1.06	0.93	0	3
c7	13,423	0.75	0.86	0	2	13,487	1.07	0.88	0	2	9,524	0.76	0.89	0	2
c8	13,423	2.82	1.04	0	4	13,487	2.48	1.14	0	4	9,524	2.34	1.14	0	4
h1	13,423	1.91	0.41	0	2	13,487	1.88	0.46	0	2	9,524	1.87	0.47	0	2
h2	13,423	2.19	0.81	0	3	13,487	2.14	0.90	0	3	9,524	2.23	0.95	0	3
h3	13,423	1.48	0.62	0	2	13,487	1.53	0.68	0	2	9,524	1.36	0.74	0	2
h6	13,423	2.03	1.26	0	4	13,487	2.60	1.27	0	4	9,524	2.49	1.29	0	4
h7	13,423	2.34	2.26	0	5	13,487	2.16	2.18	0	5	9,524	2.19	2.20	0	5
e1	13,423	1.46	0.77	0	2	13,487	0.92	0.73	0	2	9,524	0.88	0.81	0	2
ncs	13,423	12,093.24	40,214.42	0	806,297	13,487	7,753.93	25,779.61	0	404,998	9,524	1,942.92	10,485.37	0	274,025
nds	13,423	98.85	306.43	0	3,393	13,487	124.95	270.97	0	4,188	9,524	20.10	43.59	0	454
nvs	13,423	98,725.25	270,451.70	0	3,504,385	13,487	373,756.40	1,558,993.00	0	22,424,286	9,524	50,494.35	197,934.60	0	3,758,404

6.2.2 Time Periods

Along with descriptives for each market segment, descriptive statistics for each period are presented below in **table 5**. The periods in question are divided into equal periods of six months, starting from 1. Jan 2020. Period 5 is shorter as the data ends on 12 Apr 2022, explaining why observations (N) are lower than the latter. Most evident to note is the significantly higher volatility mean of period 1 (0.3; 0.3), also with a higher standard deviation (0.2; 0.2) than the later periods. The Containment & Health index sees the highest mean values in periods 2-4, with the least variation. This implies that from mid-2020 to the end of 2021, the government restrictions in place were the most severe and simultaneously the most stable among the countries in the data set. The standard deviation of the Containment & Health index reports the highest values at the beginning and the end of the period; suggesting countries differ more in their approach at these times. For COVID-19 cases, we can observe an incline throughout the periods measured, which may be due to tests being more attainable than earlier. This hypothesis is further substantiated by testing policy (*h2*), reaching higher levels towards the end of the period.

Table 5: Means and standard deviation for all countries in different periods

	Period 1			Period 2			Period 3			Period 4			Period 5		
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
30d	7,769	0.3	0.2	8,261	0.2	0.1	7,985	0.1	0.1	8,263	0.1	0.1	4,597	0.2	0.1
gjr_garch	7,769	0.3	0.2	8,261	0.2	0.1	7,985	0.1	0.1	8,263	0.1	0.1	4,597	0.2	0.1
conhel_index	7,769	40.8	28.9	8,261	57.6	12.1	7,985	65.2	11.3	8,263	60.1	11.6	4,597	55.7	14.3
c1	7,769	1.6	1.4	8,261	1.9	0.9	7,985	1.9	0.9	8,263	1.3	0.8	4,597	1.1	0.8
c2	7,769	1.2	1.2	8,261	1.7	0.8	7,985	1.9	0.7	8,263	1.6	0.7	4,597	1.5	0.8
c3	7,769	1.1	1.0	8,261	1.6	0.7	7,985	1.7	0.5	8,263	1.4	0.6	4,597	1.3	0.8
c4	7,769	1.9	1.8	8,261	3.1	1.2	7,985	3.5	1.0	8,263	2.8	1.3	4,597	2.4	1.5
c5	7,769	0.5	0.7	8,261	0.6	0.7	7,985	0.7	0.6	8,263	0.6	0.7	4,597	0.5	0.7
c6	7,769	0.8	1.0	8,261	1.2	0.9	7,985	1.4	0.9	8,263	0.9	0.9	4,597	0.6	0.7
c7	7,769	0.8	0.9	8,261	1.0	0.9	7,985	1.0	0.9	8,263	0.8	0.9	4,597	0.6	0.8
c8	7,769	2.4	1.6	8,261	2.8	0.9	7,985	2.8	0.8	8,263	2.5	0.9	4,597	2.2	1.1
h1	7,769	1.5	0.8	8,261	2.0	0.0	7,985	2.0	0.1	8,263	2.0	0.1	4,597	2.0	0.2
h2	7,769	1.3	1.0	8,261	2.2	0.7	7,985	2.4	0.6	8,263	2.6	0.6	4,597	2.6	0.7
h3	7,769	1.1	0.8	8,261	1.7	0.5	7,985	1.6	0.6	8,263	1.5	0.7	4,597	1.4	0.7
h6	7,769	0.9	1.3	8,261	2.7	1.1	7,985	3.0	0.8	8,263	2.8	0.9	4,597	2.5	1.0
h7	7,769	0.0	0.0	8,261	0.05	0.3	7,985	2.7	1.4	8,263	4.6	0.7	4,597	4.9	0.5
e1	7,769	0.7	0.8	8,261	1.4	0.7	7,985	1.3	0.7	8,263	1.1	0.8	4,597	0.9	0.8
ncs	7,769	666.3	2,712.2	8,261	4,789.4	15,836.2	7,985	6,549.3	24,129.4	8,263	6,878.8	17,724.9	4,597	28,699.0	66,690.0
nds	7,769	37.6	162.2	8,261	84.6	214.7	7,985	130.0	355.3	8,263	91.2	233.1	4,597	91.8	237.7
nvs	7,769	0.0	0.0	8,261	769.3	12,961.2	7,985	237,779.0	1,261,131.0	8,263	439,514.6	1,459,884.0	4,597	286,188.5	865,034.4

7 Analysis

In this section, the data is explored in-depth. We analyze the data by different groupings by employing panel data regression with entity fixed-effects and clustered standard errors robust to heteroskedasticity. Section **7.1** will contain an analysis of the various segments of markets; developed, emerging, and frontier, assessing the differences between them. In **7.2,** we divide our sample into periods of 6 months to determine changes over time and effects after the initial shock of the COVID-19 lockdowns. For all regressions in this analysis we employ the *GJR-GARCH volatility model*, as explained in **5.1.3**. However, all regressions are also attached in **appendix: table 12** to **15** with the *30d rolling window volatility* model. We employ the GJR-GARCH model due to research suggesting the model is a better fit for stock market data (Brailsford and Faff, 1996). However, the 30d rolling window volatility *does not* yield substantially different results.

7.1 Analysis of Segments of Markets

In the regression analysis below, the volatility (GJR-GARCH) is scaled to represent percentage points as the coefficients. All countries in the sample are represented and categorized into developed, emerging and frontier markets, following the MSCI market classification framework, commented in **4.2**. There are 12,229, 12,308, and 8,678 observations for developed, emerging, and frontier market segments, respectively. The period for the regression reaches from 1. Jan 2020 to 31. Jan 2022. The period is cut short due to stock market reactions to the conflict in Ukraine in 2022, impacting volatility severely (Adekoya et al., 2022, Hossain & Masum, 2022).

The regression is performed for the effect of *changes* in the Containment & Health index and the sub-indicators in *absolute values*. For an overview of the variables, see section **4.3**. The regression is displayed in **table 6** below, where the model (1) and (2) refers to developed markets, with (1) being the change in the Containment & Health index and (2) regression on the sub-indicators making up the Containment & Health index. Model (3) and (4) refer to emerging markets, and (5) and (6) to frontier markets.

The main finding of the model is that changes in the Containment & Health index have a significant and positive effect on volatility across all market segments, which is expected. Other studies have seen government measures contributing to increased volatility, strengthening these findings (Zaremba et al., 2020). The coefficients suggest the effect is somewhat greater in developed markets than in emerging and frontier. However, the effect is significant at the 1% level in all segments.

For the second model, where sub-indicators are the primary variables of interest, we find *c1* (school closings) significant and positive on volatility across all segments. *c2* (workplace closure) has a positive effect on volatility; however only significant in emerging markets. *c3* (cancel public events) has a positive coefficient and is significant at the 5% level for developed and emerging markets. The last of the containment and closure variables with observed significance is *c5* (closed public transport), where we observe the variable to decrease volatility in developed and emerging markets. *h1*, referring to public information campaigns is significant and positively affects volatility in all segments, but at a lower significance level in frontier markets. For other health policy variables, we observe *h2* (testing policy) to decrease volatility significantly in emerging markets, *h6* (facial coverings) significantly reduce volatility in all market segments, and *h7* (vaccination policy) to significantly decrease volatility in developed markets. The economic policy variable *e1* (income support) decreases volatility significantly in all market segments, with the largest observed coefficient in emerging markets. Also, it is worth noting that R^2 is low, which is due to daily changing volatility (dependent), while Containment & Health Index along with sub-indicators (independent) do not necessarily change every day.

Table 6: Regression of all countries in the sample, divided into 3 market segments, on change in the Containment & Health index and sub-indicators on the period from 1. Jan 2020 to 31. Jan 2022

3 Markets, All Periods :: Containment & Health, Sub-Indicators

	Dependent variable:					
	GJR GARCH Volatility Annualized					
	Developed	-	Emerging	-	Frontier	-
	(1)	(2)	(3)	(4)	(5)	(6)
dif_conhel	1.114***		1.057***		0.499***	
	t = 5.489		t = 5.854		t = 4.873	
c1		3.172***		2.057***		1.613***
		t = 4.349		t = 4.385		t = 4.487
c2		0.736		1.986***		0.516
		t = 0.904		t = 4.369		t = 1.197
c3		2.637**		2.498**		0.129
		t = 2.429		t = 2.307		t = 0.123
c4		-0.228		-0.351		-0.212
		t = -0.397		t = -0.826		t = -0.467
c5		-3.056**		-2.080**		0.273
		t = -2.159		t = -2.555		t = 0.414
c6		0.688		0.993		-0.031
		t = 0.999		t = 1.304		t = -0.050
c7		1.039		-0.106		0.261
		t = 1.190		t = -0.126		t = 0.455
c8		-0.301		0.918*		0.163
		t = -0.417		t = 1.794		t = 0.295
h1		7.757***		6.623***		2.677*
		t = 4.690		t = 4.040		t = 1.822
h2		-0.627		-2.565***		-0.151
		t = -0.548		t = -2.972		t = -0.163
h3		0.715		-0.267		0.451
		t = 0.596		t = -0.295		t = 0.694
h6		-4.846***		-3.954***		-2.432***
		t = -6.146		t = -7.021		t = -4.745
h7		-1.117***		-0.132		0.003
		t = -3.768		t = -0.590		t = 0.015
e1	-1.277*	-3.941***	-3.422***	-4.751***	-1.648**	-1.921**
	t = -1.812	t = -3.366	t = -4.555	t = -4.940	t = -2.361	t = -2.221
ncs	-0.00002	0.00001	-0.00001	0.00000	-0.0001	0.00002
	t = -1.632	t = 0.943	t = -0.378	t = 0.076	t = -0.792	t = 0.231
nds	0.005**	0.001	-0.005***	-0.006***	-0.009	-0.009
	t = 2.339	t = 0.415	t = -6.104	t = -3.117	t = -1.280	t = -1.052
nvs	-0.00001*	0.00000	-0.00000*	-0.00000**	-0.00000***	-0.00000
	t = -1.864	t = 1.480	t = -1.672	t = -2.344	t = -4.701	t = -0.754

Observations	12,229	12,229	12,308	12,308	8,678	8,678
R2	0.051	0.330	0.088	0.332	0.051	0.192
Adjusted R2	0.049	0.328	0.086	0.330	0.049	0.189
Note:				*p<0.1; **p<0.05; ***p<0.01		

Dependent variable GJR-GARCH volatility annualized is scaled to represent percentage points. *dif_conhel* represents the change (difference) in the Containment & Health index (from day t to t+1). The variables *c1-c8* refer to containment and closure policies by governments. *h1-h7* refers to health system policy, and *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables, respectively. For further explanation of the variables, see **4.3** or **appendix: table 11**. The time period of the regression reaches from 1. Jan 2020 to 31. Jan 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%.

7.2 Analysis of Time Periods

Along with assessing the segments of markets, we investigate how our variables of interest have changed during different time periods, on their effect on volatility (GJR-GARCH annualized in percentage points). To achieve this, periods are divided into 6-month segments, starting from the 1. Jan 2020. All periods contain six months of daily observations except Period 5, which reaches from 1. Jan 2022 to 12. Apr 2022. These analyses are presented in **7.2.1**. We also investigate the first period of 2020 (1. Jan - 31. Jun) to assess the effects of the initial shock of the government interventions, along with the period after the initial shock (1. Jul 2020 - 31. Jan 2022) to investigate effects after the initial shock. This analysis is displayed in **7.2.2**.

7.2.1 Analysis of time periods on half-year basis

Table 7 below contains the regression model of 5 periods on a half-year basis (Period 5 1. Jan to 12. Apr) with all countries in the sample represented. The first analysis investigated how changes in the Containment & Health index affected volatility (GJR-GARCH), *e1,* and variables on *cases*, *deaths,* and *vaccinations*. Interestingly, changes in the Containment & Health index only affects volatility significantly at the 1% level in the first, second and fifth period. In the first two periods, an increase in the Containment & Health index yields an increase in volatility, as for the fifth, an increase in the index seems to lower volatility. In

Period 3 there is no significance, and only at the 10% level for Period 4, implying the effect on volatility is weaker in 2021, than 2020. *e1*, representing income support is significant at the 1% level for period 1 and at the 10% level for period 5, with positive coefficients. Other variables, except for new cases smoothed (ncs) and new vaccinations smoothed (nvs) in Period 4 do not affect volatility significantly in this model.

Table 7: Regression on all countries in the sample, divided into 5 time periods, on change in the Containment & Health index

5 Periods, All Markets :: Containment & Health Index

	Dependent variable: GJR GARCH Volatility Annualized				
	Period 1 (1)	Period 2 (2)	Period 3 (3)	Period 4 (4)	Period 5 (5)
dif_conhel	1.732***	0.116***	0.038	0.046*	-0.253***
	t = 6.955	t = 2.907	t = 0.994	t = 1.870	t = -4.237
e1	2.937***	0.711	-0.785	-0.254	2.084*
	t = 2.643	t = 1.364	t = -1.068	t = -0.511	t = 1.676
ncs	-0.0003	-0.00003	-0.00001	-0.00003**	-0.00001
	t = -1.003	t = -0.512	t = -0.188	t = -1.977	t = -0.701
nds	0.015	0.003	0.001	0.002	0.010
	t = 1.354	t = 0.615	t = 0.367	t = 0.997	t = 1.308
nvs		-0.00002	-0.00000	0.00000*	0.000
		t = -1.457	t = -0.292	t = 1.914	t = 0.005
Observations	7,769	8,136	7,863	8,140	4,526
R2	0.082	0.009	0.009	0.011	0.039
Adjusted R2	0.080	0.006	0.006	0.009	0.036
Note:			*p<0.1; **p<0.05; ***p<0.01		

Dependent variable GJR-GARCH volatility annualized is scaled to represent percentage points. *dif_conhel* represents the change (difference) in the Containment & Health index (from day t to t+1). *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables, respectively. For further explanation of the variables, see **4.3** or **appendix: table 11**. The time period of the regression reaches from 1. Jan 2020 to 12. Apr 2022. Each period refers to half a year, with Period 1 corresponding to the first 6 months of 2020, Period 2 to the last 6 months of 2020 ect. Period 5 is shorter and corresponds to 1. Jan to 12. Apr 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%.

Next, we investigate how the sub-indicators of the Contamination & Health index affect volatility (GJR-GARCH), as seen in **table 8** underneath. Among the containment and closure variables, *c1* (school closure) and *c3* (cancel public events) are significant at the 1% level for Period 1 and *c2* (workplace closure) at the 5% level. A level increase of these variables (c1, c2, c3) increases volatility (GJR-GARCH) in the period. Variable *c5* (closed public transport) is significant at the 1% level only in Period 1, with a decrease in volatility when the indicator increases. For Period 2 and 3 the variable *c6* (stay at home requirements) is significant (at 5%), whereas an increase in the indicator contributes to increased volatility. Between Period 2 and 3 some differences occur, as *c2* is significant (5%) only in Period 2 and *c4* (restrictions on gatherings) is significant (5%) only in Period 3, with a negative coefficient. Aswell, c3 is significant for both Period 2 and 3 at the 10% level, however with different coefficients, where Period 2 is negative and 3 is positive.

The health policy variables also show varying significance, with *h1* (public information campaigns), *h2* (testing policy), and *h6* (facial coverings) having an impact on volatility for Period 1. An increase in the *h1*-indicator contributes to increased volatility, whereas the latter decreases volatility. *h1* (public information campaigns) also show significance in Period 4 (last 6 months of 2021), with an increase in the indicator affecting volatility positively. In Period 2, *h3* (contact tracing) affects volatility positively with an increase, at a significance level 5%. *h7* (vaccination policy) showed significance in Period 2 & 3, with an increase in the indicator affecting volatility negatively. For the economic policy indicator *e1* (income support), we observe a negative relationship with volatility, a significance level of 1%, and a coefficient of -5.6 percentage points on volatility for Period 1.

Table 8: Regression of all countries in the sample, divided into 5 time periods, on sub-indicators of the Containment & Health index

5 Periods, All Markets :: Sub-Indicators

	Dependent variable: GJR GARCH Volatility Annualized				
	Period 1 (1)	Period 2 (2)	Period 3 (3)	Period 4 (4)	Period 5 (5)
c1	3.696***	-0.054	0.545	0.160	-1.025
	t = 2.961	t = -0.089	t = 1.179	t = 0.420	t = -0.689
c2	2.360**	1.142*	0.504	0.454	1.470
	t = 2.147	t = 1.834	t = 0.689	t = 0.534	t = 0.570
c3	8.985***	-0.752*	1.503*	-0.132	-1.361
	t = 4.515	t = -1.721	t = 1.681	t = -0.208	t = -0.751
c4	-0.563	-0.036	-1.222**	-0.476	-1.189
	t = -0.647	t = -0.068	t = -2.075	t = -1.420	t = -1.315
c5	-4.612***	0.345	1.356	-0.025	-0.807
	t = -3.345	t = 0.333	t = 1.415	t = -0.025	t = -0.480
c6	0.279	0.794**	1.092**	0.301	2.064
	t = 0.147	t = 2.562	t = 2.102	t = 0.538	t = 1.263
c7	0.990	0.130	0.188	0.530	1.364
	t = 0.633	t = 0.264	t = 0.558	t = 0.862	t = 1.552
c8	-0.580	0.299	0.383	0.224	-0.829
	t = -0.849	t = 0.631	t = 1.287	t = 0.521	t = -1.261
h1	5.131***		2.181	2.068**	-1.249
	t = 3.616		t = 1.278	t = 2.426	t = -0.331
h2	-3.206**	-0.385	0.452	-1.112*	0.946
	t = -2.125	t = -0.272	t = 0.674	t = -1.660	t = 0.640
h3	0.814	1.953**	1.029	1.053	-2.034
	t = 0.730	t = 2.437	t = 1.471	t = 1.560	t = -0.726
h6	-5.131***	-0.215	-0.466	-0.450	-0.133
	t = -5.730	t = -0.495	t = -1.196	t = -1.428	t = -0.145
h7		-0.602**	-0.471***	0.252	2.212
		t = -2.112	t = -2.781	t = 0.482	t = 1.352
e1	-5.675***	0.836	-0.433	-0.368	1.907
	t = -5.156	t = 1.291	t = -0.743	t = -0.835	t = 1.062
ncs	0.0002	-0.00001	0.00001	-0.00002*	-0.00001
	t = 0.649	t = -0.173	t = 0.233	t = -1.691	t = -0.773

nds	0.005	0.001	-0.001	0.001	0.010*
	t = 0.619	t = 0.312	t = -0.353	t = 0.658	t = 1.886
nvs		-0.00002	0.00000	0.00000	-0.00000
		t = -1.326	t = 0.778	t = 0.690	t = -0.588
Observations	7,769	8,136	7,863	8,140	4,526
R2	0.338	0.069	0.138	0.063	0.099
Adjusted R2	0.336	0.065	0.134	0.060	0.095
Note:			*p<0.1; **p<0.05; ***p<0.01		

Dependent variable GJR-GARCH volatility annualized is scaled to represent percentage points. The variables *c1-c8* refer to containment and closure policies by governments. *h1-h7* refers to health system policy, and *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables respectively. For further explanation of the variables, see **4.3** or **appendix: table 11**. The time period of the regression reaches from 1. Jan 2020 to 12. Apr 2022. Each period refers to half a year, with Period 1 corresponding to the first 6 months of 2020, Period 2 to the last 6 months of 2020 ect. Period 5 is shorter, and corresponds to 1. Jan to 12. Apr 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%. *Note1*: *h7* is missing for Period 1 due to a standard deviation of 0. *Note2*: For Period 2 *h1* is missing due to a standard deviation of 0.

7.2.2 Analysis of during and after COVID-19 shock

For our last analysis, we wanted to see the effects of the initial shock of the government interventions introduced worldwide for the first 6 months of 2020 versus the impact of the interventions in the following one and a half years. The periods are called “shock” for the first 6 months and “after” for the period after. Note that the “shock” regression is identical to the Period 1 regression in **7.2.1**, and will not be commented on further. Notably, the difference in Containment & Health index is still significant at the 1% level in the Period After, however, with a substantially lower coefficient on volatility than Period Shock. This is supposedly related to the generally lower levels of volatility compared to the first 6 months of 2020 (Dutillo et al., 2021). Thus we cannot necessarily compare coefficients directly.

The sub-indicators show some differences between the two periods. *h1* (public information campaigns) is positive and significant at the 1% level for the shock- and after-period. However, Period Shock *c1* (school closing) is significant and positive at the 1% level. For

Period After, the significance is gone for the variable. In return *c2* (workplace closing) is positive and significant at the 5% level, which was only significant at the 10% level in Period Shock. Also worth noting is the variable *h7* (vaccine policy), which is significant at the 1% level and negative for the Period After. There was no vaccination policy in Period Shock yet, as the vaccines were not approved for use (Lamb, 2021). We can also note that for the regression including sub-indicators (4) *e1* is significant (5%) and negative for Period After.

Table 9: Regression on all countries in the sample, divided into 2 time periods (during and after shock), on change in the Containment & Health index and sub-indicators of the Containment & Health index

2 Periods, All Markets :: Containment & Health Index, Sub-Indicators

	Dependent variable:			
	GJR GARCH Volatility Annualized			
	Period Shock	-	Period After	-
	(1)	(2)	(3)	(4)
dif_conhel	1.722***		0.065***	
	t = 9.437		t = 3.291	
c1		4.485***		0.029
		t = 4.391		t = 0.179
c2		2.415*		0.447**
		t = 1.937		t = 2.312
c3		9.151***		-0.252
		t = 4.486		t = -1.026
c4		-0.438		-0.149
		t = -0.416		t = -1.069
c5		-4.359***		-0.422
		t = -2.946		t = -1.510
c6		0.248		0.175
		t = 0.180		t = 0.730
c7		-0.696		0.210
		t = -0.477		t = 1.090
c8		0.517		-0.037
		t = 0.635		t = -0.251
h1		4.298***		1.583***
		t = 3.439		t = 2.765
h2		-2.389*		0.382
		t = -1.818		t = 1.286
h3		0.847		-0.135

		t = 0.719		t = -0.398
h6		-6.331***		0.036
		t = -9.321		t = 0.228
h7				-0.278***
				t = -3.899
e1	3.418***	-6.829***	-0.053	-0.491**
	t = 3.944	t = -4.947	t = -0.224	t = -2.314
ncs	-0.001	-0.0001	0.00001**	0.00002**
	t = -1.560	t = -0.214	t = 2.492	t = 2.561
nds	0.010	0.001	-0.001	-0.001**
	t = 1.087	t = 0.212	t = -1.470	t = -2.055
nvs			-0.00000***	-0.00000***
			t = -4.327	t = -6.800
Observations	7,769	7,769	25,446	25,446
R2	0.085	0.405	0.010	0.028
Adjusted R2	0.077	0.399	0.008	0.025
Note:				*p<0.1; **p<0.05; ***p<0.01

Dependent variable GJR-GARCH volatility annualized is scaled to represent percentage points. *dif_conhel* represents the change (difference) in the Containment & Health index (from day t to t+1). The variables *c1-c8* refer to containment and closure policies by governments. *h1-h7* refers to health system policy, and *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables respectively. For further explanation of the variables, see **4.3** or **appendix: table 11**. The time period of the regression reaches from 1. Jan 2020 to 31. Jan 2022. The "Period Shock" refers to the first 6 months of 2020, while the "Period After" refers to 1. Jul 2020 to 31. Jan 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%. *Note1*: *h7* is missing for Period Shock due to a standard deviation of 0.

7.3 Discussion

7.3.1 Segments of Markets

From the analysis of market segments, our main observation is that changes in the Containment & Health index show significance at a 1% level for all market segments with a positive coefficient. Thus, we gain support for our hypothesis (Ha1) that government interventions affect volatility (GJR-GARCH) in global stock markets. Utilizing the Oxford

Stringency index (similar to Containment & Health index), other researchers have also found relationships between government restrictions and stock markets and volatility, however often within a shorter time frame (Zaremba et al., 2020, Bakry et al., 2021). Across markets, we also observe a positive effect from volatility from school closures (c1) and workplace closures (c2). These restrictions may affect volatility due to limitations on businesses' ability to generate revenue, which the stock market reacts to. Public information campaigns (h1) may also give pointers to what is to follow and which restrictions citizens and businesses have to deal with, and thus new implications for revenue streams.

The regression in **7.1** does uncover some differences between the segments of markets. c2 (workplace closing) shows significance only in emerging markets, with a positive coefficient, and h2 (testing policy) with a negative coefficient. This finding suggests that these measures only affect volatility in emerging markets. The variable h7 (vaccination policy) only shows significance in developed markets with a negative coefficient, suggesting vaccination policy affects volatility negatively in these countries. These differences yield support for the hypothesis that differences exist between the markets (Ha2). With vaccination policy, volatility may be lower due to citizens having faith in vaccines and thus believing in times with fewer restrictions. Engelhardt, 2020 found stock market volatility to be lower in high trust countries. Assuming developed countries have higher government trust, it could explain why vaccination policy is significant and negative only for these countries. However, we do not have sufficient evidence to conclude the reason behind this relationship, as we do observe the relation, but not the causality.

7.3.2 Time Periods

In the analysis in section **7.2**, we observe that the Containment & Health index has a significant relationship with volatility (GJR-GARCH) in some periods. When we assess the data during and after the initial shock, the index is significant both during and after both periods, suggesting government interventions affect stock market volatility during the two years our sample covers. However, the relationship becomes more unclear when we assess every 6 months in the data separately. The Containment & Health index shows significance in Period 1, 2, 4, and 5, with the relationship being weak in Period 4. This is interesting and may be due to stakeholders in the market adapting to the “new normal” with having government interventions in periods with high numbers of COVID-19 cases and/or deaths.

A study by Phan & Narayan (2020) implies that markets seem to be less affected by COVID-19 cases and deaths during stabilization periods, which could also be the case for government interventions (Containment & Health Index and Sub-Indicators). Another explanation could be that market participants become more optimistic about the future by the introduction of large-scale vaccinations and trust in government policy. There have been studies that showed global stock markets reacted positively to the introduction of vaccines (Chan, 2022), as our analysis also suggests with significant variables *h7* (Vaccine Policy) and *nvs* (New Vaccinations Smoothed) with negative coefficients in Period After. Nevertheless, there seem to exist differences in the explanatory variables over the two years of our sample, thus supporting the hypothesis that government interventions affect volatility differently over time (Ha3).

8 Conclusion

In this study, we have gathered data on stock market movements, with their belonging volatility (GJR-GARCH & 30d rolling) and the Containment & Health index (representing government interventions) for 64 countries worldwide. We perform multiple regression analysis from the constructed panel data sample, investigating government restriction's effect on volatility in stock markets, across segments of markets, and over time.

The main takeaway from our panel data multiple regression analysis is that changes in government interventions affect volatility in global markets over the two-year time frame. Thus, we gain support for our hypothesis **Ha1**. Our findings suggest that an increase in the Containment & Health index is associated with higher volatility. Other studies further substantiate our findings, Zaremba et al. (2020) found government restrictions associated with higher volatility. However, with our extended timeframe, we observe this effect over time.

The relationship between government measures and volatility is not consistent across segments of markets (developed, emerging & frontier), thus supporting our hypothesis **Ha2**. Our research is supported by Bakry et al. (2021), who found differences between developed and emerging markets in the relationship between COVID-19 cases and deaths and volatility. We cannot conclude with certainty why we observe differences between developed, emerging, and frontier markets, which is a limitation of a regression study; however, it may be a topic for future research.

Harjoto et al. (2020) investigated COVID-19-cases and -deaths effect on volatility in equity markets pre and post-April 2020 (until August 2020), finding the relationship to be stronger pre-April. We observe similar effects with the government interventions effect on volatility, as we observe a stronger relationship in the first six months of 2020 than in the last six months. We also observe the relationship to be weaker in 2021 than 2020, which suggests the relationship is not consistent over time, supporting our hypothesis **Ha3**.

We believe the findings in this thesis are important for policymakers, along with participants in the stock market such as investors, banks, and option writers.

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Appendix

Appendix: VIF-Values

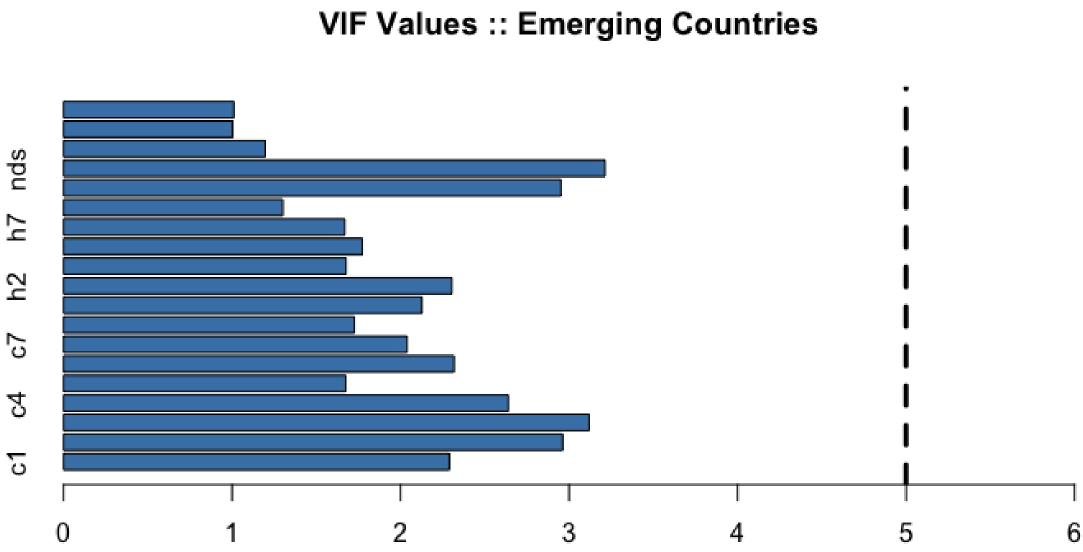

Figure 12: VIF-values for model (4, Table 6)

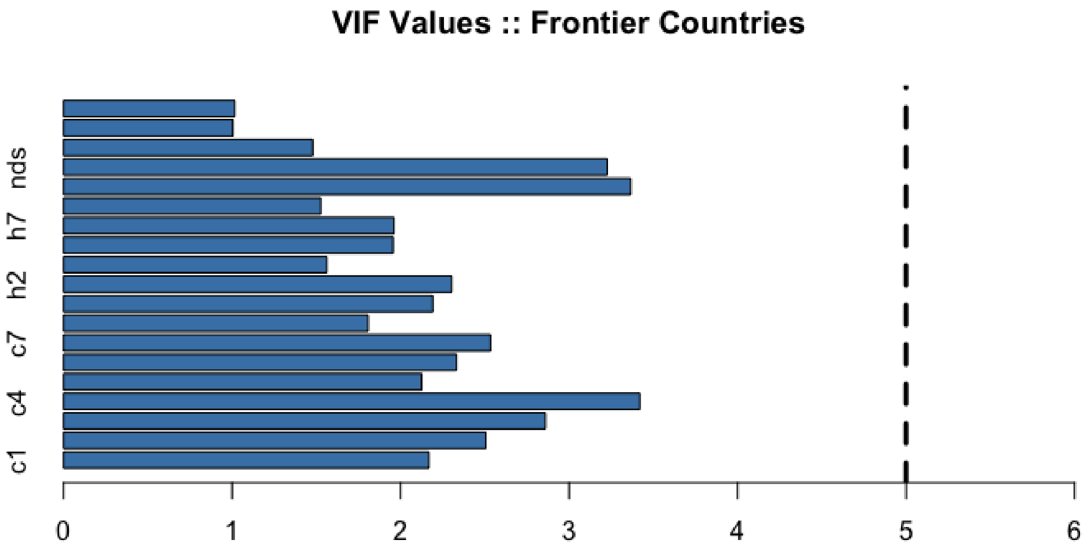

Figure 13: VIF-values for model (6, Table 6)

Appendix: MSCI Classification

Table 10: MSCI Classification (MCSI, 2022)

Criteria	Frontier	Emerging	Developed
A. Economic Development A.1 Sustainability of economic development	No requirement	No requirement	Country GNI per capita 25% above the World Bank high income threshold* for 3 consecutive years
B. Size and liquidity requirements B.1 Number of companies meeting the following Standard Index criteria - Company size (full market cap) ** - Security size (float market cap) ** - Security Liquidity	2 USD 1.171 mm USD 88 mm 2.5% ATVR	3 USD 2.343 mm USD 1.171 mm 15% ATVR	5 USD 4.685 mm USD 2.343 mm 20% ATVR
C. Market accessibility criteria C.1 Openness to foreign ownership C.2 Ease of capital inflows / outflows C.3 Efficiency of operational framework C.4 Availability of investment instrument C.5 Stability of the institutional framework	At least some At least partial Modest High Modest	Significant Significant Good and tested High Modest	Very high Very high Very high Unrestricted Very high

* High income threshold: 2019 GNI per capita of USD 12.536 (World Bank, Atlas method)

** Minimum in use for the May 2021 Semi-Annual Review, updated on a semi-annual basis

Appendix: Sub-indicators

Table 11: All sub-indicators with explanation (Hale et al., 2021)

ID	Description	Coding
C1	Record closings of schools and universities	0 - no measures 1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations 2 - require closing (only some levels or categories, eg just high school, or just public schools) 3 - require closing all levels Blank - no data

C2	Record closings of workplaces	0 - no measures 1 - recommend closing (or recommend work from home) or all businesses open with alterations resulting in significant differences compared to non-Covid-19 operation 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) for all-but-essential workplaces (eg grocery stores, doctors) Blank - no data
C3	Record canceling public events	0 - no measures 1 - recommend canceling 2 - require canceling Blank - no data
C4	Record limits on gatherings	0 - no restrictions 1 - restrictions on very large gatherings (the limit is above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less Blank - no data

C5	Record closing of public transport	0 - no measures 1 - recommend closing (or significantly reduce volume/route/means of transport available) 2 - require closing (or prohibit most citizens from using it) Blank - no data
C6	Record orders to "shelter-in-place" and otherwise confine to the home	0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - require not leaving house with minimal exceptions (eg allowed to leave once a week, or only one person can leave at a time, etc) Blank - no data
C7	Record restrictions on internal movement between cities/regions	0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place Blank - no data

C8	Record restrictions on international travel Note: this records policy for foreign travelers, not citizens	0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure Blank - no data
E1	Record if the government is providing direct cash payments to people who lose their jobs or cannot work. Note: only includes payments to firms if explicitly linked to payroll/salaries	0 - no income support 1 - government is replacing less than 50% of lost salary (or if a flat sum, it is less than 50% median salary) 2 - government is replacing 50% or more of lost salary (or if a flat sum, it is greater than 50% median salary) Blank - no data
H1	Record presence of public info campaigns	0 - no Covid-19 public information campaign 1 - public officials urging caution about Covid-19 2- coordinated public information campaign (eg across traditional and social media) Blank - no data

H2	Record government policy on who has access to testing Note: this records policies about testing for current infection (PCR tests) not testing for immunity (antibody test)	0 - no testing policy 1 - only those who both (a) have symptoms AND (b) meet specific criteria (eg key workers, admitted to hospital, came into contact with a known case, returned from overseas) 2 - testing of anyone showing Covid-19 symptoms 3 - open public testing (eg "drive through" testing available to asymptomatic people) Blank - no data
H3	Record government policy on contact tracing after a positive diagnosis Note: we are looking for policies that would identify all people potentially exposed to Covid-19; voluntary bluetooth apps are unlikely to achieve this	0 - no contact tracing 1 - limited contact tracing; not done for all cases 2 - comprehensive contact tracing; done for all identified cases

H6	Record policies on the use of facial coverings outside the home	0 - No policy 1 - Recommended 2 - Required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible 3 - Required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible 4 - Required outside the home at all times regardless of location or presence of other people

H7	Record policies for vaccine delivery for different groups	0 - No availability 1 - Availability for ONE of following: key workers/ clinically vulnerable groups (non elderly) / elderly groups 2 - Availability for TWO of following: key workers/ clinically vulnerable groups (non elderly) / elderly groups 3 - Availability for ALL of following: key workers/ clinically vulnerable groups (non elderly) / elderly groups 4 - Availability for all three plus partial additional availability (select broad groups/ages) 5 - Universal availability

Appendix: Graphs

Figure 14: Portugal, Containment & Health index, and stock market index

Figure 15: Sweden, Containment & Health index, and stock market index

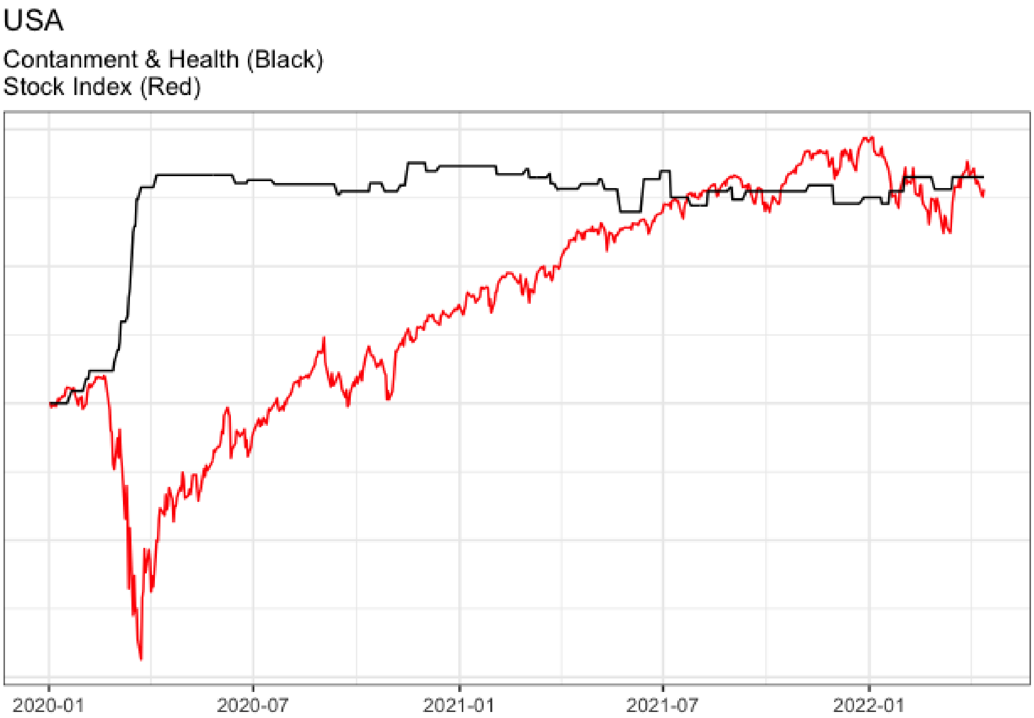

Figure 16: USA, Containment & Health index, and stock market index

Figure 17: France, Containment & Health index, and stock market index

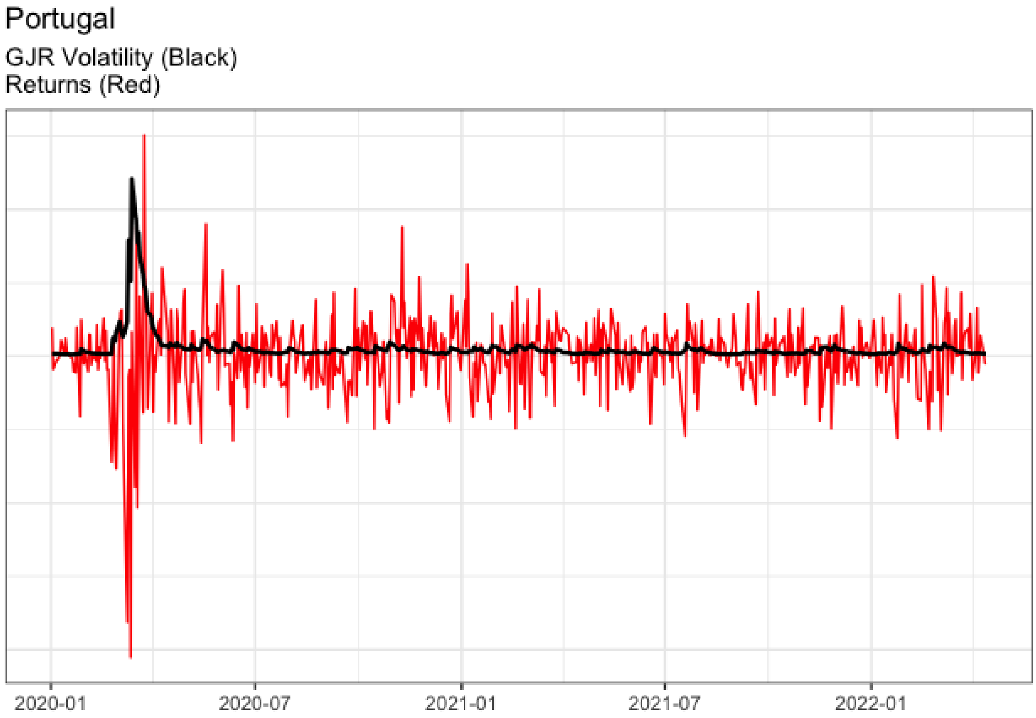

Figure 18: Portugal, Volatility and stock market returns

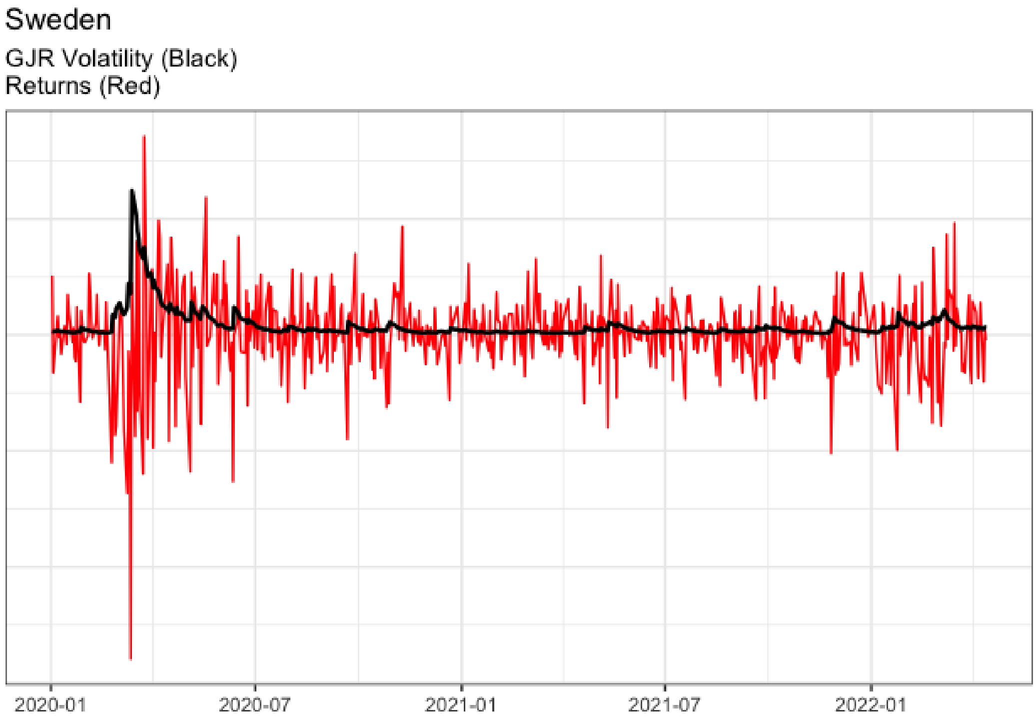

Figure 19: Sweden, Volatility and stock market returns

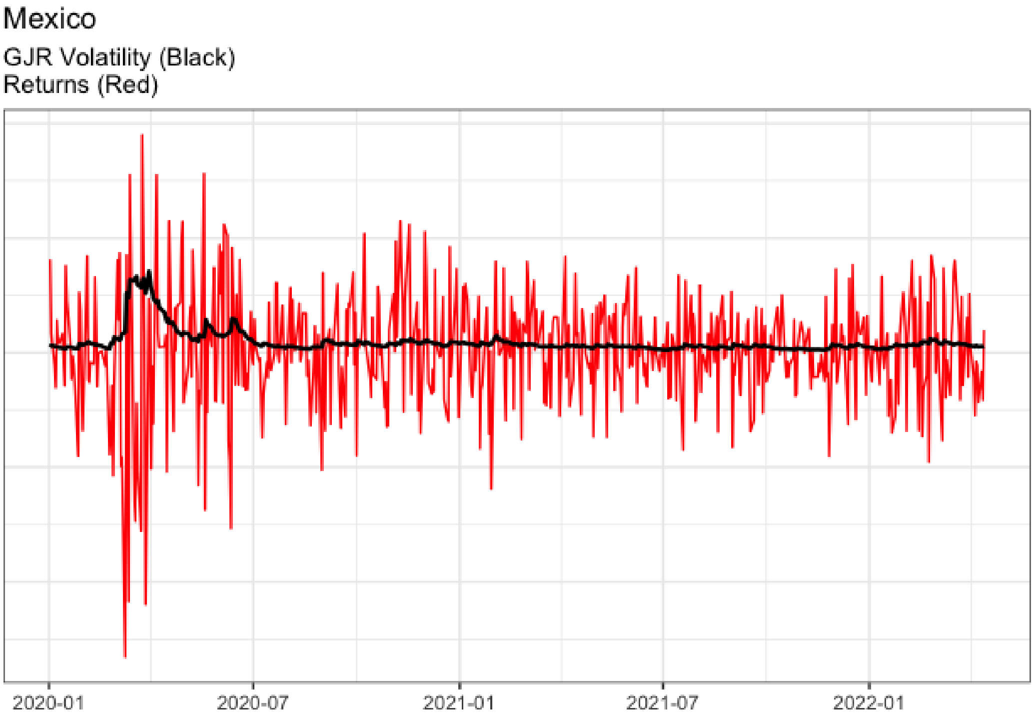

Figure 20: Mexico, Volatility and stock market returns

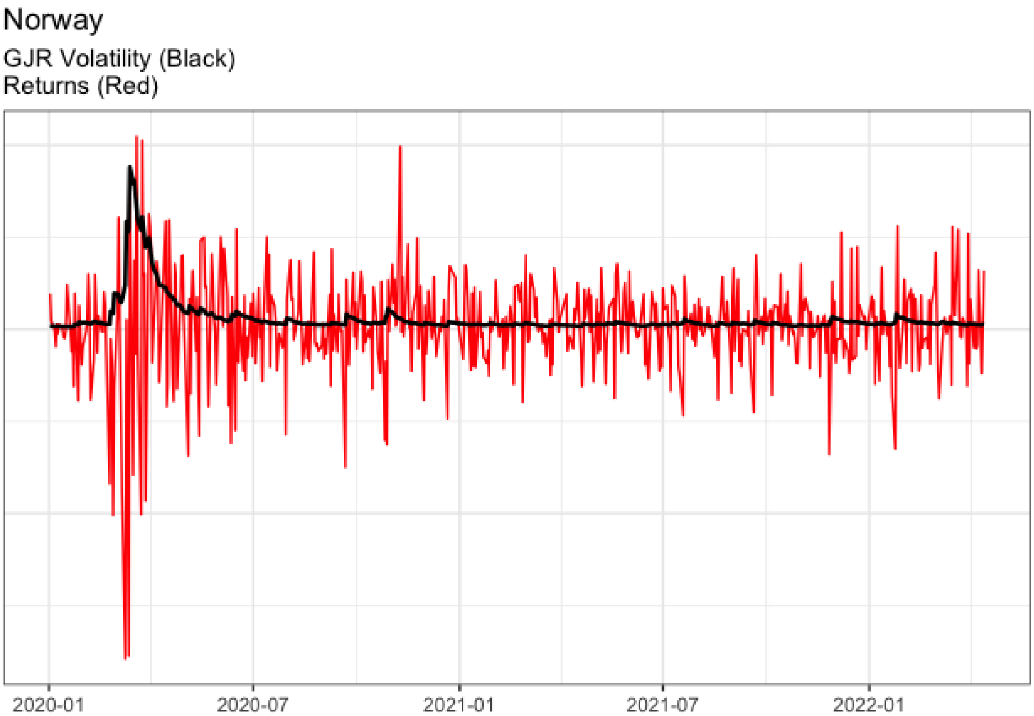

Figure 21: Norway, Volatility and stock market returns

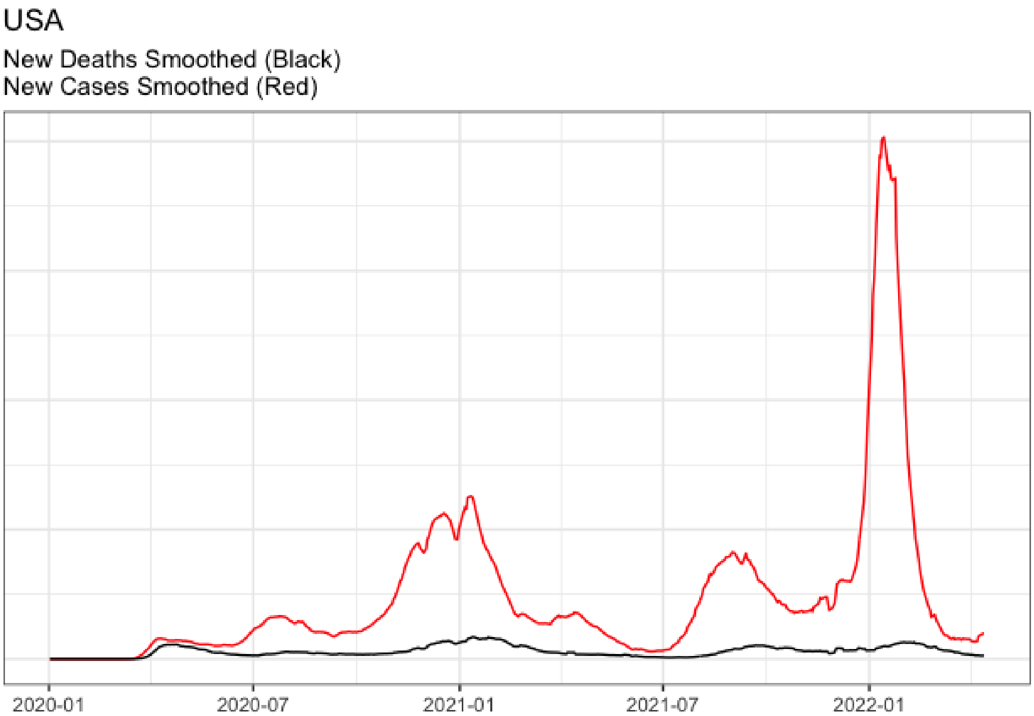

Figure 22: USA, (*Note: Deaths scaled by x10 for visibility*)

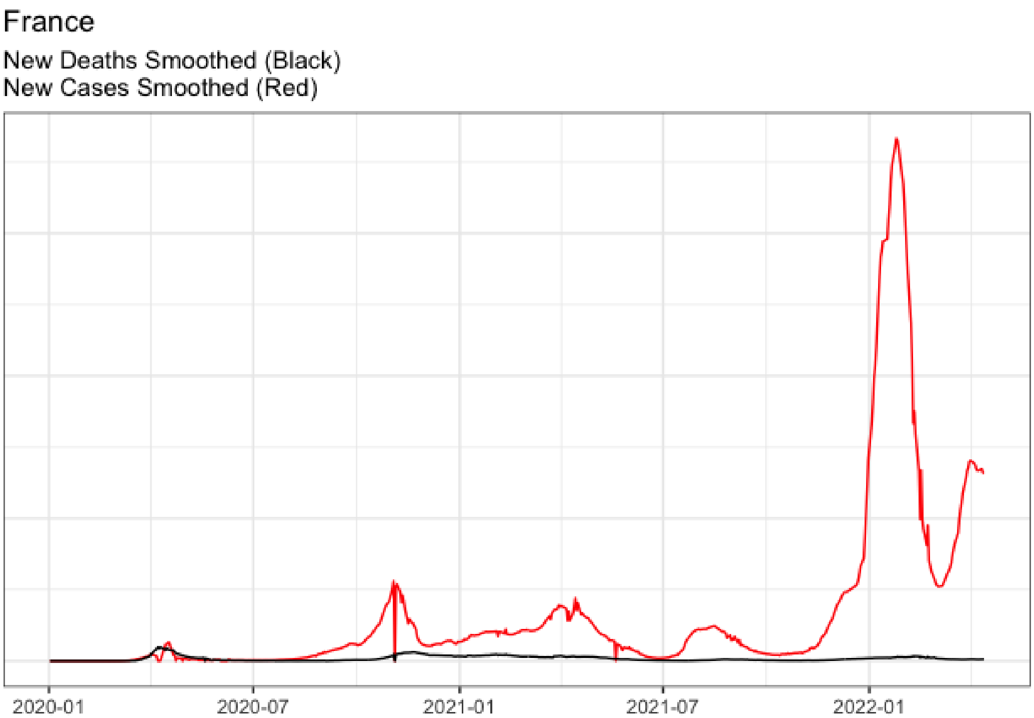

Figure 23: France, (*Note: Deaths scaled by x10 for visibility*)

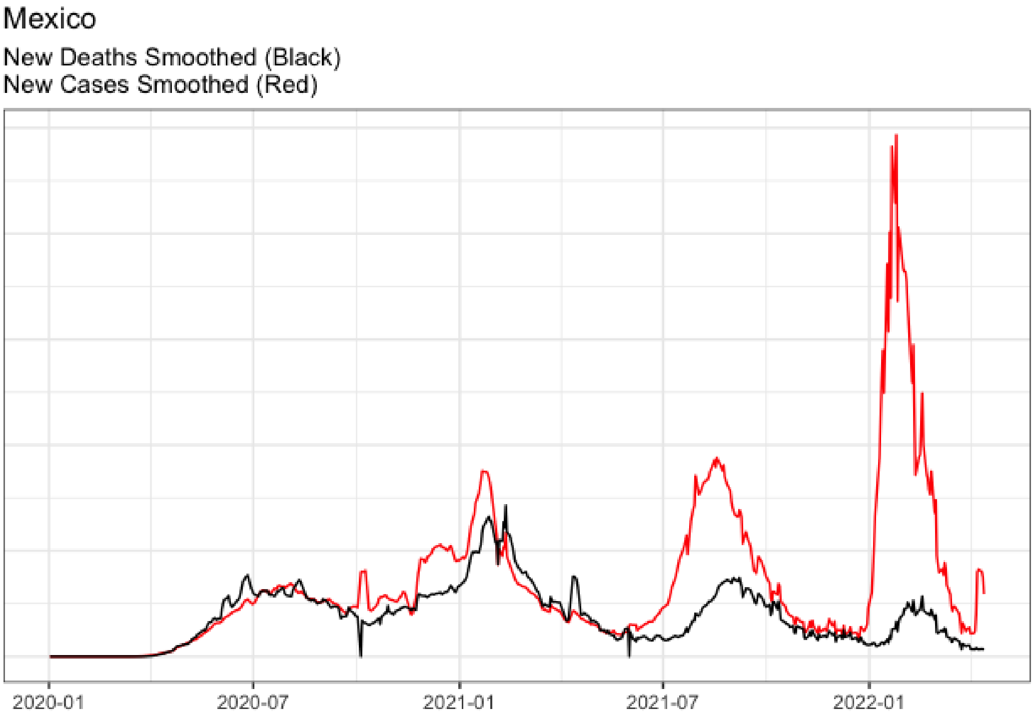

Figure 24: Mexico, (*Note: Deaths scaled by x10 for visibility*)

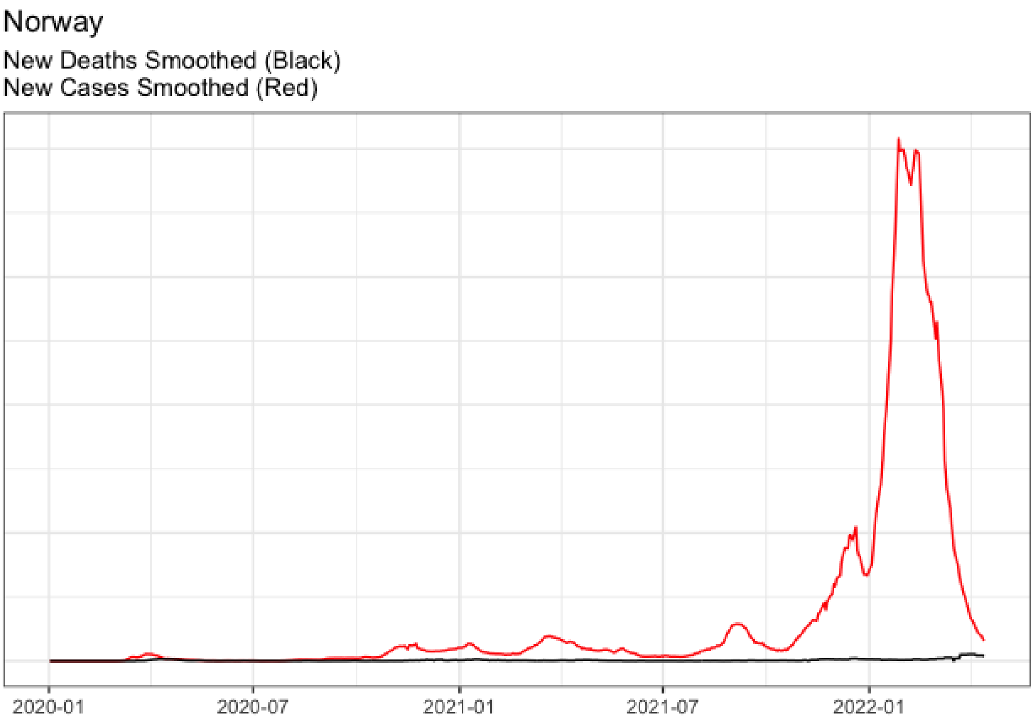

Figure 25: Norway, (*Note: Deaths scaled by x10 for visibility*)

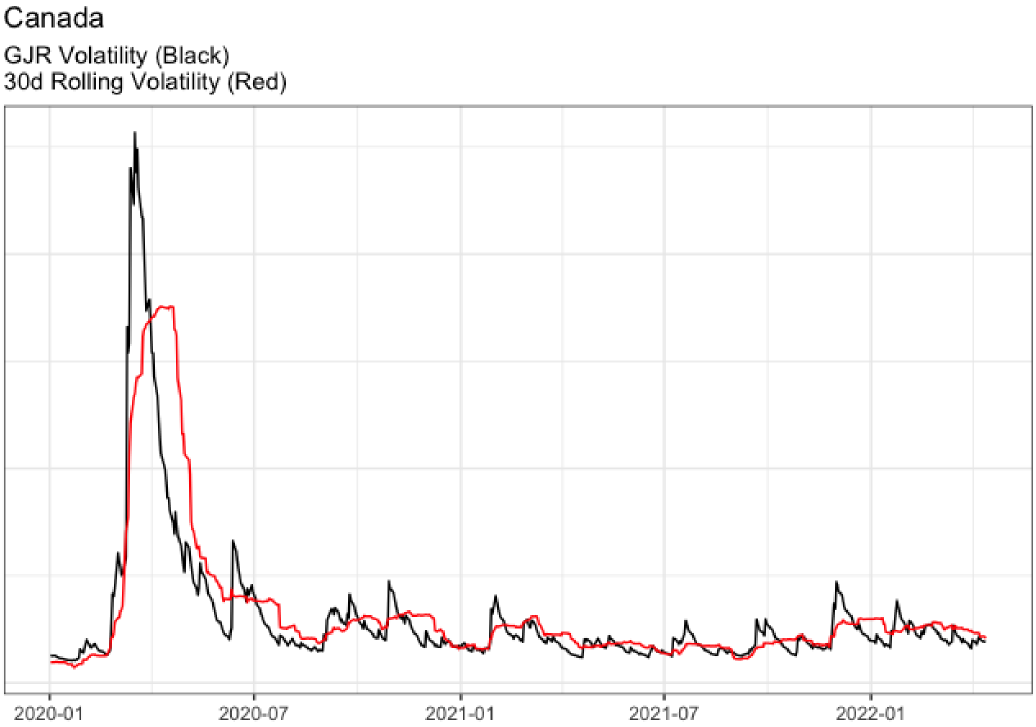

Figure 26: Canada, GJR-GARCH and 30d rolling volatility

Figure 27: Australia, GJR-GARCH and 30d rolling volatility

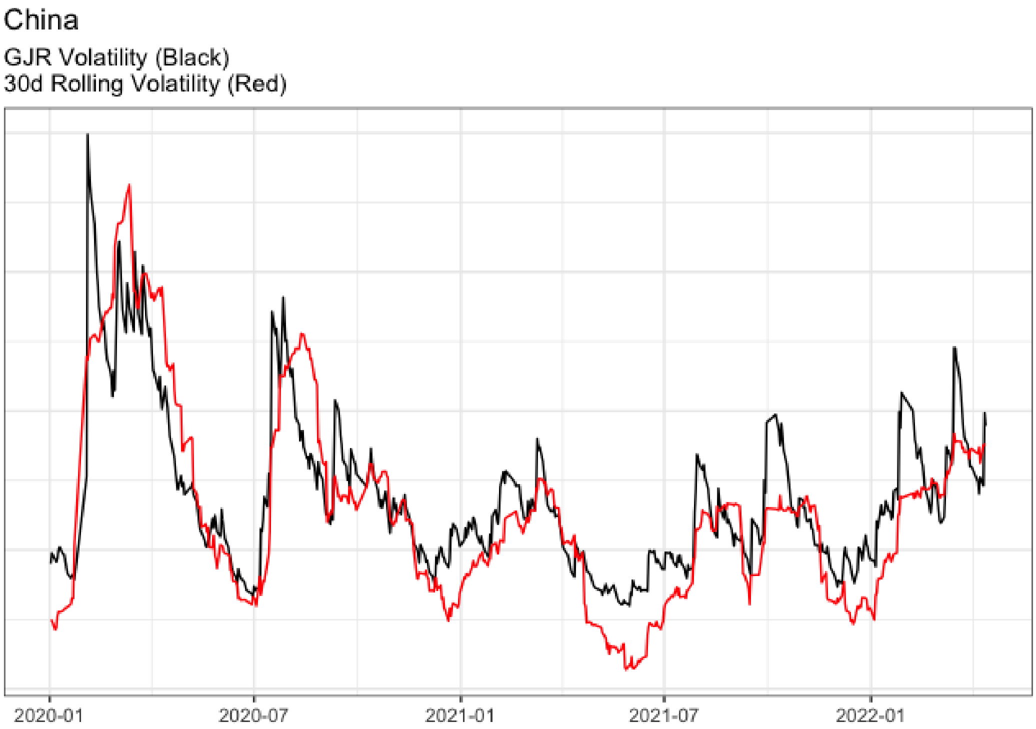

Figure 28: China, GJR-GARCH and 30d rolling volatility

Appendix: Analysis

Table 12: Regression of all countries in the sample, divided into 3 market segments, on change in the Containment & Health index and sub-indicators on the period from 1. Jan 2020 to 31. Jan 2022

3 Markets, All Periods :: Containment & Health, Sub-Indicators

	Dependent variable:					
	30d Rolling Volatility Annualized					
	Developed	-	Emerging	-	Frontier	-
	(1)	(2)	(3)	(4)	(5)	(6)
dif_conhel	0.503***		0.629***		0.302***	
	t = 5.415		t = 5.287		t = 4.072	
c1		2.697***		2.397***		1.279***
		t = 3.936		t = 4.741		t = 2.626
c2		2.252***		3.001***		0.735
		t = 2.624		t = 3.749		t = 1.154
c3		1.439		1.411		0.083
		t = 1.644		t = 1.302		t = 0.085
c4		0.169		-0.665		0.046
		t = 0.322		t = -1.611		t = 0.125
c5		-2.513		-1.722**		0.993
		t = -1.586		t = -1.962		t = 1.315
c6		0.528		2.112***		0.625
		t = 0.792		t = 2.605		t = 1.036
c7		1.891**		0.966		0.352
		t = 2.084		t = 1.088		t = 0.565
c8		0.376		1.814***		1.188**
		t = 0.555		t = 3.540		t = 2.219
h1		5.969***		4.714***		2.632**
		t = 5.797		t = 2.991		t = 2.101
h2		-0.914		-1.834*		-0.322
		t = -0.784		t = -1.882		t = -0.343
h3		0.195		-1.558		0.443
		t = 0.193		t = -1.241		t = 0.669
h6		-4.919***		-3.222***		-2.939***
		t = -6.062		t = -4.828		t = -5.714
h7		-1.463***		-0.643**		-0.248
		t = -4.810		t = -2.529		t = -1.148
e1	1.528**	-1.150	-1.441*	-3.582***	-0.221	-0.704
	t = 2.122	t = -1.209	t = -1.683	t = -4.030	t = -0.261	t = -0.742
ncs	-0.00004*	-0.00000	0.00001	0.00003	-0.0003*	-0.0001
	t = -1.659	t = -0.084	t = 0.371	t = 1.154	t = -1.697	t = -1.039
nds	0.012**	0.005	-0.006***	-0.009***	-0.009	-0.009
	t = 2.173	t = 1.194	t = -4.249	t = -3.046	t = -0.846	t = -0.914

nvs	-0.00001**	0.00000	-0.00000**	-0.00000***	-0.00000***	-0.00000
	t = -2.145	t = 0.337	t = -2.133	t = -2.795	t = -4.532	t = -0.246
Observations	12,229	12,229	12,308	12,308	8,678	8,678
R2	0.076	0.475	0.045	0.397	0.033	0.329
Adjusted R2	0.074	0.474	0.042	0.395	0.031	0.327
Note:				*p<0.1; **p<0.05; ***p<0.01		

Dependent variable 30d rolling volatility annualized is scaled to represent percentage points. *dif_conhel* represents the change (difference) in the Containment & Health index (from day t to t+1). The variables *c1-c8* refer to containment and closure policies by governments. *h1-h7* refers to health system policy, and *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables, respectively. For further explanation of the variables, see **4.3** or **Appendix: Table 11**. The time period of the regression reaches from 1. Jan 2020 to 31. Jan 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%.

Table 13: Regression on all countries in the sample, divided into 5 time periods, on change in the Containment & Health index

5 Periods, All Markets :: Containment & Health Index

	Dependent variable: 30d Rolling Volatility Annualized				
	Period 1 (1)	Period 2 (2)	Period 3 (3)	Period 4 (4)	Period 5 (5)
dif_conhel	0.870***	0.038	0.020	0.012	-0.139***
	t = 7.294	t = 0.746	t = 0.836	t = 0.894	t = -2.996
e1	8.050***	1.602**	-0.836	-0.381	1.120
	t = 8.320	t = 2.179	t = -0.983	t = -0.732	t = 0.797
ncs	-0.001***	-0.0001	-0.00000	-0.00002	-0.00000
	t = -2.743	t = -1.519	t = -0.129	t = -1.257	t = -0.429
nds	0.032***	0.011*	0.001	0.001	0.007
	t = 3.335	t = 1.803	t = 0.331	t = 0.621	t = 0.965
nvs		-0.00004***	-0.00000**	0.00000	-0.00000
		t = -3.086	t = -2.394	t = 1.327	t = -1.409
Observations	7,769	8,136	7,863	8,140	4,526
R2	0.196	0.048	0.013	0.008	0.021
Adjusted R2	0.194	0.045	0.011	0.006	0.018
Note:			*p<0.1; **p<0.05; ***p<0.01		

Dependent variable 30d rolling volatility annualized is scaled to represent percentage points. *dif_conhel* represents the change (difference) in the Containment & Health index (from day t to t+1). *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables, respectively. For further explanation of the variables, see **4.3** or **Appendix: Table 11**. The time period of the regression reaches from 1. Jan 2020 to 12. Apr 2022. Each period refers to half a year, with Period 1 corresponding to the first 6 months of 2020, Period 2 to the last 6 months of 2020 ect. Period 5 is shorter and corresponds to 1. Jan to 12. Apr 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%.

Table 14: Regression of all countries in the sample, divided into 5 time periods, on sub-indicators of the Containment & Health index

5 Periods, All Markets :: Sub-Indicators

	Dependent variable:				
	30d Rolling Volatility Annualized				
	Period 1	Period 2	Period 3	Period 4	Period 5
	(1)	(2)	(3)	(4)	(5)
c1	2.452***	-0.560	0.738	0.290	-0.685
	t = 2.694	t = -0.782	t = 1.556	t = 1.208	t = -0.447
c2	4.359***	1.258	0.750	0.598	2.396
	t = 4.082	t = 1.532	t = 1.007	t = 0.695	t = 0.904
c3	4.841***	-0.829*	1.383*	-0.429	-2.981
	t = 4.391	t = -1.763	t = 1.715	t = -0.637	t = -1.430
c4	-0.489	0.282	-1.278**	-0.418	-1.766
	t = -0.778	t = 0.493	t = -2.184	t = -1.162	t = -1.617
c5	-2.939**	-0.204	0.947	-0.384	-0.738
	t = -1.999	t = -0.165	t = 0.964	t = -0.360	t = -0.425
c6	2.320	1.439***	1.319***	0.249	1.676
	t = 1.381	t = 4.727	t = 2.893	t = 0.535	t = 1.009
c7	1.930	0.301	0.384	0.647	1.556*
	t = 1.442	t = 0.521	t = 0.965	t = 1.088	t = 1.753
c8	0.848	0.519	0.658*	0.204	-1.258**
	t = 1.588	t = 0.996	t = 1.775	t = 0.471	t = -2.025
h1	3.044***		0.796	2.146**	-0.339
	t = 2.889		t = 0.214	t = 2.111	t = -0.070
h2	-2.515*	-0.506	0.804	-0.932	0.016
	t = -1.866	t = -0.385	t = 1.004	t = -1.546	t = 0.008
h3	0.010	1.789*	0.831	1.137	-2.225
	t = 0.008	t = 1.787	t = 1.126	t = 1.502	t = -0.860
h6	-3.204***	-0.644	-0.824**	-0.367	-0.450
	t = -3.659	t = -1.435	t = -1.964	t = -1.085	t = -0.440
h7		-1.263***	-0.477***	0.179	2.088
		t = -3.655	t = -2.625	t = 0.303	t = 1.129
e1	-1.333	1.553*	-0.626	-0.563	1.216
	t = -1.244	t = 1.911	t = -1.054	t = -1.226	t = 0.691
ncs	-0.001**	-0.0001	0.00000	-0.00001	-0.00000

	t = -2.336	t = -1.486	t = 0.143	t = -0.594	t = -0.358
nds	0.023***	0.009*	-0.001	0.0001	0.008*
	t = 2.900	t = 1.943	t = -0.278	t = 0.089	t = 1.648
nvs		-0.00003**	-0.00000***	0.00000	-0.00000
		t = -2.340	t = -2.734	t = 0.134	t = -1.272
Observations	7,769	8,136	7,863	8,140	4,526
R2	0.523	0.130	0.182	0.070	0.169
Adjusted R2	0.522	0.126	0.179	0.067	0.165
Note:					*p<0.1; **p<0.05; ***p<0.01

Dependent variable 30d rolling volatility annualized is scaled to represent percentage points. The variables *c1-c8* refer to containment and closure policies by governments. *h1-h7* refers to health system policy, and *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables respectively. For further explanation of the variables, see **4.3** or **Appendix: Table 11**. The time period of the regression reaches from 1. Jan 2020 to 12. Apr 2022. Each period refers to half a year, with Period 1 corresponding to the first 6 months of 2020, Period 2 to the last 6 months of 2020 ect. Period 5 is shorter, and corresponds to 1. Jan to 12. Apr 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%. *Note1*: *h7* is missing for Period 1 due to a standard deviation of 0. *Note2*: For Period 2 *h1* is missing due to a standard deviation of 0.

Table 15: Regression on all countries in the sample, divided into 2 time periods (during and after shock), on change in the Containment & Health index and sub-indicators of the Containment & Health index

2 Periods, All Markets :: Containment & Health Index, Sub-Indicators

	Dependent variable:			
	30d Rolling Volatility Annualized			
	Period Shock	-	Period After	-
	(1)	(2)	(3)	(4)
dif_conhel	0.895***		0.034***	
	t = 8.539		t = 2.636	
c1		2.779***		0.010
		t = 3.873		t = 0.057
c2		4.650***		0.559**
		t = 4.369		t = 2.188
c3		4.714***		-0.058
		t = 3.525		t = -0.178
c4		-0.095		-0.109
		t = -0.122		t = -0.670
c5		-2.782*		-0.809***
		t = -1.902		t = -2.664
c6		2.901**		0.300
		t = 2.495		t = 1.041
c7		0.839		0.502*
		t = 0.809		t = 1.796
c8		1.369**		-0.126
		t = 2.057		t = -0.655
h1		1.872*		0.978
		t = 1.799		t = 0.664
h2		-1.702*		0.391
		t = -1.669		t = 0.981
h3		-0.154		-0.564
		t = -0.153		t = -1.263
h6		-3.977***		0.011
		t = -6.550		t = 0.045
h7				-0.645***
				t = -6.415
e1	9.497***	-2.044**	0.476	-0.509*

	t = 10.766	t = -1.978	t = 1.533	t = -1.868
ncs	-0.001***	-0.001**	0.00001*	0.00001**
	t = -3.211	t = -2.169	t = 1.957	t = 2.563
nds	0.034***	0.024***	-0.0002	-0.001
	t = 3.459	t = 3.360	t = -0.279	t = -1.577
nvs			-0.00000***	-0.00000***
			t = -3.546	t = -6.319
Observations	7,769	7,769	25,446	25,446
R2	0.238	0.607	0.020	0.107
Adjusted R2	0.231	0.603	0.017	0.104
Note:		*p<0.1; **p<0.05; ***p<0.01		

Dependent variable 30d rolling volatility annualized is scaled to represent percentage points. *dif_conhel* represents the change (difference) in the Containment & Health index (from day t to t+1). The variables *c1-c8* refer to containment and closure policies by governments. *h1-h7* refers to health system policy, and *e1* refers to income support. *ncs*, *nds* & *nvs* refer to new cases, new deaths, and new vaccinations, smoothed variables respectively. For further explanation of the variables, see **4.3** or **Appendix: Table 11**. The time period of the regression reaches from 1. Jan 2020 to 31. Jan 2022. The "Period Shock" refers to the first 6 months of 2020, while the "Period After" refers to 1. Jul 2020 to 31. Jan 2022. Robust and clustered standard errors by country and day are reported below the coefficient. *, **, & *** after coefficients represent significance levels of 10%, 5% & 1%. *Note1*: *h7* is missing for Period Shock due to a standard deviation of 0.