The Impact of COVID-19 on Returns and Volatility: a case study of the United States, China, Switzerland and Japan

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Abstract

The year 2020 observed a huge shock that affected every industry on an unprecedented scale. The financial market, taking part in and situated in the centre of almost all domains, has itself recorded diverse and extreme movements. The current study took a closer look into these phenomena while analysing the impact of the pandemic on returns and volatility on four of the world's major financial markets - the US, China, Switzerland, and Japan - which simultaneously belong to four countries that have been severely hit (based on the number of cases and deaths) by the virus. We specifically looked into the relationship between the dynamics of the pandemic and that of the returns and subsequently of the volatility/uncertainty on each of the markets. Using the Granger causality as the principal metric, we found some significant evidence to suggest that COVID-19 was the direct cause of the movements on the studied markets. This implies the importance of the inclusion of COVID-19's cases and deaths (and any COVID-19's directly related policies) in price- and/or volatility-forecasting financial models.

1 Introduction

Since its first presence in China in late 2019, COVID-19 has been the driving factor behind a multitude of changes in society, from specific industries to our every-day life. Over the course of one year, the virus as well as the global response to it has also gone through a number of stages, the most notable of which being the WHO's official declaration of it bearing the status of a "pandemic"[1], and the national (and local) lock-downs that followed suit in most territories in the world. Since this first "wave", the world, most especially in the North America and Europe, has continuously been struggling to contain infections through various measures, the COVID-19 vaccines being the latest of these.

It is therefore not an overstatement to say that almost every aspect of life has more or less been affected by the movement of the pandemic, its indicators including, for examples, the amount of new cases/deaths recorded everyday, the level of the virus' reproduction rate (R0) and the evolution of the positive-test rate, as these are pivotal in governmental decisions to impose lock-downs or other restrictions that involve the operations in other life domains. The current project focuses on

[1] World Health Organization. (2020). *WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020* [Accessed: December 2020]. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

a specific domain, namely the financial market, in four countries - the United States (US), China, Switzerland, and Japan - where the virus has been a contentious subject in the past year. It looks at the movement of these countries' stock markets next to that of the pandemic over an 11-month period from January 1st 2020 to December 1st 2020, a period long enough to have captured the most prominent events. Furthermore, the study looks at movements not only on the daily but intraday frequency, since this data proves more useful in capturing more interesting events such as uncertainty. In fact, studies in literature have shown that intraday movements and uncertainty were higher during COVID-19 than before for certain assets. Specifically, Johnson (2020) demonstrated in her article a siginificant increase in bitcoin's intraday price movements during and post-COVID time compared to previous periods[2]. Meanwhile, Lyócsa et al. (2020) established a connection between the "fear of [COVID-19]", measured by the excess "search volume" related to the pandemic, and the stock market, showing that this indicator could serve as a valuable source for price variation forecasting around the world[3].

2 Data and Variables

This section describes in details the main resources for the project as well as the calculations that we performed to get the variables of interest, which are COVID-19's daily new cases, daily returns of selected stocks on each of the four markets, and their daily realised variance. It also describes the main findings that we got from these data, through relevant time-series analyses and metrics.

Table 1 outlines briefly the data that the study used to investigate the research questions, as well as some initial modifications that we made while treating some common problems such as missing values. Note that for the financial data, the study used two types of data, daily and intraday, from two different sources. Details and in-depth explanations for our choices are presented in subsequent (sub)sections.

For the sake of brevity, here we report only some of the plots we obtained. A complete collection of the plots can be found in the relevant Jupyter Notebooks in the link presented in Appendix A.

	COVID-19's Cases	Daily Returns	Intraday Prices
Period	2020-01-01 to 2020-12-01		
Source	Johns Hopkins	Yahoo! Finance	Dukascopy
Short description of Source and Data	A daily-updated database of the global number of cases & deaths[4]	Yahoo! Finance provides financial information such as prices of main stocks in the world's big markets[5]	Historical database of Swiss Forex Bank that provides intraday data on important indices[6]. The data retrieved are for four major indices, S&P500, FTSE A50, SMI, and JPN225, representing the market portfolios of the four selected countries. Data is on an one-minute frequency.

Table 1: Brief description of the data used for this project

[2]Johnson, J. (2020). Bitcoin's intraday price dynamics: Pre and post covid-19. *Available at SSRN 3650673*.

[3]Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. *Finance Research Letters*, *36*, 101735. https://doi.org/https://doi.org/10.1016/j.frl.2020.101735.

2.1 COVID-19's Daily Confirmed Cases

The number of COVID19's daily confirmed cases for the period from the first day of 2020 to the first day of December 2020 was retrieved from the Johns Hopkins data portal, which collects data from governmental sources[7]. This portal is constructed through a public repository that gets fed data on a daily basis, but unfortunately does not itself provide an API. The project proceeded to access the data through an unofficial, but very complete and well-documented, API that pulls data from the Johns Hopkins original source. It is worth noting, however, that the figures of cases obtained from this API are cumulative, meaning some middle step needed to be taken to get the number of daily new cases, while a **7-day-rolling mean**, which uses samples of consecutive existing observations to create overlapping windows, was also carried out to take care of missing values, mainly from unreported cases on weekends (in the case of Switzerland, for example) or late reporting, or the particular problem of less testing on weekends and holidays.

Figure 1 illustrates the cumulative and daily confirmed cases in the four selected countries (coded by the ISO 3166 standard). It can be easily observed from these time series that the four countries differ substantially in the evolution of the pandemic. While China, the first country where the virus was detected, suffered from a disproportionately high number of cases at the beginning, the country's success in containing the virus is apparent from the plateau-ing of the cumulative curve. Meanwhile, the peak for Switzerland seems to have happened later in the year, during what could be called the "second wave" of the virus in Europe. The US and Japan, on the other hand, demonstrate a three-peak dynamics, with a second peak at around July, August and the third one towards the end of the year, but with the US manifesting the figures on a much greater scale (even though the US population is only less than three times bigger than that of Japan). One detail that should also be included in the interpretation of these figures is the fact that as the virus evolved over the year, testing was made more and more available and the testing rate therefore increased all over the world, thus also raising the number of daily new cases[8].

2.2 Daily Returns on Selected Stocks

We analysed for each of the four selected countries the 50 most important stocks based on their market capitalisation. The data for this part was taken from Yahoo! Finance[9], over the indicated period and on a daily frequency.

We recreated the S&P500 index using the stocks that constitute it, which we obtained from Wikipedia[10] and whose prices were retrieved from Yahoo! Finance. This index would serve as the benchmark for our analyses of the returns' movements later on. Even though S&P500 is composed of mainly US stocks, it is the biggest index on the global market and is also capable of conveying the global market's dynamics due to the multinational stocks that take part in it.

We then performed the analysis of the stocks divided by country. For each country, after plotting the correlation matrix between all the stocks, we identified the five stocks that, on average, present the highest adjusted prices. These stocks would play the most important roles in the whole analysis. The remaining stocks were employed in Section 2.3 for the construction of country-specific portfolios.

2.2.1 The United States

In contrast to China, whose stocks are highly correlated (at least 0.86) (as will be discussed below), the US' stocks in Figure 2 show lower levels of correlation. The only exception is GOOG and

[7] Johns Hopkins University of Medicine. *Johns hopkins coronavirus resource center* [Accessed January 2021]. https://coronavirus.jhu.edu/map.html.

[8] Our World in Data. *Daily covid-19 tests per thousand people* [Accessed: January 2021]. https://ourworldindata.org/grapher/full-list-daily-covid-19-tests-per-thousand?time=2020-02-18..latest.

[9] Yahoo! *Yahoo! Finance* [Accessed: December 2020]. https://finance.yahoo.com/.

[10] Wikipedia. *List of s&p 500 companies* [Accessed: December 2020]. https://en.wikipedia.org/wiki/List_of_S%5C%26P_500_companies.

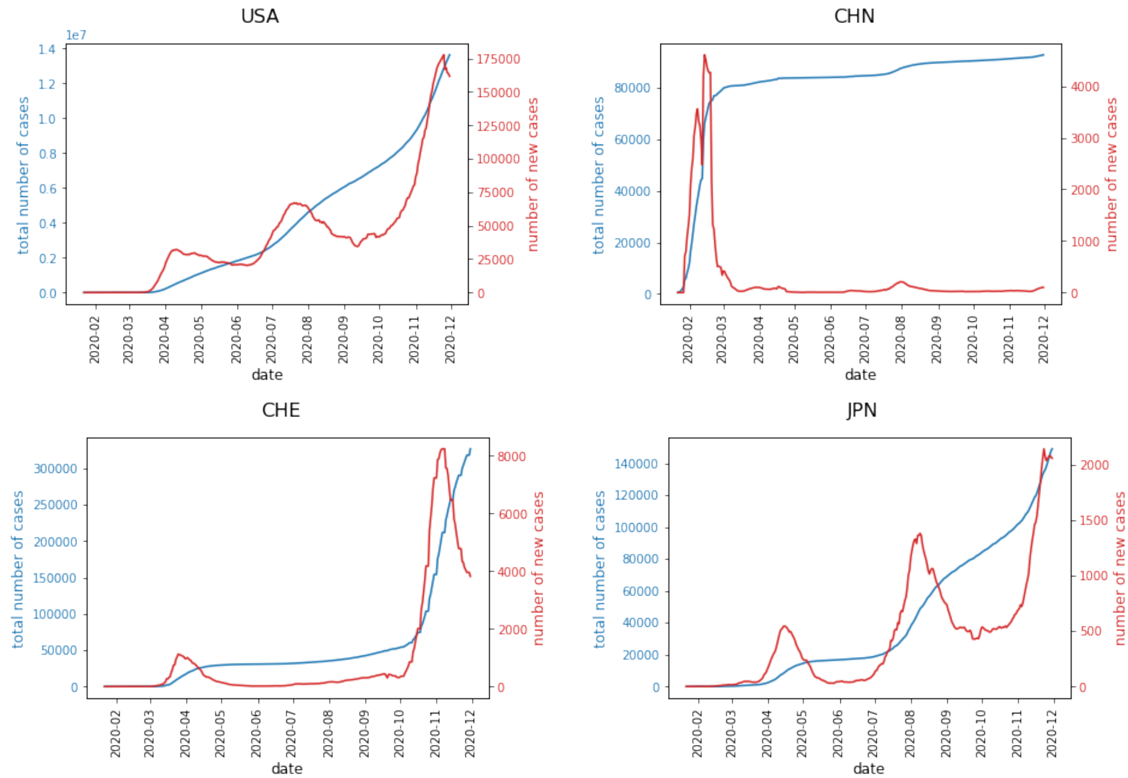

Figure 1: COVID-19's Daily and Cumulative Number of Cases in Four Selected Countries

	BRK-A	AMZN	GOOG	GOOGL	NFLX
BRK-A	1.00	0.15	0.60	0.60	0.03
AMZN	0.15	1.00	0.73	0.73	0.97
GOOG	0.60	0.73	1.00	1.00	0.65
GOOGL	0.60	0.73	1.00	1.00	0.65
NFLX	0.03	0.97	0.65	0.65	1.00

Figure 2: Correlation matrix
USA stocks.

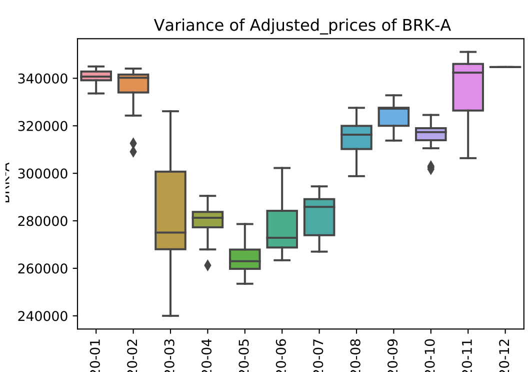

Figure 3: Variance BRK-A adjusted prices.

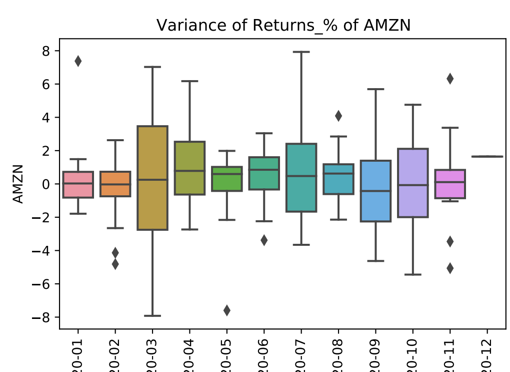

Figure 4: Variance AMZN returns.

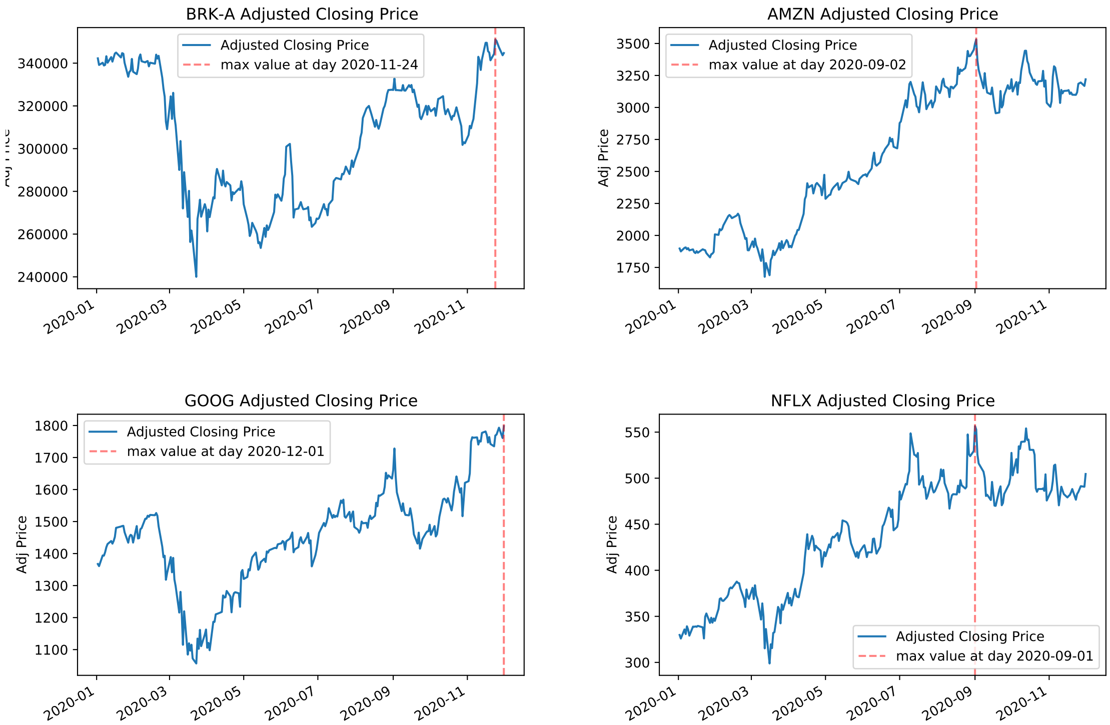

Figure 5: American stocks adjusted prices plots.

GOOGL: Google created two classes of its shares to differentiate between shares without voting rights, GOOG, and shares with voting rights, GOOGL[11]. The lower correlation in these American stocks is reflected also in the time series of adjusted prices in Figure 5, which follow different trends: Amazon increase almost constantly until July, while prices of Google and Netflix suffered many ups and downs. Berkshire Hathaway is one that decreased the most. Also in terms of volatility, Figure 3 shows that the situation was dangerously variable for the company in March, when the BRK-A stock lost almost 30% of its value.

If we look at US stocks' prices, we see that Berkshire Hathaway's prices are remarkably higher than the others. By market capitalisation, this company is one of the biggest ones in the world and operates in different sectors. The reason why its stocks are so expensive is that they decided not to split their shares as many other big companies did[12].

For each stock, we also computed the returns. If S_t is the adjusted price of a certain stock at t, the return of that stock at t is given by $\frac{S_t - S_{t-1}}{S_{t-1}}$. While Berkshire Hathaway represents a unique case in terms of adjusted price's variance, if we look at returns' variance we see that also the other companies experienced periods of great uncertainty. For example, Amazon returns' variance in Figure 4 is high for many months, even if its adjusted prices' variance remains relatively slow throughout the year.

Comparing American returns to the S&P500, we see that, as expected, all the USA stocks follow the index' behaviour, especially Google during the first half of the year. In general, when we want to compare returns, rolling windows play a fundamental role: without them the variation of the time series would not allow to capture any trend, as Figure 6 shows. Rolling windows dramatically improves the situation, smoothing the curve as demonstrated in Figure 7.

[11] Investopedia. (2020). *What is the difference between alphabet's goog vs. googl?* [Accessed: December 2020]. https://www.investopedia.com/ask/answers/052615/whats-difference-between-googles-goog-and-googl-stock-tickers.asp.

[12] Cliffcore. (2020). *Why is berkshire hathaway stock so expensive?* [Accessed: December 2020]. https://cliffcore.com/why-is-berkshire-hathaway-stock-so-expensive/.

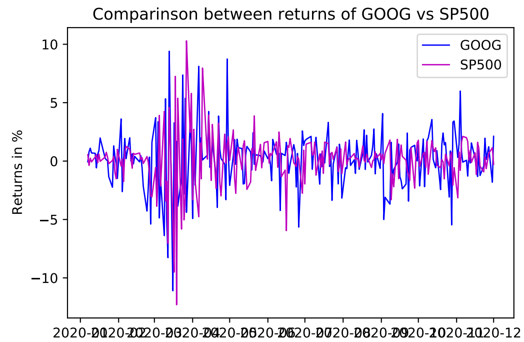

Figure 6: Comparison: SP500 and GOOG returns.

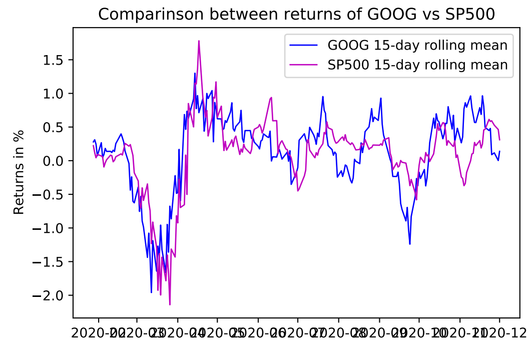

Figure 7: Comparison: SP500 and GOOG returns with 15-days rolling.

2.2.2 China

China was the first country to experience the effects of COVID-19 at the beginning of 2020. Therefore, its trends are a bit different from the other countries'. For instance, their biggest stocks experienced an important increase during the year, quickly overcoming the problems of the first months. We reported the evolution of adjusted prices (and their rolling means) of one of them in Figure 8 as an example. This positive reaction of Chinese stocks can be seen also in the variation of adjusted prices in Figure 9: in contrast to other countries, variance remains relatively low for Chinese stocks. This is not the case for returns: studying the variance of returns in Figure 10, we found out that they are much more variable than the simple adjusted prices.

While most US stocks behaves similarly to the S&P500 index, in China different stocks exhibit different behaviours. Some are close to the index, while some others are completely different.

2.2.3 Switzerland

Swiss stocks all suffered a drastic decrease in March, when the virus arrived in the country. Some edged back quickly, while some other have been seeing ups and downs. In general, most of the companies, such as Lindt & Sprüngli, were not able to reach the price they had before the pandemic. Figure 11 shows that the Swiss chocolatier reached its maximum price in February.

In terms of volatility, both adjusted prices and returns were extremely volatile during certain months. Lindt & Sprüngli, in a press release published on March 31st 2020 [13], claimed that they imposed severe restrictions on the companies in order to limit the spread heavily affected their business. They wrote: "the impacts affect mainly travel retail, the own store network, food service as well as the grocery trade in certain markets". The company was also confident that its solid fundamentals would have allowed them to overcome the economic slowdown. In another press release in July[14], they reassured that they have been continuing to do initiatives and invest in advertising, in order to ensure profitable growth in future. Of course, they also worked to strengthen their online business. Thanks to these measures, even if since October the situation has been worse in Switzerland in terms of daily new cases (see Figure 1), the company's stock price did not experience another serious fall. The Lindt & Sprüngli case is the only example to explain how companies were impacted by COVID consequences and what they are doing to limit their losses.

[13] Lindt & Sprüngli. (2020a). *Lindt & sprüngli - covid-19 update* [Accessed: December 2020]. https://www.lindt-spruengli.com/press-releases-and-news/english/lindt-sprungli-covid-19-update/

[14] Lindt & Sprüngli. (2020b). *Update: Lindt & sprüngli half-year results 2020* [Accessed: December 2020]. https://www.lindt-spruengli.com/press-releases-and-news/update-lindt-sprungli-half-year-results-2020/.

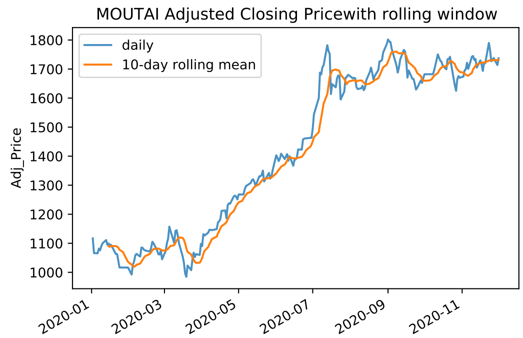

Figure 8: Evolution Adjusted Stock Price MOUTAI.

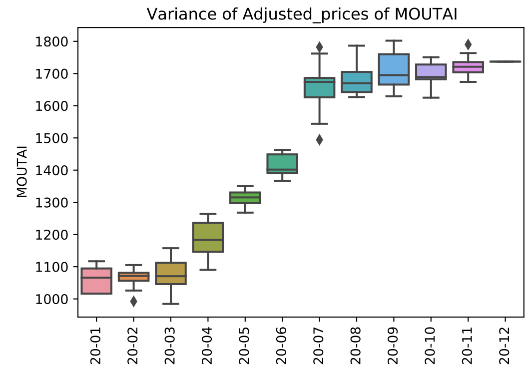

Figure 9: Adjusted Closing price variance MOUTAI.

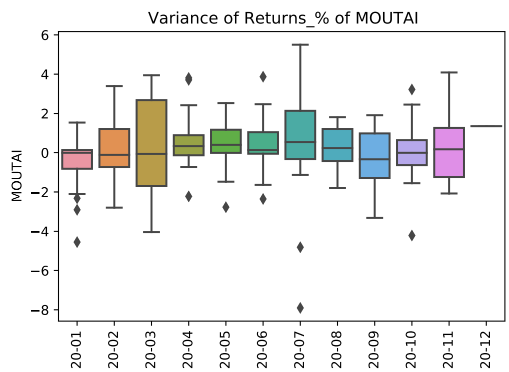

Figure 10: Returns variance MOUTAI.

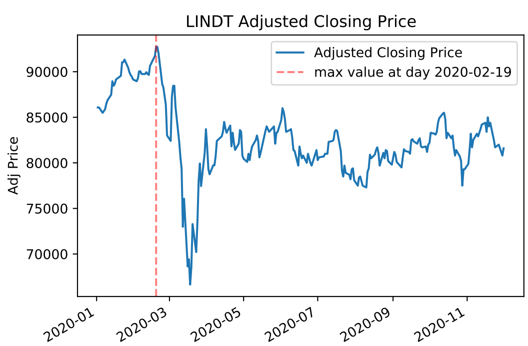

Figure 11: Lindt's adjusted prices.

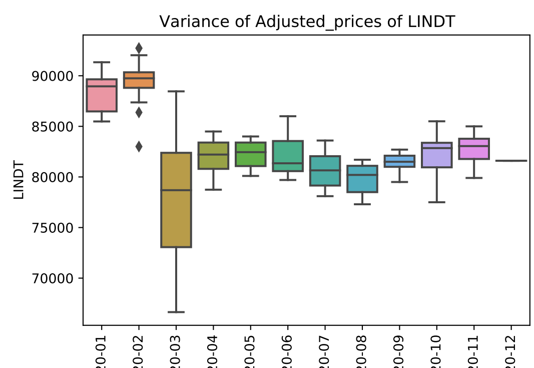

Figure 12: Lindt's adjusted prices volatility.

2.2.4 Japan

Japanese stocks were, without exceptions, drastically affected by the COVID-19's spread. There were three peaks in the new COVID daily cases, as the American one (see Figure 1). However, while US stocks usually do not show drops corresponding to COVID-19 surges, Japanese stocks do, as Figure 13 shows. In terms of prices' variance, they registered levels of variability relatively fairly distributed among the months, showing a behaviour more similar to Chinese stocks than Swiss ones.

Both Japan's and Switzerland's stocks' trend does not differ much from the S&P500 index, especially Suzuki in Japan and Partners Group Holding in Switzerland. This result is more relevant than the similarity shown by the American stocks, because these companies are not included in the S&P500 list. This shows the universality in the extreme movements of prices and returns over the studied period.

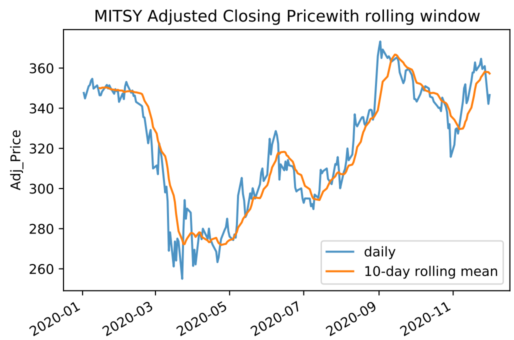

Figure 13: Caption

2.3 Returns on Portfolios

In order to study the causality among stocks and COVID-19's daily confirmed cases, we first created two portfolios of returns for each country: one equally weighted (EW) and the other value weighted (VW). The EW portfolio is obtained by averaging the daily returns of all the stocks we considered for each country, whereas for the VW counterpart, we took inspiration from the 60-40 portfolio. The classical 60-40 portfolio is a well-know asset allocation method by which the portfolio is composed of 60% equities and 40% bonds. However, as we did not include bonds, we simply gave 60% of the total weight to the five most important stocks and the 40% to the rest.

2.4 (Annualised) Realised Variance of Intraday Prices

Apart from returns, the current study looked at the impact of COVID-19 on the daily volatility of stocks. The volatility, which describes market uncertainty, was here measured by the annualised realised variance (RV) of intraday prices, the square-root of which would capture the estimated volatility in financial terms. We kept the realised variance as the main measure since it measures the same entity with the same magnitude. The intraday data used for this study was, as explained in table 1, obtained for four major indices that capture the most prominent stocks on the markets of the four selected countries - S&P500 for the US (500 stocks, in USD), FTSE A50 for China (50 stocks, in USD), SMI for Switzerland (20 stocks, in CHF), and JPN225 (225 stocks, in JPY).

Another important detail of this data is its frequency, which is one-minute. The original intention was to get tick-data, which provides more granularity and is more capable of capturing the micro-bursts in the market. However, this proved to be impossible due to two main reasons. First of all, a source that offers free, live and historical intraday data on the Internet is extremely rare. Dukascopy, being the only viable source that we found for this project, offers the option of direct download from their historical data feed platform, but the download is restricted to only one underlying for one day at a time, which would be too time-consuming. This led us to use a proxy option called the dukascopy-cli to obtain the data over longer periods from the command-line. But the second problem emerged, which is the fact that retrieving tick data over periods longer than a few days was too much for the Dukascopy server to handle, no matter how small we divided the call batches or the time between batches. Due to these two reasons, we had to opt for the next best solution, which was one-minute data, retrieved for one month at a time from the command-line (around 7,500 entries each time).

The annualised RV for each day was calculated as in Lyócsa's article[15]. That is, the daily annualised RV was modelled as:

$$RV_t = 252 \times (j_t^2 + \sum_{i=1}^{M} r_{i,t}^2) \tag{1}$$

$$r_{i,t} = 100 \times \ln\left(\frac{P_{t,i}}{P_{t,i-1}}\right) \tag{2}$$

$$j_t = 100 \times \ln\left(\frac{P_{t,1}}{P_{t-1,M}}\right) \tag{3}$$

where $r_{i,t}$ is the ith intraday continuous return (on day t and between two consecutive minutes of the day i and $i-1$), $P_{t,i}$ is the price of the stock on day t at intraday time i, j_t is the the return between the closing value of the index on day $t-1$ (moment M) and the opening value on day t (moment 0).

Figure 14 demonstrates the dynamics of daily RVs over the course of 11 months. It is evident that the uncertainty achieved its extremum during the first wave of the pandemic, between March and April 2020, as the virus started to push governments to roll out lock-downs and restrictions on a national level, affecting drastically a number of industries in society. While Figure 1 of COVID-19's movement in four countries showed the some differences in the moment of peaks or in the scale of magnitude, the plots for RVs are pretty uniform in the peak and the fact that other periods of high uncertainty, which happened later in the year, appear insignificant compared to this strong reaction in the market at the beginning of the pandemic.

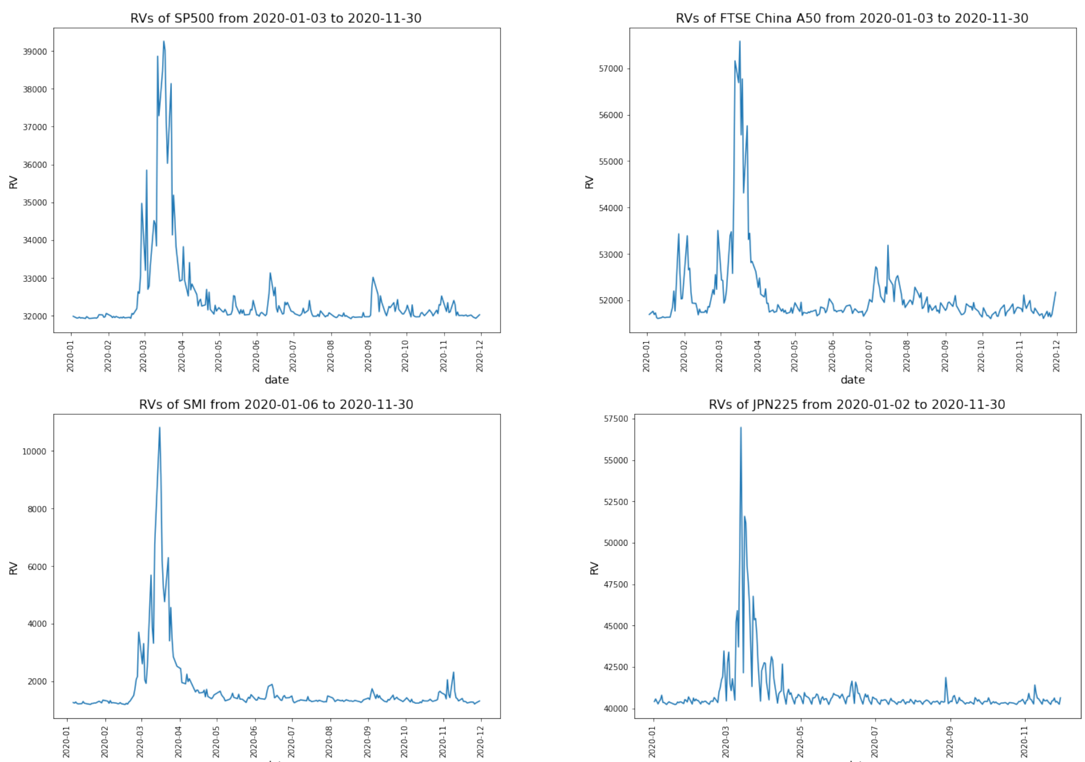

Figure 14: Annualised Daily RVs on Four Selected Indices

[15] Lyócsa et al., "Fear of the coronavirus and the stock markets".

3 Methodology and Results

This section presents multi-variate analyses that were conducted on the data - the multi-variate relationships being those between countries' COVID-19's daily cases, between the selected stocks within a country, and between COVID-19 and each of the market indicator. It essentially seeks to answer the question of the extent to which COVID-19 had on the financial market. The following sub-sections outline the main results that were obtained and their main implications with regard to this question.

3.1 Granger causality

While there are a number of ways to approach the problem of investigating the effect of COVID-19 on returns and volatility, in this study we modelled this impact with Granger causality, a metric of correlation for two time series that could potentially reveal a causal relationship. Again, for the sake of brevity, we cannot include all the plots in the report, but these can be found in the code attached to the report. All the needed functions are implemented in the `granger_causality_functions.py` file.

General economic equilibrium theory assumes that everything depends on everything else. Therefore, it is not a surprise that, already in 1969, Clive W.J. Granger investigated causal relations between different time series, basing his study on linear regression modelling[16].
According to Granger, causality is tested by measuring the capability to predict the future values of a time series Y using prior values of another series X. In other words, if we better predict Y by using causal side information X, we say that X is Granger-causing Y. Formally, let us consider two cases, one including past values of X_t and the other not including them:

$$Y_t = \sum_r \alpha_r Y_{t-r} + E_t, \tag{4}$$

$$Y'_t = \sum_r \alpha'_r Y'_{t-r} + \sum_\gamma \beta_\gamma X_{t-\gamma} + E'_t. \tag{5}$$

We can say here that X Granger-causes Y if $Var(E_t) > Var(E'_t)$.

We can study the Granger causality among any kind of time series. For instance, we can study the causality between COVID-19 new cases and stock market returns. Considering that these time series can have different magnitudes, data must be normalised before applying the test.

Another necessary condition is that the studied time series must stationary. We thus checked for stationarity and, in the case where the series were not stationary, they were turned to be by applying some operations. To test for stationarity, one needs to show that mean and variance remain constant over time. In the current study, we used the **Dickey–Fuller test** (ADF test) for this. There is a null hypothesis, a unit root present in a time series, and an alternative hypothesis, which supposes that the data are stationary. Specifically, unit root is a characteristic of a time series that makes it non-stationary. The resulting test statistic and their corresponding p-values are then computed. Since the null hypothesis supposes the presence of unit root, $\alpha = 1$, the p-value obtained should be less than the significance level in order to reject the null hypothesis, inferring stationarity[17].

[16] Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424–438. http://www.jstor.org/stable/1912791.

[17] Chaudhary, M. (2020). *Why is augmented dickey–fuller test (adf test) so important in time series analysis* [Accessed: December 2020]. https://medium.com/%5C@cmukesh8688/why-is-augmented-dickey-fuller-test-adf-test-so-important-in-time-series-analysis-6fc97c6be2f0.

The easiest way to make a time series stationary is through differentiation: $y'_t = y_t - y_{t-1}$. Differentiating helps stabilise the mean of the time series by removing changes in the level of a time series, and hence reducing trends and seasonality.[18].

Once the data are normalised and transformed to be stationary, we calculated the Granger causality matrix. In addition, we also implemented a function to plot the network which graphically shows the causality structure between the time series. For this project, a Granger causality test is principally employed to investigate the causalities among COVID-19 and stock market returns. In all the tables in this work, the direction of Granger causality is oriented from the entries with the "_x" post-fix to those with the "_y" post-fix.

3.2 Causality among Countries' COVID-19's Daily Confirmed Cases

In this section, we analysed the Granger causality between the number of COVID-19 daily new cases in different countries. Note that, by construction, the COVID-19 daily new cases are given by differentiating the total cases. Therefore, the daily new cases time series is stationary by construction.

Calculating the Granger causality between the four countries we are analysing, we obtained the Granger matrix in Table 2.

	USA_x	**CHE_x**	**JPN_x**	**CHN_x**
USA_y	0.0	0.0	0.0	0.568
CHE_y	0.0	0.0	0.0	0.347
JPN_y	0.0	0.0	0.0	0.57
CHN_y	0.0	0.423	0.0	0.0

Table 2: Granger causality matrix COVID cases.

The first country in which COVID-19 spreads is China and from there, it went viral. Therefore, these results make sense: China's Granger causes the other countries in different measures. Looking at the time series in Figure 1, also the weights are clear: after the China peak, also USA and Japan experience noticeable increases around April. While Switzerland, compared to the cases registered in Autumn, does not shows a evident rise in daily new cases during the first half of the year.

Japan and USA time series show similar patterns and this similarity is captured by the Granger causality test: they are both caused by China by ~ 0.57 and they do not cause anything. This is a good example to show the difference between correlation and Granger causality. The correlation between USA and Japan is 0.85, as the time series suggests, but USA does not Granger-cause Japan at all, neither the reverse. The fact that they both are Granger-caused by China does not imply that they are correlated. In this case they are, but this is not a rule.

3.3 Causality among Stocks returns

For each country, we tested the Granger causality between the five most important stocks of that country. This is useful to draw some conclusions in Section 3.4. The time series we used for this part are the stocks returns calculated in Section 2.2. Also in this case, data are already stationary by construction and this was also confirmed by the ADF test. Therefore, we only normalised before performing the Granger test.

In this case, it is much harder to understand more or less the Granger causality structure form the time series plots: returns are much more volatile than daily COVID new cases (see Figure 15 for example) and this complicates the Granger causality test. As a matter of fact, now the causality weights are much lower. Probably high volatility does not allow to understand if a specific movement

[18]Brownlee, J. (2017). *How to remove trends and seasonality with a difference transform in python* [Accessed: December 2020]. https://machinelearningmastery.com/remove-trends-seasonality-difference-transform-python/.

is caused by another time series or is only a consequence of the volatility. This is true for all the countries of concern. We also try to consider ten stocks instead of five for USA, but the results are similar. For instance, Table 3 shows the Granger causality matrix for Japan. For this reason, we decided to analyse the Granger causality among COVID19 and volatility in Section 3.5 and not among COVID19 and returns.

	MITSUB_x	MITSY_x	SZKMY_x	TM_x	SNE_x
MITSUB_y	0.0	0.0	0.119	0.0	0.193
MITSY_y	0.0	0.0	0.0	0.0	0.0
SZKMY_y	0.0	0.0	0.0	0.0	0.0
TM_y	0.0	0.0	0.0	0.0	0.0
SNE_y	0.0	0.145	0.232	0.127	0.0

Table 3: Granger causality matrix COVID cases.

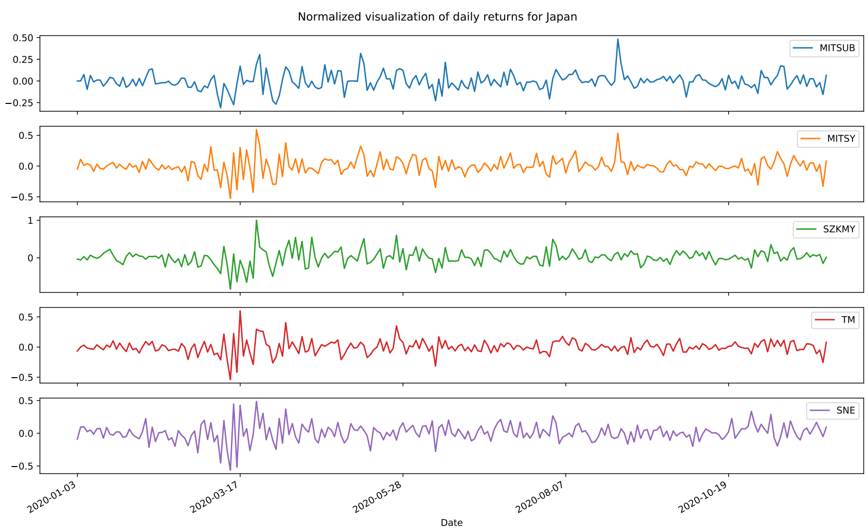

Figure 15: Time Series returns of Japanese stocks.

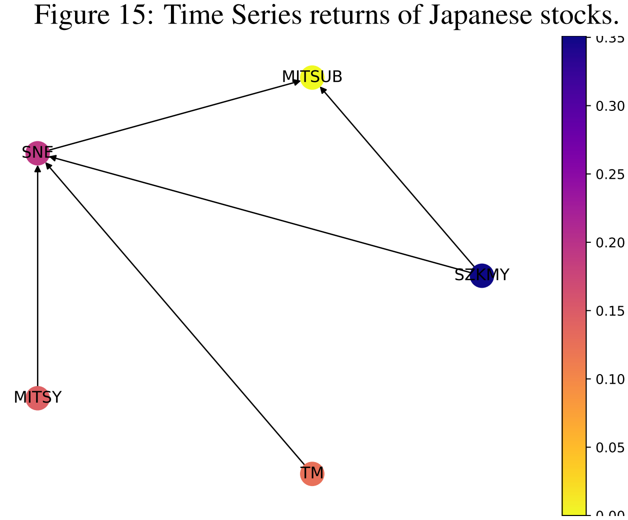

Figure 16: Granger causality network Japanese stocks.

3.4 COVID-19 vs. Portfolios of Returns

The study of Granger causality between COVID-19 new cases and portfolios returns is the most interesting one so far, because it relates time series of completely different areas: one related to finance and one to public health. The first important thing to mention is that we are not interested in the Granger causality from portfolios to COVID-19 daily new cases, because, using common sense, it is clear that stocks behaviour cannot influence a virus. We want to study if COVID-19 daily new cases Granger-cause portfolio returns instead. We used a 7-day-rolling mean window for the COVID-19 daily new cases smooth sudden movements due to unreported cases on weekends and holidays.

For each country, we tested the Granger causality both for the EW and the VW portfolios, defined in Section 2.3. Table 4 summarises our results.

	COVID-19 daily new cases			
	China_x	**USA_x**	**Japan_x**	**Switzerland_x**
EW portfolio_y	0.266	0.585	0.395	0.616
VW porfolio_y	0.185	0.6	0.465	0.314

Table 4: Granger causality matrix from COVID-19 daily new cases to stocks portfolios.

Japan and the US exhibit similar trends for COVID-19 new cases (three peaks), but they perform quite differently in terms of Granger causality in stocks. This gap is probably due to the portfolios time series: Japanese stocks' returns are relatively less volatile than the USA ones and this may affect the Granger Causality results. Our guess is that the test erroneously interprets the shifts in the USA returns, due to its volatility, as consequences of the COVID-19 new cases movements. We verified this idea by lowering the variance of USA portfolios using a rolling window of 10 days. The results confirm that, with rolling window, the Granger causality weights decreases to 0.178 for the EW portfolio and to 0.317 for the VW portfolio.

Another interesting peculiarity is that the time series of Japan's COVID-19 new cases is more variable than the American one, while for the portfolio returns it is the opposite. This shows that we cannot always conclude that if a period is highly fluctuating for the COVID-19 new cases, this will be reflected into the stocks. There are also many more aspects to consider, such as the market stability of the stocks of each market, but this is out of the scope of this report.

What is clear from this work is that the abrupt spread of the virus in China had consequences in many countries. It would be too restrictive to conduct an analysis only by country. So, we also studied how the COVID-19's daily new cases in China have influenced the portfolios of the other countries. We included a rolling window of 10 days for the portfolios returns in order to avoid misleading results due to the high volatility of some countries' portfolios. Table 5 show that, even if at different degrees, China's COVID-19 outbreak has influenced almost all of the portfolios in the other countries.

	Japan_y		**USA_y**		**Switzerland_y**	
	EW	**VW**	**EW**	**VW**	**EW**	**VW**
China's Daily New Cases_x	0.657	0.607	0.306	0.372	0.0	0.285

Table 5: Granger causality matrix from COVID-19 daily new cases in China to portfolios in other countries.

3.5 COVID-19 vs. Volatility

Table 6 illustrates the causal relationship between COVID-19's daily new confirmed cases and the calculated daily RVs of four indices that represent the four selected countries. Based on these figures, the Swiss and the Japanese stock market were the ones where the uncertainty was most explained by the dynamics of COVID-19's daily cases. Meanwhile, S%P500, the biggest index on the US stock market, reported a close to 0.5 in Granger causality, conveying some potential of COVID-19's daily cases being a factor in explaining and forecasting market variation. This weak relationship could be due to the large number of stocks, which come from vastly different domains, included in the S&P500, making the variation of the index harder to model and generalise.

The zero causality observed in the case of the A50 index may seem surprising at first glance, but this figure is in accordance with the figures seen in the time series in Figure 1 and 14. From these plots it is clear that the peak of the pandemic in China happened a month before the highest point of the A50's RV, even though the plot for A50's RVs did also record a high burst during the first outbreak of China. This shows that the uncertainty on the Chinese market only "flourished" when the whole world was in turmoil over the pandemic. This implies the strong inter-connectivity between the Chinese market and the rest of the world's financial market, where industries today rely on a supply chain that spans continents instead of just locally, most of which links to the manufacturing sector in China[19].

Index (Country)	Granger Causality Daily Confirmed Cases -> RV
S&P500 (US)	0.537
FTSE A50 (China)	0.0
SMI (Switzerland)	0.661
JPN225 (Japan)	0.923

Table 6: Granger Causality between COVID-19's Daily Confirmed Cases and Daily RVs in Four Selected Countries

3.6 Do periods of lock-downs (or of restrictive measures) affect the financial market?

Through the current project we would also like to see if the periods of lock-downs in each of the four countries had significant impact on the market's returns and variation. Table 7 gives the periods in the four countries during the first phase of the pandemic when the government imposed strict measures such as lock-downs to contain the virus[20]. The analysis in this part extends some of these periods a little longer to account for any post-lockdown effect.

Country	Period of Lock-down
US	March 20th - May 15th (on average)
China	Jan 23rd - March 10th
Switzerland	March 17th - April 27th
Japan	April 7th - May 25th

Table 7: Lock-down Periods in Four Selected Countries

Figure 17 illustrate the dynamics of the pandemic's daily new cases during (and after) lock-down periods, showing the peak of the virus towards the middle and, with the exception of the US, the gradual descent which signifies the effectiveness of the measures.

Figure 18 and 19 represent zoomed-in dynamics of the market during periods of lock-downs or highly restrictive measures. They illustrate respectively the daily returns of the five biggest stocks

[19] Srai, J. S., & Shi, Y. (2008). *Understanding china's manufacturing value chain: Opportunities for uk enterprises in china: Selected case studies in white goods, tft-liquid crystal display and pharmaceutical sectors*. University of Cambridge Institute for Manufacturing.

[20] Wikipedia. (2020). *National responses to the covid-19 pandemic* [Accessed: December 2020]. https://en.wikipedia.org/wiki/National_responses_to_the_COVID-19_pandemic#Lockdowns.

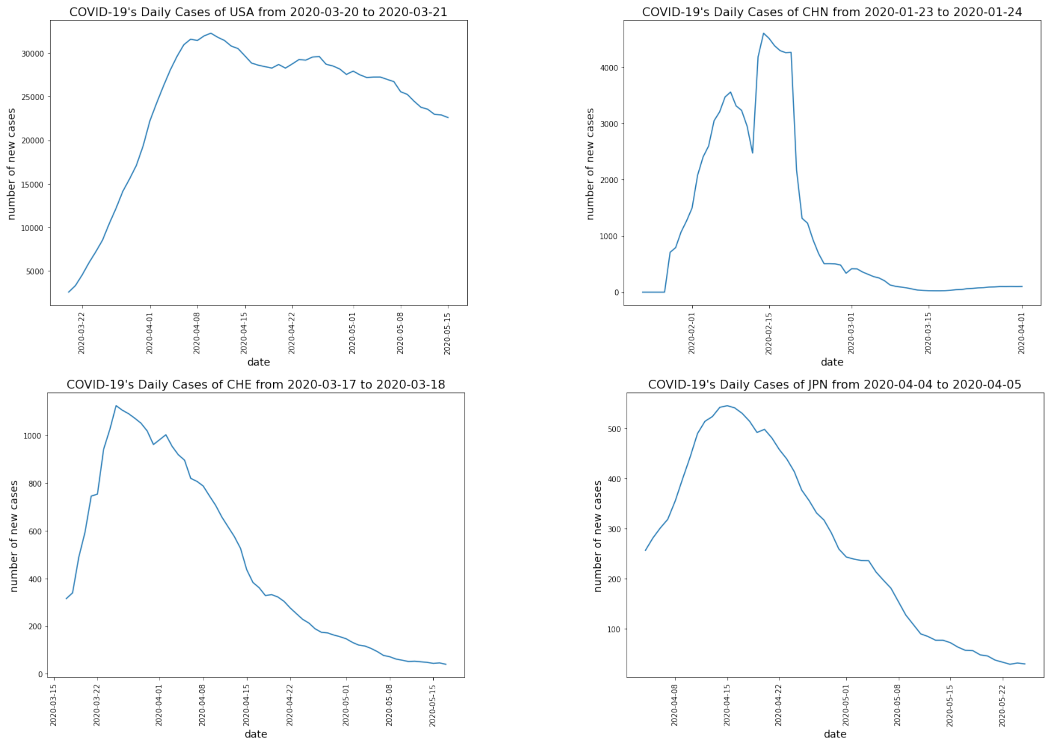

Figure 17: COVID-19's Daily Confirmed Cases during Periods of Lock-down

in each country's market and the daily RVs of the four countries' major indices during lock-downs. It is hard to say whether the lock-down policies themselves had any effect on market's returns and volatility: while the returns exhibit no clear, distinctive patterns within this brief period, the RVs of China's A50 index, for example, only observed peaks at the end of lock-down period in China, which aligns with the beginning of the lock-down periods in other countries like the US, Switzerland and Japan, whose data indeed conveys a peak in RVs at the beginning of the nationwide governmental restrictions. However, this uncertainty in the market is more likely attributed to the dynamics of the pandemic itself, instead of the social policies which only took place after the steep rise in the number of daily cases.

Figure 18: Daily Returns During Periods of Lock-down

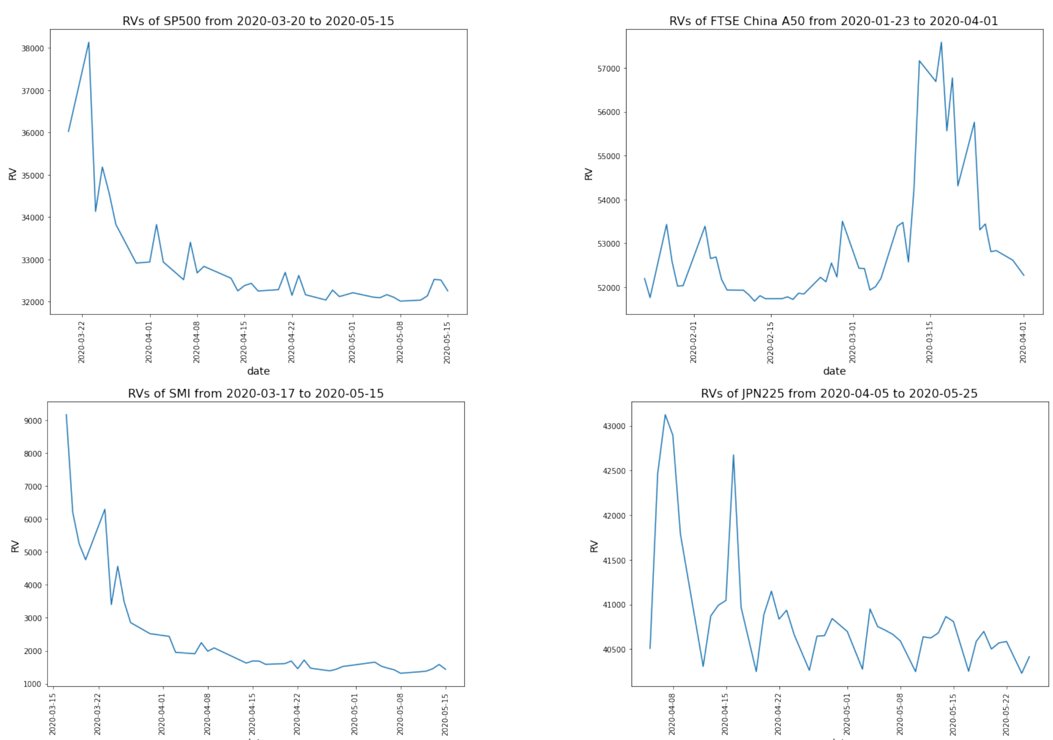

Figure 19: Daily RVs During Periods of Lock-down

4 Conclusion

The current study explored the dynamics of COVID-19's daily confirmed cases in parallel with that of two indicators of the financial market, returns and volatility (or uncertainty) in four countries - the US, China, Switzerland and Japan - in order to identify any causal relationship between the two sources of events. In particular, we first performed analyses on the COVID-19 side and the financial-market side separately, giving an overview of the movements that took place in the course of 11 months in 2020 from the perspective of the pandemic and that of the stock markets. The visualisation of these analyses revealed some stark differences between the studied countries when it comes to the dynamics of the virus' infections, manifesting (potentially) differences in governmental responses to the pandemic. Similarly, on the financial side, the countries showed important differences, both for how their stocks were affected by the virus' spread and for how they reacted to prices drops. China overcame the crisis very quickly, while the other countries are still struggling against substantial ups and downs. These observations reflect not only the evolution of the virus and but the strong impact of containment measures. As for the market uncertainty, the daily annualised realised variance (RV) was used as the principal metric. This measure showed that despite the differences in the evolution of the virus in the four countries, their markets' uncertainty aligned at around the same time, namely the period when the virus started spreading in the Western continents i.e between March and April and when governments started rolling out social policies to contain infections.

To give a conclusive response to the question of whether COVID-19's daily confirmed cases could serve as a reliable factor for modelling and/or predicting returns and variation, we used Granger causality as the main metric and found some significant values for both the relationship with returns and with RVs. In particular, even though the Granger causality test proved to be at times misleading, we found good evidence to suggest that the initial spread of the virus in China affected the stocks prices of the other countries. Meanwhile, COVID-19's daily cases in Japan and in Switzerland exhibited high causality with the variation of the major indices in these two countries. One sub-question that we tried to explore was whether the periods of lock-down had any effect on the market. However, our analyses, through the visualisation of time series and reasoning in relation with other figures, proved inconclusive - it is difficult to say whether the movements on the market were due to lock-downs or just purely the number of cases, or both.

Our study has therefore demonstrated that, to a certain degree, COVID-19's daily cases can prove to be a good factor in forecasting returns and variation of stock markets in certain countries. This has certain useful implications for investors, asset managers and traders around the world and at the same time leaves interesting open-ended questions to be explored. For example, should we also look for other COVID-19 indicators to predict the market? A potential metric could be "fear of COVID-19", as the study of Lyócsa et al. suggested[21]. Moreover, what other elements of the market may exhibit a higher level of causality with COVID-19? How can we take into consideration governments restrictions? How should we extend our analyses to more specific domains e.g those that are more affected by lock-downs? A complex model that takes into account these questions may prove very successful in the forecasting market's prices and volatility.

[21] Lyócsa et al., "Fear of the coronavirus and the stock markets".

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A Appendix: GitHub Repository of the Project

All the code for this project (as well as descriptions of the main files in the README) can be found in the following link: https://github.com/anitamezzetti/covid_impact_stocks_volatility.