The effect of the COVID-19 crash on market correlations

Maurits van den Oever (2613642) - m.c.vanden.oever@student.vu.nl

June 28, 2020

Table of content

1 Introduction

Modern portfolio theory (Markowitz, 1952) states that one can diversify away risk by carefully selecting a portfolio of different assets. This principal holds when these stocks are not highly correlated. This seems to be the case for when economic times are well, but it might not be the case when a crash appears. When volatility 'spreads' to other markets, it is called volatility contagion. This principle can have a significant negative impact on the ability to diversify an investment portfolio. For instance, Lessard (1973) discussed the disadvantages of return co-movement when diversifying a portfolio. Diversification is not useful anymore when correlations are high at the time the need for risk mitigation is the highest, i.e. a crisis. Leibowitz and Hendriksson (1988) discussed similar points as Lessard (1973), stating that diversification only works if the assets are not correlated. Leibowitz and Hendriksson also stated that selecting different asset classes help with reducing co-movement within a portfolio. Should volatility contagion occur between different asset classes however, the diversification advantages of selecting multiple asset classes might be substantially reduced.

Existing literature has found evidence for volatility contagion in stock markets. Chiang et al. (2007) found strong evidence of contagion in Asian stock markets. During the Asian crisis of the nineties and early two-thousands increasingly positive correlations between stock markets were found. Echaust and Just (2020) found similar results. They investigated correlations between different American stocks from companies in different sectors and found an increase in correlations in high volatility times. Laloux et al. (2000) used random matrix theory to assess correlation changes in American stocks in different crises times. Their approach was similar to the research done by Sandoval and Franca (2012). Both Laloux et al. (2000) and Sandoval and Franca (2012) found increasing correlations when volatility shocks occurred. Ahmadu-Bello and Rogers (2016) investigated contagion between American stock markets and African frontier stock markets. In the financial crisis of 2007-09, they found shocks in the American stock market to have significant effects on the African frontier market. Shocks in interest rates in the US in the eighties caused shocks and ultimately a debt-crisis in highly indebted Latin American countries (Zenalda, 2015).

Volatility contagion can be found not just in international stock markets between themselves but commodity and stock markets as well. Aloui et al. (2012) found evidence of this. They analized the effects of oil shocks on emerging stock market returns and found postive correlations when shocks occur. Contagion can also be found in commodity markets between themselves. Jin et al. (2012) used futures markets to investigate volatility transmission in crude oil markets. They have found that large shocks in one market results in an increase in expected conditional volatilities. In other words, they have found evidence that large shocks in one market leads to an increase in volatility in another. The fact that volatility transmission can be found in commodity markets holds significant implications for portfolio selection, since commodities can be used for diversification purposes. According to Georgiev (2001), direct commodity investing had become more popular at the time the paper was written for diversification purposes, and found that investing in commodities can increase risk-adjusted performance. The same was found by Becker and Finnerty (2000). Their result was predominantly driven by inflation risk of the seventies, which one can partially hedge using commodity futures. Abanomey and Mathur (2001) also found effective foreign exchange risk hedging strategies by investing in commodity futures and currency forwards. Kaplan and Lummer (1998) investigated inflation hedging and found commodities to be more effective than stocks in this regard. Anson (1999) found utility of commodity future investing is higher when the investor is more risk averse, pointing to the risk hedging properties of commodity futures investing. Commodities are believed to have low correlation with other asset types (Jensen et al., 2000). However, should these correlations rise significantly in crisis times, the diversification uses of commodity investing ultimately disappear.

Literature seems to find different conclusions when it comes to volatility contagion and bond markets. Bunda et al. (2009) found contagion, which they classify as excess co-movement, in Asian bond markets in several crises including the Hong-Kong market crash of 1997 and the collapse of LTCM. Dungey et al. (2002) found volatility transmission in the Russian crisis and LCTM near collapse in 1998. Affected were emerging, but also developed, bond markets. Between stock and bond markets however, there is some evidence against volatility contagion. The correlations between UK stock and government bond markets have negative correlations as investigated by Steeley (2006). According to this paper, correlations between short term bonds and long term bonds seem stable. When shocks occur, correlations between stock and premium government bond markets become significantly negative. This could be due to the flight-to-quality principle, as discussed by Baur and Lucey (2006). When stock markets crash, investors are likely to invest in less risky assets instead, such as premium government bonds. When an increase in investing in these bonds takes place, their price will be driven upward. This results in negative correlations, since the movements of these markets goes in the opposite direction. This is good news for diversification, since bonds, especially government bonds, are used as a safe-haven, due to their low volatility nature (Leibowitz and Henriksson, 1988, Jensen et al., (2000). This of course excludes bonds that are seen as risky, such as junk bonds.

All in all, volatility contagion seems to be present in multiple types of markets in multiple countries. This paper aims to add to existing literature by investigating the behaviour of correlations in the recent Corona virus crash. The main research question is as follows:

What is the effect of the COVID-19 crash on the absolute value of contemporaneous market correlations?

This main question is subdivided in two sub-questions:
1. *How do crashes affect contemporaneous market correlations as opposed to normal times and booms?*
This question will be investigated by comparing correlations estimated during crashes, i.e. negative shocks, positive shocks, and 'normal' times as well.

2. *How do contemporaneous correlations act throughout time?*
This question will be researched by regressing estimated correlations on estimated volatilities in a panel data model, to get an idea of whether there is an increase in contagion throughout time.

From these questions a set of hypotheses are derived:
1a. *Correlations are higher is crises than in normal times.*
1b. *Correlations that correspond to negative shocks are more extreme than those that correspond to positive shocks.*
2. *Correlations are increasing throughout time.*

The idea behind hypotheses 1a is that correlations increase due to volatility contagion. When a market crashes and thereby increases volatility, it is likely that another market experiences a similar increase in volatility, or a similar crash. The hypothesis 1b is made because of the leverage effect, which states that volatilities increase more when a negative shock occurs in returns compared to a positive shock of the same magnitude. Hypothesis 2 is made because of the fact that the Corona virus is a worldwide phenomenon. This makes it more likely to have a similar effect on worldwide markets, increasing correlations compared to other years. Another reasoning behind hypothesis 2 is that globalisation is increasing as well. The more open an economy is, the more dependent it is on the consumption of other economies.

2 Data description

The data used for this paper are 7 series ranging from July 3rd 2000 to April 30th 2020. This data includes some crises, including the dot com bubble burst, the 2008 financial crisis, the late 2000s sovereign debt crisis, and the beginnings of the Covid-19 crash.

The series include daily price level data in three main geographical locations on three asset classes. These locations are the US, Europe, and Asia. The asset classes are stocks, bonds and commodities. The reason for choosing these three regions is because they are the main economic centers of the world. The three asset classes were chosen because they represent a large part of modern portfolios.

The three series of stock prices are the S&P500 for the US, the FTSE 100 as a proxy for Europe, and the Hang Seng as a proxy for Asia.

The three series of bond prices are the Bloomberg Barclays US treasury total return index as an index for US bonds, the Bloomberg Asian-Pacific aggregate total return index for Asian bonds, and the Europe aggregate total return index which serves as a proxy for European bond prices.

Lastly, the Bloomberg commodity index was used to serve as a proxy for commodity prices. This is an international index. This fact does not pose many problems, since we can assume that investors can trade internationally.

Since the locations are different from each other, there is some heterogeneity in the trading dates. As a result, there were a low number of missing observations in the Asian and European data. The method of dealing with these missing observations was the same as in the paper of Echaust en Just (2020), where if the majority of the series had data, the missing observations were filled in with the previous observation in the series. If the majority of the series did not have an observation at a given date, that date was dropped entirely from the dataset.

All series were converted to USD using daily spot rates, since currency exchange rates can bias shocks to an index. If one currency appreciates while others do not, there is still a shock to the value while this is not necessarily shown in the data.

From these price level series log-returns were calculated. Log-returns are defined as the following:

$$y_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Log-returns are used because they are symmetrical, meaning an average return of 0% will result in the price staying the same. This is not always the case with simple returns. They are also aggregatable over time, which simple returns are not.

In table 1 summary statistics are shown for the series. The summary statistics shown are the amount of observations, the mean, minimum, maximum, standard deviation, skewness, and kurtosis.

	Obs	Mean	Min	Max	std.dev	Skewness	Kurtosis
Price							
US stock price	5013	1602.052332	676.530000	3386.150000	616.821664	0.958630	-0.162816
Asia stock price	5013	327.758445	138.230224	542.501791	94.824236	-0.213406	-0.946828
Euro stock price	5013	14736.456070	6670.640869	29052.403430	408.9923927	1.131491	1.095959
US bond price	5013	1762.954886	1009.400000	2596.070000	395.452082	-0.182145	-1.286454
Asia bond price	5013	126.588724	99.035700	156.293600	16.482122	0.301454	-1.313819
Euro bond price	5013	186.362286	107.731100	272.611210	47.542815	0.166771	-1.299475
Commodity price	5013	124.886468	59.479500	237.953100	34.435367	0.406610	-0.470014
Returns							
US stock returns	5012	0.000136	-0.127652	0.109572	0.012444	-0.374679	11.797784
Asia stock returns	5012	0.000087	-0.135969	0.134449	0.014282	-0.038906	8.287082
Euro stock returns	5012	-0.000092	-0.178869	0.182192	0.017450	-0.364255	11.538777
US bond returns	5012	0.000187	-0.019240	0.020943	0.002898	-0.112025	3.647732
Asia bond returns	5012	0.000086	-0.009156	0.014952	0.001473	0.012674	5.743273
Euro bond returns	5012	0.000179	-0.012883	0.010754	0.001955	-0.391617	3.167858
Commodity returns	5012	-0.000108	-0.064023	0.056475	0.010230	-0.232243	2.866604

Table 1: Summary statistics on price level and returns of the S&P 500, the Hang Seng stock index, the FTSE 100, the Bloomberg Barclays US treasury total return index, the Bloomberg Barclays Asian-Pacific aggregate total return index, the Bloomberg Barclays Europe aggregate total return index and the Bloomberg Commodity index. The summary statistics show the amount of observations, the mean, min, max, standard deviation, skewness and kurtosis.

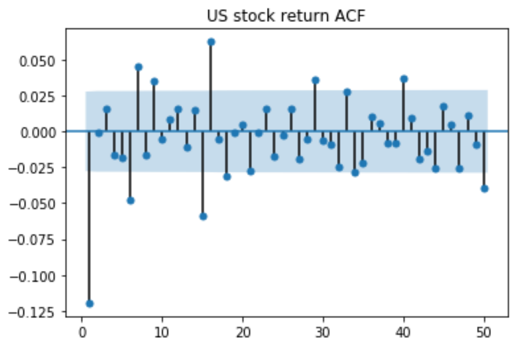
In table 1, one can see that the amount of observations of the price level data is 5013, about 20 years worth of daily return data. The amount of observations of returns is 5012, as one observation always gets dropped when calculating returns.
One can also see that the mean of the returns is close to zero. The highest mean is a result of the US stocks, and the lowest of the means is a result of the commodity index.

The minimum returns of the series range from -0.9% to -17.9%. The maximum returns range from 0.01% to 18%. Bonds show the least extreme minimum and maximum returns, while stocks show the highest. This fits in with the risk profile associated with bonds as a defensive asset. This can also be seen in the standard deviation, where bonds have an average of 0.002. Stocks have an average standard deviation of 0.014. The most volatile are European stocks, and US bonds. The least volatile are US stocks and the Asian bonds.

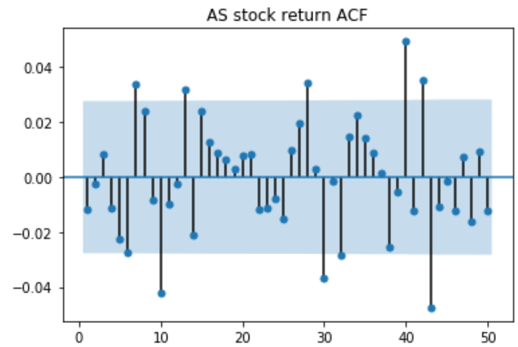
One can see that the data are not symmetrically distributed. Most series are negatively skewed, meaning more extreme values are to the to the left of the mean, but more probability mass is to the right of the mean. This means that large losses are more likely to take place than large positive returns, but it is more likely to see a slight positive return for any given day. On average, stocks are more skewed than bonds, exhibiting more extreme values. The most skewed are US stocks and European bonds. The least skewed are Asian stocks and Asian bonds. Asian bonds is also the only series to be positively skewed. The fact that bonds are less skewed than stocks also fits within the risk profile discussed above.

The data are leptokurtic as well, meaning the tails of the distribution are fat. This can be seen especially in the stock returns, averaging a kurtosis of 10.53, which is higher than the kurtosis of the normal distribution, which is 3. Bonds are leptokurtic as well, albeit not as much as stocks. The commodity index returns are platykurtic, meaning that the data are less kurtose than the normal distribution.

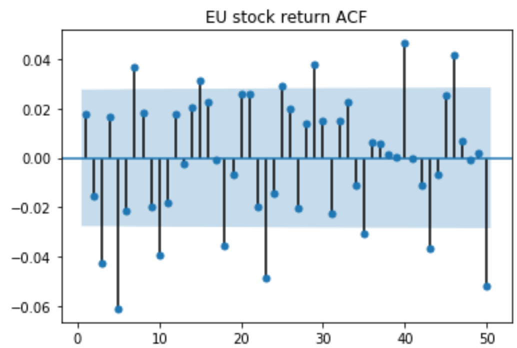
To determine whether or not there is autocorrelation in the returns, autocorrelation function (ACF) plots were made of each individual series of returns, shown below in figure 1. One can see that the series do not exhibit significant autocorrelation. The effect of this fact will be discussed later in this paper.



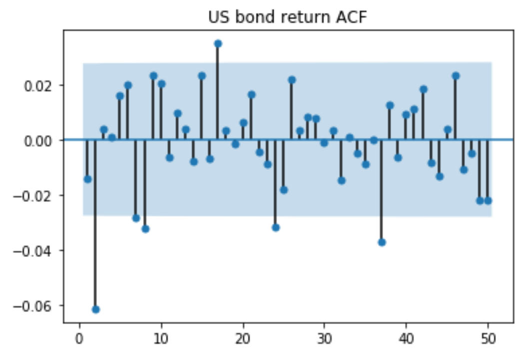
(a) US stock returns ACF plot



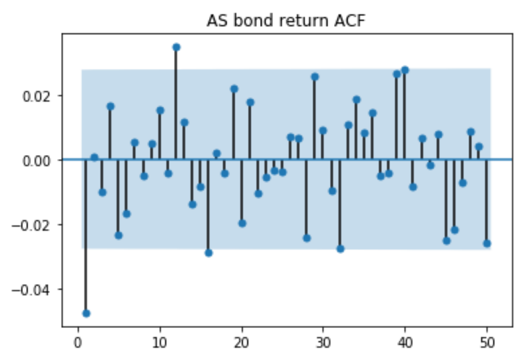
(b) Asian stock returns ACF plot



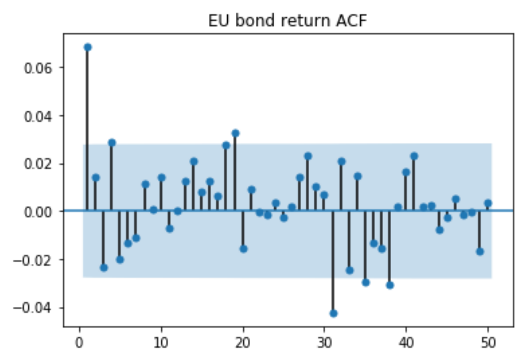
(c) Euro stock returns ACF plot



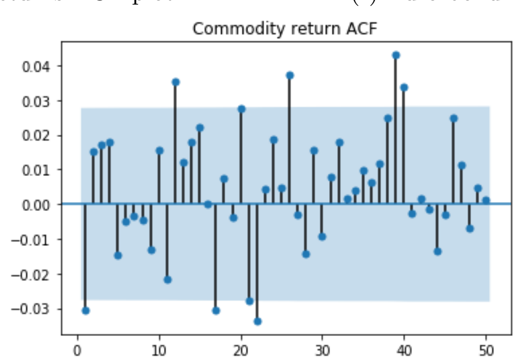
(d) US bond returns ACF plot



(e) Asian bond returns ACF plot



(f) Euro bond returns ACF plot



(g) Commodity returns ACF plot

Figure 1: Autocorrelation plots of stocks, bonds and commodities for Europe, Asia and the US.

3 Methodology

3.1 Estimating correlations

To estimate correlations, the Implied Correlation Index (ICI) is used. The ICI, as used by Echaust & Just (2020), is a time-varying measure of correlation between assets in a given portfolio. The ICI is used because it is a relatively simple but consistent and effective measure of market dependencies. The ICI is derived from the portfolio variance formula, which is shown in equation (1):

$$\sigma_{p,t}^2 = \sum_{i=1}^{n}(w_i\sigma_{i,t})^2 \; + 2\rho_t \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} w_i\sigma_{i,t}w_j\sigma_{j,t} \tag{2}$$

Where $\sigma_{p,t}$ denotes the portfolio variance at time t, w_i denotes the weight of the portfolio invested in asset$_i$, and $\sigma_{i,t}$ denotes the volatility of asset$_i$ conditional on time t. This equation can be written in terms of ρ_t, denoting the correlation between assets at time t. When written in terms of ρ_t, the equation looks like the following:

$$\text{ICI} = \rho_t = \frac{\sigma_{p,t}^2 - \sum_{i=1}^{n}(w_i\sigma_{i,t})^2}{2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} w_i\sigma_{i,t}w_j\sigma_{j,t}} \tag{3}$$

This paper will focus itself on bivariate portfolios, so that correlations between pairs can be analyzed separately. From all the series, 21 pairs are made and analyzed separately. Furthermore, the assets in the bivariate portfolios are equally weighted. The portfolio return is calculated as the following:

$$y_{p,t} = \sum_{i=1}^{n} w_i y_{i,t} \tag{4}$$

where the $w_i = 0.5 \; \forall$ asset$_i$ and $t = 1, 2, ...,$.

3.2 Estimating volatilities using GARCH-models

In order to calculate ρ_t, estimations of $\sigma_{i,t}$ and $\sigma_{p,t}$ need to be made. The model used to make these estimations is a General Auto-Regressive Heteroskedasticity (GARCH) model, introduced by Bollerslev (1986). An extension of the ARCH model, it adds the previous observations conditional variance into the equation, since conditional variance usually has high autocorrelation.
A GARCH-type model consists of two parts, the mean equation and the volatility equation. The mean equation, in this case, models the returns of an asset, and is in this paper assumed to be an AR(0) without constant:

$$y_t = \epsilon_t \text{where } \epsilon \sim skewed\ student - t \tag{5}$$

The reason an AR(0) without constant can be used is that the mean daily return is not significantly away from zero. The reason we select an AR(0) instead of a higher order AR model is because returns do not exhibit significant auto-correlation. Because of the log-returns mathematical symmetry, returns can be treated as 'innovations', denoted as ϵ_t, that shock the system, and thereby shock conditional volatility. We assume that ϵ_t is skewed student-t distributed. This is necessary because the returns are differently distributed than a normal distribution is a couple of key moments.

Returns typically exhibit a leptokurtic distribution, meaning that the tails of the distribution are fat. This is important to take into account because it means that σ^2 alone is not sufficient to model the impact of shocks in return volatility. We need another parameter, ν, that can model the fat tails that return distribution exhibit. In a student-t distribution that has fat tails, large shocks do not affect the volatility as much a normal distribution, since the shocks are more 'expected'. The second moment in which returns differ from the normal distribution is in its symmetry. This potential skewness needs to be taken into account, since this can affect the way negative shocks affect volatility compared to positive shocks. There are more large negative shocks than large positive shocks in returns. To achieve this, we use the parameter λ, a skewness parameter.

The volatility equation of a standard GARCH model is shown in equation (4).

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

This model does require some impositions to ensure σ_t^2 does not become negative. These restrictions are $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$. $\alpha\epsilon_{t-1}$ is the 'news' term. A large shock in the returns causes a shock in volatility of the asset. This is where the GARCH-type model outperforms the EWMA or other simpler volatility models, since it can adapt to new volatility regimes quickly. This is important, since the conditional volatility of returns are usually clustered together, especially in times of crises. This standard GARCH model can not take asymmetry into account, which is why a GJR-GARCH model is used to estimate σ_t. The GJR-GARCH model, introduced by Glosten, Jagannathan and Runkle (1993), is an extension of the standard GARCH model. Its volatility equation is given in equation (5).

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma D_{t-1}\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

Where ω is the constant, $\alpha\epsilon_{t-1}^2$ is the news term, $D_{t-1} = 1$ for $\epsilon_{t-1} < 0$, $D_{t-1} = 0$ for $\epsilon_{t-1} \geq 0$, and $\beta\sigma_{t-1}^2$ is the auto-regressive term. The way this model can seperate the effect of a negative shock versus a positive shock in returns is with the dummy variable D_t. When $\epsilon_{t-1} < 0$, the effect on the conditional volatility is $\alpha + \gamma$, while when $\epsilon \geq 0$, the effect is α.
Since we want to estimate σ_i, and not forecast it, we fit the GJR-GARCH model over the entire sample. Normally, this would cause overfitting, but since no forecasts are made this will not be a problem.

3.3 Comparing correlations

Once the correlations are estimated, they are compared. The returns, and their matching estimated volatilities and correlations are split into three parts. The three parts consist of the lowest 5% of returns, the 5% returns around the mean, and the 5% higher returns. This is done so the behaviour of correlations can be investigated for crises, booms and 'normal' times.

The estimated correlations are compared using the Wilcoxon rank-sum test. It tests the following hypothesis: H0: $\mathbf{A} = \mathbf{B}$, versus the alternative Ha: $\mathbf{A} \neq \mathbf{B}$. This test is done by combining, and then sorting both series of correlations. Every observation is then given a rank. The ranks are then summed for both series separately. From the difference of these two sums a p-value is then calculated to show whether or not that one of the series is significantly different than the other.

3.4 Testing for volatility contagion through time

The estimated correlations, and their corresponding volatilities are also split into different time periods. This is done in order to be able to assess whether or not estimated relationship between volatility and correlation changes over time.

In order to test whether or not volatility contagion becomes more prominent over time, the following regression model is fitted to the data:

$$\rho_{it} = \beta_{1,it}\sigma_{i1,t} + \alpha_i + \eta_t + \epsilon_{it} \tag{8}$$

Where ρ_{it} denotes the ICI for pair i at time t, α_i is the fixed-in-time constant for pair i. $\beta_{1,it}\sigma_{i1,t}$ is the term that measures the effect that the volatility of the first asset in pair i has on ρ_{it}, and η_t is the time varying effect on volatility. $t = 1, ..., 21$ represent different time periods in the sample, which is split in years. The reason the volatility of the second asset in the pair is not included is because there is multicollinearity between the two volatilities when $\rho_{i,t}$ is high.
After the panel data model is fitted, the coefficients within η_t are regressed on their index, meaning a range from 1 to 21. The idea is to find some form of upward tendency throughout these coefficients, meaning that correlations do in fact increase throughout time.

4 Results

4.1 Implied Correlation Index estimates

The estimated ICI's for all pairs and return quantiles are shown in table 2 below. One can see that the ICI seems to underestimate correlations. One reason for this could be that correlation between different indices are estimated. When all indices are well diversified, they should not show a severe reaction to a return shock. Biases of the ICI estimator were also discussed by Echaust & Just (2020), where their ρ estimates failed to meet the basic correlation scaling: $|\rho| \leq 1$. According to them however, the ICI is still a good proxy for the dependency structure of a portfolio, meaning we can still interpret the changes in correlations given different return quantiles.

One can see that most of the correlations follow the same pattern given the low, middle, or high returns. The absolute value of the correlations is the highest for the low returns, followed by the high returns, and followed lastly by the mid returns. The stock indices are positively correlated. The bonds of the US and the EU are positively correlated as well, but the Asia and US bonds are not positively correlated. The commodity index is estimated to be positively correlated with all stock indices and the Asian bond index, and negatively correlated with the US and EU bonds. These estimates coincide with the flight-to-quality principle, as discussed by Baur & Lucey (2006). However, Asian bonds do not show this principle. An explanation could be that international investors do not view Asian-Pacific bonds as a safe-haven in a crisis, but more as an emerging market, which is more risky and therefore not desirable to own in economic turmoil.

4.2 Rank-sum tests results

These estimated ICI's for the different return quantiles were then rank-sum tested. The results of the Wilcoxon rank-sum tests are shown in table 3. It can be seen that most differences in correlations between low and middle return quantiles are significant. This means that correlations do increase whenever negative shocks occur in returns.
There are also some non-significant tests in certain pairs. Correlation between Asian stocks and US bonds do not increase given large negative return observations, but their correlation do increase given large positive returns. Asian stocks and European bonds show no evidence of volatility contagion as well. One thing to note is that commodities show evidence of volatility contagion given low returns. However, there seems to be no volatility contagion between European assets and commodities given high returns. Another thing to note is that correlations given low returns are higher than correlations given high returns. This asymmetry makes sense given the return distribution. The fact that large negative shocks in returns shock volatility more upwards than large positive shocks is called the leverage effect.

Pair	Low return ICI	Mid return ICI	High return ICI
stocks US & stocks AS	0.056	0.034	0.051
stocks US & stocks EU	0.125	0.082	0.112
stocks US & bonds US	-0.046	0.035	-0.042
stocks US & bonds AS	0.003	0.012	0.007
stocks US & bonds EU	-0.020	-0.001	-0.015
stocks US & commodities	0.071	0.049	0.082
stocks AS & stocks EU	0.116	0.063	0.097
stocks AS & bonds US	-0.013	-0.015	-0.010
stocks AS & bonds AS	0.010	0.004	0.006
stocks AS & bonds EU	-0.002	-0.004	-0.002
stocks AS & commodities	0.071	0.033	0.054
stocks EU & bonds US	-0.020	-0.006	-0.015
stocks EU & bonds AS	0.012	0.005	0.007
stocks EU & bonds EU	-0.006	-0.001	-0.006
stocks EU & commodities	0.104	0.073	0.117
bonds US & bonds AS	-0.004	-0.023	-0.005
bonds US & bonds EU	0.115	0.112	0.129
bonds US & commodities	-0.007	-0.003	-0.004
bonds AS & bonds EU	0.045	-0.002	0.031
bonds AS & commodities	0.012	0.007	0.011
bonds EU & commodities	-0.007	-0.002	-0.004

Table 2: The average of the estimated ICI's for different return quantiles, where low return is the lowest 5% of returns, mid is the 5% returns around the mean, and high is the 5% highest returns. US, AS, and EU stand for United States, Asia, and Europe respectively.

Pair	Low vs Mid	Low vs High	Mid vs High
stocks US & stocks AS	4.83***	0.84	-4.18***
	[0.000]	[0.403]	[0.000]
stocks US & stocks EU	10.40***	3.29**	-7.10***
	[0.000]	[0.001]	[0.000]
stocks US & bonds US	-3.88***	-2.32*	1.83'
	[0.000]	[0.020]	[0.067]
stocks us & bonds AS	-5.80***	-2.48*	3.300**
	[0.000]	[0.013]	[0.001]
stocks US & bonds EU	-7.51***	-2.73**	5.13***
	[0.000]	[0.006]	[0.000]
stocks US & commodities	3.02**	-1.73'	-5.028***
	[0.002]	[0.084]	[0.000]
stocks AS & stocks EU	11.33***	4.42***	-7.33***
	[0.000]	[0.000]	[0.000]
stocks AS & bonds US	1.37	-1.93'	-3.36**
	[0.169]	[0.053]	[0.001]
stocks AS & bonds AS	4.35***	3.04**	-1.60
	[0.000]	[0.002]	[0.109]
stocks AS & bonds EU	0.14	0.96	-1.11
	[0.887]	[0.339]	[0.267]
stocks AS & commodities	8.26***	3.55***	-5.79***
	[0.000]	[0.000]	[0.000]
stocks EU & bonds US	-7.10***	-3.02**	4.62***
	[0.000]	[0.002]	[0.000]
stocks EU & bonds AS	5.17***	4.14***	-1.35
	[0.000]	[0.000]	[0.176]
stocks EU & bonds EU	-4.089***	-0.056	4.585***
	[0.000]	[0.955]	[0.000]
stocks EU & commodities	6.11***	-2.45*	-8.51***
	[0.000]	[0.014]	[0.000]
bonds US & bonds AS	5.06***	0.54	-4.71***
	[0.000]	[0.588]	[0.000]
bonds US & bonds EU	1.72'	-5.41***	-6.41***
	[0.085]	[0.000]	[0.000]
bonds US & commodities	-2.86**	-2.43*	0.75
	[0.004]	[0.015]	[0.450]
bonds AS & bonds EU	9.19***	2.77**	-6.96***
	[0.000]	[0.005]	[0.000]
bonds AS & commodities	3.82***	1.83'	-1.97*
	[0.000]	[0.067]	[0.049]
bonds EU & commodities	-2.86**	-2.43*	0.75
	[0.004]	[0.015]	[0.450]

Table 3: Results of the Wilcoxon rank-sum tests for low return correlations, mid return correlations, and high return correlations. Shown are the test-statistic, and the corresponding [p-values]. '$p<0.10$, *$p<0.05$, **$p<0.01$, ***$p<0.001$

4.3 Panel data model results

	Dependent variable:
	$\rho_{i,t}$
$\sigma_{i,t}$	7.243^{***}
	(0.380)
Pair-specific effects included:	Yes
Time-varying effects included:	Yes
Observations	105,252
R^2	0.615
Adjusted R^2	0.615
Residual Std. Error	0.036 (df = 105210)
F Statistic	$4{,}001.909^{***}$ (df = 42; 105210)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Panel data model estimation results, and (standard errors). Pair-specific and time-varying effects were omitted for size. $\rho_{i,t}$ denotes the ICI estimate and $\sigma_{i,t}$ denotes the estimated volatility.

In table 4 one can see the estimated effect of the first-in-the-pair's volatility, $\sigma_{i1,t}$, on the ICI of the pair, $\rho_{i,t}$. This model takes fixed-in-time pair-specific and time-varying random effects into account. These coefficients were omitted from the regression table for size, as there are 42 total coefficients. One for the independent variable $\sigma_{i1,t}$, 20 for the years in the dataset, 2000 to 2020, and 21 for each pair. One can see that the estimated effect of volatility on correlation is positive, and highly significant. The R^2 is 0.615, meaning that about 60% of variation in correlations are explained by variation in volatility of an asset. This fact has negative implications for diversifying portfolios, as there is evidence that correlations do increase in crisis times.

In table 5, one can see summary statistics for the pair-specific and time-varying effects. In this table one can see that pair-specific characteristics have a larger effect on correlations than year-specific characteristics. Time-varying effects deviate less compared to their mean than pair-specific effects do.

	N	Mean	s.e.	Min	Max
Pair-specific effects	20	0.011	0.042	-0.048	0.109
Time-varying effects	21	0.009	0.007	-0.003	0.022

Table 5: Summary statistics of pair-specific and time-varying effects. The statistics shown are the amount of coefficients, their mean, standard deviation, minimum and maximum.

Shown in figure 2 are the time-varying coefficients associated with each year. One can see that except for 2008, there seems to be an upward trend. This raises some questions, as one would expect to see higher correlations in years with more economic turmoil. However, crises make correlations more extreme according to the rank-sum test results, so perhaps the bigger increase in absolute value for negative correlations as apposed to positive correlations brings the 'baseline' for that year closer to zero. Another explanation could be that the variance of that years correlations are explained by volatility, of which there is a big increase in 2008, and pair-specific effects alone, leaving the 'baseline' for 2008 closer to zero. A regression was done to confirm whether or not the estimated coefficients

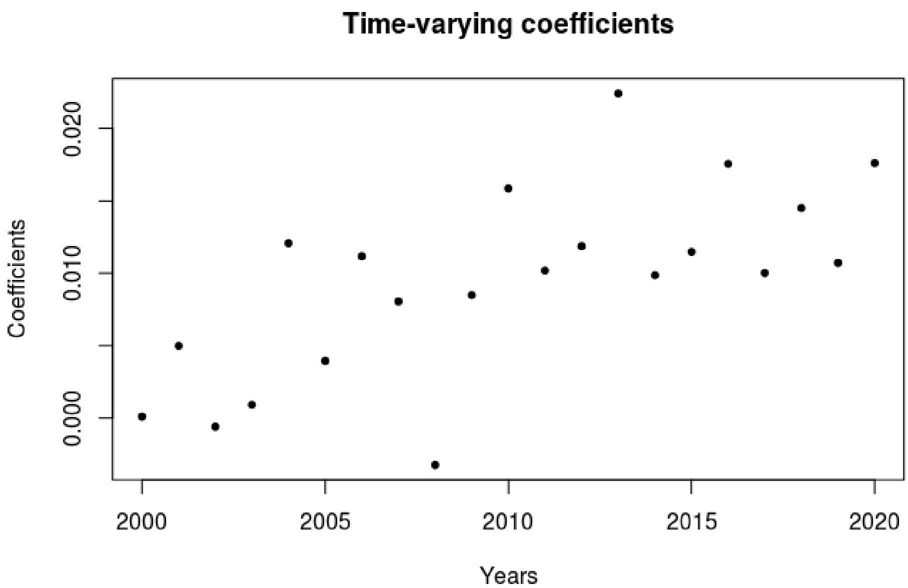


Figure 2: Scatter plot of time-varying effects trough out the data-set.

indeed show a significant upward relation with time. Results of this regression are shown in table 6. This table shows the linear upward trend to be significant. This means that there is statistical evidence that shows that correlations are indeed upward trending trough out time. One thing to note is that the R^2 is 0.457, which means that the time index explains a little less than half of the variation in the time-varying coefficients.

	Dependent variable:
	η_t
Index	0.001***
	(0.0002)
Constant	0.002
	(0.002)
Observations	21
R^2	0.457
Adjusted R^2	0.428
Residual Std. Error	0.005 (df = 19)
F Statistic	15.982*** (df = 1; 19)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression of η_t's on their index (column vector of numbers 1 through 21).

5 Conclusions

Looking at the results of the rank sum tests of the ICI's, certain implications for portfolio management can be concluded. When an investor holds one asset class only, a significant increase in correlations can be seen when crises occur. This holds some implications for risk management. Estimated simple correlations do not give an accurate view of correlations in crisis times, such that risk is underestimated. This is especially true for stocks, as diversifying a stock portfolio might not be enough to fully mitigate price risk. The best way to diversify risk according to the rank sum results would be to invest into multiple asset classes, especially since a significant increase in negativeness of the correlations between stocks and bonds can be observed over the last 20 years.

Using these results, it can be concluded that the Corona virus crash holds significant effects on the absolute values of correlations, confirming hypothesis 1a. This can be due to the fact that the Corona virus is a worldwide phenomenon, affecting economies internationally. The Corona virus affects markets through volatility contagion, but also directly, as the Corona has direct effects on economies worldwide, limiting trade and production. Furthermore, negative shocks in market prices show a higher increase in correlations than positive shocks, confirming hypothesis 1b, which states that correlations are higher surrounding negative shocks than positive shocks. This reinforces the conclusion that the Corona virus has a drastic effects on market correlations, since it caused large market crashes and rising correlations between equity and commodities.

Looking at the results from the panel data model, and subsequently the regression of η_t's on their index, a significant increase in correlations over time can be seen. This is likely due to increased globalisation. When a country's economy becomes is partially dependent on another, crashes in one economy will have a significantly bigger effect on the other than if the economies were not mutually dependent. Increased international trading and capital flows increases this dependency, and therefore increases risk of volatility contagion.

Based on the conclusions in the previous paragraph, it can be said that the Corona virus crisis has a significantly higher effect on market correlations than previous crises, thereby confirming hypothesis 2. As stated earlier, this is likely due to increased globalisation and the fact that the Corona virus is present across the globe. The data during the period of the Corona virus crash end at the beginning of May 2020. This means that at the time of writing this thesis, the Corona-crisis has not come to an end as of yet. Apart from causing more pain and suffering, the financial and economic upheaval continues. As a consequence, we cannot extrapolate the initial results of this particular period, nor can all the the results be treated as foregone conclusions.

5.1 Discussion and further research

This research does have some limitations. For instance, indices are used. Perhaps it would be better to use individual stocks of sector indices as data, so that effects on certain sectors of the economy can be analyzed separately. Another note can be made concerning the use of indices, which is that the amount of components in the different indices are heterogeneous. Perhaps, if an index has more components it is inherently more diversified, and therefore less sensitive to volatility contagion.

The second limitation is the fact that only contemporaneous correlations are considered. A recommendation for future research would be to include lagged correlations or lagged volatility estimates in the panel data model, since it is known that quotes decrease structurally over time after crashes.

Another point of discussion is that the panel data model presented in this paper is somewhat limited.

Assuming non-linear dependency in correlations, perhaps other variables aside from volatility can explain part of the variance in the correlations. This can remove potential bias in the panel data estimator, and perhaps in the time-varying effects estimations as well. This would give a clearer picture of these time-varying effects.

A recommendation for future research would be to include more data. Data was taken up until the 30th of April, 2020. The pandemic does however show effects on the economy after this date. To get the full picture of the effects of the Corona virus crisis on market correlations, more data should be included in further studies.

References

Abanomey, W. S., & Mathur, I. (2001). International portfolios with commodity futures and currency forward contracts [Publisher: Institutional Investor Journals Umbrella Section: Primary Article]. *The Journal of Investing*, *10*(3), 61–68. https://doi.org/10.3905/joi.2001.319474

Ahmadu-Bello, J., & Rodgers, T. (2016, January 1). Chapter 6 - financial contagion from US to african frontier markets during the 2007–09 global financial crisis (P. Andrikopoulos, G. N. Gregoriou, & V. Kallinterakis, Eds.). In P. Andrikopoulos, G. N. Gregoriou, & V. Kallinterakis (Eds.), *Handbook of frontier markets*. Academic Press. https://doi.org/10.1016/B978-0-12-803776-8.00006-9

Aloui, C., Nguyen, D. K., & Njeh, H. (2012). Assessing the impacts of oil price fluctuations on stock returns in emerging markets. *Economic Modelling*, *29*(6), 2686–2695. https://doi.org/10.1016/j.econmod.2012.08.010

Anson, M. J. P. (1999). Maximizing utility with commodity futures diversification [Publisher: Institutional Investor Journals Umbrella Section: Primary Article]. *The Journal of Portfolio Management*, *25*(4), 86–94. https://doi.org/10.3905/jpm.1999.319753

Baur, D., Lucey, B. M., Baur, D., Lucey, B., & Lucey, B. M. (2006). *Flight-to-quality or contagion? an empirical analysis of stock-bond correlations.*

Becker, K. G., & Finnerty, J. E. (2000, October 21). *Indexed commodity futures and the risk and return of institutional portfolios* (SSRN Scholarly Paper ID 5499). Social Science Research Network. Rochester, NY. Retrieved April 30, 2020, from https://papers.ssrn.com/abstract=5499

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bunda, I., Hamann, A. J., & Lall, S. (2009). Correlations in emerging market bonds: The role of local and global factors. *Emerging Markets Review*, *10*(2), 67–96. https://doi.org/10.1016/j.ememar.2009.02.003

Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from asian markets. *Journal of International Money and Finance*, *26*(7), 1206–1228. https://doi.org/10.1016/j.jimonfin.2007.06.005

Dungey, M., McKibbin, R., González-Hermosillo, B., & Martin, V. L. (2002). The transmission of contagion in developed and developing international bond markets.

Echaust, K., & Just, M. (2020). Implied correlation index: An application to economic sectors of commodity futures and stock markets. *Engineering Economics*, *31*. https://doi.org/10.5755/j01.ee.31.1.22247

Georgiev, G. (2001). Benefits of commodity investment [Publisher: Institutional Investor Journals Umbrella Section: Primary Article]. *The Journal of Alternative Investments*, *4*(1), 40–48. https://doi.org/10.3905/jai.2001.318997

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks [Publisher: American Finance Association]. *Journal of Finance*, *48*(5), 1779–1801. Retrieved May 5, 2020, from https://econpapers.repec.org/article/blajfinan/v_3a48_3ay_3a1993_3ai_3a5_3ap_3a1779-1801.htm

Jensen, G. R., Johnson, R. R., & Mercer, J. M. (2000). Efficient use of commodity futures in diversified portfolios [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/%28SICI%291096-9934%28200005%2920%3A5%3C489%3A%3AAID-FUT5%3E3.0.CO%3B2-A]. *Journal of Futures Markets*, *20*(5), 489–506. https://doi.org/10.1002/(SICI)1096-9934(200005)20:5⟨489::AID-FUT5⟩3.0.CO;2-A

Jin, X., Xiaowen Lin, S., & Tamvakis, M. (2012). Volatility transmission and volatility impulse response functions in crude oil markets. *Energy Economics*, *34*(6), 2125–2134. https://doi.org/10.1016/j.eneco.2012.03.003

Kaplan, P. D., & Lummer, S. L. (1998). Update: GSCI collateralized futures as a hedging and diversification tool for institutional portfolios [Publisher: Institutional Investor Journals Umbrella Section: Primary Article]. *The Journal of Investing*, *7*(4), 11–17. https://doi.org/10.3905/joi.1998.408472

Laloux, L., Cizeau, P., Potters, M., & Bouchaud, J.-P. (2000). Random matrix theory and financial correlations [Publisher: World Scientific Publishing Co.]. *International Journal of Theoretical and Applied Finance*, *03*(3), 391–397. https://doi.org/10.1142/S0219024900000255

Leibowitz, M. L., & Henrikssan, R. D. (1988). Portfolio optimization within a surplus framework [Publisher: Taylor & Francis Ltd]. *Financial Analysts Journal*, *44*(2), 43. https://doi.org/10.2469/faj.v44.n2.43

Lessard, D. R. (1973). International portfolio diversification: A multivariate analysis for a group of latin american countries [Publisher: [American Finance Association, Wiley]]. *The Journal of Finance*, *28*(3), 619–633. https://doi.org/10.2307/2978634

Markowitz, H. (1952). Portfolio selection [Publisher: [American Finance Association, Wiley]]. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.2307/2975974

Sandoval, L., & Franca, I. D. P. (2012). Correlation of financial markets in times of crisis. *Physica A: Statistical Mechanics and its Applications*, *391*(1), 187–208. https://doi.org/10.1016/j.physa.2011.07.023

Steeley, J. M. (2006). Volatility transmission between stock and bond markets. *Journal of International Financial Markets, Institutions and Money*, *16*(1), 71–86. https://doi.org/10.1016/j.intfin.2005.01.001

Zanalda, G. (2015, January 1). Financial crises, history of (J. D. Wright, Ed.). In J. D. Wright (Ed.), *International encyclopedia of the social & behavioral sciences (second edition)*. Oxford, Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.71074-9