Financial markets turbulence during highly anxious times

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Abstract

Financial turbulences are a common phenomenon that have multiple times taken place and affected the global economy during the last decades. The spillover effects from different sectors of the economy into the real economy have caused it to crash numerous times along the years, effectively creating financial crises. This thesis adds to the extensive literature and research focusing on the effects of the financial markets during anxious times, a case that has troubled researchers for a long time. Utilizing the GARCH and VAR models methodologies, a thorough analysis of 4 indices takes place: Belgium's BEL20, Hong Kong's HSI, Mexico's MXX and finally USA's NASDAQ. This analysis focuses on 4 periods in total, starting from 2005 to 2007, regarding the pre 2008 Subprime Mortgage Crisis, as well as 2008 to 2009 covering the effects of said crisis. Furthermore, the period before the latest global health crisis – Covid – 19 – is also monitored, for the 2 years 2018 and 2019, while the last period covers the virus outbreak for 2020 and 2021. A brief analysis of other significant crises takes place, explained briefly by Random Matrix Theory. The overall results for the 4 indices show that indeed financial markets tend to move together during financial hardships, while volatility and risk increases.

Keywords: Financial turbulence, Subprime Mortgage Crisis, Covid – 19, Financial markets, VAR, GARCH

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Chapter 1

Introduction

The world's economy has come under numerous hardships in the last decades, following many events that eventually shaped some of the sincerest economic crises. Some nations affected by financial turbulences had had a level of success in reforming the economy and thus evading complete economic ruination, however, the years of crucial financial crises are what is mostly remembered. The financial crisis that commenced in 2007 is one of the most devastating turbulences that occurred since the Great Depression, beginning in the United States and rapidly spreading throughout the globe, directly affecting the international financial markets and subsequently the world's economy. Moreover, the second most severe turbulence that has taken place since 2008 is the recent stock market crashes that were caused by the Covid – 19 pandemic. However, looking at the financial markets' movement in the last decades, it is clear that they have been affected in many more situations, with the earliest examined occurrence being the Black Monday in 1987. More occasions that will be briefly examined later are namely a part of the Asian crisis that took place in 1997, the Russian crisis one year later in 1998, the after effects of September 11 terrorist attack in the United States in 2001 combined with the burst of the dot – com bubble and, of course, the most severe aforementioned turbulence, the Subprime Mortgage Crisis in 2008 and the latest Covid – 19 crisis.

Financial globalization has grown rapidly over the last decades, assisting in the elimination of the financial flow barriers between countries, but also providing the possibility of imbalance and destabilization of some financial markets. Through financial globalization, uncertainty can be easily transmitted from one financial market to others, aiding eventually the rapid spread of a financial turbulence throughout the international markets. Thus, it has been observed that during global financial turbulences, financial markets tend to crash simultaneously, revealing a propagation of volatility from one to another. As it will be examined later for the aforementioned anxious times, during such times there is a clear co – movement of the average volatility and average correlation of the markets, sloping upwards. This increasing correlation leads to spillover effects from the financial markets sector into the real economy sector, forming the large scale financial crises that ultimately lead to unemployment, decreasing profitability, inflation and bankruptcies.

As mentioned before, in the next chapters the aforementioned highly anxious times will be briefly examined so as to better understand the connections and correlations between the international financial markets during times of high volatility. Adding to those occasions, the analysis will focus specifically on the Subprime Mortgage Crisis and the Covid – 19 after effects in the financial markets primarily. The data gathered are for the following financial indices: BEL20 (Belgium), HANGSENG (Hong Kong), MXX (Mexico) and NASDAQ (USA), for four periods in total. The first examination ranges from 2005 to late 2007 and 2008 to late 2009 for the Subprime Mortgage Crisis. The second period regarding the Covid – 19 influence on the financial markets splits between 2 periods again with the first being from 2018 to late 2019 and the second one from 2020 to the end of 2021. The objective is to study the financial influence that both crises had on the international markets, both for the periods pre – crises, as well as for the duration. In order to do that, it is essential to create a TGARCH model in order to examine the level of effect each crisis had on each index during these periods. Furthermore, a Vector Autoregression (VAR) model will be established to examine if there is correlation between those 4 indices during both periods again. The methodology of VAR and TGARCH models, as well as the exact procedure that will take place will be thoroughly explained in the next chapters. Moreover, a literature review will be provided, that will be followed by the methodology and the data examinations, while the results and conclusion will be presented in the final chapters.

Chapter 2

Literature Review

There has been extensive research covering the topic of financial turbulences and the way they affect the international markets, as well as the reasons of transmission. Economists have focused on the reasons that lead financial markets to crash and why there is a propagation of increased volatility from one market to another, during anxious times. The incident of the Black Monday in 1987 was the starting point for many studies to examine the contagion of volatility between financial markets. Also, these studies, using econometric models, have focused on the similar movement or co – movement of the markets, along with the rising correlation in high volatility times.
However, it is a concerning issue that is still the target of ongoing researches, since the last two years the economy has been affected by the Covid – 19 pandemic. The literature used in this thesis consists of two parts. The first part focuses on the Subprime Mortgage Crisis that started in the United States, a multinational financial crisis that eventually assisted to the global financial crisis that started between 2007 and 2008. Being the result of the collapse of the housing bubble, it was triggered by the deteriorating quality of US subprime mortgages.

Frank & Hesse (2009) discuss the financial spillovers that the global financial crisis, created by the burst of the housing bubble, presented on the Emerging Markets. Employing a multivariate GARCH model, they aim to estimate and analyze potential financial linkages between advanced economies and emerging markets, as well as the extent of the co – movements of the individual financial markets. Frank & Hesse (2009) find that market volatility and default risk that can be observed in major financial institutions of major advanced economies can be linked to some specific emerging economies, regarding the stock markets, Credit Default Swap (CDS) indices and bond spreads. This paper uses a Dynamic Conditional Correlation (DCC) GARCH model created by Engle (2002) in order to avoid biased standard correlations, a result that may potentially occur in the examination of spillovers. The DCC GARCH model allows for the analysis of the co – movement of the markets. The results given by the model present that the correlations between the US London Interbank Offered Rate (LIBOR) and the Overnight Indexed Swap (OIS), along with the Emerging Markets Bond Index (EMBI) sovereign bond spreads of some countries of Europe, Asia and Latin America, show a dramatic increase after the mortgage crisis commenced.

However, the event that saw the correlations reach their peak was the collapse of the Lehman Brothers financial firm. After this institution's bankruptcy, the correlations of the aforementioned indices spiked. Frank & Hesse (2009) suggest that during this specific financial crisis the financial markets of advanced economies and emerging markets remain correlated, though the correlations tend to peak during specific events, like the Lehman Brothers collapse. Since global financial markets are interconnected, turbulences in advanced economies' markets may lead investors to pull their investments out of the emerging markets, responding to the increased risk aversion. Their findings include results from Mexico, South Africa, Brazil, Russia and Turkey and they conclude that there is a similar co – movement during the US mortgage crisis, proving their interconnection. However, these findings also suggest that co – movements are much more evident in markets close to the turbulence source. For example, Mexico shows a more pronounced co – movement of its financial variables with the United States, than Russia or South Africa, since it is very close to the United States and thus, affected in a higher level.

Mollah et al. (2014) contribute to this research by providing empirical insights on the phenomenon called contagion. As with the case of Frank & Hesse (2009), this paper also uses a DCC GARCH model and a Vector Error Correction (VEC) model in order to examine the multi- dimensional phenomena that create the contagion in the financial markets during the economic crisis of 2008. As this paper mentions, the collapse of the Lehman Brothers along with the takeover of Merrill Lynch investment management firm from the Bank of America and the rescue of American International Group (AIG) insurance company, were the start of the imminent crisis that was about to spread. Eventually, the 2008 financial crisis lead to immense deficits and national debts throughout the globe. Many emerging markets including Iceland, Latvia, Hungary, Ukraine and Greece requested emergency assistance from the International Monetary Fund (IMF). It was now clear that the spread from the collapse of the housing market had undoubtedly affected the entire real sector economy.

Mollah et al. (2014) employ multi – approach econometric techniques to examine the contagion. First of all, they use a model by Engle and Sheppard (2001) in order to better determine the type of correlation between financial indices. The type of correlation in question is either the Dynamic Conditional Correlation (DCC) or the Constant Conditional Correlation (CCC). Moreover, the DCC GARCH model that is used again is able to analyze the dynamic correlation between world markets indices. Finally, Principal Component Analysis (PCA) provides results in the examination of the contagion at a regional degree and the Vector Error Correlation (VEC) model provides the ability to test for Granger causality, along with the Impulse Response Function (IRF).

Using daily data from January 2006 to December 2010, Mollah et al. (2014) target the source of the crisis, which is believed to be the period between September 2008 to December 2009. Obtaining a total of 64 indices, they observe that the individual international financial markets are clearly affected by the returns provided by the United States, with the latter being highly significant. Furthermore, they show a clear a clear rise in correlation between global and US markets in this specific time period. Within the aforementioned Vector Error Correlation (VEC) framework, the Impulse Response Function (IRF) provides a clear reflection of the countries (Switzerland, United Kingdom, France, Germany, Austria etc.) tested, regarding their impulse response. The result is an immediate response of the countries to a standard deviation shock of the United States, confirming the contagion from the United States to the smaller markets. However, Sweden was found to be the only country that adopted exceptionally efficient measures to counter the financial crisis.

Luchtenberg & Vu (2014) make their contribution to the literature by investigating the contagion determinants of the 2008 financial crisis, proving that there is bi – directional causality in the contagion. This means that the United States, being the source of the transmission, not only transmits the contagion to the more mature and emerging markets, but also receives from them. Economic fundamentals such as interest and inflation rates, industrial production and risk aversion from the investors, eventually contribute to this propagation. Previous literature has specific findings that do not particularly find contagion during crisis. For example, Forbes and Rigobon (2002) found that increased volatility is the cause for extensive co – movement of the markets, while studying the 1997 East Asian Crisis and the 1987 Stock Market Crash of the United States. However, the contagion effect is greatly limited after controlling for the increased volatility. The financial crisis that started in 2008, though, was on a different scale than the previous crises. Luchtenberg & Vu (2014) make use of the definition for contagion given by Forbes and Rigobon (2002), thus testing if the correlations of cross – markets present a significant increase after controlling for the high volatility. If this is the case, then contagion can be accepted. The 10 most significant international financial markets from Europe, North America and East Asia are used as data to conduct the tests. More specifically, this research includes indices from the United States and Canada for the North American category, Germany, United Kingdom and Spain for the European category and finally Japan, China, Hong Kong, India and Australia for the East Asian category. As the previous papers did, Luchtenberg & Vu (2014) also test for causal relations between cross – markets with Granger causality tests, while the tests for contagion are implemented by an Asymmetric GARCH model proposed by Glosten et al. (1993). After following the standard procedure to try for stationarity, simple VAR models allow for Granger causality and cointegration tests. The results point to significant cointegration among the three regional groups, while the Granger causality test shows that the United States had the most influence among the other markets. This result can be estimated since for the period before the 2008 financial crisis, inserting shocks in the United States stock market provides the ability to predict the next period returns of all the other markets. However, this influence seems to diminish during the period of crisis, regarding the developed markets.

There is strong evidence that the United States, Japan and Germany are the primary sources of the shocks transmission to other countries, with the United States transmitting to all but China, Germany and Japan, but receives financial shock from the collective crisis and not by any specific country market. On the other hand, India, Hong Kong and Australia are the recipients of the highest contagion effects. Luchtenberg & Vu (2014) find that the primary reasons for shock transmissions or contagion between two countries include alterations in inflation and interest rates ratios, industrial production and exports from one country to another. This conclusion can be supported by the fact that the United States decreased their imports during the crisis period, but their exports did not show significant drop. Therefore, their influence is imminent. Capital flow has a significant role as well, since investors increase or decrease their risk aversion depending on changes of the relative market volatility.

The second part of the literature focuses on the financial turbulence that was created in the last two years from the Covid – 19 pandemic. There has been some research covering the financial turmoil created by the rise of the pandemic, the subsequent measures taken to counter it and its effects on financial markets and world's economy as a whole. However, the extent of the research is not the same as the research conducted for the 2008 financial crisis, since the consequences of Covid – 19 are a much more recent problem.

Zhang et al. (2020) focus on the economic impact of the pandemic on the financial markets, as well as the policies that governments introduce that could also potentially produce more financial uncertainties. The main issues that Zhang et al. (2020) attempt to solve concern the financial markets' reaction to the Covid – 19 outbreak, the patterns of the systemic risks and the effects of government interventions regarding policies. Conducting a volatility analysis, they come to the conclusion that there was indeed a strong influence of the pandemic on the markets, since the risk levels had a remarkable increase for all countries tested, though some sentimental factors also had assisted to this end. The dramatic change in volatility can be attributed to the rapid market sentiment change, which is certainly augmented by the trend in social media and as a result trade activities are affected, leading to destabilization of the stock markets. China presented the highest volatility during the early months of the outbreak, January to March, while the United States saw their financial market volatility skyrocket after the worldwide transmission. Moreover, a correlation analysis for 12 countries, the United States, major European and East Asian markets, indicates low correlations among them during February 2020, but they show a very substantial rise during March, when the American and European stock markets showed lack of control over this outbreak. However, different governmental policies among countries, drove the correlations into a lower level again during March 2020. Zhang et al. (2020) find a clear co – movement of the markets regionally. More specifically, US and European markets show correlation both before and after the outbreak announcement, while the East Asian markets were correlated as a group in the same time frames. This difference in correlations and the regional grouping could potentially rise from the policy interventions such as the unlimited Qualitative Easing measure that the United States introduced.

Last but not least, Wang and Enilov (2020) add to the growing literature for this topic, by discussing how the rising number of the Covid – 19 cases directly influences the international financial markets. The countries under examination are the G7 countries (United States, Canada, France, Germany, Italy, United Kingdom, Japan), because of their economic advancement and significance. Using daily stock market returns and Covid – 19 confirmed cases as variables, Wang and Enilov (2020) employ three panel unit root test, namely the LLC (Levin, Lin & Chu, 2002) the IPS (Im, Perasan & Shin, 2003) and the PP – Fisher (Maddala & Wu, 1999). In order to achieve a non – biased estimation, the data are tested for cross – sectional dependence with the CD_{BP} (Breusch & Pagan, 1980), CD_{LM} (Pesaran, 2004) and CD (Pesaran, 2004) tests. Moreover, two Granger non – causality tests are employed, the Kónya (2006) and Dumitrescu & Hurlin (2012) panel non – causality tests. Their findings suggest a clear indication of causality from the pandemic to the international stock markets. The only country for which this in not the case is Japan, which quickly adopted counter measures to limit the spread of the virus and the financial downfall. Stock movements were driven by the rising cases of the pandemic and the short – term effect on the financial markets is proven again.

Chapter 3

Modern financial crises overview

During the previous chapter's literature review, a very important topic was not covered. In this chapter, the work of Sandoval & Franca (2012) will be discussed, presenting the movements of the financial markets during the modern financial crisis. The first financial crises that here are considered as modern, are the ones that took place in the last three decades. First, it's Black Monday that took place in 1987, while the second one is the Russian Crisis that happened in 1998. The crisis that commenced in 2001 in the United States was the result of two events. The first event was the burst of the so called dot – com bubble, a stock market bubble that was created by excessive speculation of internet related companies and the second event was the terrorist attack of September 11, 2001. The aim of this work is to discover the correlations that the international financial markets have during such periods of financial disturbances. Additionally, a specific method, the Random Matrix Theory is used in this work, in order to examine and draw a conclusion regarding the correlations. It must be noted, however, that the financial disturbance caused by the Covid – 19 outbreak is not included in this overview, since it is a very recent event and it has not been covered by literature with the Random Matrix Theory yet.

In order to provide an accurate definition of a global financial crisis, Sandoval & Franca (2012) utilize the financial data of 15 international markets from across the globe, starting in 1985 and ending in 2010. The closing indices of every negotiation day give the following log – returns formula, which eases the process of comparison of indices:

$$S_t = \ln(P_t) - \ln(P_{t-1}) \approx \frac{P_t - P_{t-1}}{P_t}$$

For better understanding of the procedure through illustration, Figure 1 below, presents the log – density distribution of Dow Jones index of the New York Stock Exchange, where *log – density = ln(1 + density).*

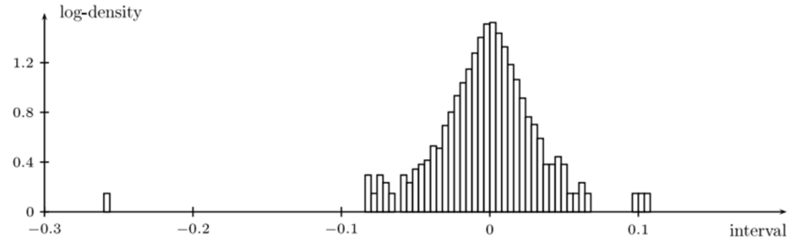


Fig. 1. Log-density distribution of the Dow Jones index of the NYSE, from 01/02/1985 to 12/31/2008.

This examination showed that the 10 most negative values of the log-returns were below −0.07, a result that is not clearly illustrated in the above Figure 1. These negative values represent the following events, for the most part: The Black Monday in 1987, a part of the Asian Crisis of 1997, the Russian Crisis in 1998, the after – effects of September 11, 2001 and finally the Subprime Mortgage Crises that started in the US in 2008.

The same procedure is also used for the following indices: Nasdaq (USA), S&P/TSX Composite (Canada), FTSE 100 (UK), DAX (Germany), ISEQ (Ireland), AEX (Netherlands), Ibovespa (Brazil), SENSEX 30 (India), Colombo All-Share (Sri Lanka), Nikkei (Japan), Hang Seng (Hong Kong), Kuala Lumpur Composite (Malaysia), Jakarta Composite (Indonesia), TAIEX (Taiwan) and finally Kospi (South Korea).

Table 1
Number of occurrences per year of major drops in fifteen diverse stock markets in the world.

Year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
Occurrences	3	0	29	2	9	13	2	4	0	0	0	1	10
Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Occurrences	11	1	4	8	1	3	4	3	0	0	50	2	0

Table 1 shows the number of financial markets that plunged during major crises. It can be observed that the major crashes happened in 1987 and 2008, during the Black Monday and the Subprime Mortgage Crisis respectively, while minor ones took place in 1989 referring to USA's saving – loan crisis, 1990 when Scandinavian banking crisis and Japanese asset price bubble happened. Black Wednesday took place in 1992, while Asian financial crisis and Russian crisis followed in 1997 and 1998 respectively. Finally, the 2001 minor crash followed after September 11 and the event of the Burst of the dot – com bubble.

Random Matrix Theory

As mentioned before, the Random Matrix Theory is used in order to calculate the correlations between financial markets in periods of crisis. A theory originally developed to calculate the distance between the energy levels of complex atomic nuclei, it supported that the distances between those energy levels should be close to the distances between the eigenvalues of a random matrix. Using this method, the relation between those energy levels could ultimately be found. In the present day, this theory can be practiced in a variety of sectors, namely quantum physics, ecology linguistics and finance, or in any sector in which seemingly unrelated information can be shown to have some sort of connection.

For this examination, a specific distribution called the Marčenku–Pastur distribution is utilized in order to analyze the data that will be presented in a later segment. Assuming a matrix L x N has random numbers deriving from a Gaussian distribution with average 0 and standard deviation σ, when L, N → ∞, then the matrix Q = L / N is finite and greater than 1 and the eigenvalues λ will follow the aforementioned distribution. This distribution is given by the formula:

$$\rho(\lambda) = \frac{Q}{2\pi\sigma^2}\frac{\sqrt{(\lambda_+ - \lambda)(\lambda - \lambda_-)}}{\lambda}$$

Where $\lambda_\pm = \sigma^2\left(1 + \frac{1}{Q} \pm 2\sqrt{\frac{1}{Q}}\right)$ and is defined by the restriction $[\lambda_-, \lambda_+]$.

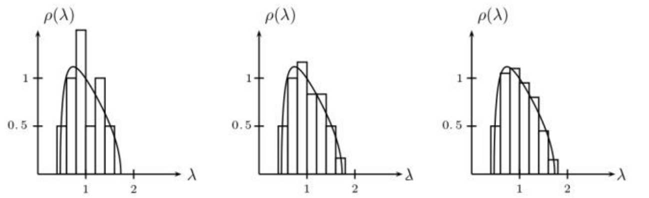


Fig. 2. Theoretical and sample finite distributions for a random matrix with $N = 10$ and $L = 100$, $N = 30$ and $L = 300$, and $N = 100$ and $L = 1000$.

As Marčenku–Pastur distribution works when L and N tend to infinity, it is expected that finite distributions will have different outcomes. Figure 2 presents a theoretical distribution where Q = 10 and σ = 1, which is compares to 3 finite correlation matrices L x N, where Q= L / M = 10. The other elements of these matrices are random numbers that have mean zero and standard deviation 1. However, it is certain that real data will present some deviation of this theoretical approach. In order to make all the series have the same average, which is zero and the same standard deviation, which equals 1, the formula $X_t = \frac{S_t - \langle S \rangle}{\sigma}$ is used where ⟨S⟩ is the average of the time series used.

The data used in the following analysis cover the years from 1980 to 2010 and, more specifically, include 23 indices for the 1987 Black Monday, 63 indices for the 1998 Russian Crisis, 79 indices for the September 11 terrorist attack and burst of the dot – com bubble events and finally 92 indices for the case of the 2008 crisis. For each of the 4 turbulences, the aim is to discover how the indices affect each other.

The Black Monday, 1987

The Black Monday was the first of three days that financial collapse took place, when during those 3 days the stock markets all around the world lost almost 30% of their value and the loss amounted to trillions of dollars collectively. The Dow Jones Industrial Average (DJIA) index marked a drop of almost 22% in a single day, starting a chain reaction leading to a stock market decline internationally. This stock market crisis can be attributed to a number of factors, the panic created among investors being the main reason. During 1986, the United States economy that had already undergone a rapid recovery from the previous years recession, shifted to a slower economic growth with low inflation rates. The rapid recovery, however, created an overvaluation of the stock markets. Additionally, the United States Department of Commerce announced high trade deficit figures on October 14, 1987, resulting in the value depreciation of the US dollar. This decision of value depreciation came under accord between the central banks of G5 nations and the Federal Reserve, in order to control us trade deficits of the United States. The sudden depreciation caused high interest rates and lowered the stock prices, creating a significant selling pressure. The large imbalance between sell orders and buy orders diminished the value of stock prices, plunging the Dow Jones Industrial Average by 20%, affecting the international stock markets.

Sandoval & Franca (2012) examine the Black Monday by using 23 stock market indices. The Random Matrix Theory that was analyzed before is used, creating a correlation matrix of 23x23. The average correlation is ⟨C⟩ = 0.16, with standard deviation σ = 0.04. The number of days used for the calculation is 256, so the matrix Q = L / M = 256 / 23 ≈ 11.130 is formed, with the upper and lower bounds of the eigenvalues $\lambda_- = 0.490, \lambda_+ = 1.689$.

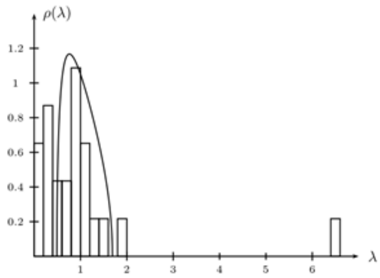


Fig. 3. Frequency distribution of the eigenvalues of the correlation matrix for 1987. The theoretical distribution for a random matrix is superimposed on it.

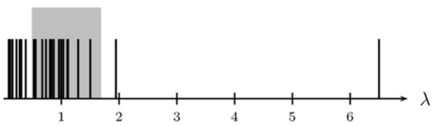


Fig. 4. Eigenvalues in order of magnitude. The shaded area corresponds to the eigenvalues predicted for a random matrix.

Figure 3 shows a frequency distribution of the 23 eigenvalues, with the theoretical distribution of the aforementioned infinite matrix Q = 11.130 over it, while Figure 4 shows the same distribution with the eigenvalues organized in order of magnitude. The grey area that contains 60% of the total eigenvalues is the area predicted by the Random Matrix Theory, meaning these are the log - returns that are randomly correlated. The single observation on the right is the highest eigenvalue out of bounds and it possibly represents the action of only one market that also has influence on the others.

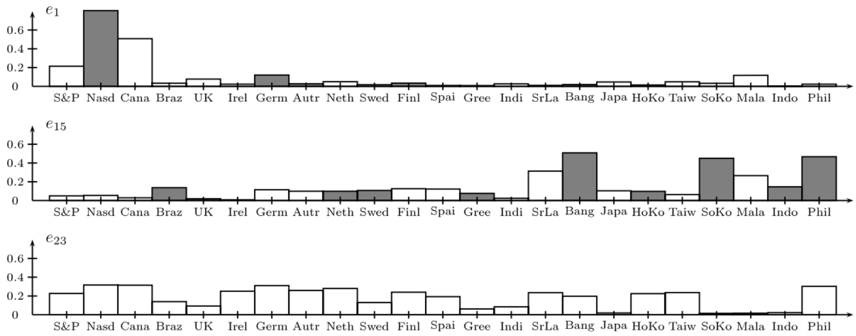


Fig. 5. Contributions of the stock market indices to eigenvectors e_1, e_{15}, and e_{23}. White bars indicate positive values, and gray bars correspond to negative values.

In Figure 5, the contribution of the many indices to 3 of the correlation matrix eigenvectors is presented, with the white indices representing a positive value, while the gray area shows a negative one. In this particular Figure, it can be noted that the highest eigenvalues represent higher risk or a riskier portfolio. For example, in eigenvector e1 the eigenvalues show that one should buy S&P (USA) and S&P TSX (Canada) indices and sell Nasdaq (USA). It can also be seen that these three indices are connected, since they are very close to each other. On the other hand, eigenvector e15 shows a random combination of financial markets indices and their eigenvalues are included in the grey area of Figure 4 that represents randomness.

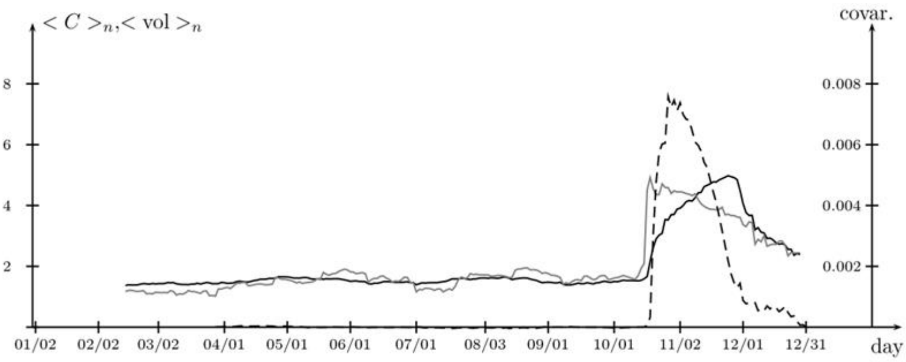


Fig. 9. Average volatility of the market mode (black) and average correlation (gray) based on the log-returns for 1987, both calculated in a moving window of 30 days and normalized so as to have mean two and standard deviation one. The covariance between volatility and average correlation is plotted in the same graph, in a dashed line.

Figure 9 plots the average correlation with the average volatility of the markets collectively. The average volatility is a linear combination of all indices, having the elements of eigenvector e23 as coefficients. The above data are calculated in a moving window of 30 days, with the black line representing the average volatility, the grey line representing the average correlation and the dashed line representing the covariance between volatility and average correlation. Figure 9 shows that a rise in correlation between global financial indices is followed by a rise in volatility. Therefore, it seems that there is a relationship between global market volatility and market indices correlation. Also, it can be noted that this correlation persists for some time after a turbulence has taken place.

The Russian Crisis, 1998

The Russian financial crisis of 1998 was a result of a few combined factors that ultimately led to many neighboring countries being affected primarily. During this time, Russia was undergoing a decline in productivity. Furthermore, there was a high fixed exchange rate between the Russian ruble and the currencies of foreign countries and a deficit of the government fiscal balance. The war with Chechnya that lasted from 1994 to 1996 was also a crucial factor that assisted in the financial deficit of Russia, since it is estimated that Russia was investing almost 30$ million per day during the war. By the end of the hostilities, Russia had dedicated to this war almost 1.4% of its GDP, a percentage that translated to almost 5.5$ billion. Adding to this situation, Russia also found itself under the effects of 2 external financial shocks. During 1997, Asia entered the period of the Asian financial crisis, battering heavily the Russian financial situation, as the demand for crude oil and metals plummeted. It must be noted that Russia was a leading exporter of these commodities, therefore their decline in demand took a heavy toll in its economy. Furthermore, the transition from a communist regime to a capitalist economy created an internal political crisis that directly affected the already impaired economy. All these factors led to the inevitable devaluation of the ruble during the summer of 1998, commencing the Russian crisis. As mentioned before, the countries in close proximity with Russia were primarily affected, but most of the world's financial markets were also struck down, since there was a lot of capital invested in Russia.

Sandoval & Franca (2012) study the Russian financial crisis by using 63 indices from all continents, with the majority being from Europe and Asia. The inclusion of this large number of indices has the purpose of diversification. Their analysis also includes Russia's MICEX index, since its inclusion is crucial.

Using the modified log – returns from the indices for a period between 2/1/1998 to 30/12/1998, a 63x63 correlation matrix is constructed, with average correlation ⟨C⟩ = 0.17, standard deviation σ = 0.04, and is based on L = 257 days for M = 63 indices, giving the matrix Q = L / M = 257/63 ≈ 4.079. The upper and lower bounds for the Marěnko–Pastur distribution are $\lambda_- = 0.255, \lambda_+ = 2.235$.

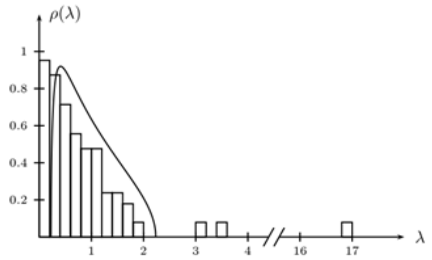


Fig. 10. Frequency distribution of the eigenvalues of the correlation matrix for 1998. The theoretical distribution is superimposed on it.

Fig. 11. Eigenvalues in order of magnitude. The shaded area corresponds to the eigenvalues predicted for a random matrix.

As practiced before, Figure 10 shows the frequency distribution of the correlation matrix eigenvalues with the theoretical Marčenku–Pastur distribution superimposed over it, while Figure 11 shows the eigenvalues in order of magnitude. The grey area represents the noise, or the eigenvalues that are randomly correlated. It can be seen that the largest eigenvalue is very far from the others, while two more are larger than the maximum theoretical eigenvalue and several others are below minimum. The out of scale eigenvalues represent the indices that most likely affect the majority.

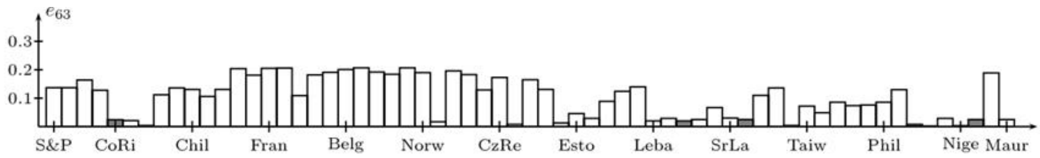


Fig. 12. Contributions of the stock market indices to eigenvector e_{48}, corresponding to the largest eigenvalue of the correlation matrix. White bars indicate positive values, and gray bars correspond to negative values. The indices are aligned in the following way: *S&P*, Nasd, Cana, Mexi, *CoRi*, Berm, Jama, Bra, Arg, *Chil*, Ven, Peru, UK, Irel, *Fran*, Germ, Swit, Autr, Ital, *Belg*, Neth, Swed, Denm, Finl, *Norw*, Icel, Spai, Port, Gree, *CzRe*, Slok, Hung, Pola, Roma, *Esto*, Ukra, Russ, Turk, Isra, *Leba*, SaAr, Ohma, Paki, Indi, *SrLa*, Bang, Japa, HoKo, Chin, *Taiw*, SoKo, Thai, Mala, Indo, *Phil*, Aust, Moro, Egyp, Ghan, *Nige*, Keny, SoAf, *Maur*.

Figure 12 presents the eigenvector e63, which represents a combination of all 63 indices of the market movement that explains almost 36% of the cumulative movement of the indices. In this Figure, it is clear that European and USA indices are have the highest values. On the other hand, the smallest participations come from all of the Arab countries, the majority of the southern Asian and African ones, with the exception of South Africa and finally the Caribbean.

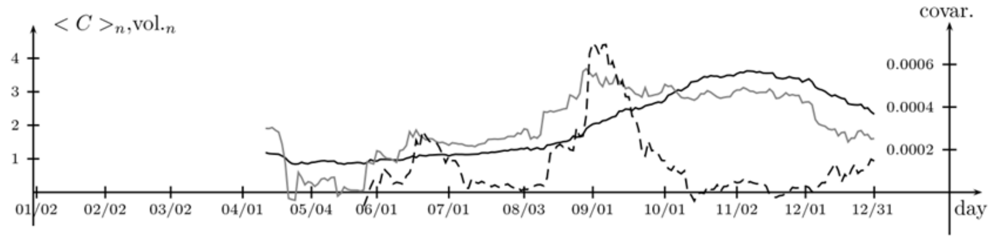


Fig. 13. Average volatility of the market mode (black) and average correlation (gray) based on the log-returns for 1998, both calculated in a moving window of 70 days and normalized so as to have mean two and standard deviation one. The covariance between volatility and average correlation as a function of time is plotted in the same graph, in a dashed line.

Concluding with the Russian crisis, Figure 12 shows the average volatility of the collective market, represented by the black line, along with the average correlation represented by the grey line between indices. One can observe high correlation in August 1998, when the Russian crisis started, as well as the rise of volatility. Also, the covariance, represented by the dashed line, between these two variables peaks at that time. Therefore, it seems that average volatility and average correlation of the markets are clearly related.

<u>Burst of the dot – com bubble and September 11, 2001</u>

The year of 2001 was stained by 2 events that led to a smaller scale financial crisis. The first event that marked the early 2000s was the burst of the dot – com bubble, the collapse of a stock market bubble that was the result of excessive speculation of various internet related companies in the United States. During the late 1990s, internet based companies experienced a massive growth since the internet had already started to become a tool of crucial importance in trading and communicating. The shift for the personal computers from luxury to necessity, led to their commercial availability and also made it possible for their owners to have access to the internet. These was the initiative for many internet – related companies to be established, leading to the economy to be directly linked to the fast information transmitted through the internet. Moreover, during the late 1990s, the interest rates in the United States saw a decline, increasing the more speculative investments. Investors saw opportunity in investing in internet related companies that had started to bloom. Being also encouraged by investment banks to invest in this new technology, many placed their confidence blindly on technological advancements, eventually creating this stock market dot – com bubble.

The burst of the dot – com bubble possibly initiated after the excessive raising of the interest rates by the Federal Reserve, with numerous internet based companies losing stock value, eventually being led to bankruptcy. The continuous spending on advertising campaign whilst having minimal profits drove many companies out of market. Ultimately, NASDAQ – 100 index saw a drop of 78% during that year, a remarkable downturn caused by the bubble collapse.

This downturn process was significantly accelerated by the terrorist attack of September 11. An unprecedented act of terrorism on American soil, it triggered many chain events to take place. The economic impact was of immense significance, since the stock markets were closed for almost a week after the attack. The Dow Jones Industrial Average dropped about 14% from the previous week, while the consequences were notable also in the wages and exports of the United States. The declining exports drove the GDP to fall by about 27$ billion, while the war that initiated after the attacks in Middle East cost the United States an estimated 5$ trillion.

Sandoval & Franca (2012) analyze this complicated two – factor crisis by using 79 indices from international financial markets. The modified log – returns, based on the indices of the whole year 2001, provides a 79x79 correlation matrix. The average correlation in this examination for the log - returns is ⟨C⟩ = 0.11, standard deviation σ = 0.03. The average correlation is based on L = 260 days for M = 79 indices. Therefore, the Marěnko–Pastur distribution is Q = L/M = 260/79 ≈ 3.29. Additionally, the upper and lower bounds of the eigenvalues are $\lambda_{-} = 0.295, \lambda_{+} = 2.122$.

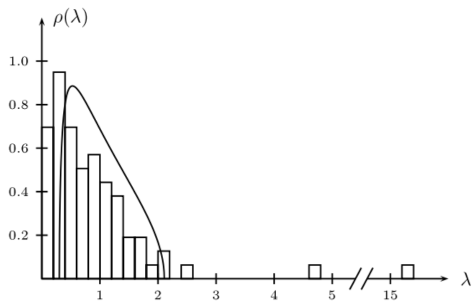


Fig. 14. Frequency distribution of the eigenvalues of the correlation matrix for 2001. The theoretical distribution is superimposed on it.

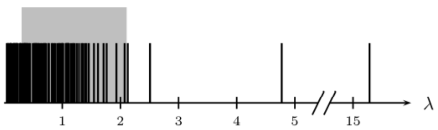


Fig. 15. Eigenvalues in order of magnitude. The shaded area corresponds to the eigenvalues predicted for a random matrix.

This time, Figure 15 which shows the frequency distribution against the theoretical Marčenku–Pastur distribution, along with Figure 15 which presents the same frequency distribution in order of magnitude, illustrate an eigenvalue that is placed entirely out of scale, corresponding to an eigenvalue that influences the rest.

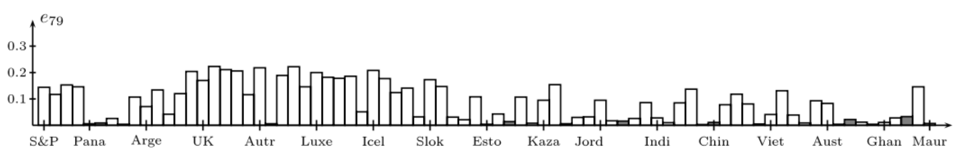


Fig. 16. Contributions of the stock market indices to eigenvector e_{79}, corresponding to the largest eigenvalue of the correlation matrix. White bars indicate positive values, and gray bars correspond to negative values. The indices are aligned in the following way: *S&P*, Nasd, Cana, Mexi, *Pana*, CoRi, Berm, Jama, Braz, *Arge*, Chil, Vene, Peru, *UK*, Irel, Fran, Germ, Swit, *Autr*, Ita, Malt, Belg, Neth, *Luxe*, Swed, Denm, Finl, Norw, *Icel*, Spai, Port, Gree, CzRe, *Slok*, Hung, Pola, Roma, Bulg, *Esto*, Latv, Lith, Ukra, Russ, *Kaza*, Turk, Isra, Pale, Leba, Jord, SaAr, Qata, Ohma, Paki, *Indi*, SrLa, Bang, Japa, HoKo, *Chin*, Mong, Taiw, SoKo, Thai, *Viet*, Mala, Sing, Indo, Phil, *Aust*, NeZe, Moro, Tuni, Egyp, *Ghan*, Nige, Keny, Bots, SoAf, *Maur*.

In Figure 16, one can see the 79th eigenvector, which is a combination of all indices. The indices than have the lowest participation rates are mostly from Eastern Europe, Arab countries and Asia. The highest participation rates come from North American countries, the major South American ones, Central and Western Europe and some major Asian countries.

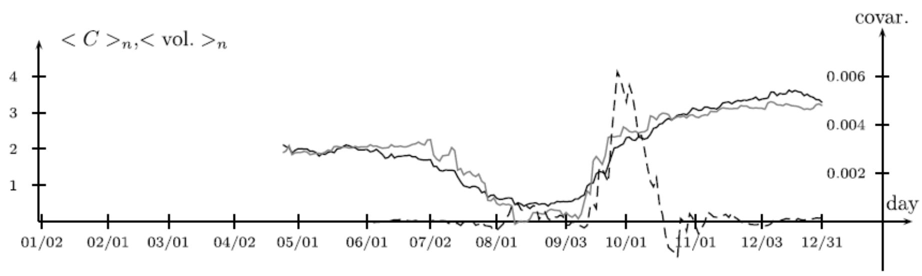


Fig. 17. Average volatility (black) and average correlation (gray) based on the log-returns for 2001, both calculated in a moving window of 80 days and normalized so as to have mean two and standard deviation one. The covariance between volatility and average correlation as a function of time is plotted in the same graph, in a dashed line.

Finally, Figure 17 presents the high volatility, presented by the black line, that occurred right after September 11, along with the high average correlation, presented by the gray line, between world market indices. Moreover, the high correlation and volatility depicted before September is attributed to the burst of the dot – com bubble, which affected the markets worldwide. It is visible again that the average volatility and average correlation are linked, since one precedes the other into a similar behavior.

The Subprime Mortgage Crisis, 2008

The last case that Sandoval & Franca (2012) examine is the Subprime Mortgage Crisis that initially started in the United States and eventually spread to the whole world, crashing the international financial markets as well as the real economy. Starting in 2007, the Subprime Mortgage Crisis was the result that was triggered by the lending of mortgage credit to borrowers that had low credit ratings. Borrowers with low credit ratings were not always able to be issued a prime conventional mortgage, since they carried more risk than those with high ratings. Therefore, the interest rate of the subprime mortgages was often higher, in order to counter the high risk of defaulting, keeping a balance in this way. During 2007, the mortgage credit expansion allowed the lower rating borrowers who could not easily acquire mortgages, since lenders were not willing to provide, to finally be able to obtain them, therefore driving housing prices to rise. The subprime mortgages were financed by private mortgage – backed securities, which were positively rated by rating agencies for having low risk, since other securities would be primarily affected if loses were taken place, absorbing the risk. Higher mortgage rates led to higher demand for house purchases, also increasing the prices. As the aforementioned borrowers bearing high risk could not ultimately afford to pay the loans they received, they either sold their properties or borrowed more. Eventually, these securities proved to be less risk free than initially expected and while the house prices skyrocketed, losses started appearing both for lenders and borrowers. During this time, many financial lending institutions went bankrupt and the securities lost their credibility, plummeting the demand and prices for houses. This financial turmoil quickly spread to the other sectors of economy, affecting financial markets, also decreasing constructions and exports.

Sandoval & Franca (2012) use 98 indices for the Subprime Mortgage Crisis analysis, and therefore their log – returns provide a 92 x 92 correlation matrix for the entire year of 2008 with the average correlation ⟨C⟩ = 0.26 and standard deviation σ = 0.05. The correlation matrix is based on L = 253 days for the M = 92 indices, with the Marĕnko–Pastur distribution being Q = L/M = 256/92 ≈ 2.78. The upper and lower limits of this distribution are $\lambda_- = 0.160, \lambda_+ = 2.558$.

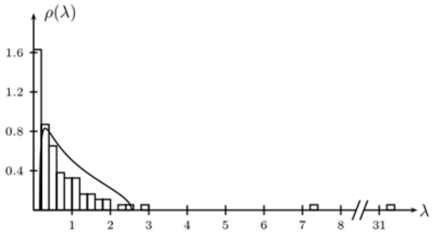


Fig. 18. Frequency distribution of the eigenvalues of the correlation matrix for 2008. The theoretical distribution is superimposed on it.

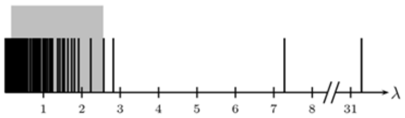


Fig. 19. Eigenvalues in order of magnitude. The shaded area corresponds to the eigenvalues predicted for a random matrix.

As with the previous examinations for the other crises, Figure 18 presents the frequency distribution of the eigenvalues with the theoretical distribution over it, while Figure 19 shows the eigenvalues in order of magnitude, with the predicted eigenvalues in the shaded area. The completely out of scale eigenvalue is indicative of high correlation levels between financial markets, as well as a unified market movement, since one variable seems to highly affect the others.

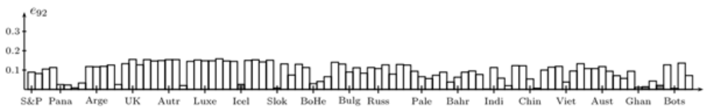


Fig. 20. Contributions of the stock market indices to eigenvector e_{92}, corresponding to the largest eigenvalue of the correlation matrix. White bars indicate positive values, and gray bars correspond to negative values. The indices are aligned in the following way: *S&P*, Nasd, Cana, Mexi, *Pana*, CoRi, Berm, Jama, Braz, *Arge*, Chil, Colo, Vene, Peru, *UK*, Irel, Fran, Germ, Swit, *Autr*, Ital, Malt, Belg, Neth, *Luxe*, Swed, Denm, Finl, Norw, *Icel*, Spai, Port, Gree, CzRe, *Slok*, Hung, Serb, Croa, Slov, *BoHe*, Mont, Mace, Pola, Roma, *Bulg*, Esto, Latv, Lith, Ukra, *Russ*, Kaza, Turk, Cypr, Isra, *Pale*, Leba, Jord, SaAr, Kuwa, *Bahr*, Qata, UAE, Ohma, Paki, *Indi*, SrLa, Bang, Japa, HoKo, *Chin*, Mong, Taiw, SoKo, Thai, *Viet*, Mala, Sing, Indo, Phil, *Aust*, NeZe, Moro, Tuni, Egyp, *Ghan*, Nige, Keny, Tanz, Nami, *Bots*, SoAf, Maur.

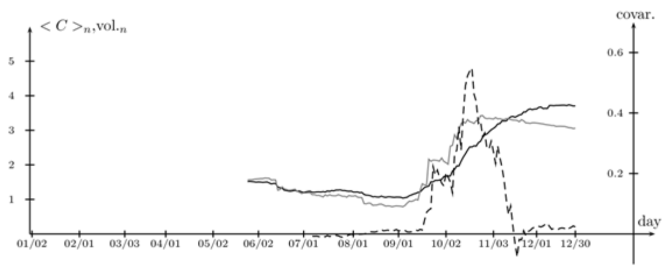


Fig. 21. Average volatility (black) and average correlation (gray) based on the log-returns for 2008, both calculated in a moving window of 100 days and normalized so as to have mean two and standard deviation one. The covariance between volatility and average correlation as a function of time is plotted in the same graph, in a dashed line.

Figure 20 presents the 92^{nd} eigenvector. Iceland and some African countries seem to have the smallest negative contributions, meaning that they were affected the most by this financial crisis, while the highest contributions are presented by South American, most of the European and also most of the eastern Asian countries.

Concluding for the 2008 crisis, Figure 21 once again presents the average correlation, average volatility and their covariance. It is clear that average volatility increases after the rise of correlation between world markets, confirming again the correlated movements between international financial indices. Through the examination of Sandoval & Franca (2012), one can clearly grasp that during anxious times of crises, the world financial markets tend to behave similarly, eventually affecting each other.

In the next chapter, the methodology that will later be used for examination is explained thoroughly, and then the analysis of 4 financial indices will follow, covering the periods of the Subprime Mortgage Crisis of 2008 and the period of the latest financial turbulence caused by the Covid – 19 outbreak.

Chapter 4

Methodology

As previously discussed, this thesis examines how the international financial markets tend to behave when they are under financial hardships. In order to further add to the previous literature, 4 financial indices will be analyzed regarding their response to risk, using GARCH models, for the two most recent periods of financial turmoil, the 2008 Subprime Mortgage Crisis and the Covid – 19 pandemic. In addition, a VAR model will present the correlations between those 6 indices during the two crises. However, it is essential to separate the 2 crisis periods into 2 sub – periods, eventually examining 4 time periods for the 4 indices. The point of this division is to examine the financial indices for both before the period of financial turbulence and for its duration.
Since the 4 indices practically consist of time series data, the use of a GARCH model is required for analysis. This chapter focuses mainly on explaining the methodology that will be followed in the next chapter in order to understand and also visualize the reaction of the financial markets to the periods of turbulence. However, the more advanced form of the GARCH model, a TGARCH model will be used since it provides more information about the reaction of an index, regarding the leverage.

ARCH / GARCH / TGARCH models

The ARCH (Autoregressive Conditionally Heteroscedastic), GARCH (Generalized Autoregressive Conditionally Heteroscedastic) and TGARCH (Threshold Autoregressive Conditionally Heteroscedastic) models are widely used in the analysis of time series, as mentioned before. The first 2 models are very important regarding the forecasting and analysis of the volatility of the variance of the aforementioned time series, providing information about the indices' reaction, taking into consideration the volatility clustering and also the leverage. More specifically, a GARCH model is able to provide predictions and measurements about the volatility, since it has a different approach regarding heteroscedasticity. The basis of least square models requires homoscedasticity, meaning that the expected value of all the error terms of a time series must be identical. If this is not the case and the error terms present differentiated variances, then the model accepts the hypothesis of heteroscedasticity. This is especially common for larger time series or samples. However, a GARCH model approaches the heteroscedasticity inconvenience as a variance that can be modeled. The ability to explain and predict a potentially volatile variance is a crucial factor to finance, making GARCH models essential.

Moreover, their usefulness is higher when trying to examine increased variance volatility during short periods of time, such as a financial turmoil, making it possible to identify how different financial indices of international markets are affected and study their reaction. Eventually, GARCH models can, in this way, assist investors to make financial decisions about their portfolios, which indices should be selected for investments, as well as the quality of each international market.

The ARCH and GARCH models formulas both consist of 2 equations. The first one is the mean equation, which includes the non – constant variance, while the second one is the variance equation that is included in the former. The structure of an GARCH model is given by the following formulas:

$$R_t = \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_o + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + \cdots + a_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2$$

In the variance equation, a_o is the constant, a_1 is a coefficient multiplying the ε_{t-1}^2 lag squared and β_1 is the last coefficient multiplying the variance itself with another lag squared. Moreover, the A coefficient in the mean equation represents the risk aversion

However, it is essential to note that in order for the GARCH model to be fully formed some conditions must be met. Firstly, in the variance equation the $a_o$constant must be greater than 0, since any other case would mean the variance equation would not have a functional form. Secondly a_1, $\beta_1$must also be greater than 0. If both coefficients are 0 then the variance would be equal to the constant, meaning that it would be constant itself. Therefore, the mean equation would be a White Noise, a random variable with constant variance and no autocorrelation.

One could also enhance this methodology, since it is possible to calculate the risk aversion that a financial index may present, by adding one more coefficient in the mean equation. This risk aversion coefficient is represented by A and can be added in the mean equation as follows:

$$R_t = A\sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)$$

However, the risk aversion coefficient will not be included in the data analysis in the next chapter. It should be mentioned that when the risk aversion coefficient is included, the initial model transforms into a GARCH – M model.

The analysis will utilize the robust method of Bollerslev – Wooldridge, since this method assists in correcting the heteroscedasticity of the covariance. It should be noted that this examination will also target the volatility clustering that may be formed during periods of crisis, hence the more complete GARCH form will be used for analysis instead of the simplified ARCH. Nonetheless, if during data analysis for any given crisis period the GARCH model proves to be of no statistical significance, then the model will be reduced to a simple ARCH to continue the examination. The ARCH model takes the more basic form with the 2 equations:

$$R_t = \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_o + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + \cdots + a_p\varepsilon_{t-p}^2$$

Last but not least, the next chapter examination will also focus on the leverage phenomenon that may take place during a financial crisis for some indices. Leverage is a technique used by investors in order to potentially increase the returns of an investment, by investing borrowed capital. This strategy, however, amplifies the risk when financial markets tend to present lower values, since the borrowed capital that was invested may not have the returns initially expected. It is worth adding that it is common that in markets where investors tend to hold their assets when prices devaluate, in hoping that they may present a future increase again in order to minimize their losses, the risk increases substantially during such times of devaluation. For the purpose of leverage inclusion in this examination, it is essential to begin the data analysis process using a TGARCH model and gradually simplify the model if no statistical significance is eventually found.

The complete TGARCH model has a slightly different structure than the 2 previously mentioned models. This time a new variable I is inserted in the variance equation, forming again the 2 equations:

$$R_t = \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_o + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + \cdots + a_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2 + \gamma_1\varepsilon_{t-1}^2 I_{(\varepsilon_{t-1}<0)}$$

In the variance equation, the dummy variable I has the value 1 when $\varepsilon_{t-1} < 0$ and the value 0 when $\varepsilon_{t-1} > 0$.

It should be stated, however, that in order to conduct the data testing in a GARCH model, all data should be transformed from non – stationary into stationary. It must be noted that when the $\gamma_1$coefficient is positive and statistically significant, then the TGARCH model can detect the leverage phenomenon.

VAR model

After the construction of the TGARCH model and the thorough examination of the financial indices, it is important to build a VAR (Vector Autoregressive) model in order to examine for causality between them. The VAR model will analyze the 6 financial indices for both periods of financial turbulence, also considering the market behavior during the pre – period of financial disturbance. Before proceeding to the data analysis, an explanation of the methodology of a VAR model will be given, emphasizing the 2 specific methods that will be used. These methods are the Granger causality and the Impulse Response Function.

The VAR model is one of the most flexible models used for analysis of multivariate time series and since it is a statistical model, it is especially useful in examining the dynamic relationship that two or more variables have within a system. It is also possible for a VAR model to examine the variables and provide a forecast for future values. Such models are widely used in economic and financial multivariate time series, as the previously explained GARCH models. In addition, a VAR model can be used for structural analysis, where variables and equations can be examined and provide information about causal relationships between them, as well as information about the responses if shocks are applied into the system. Such causality hypothesis can be examined with the Granger causality test, as mentioned before, where two hypotheses, the null and the alternative, are formed and the test provides an answer about if and which variables are affected by lags. Furthermore, impulse responses functions give a clear picture for the responses of the selected variables if they are presented to a shock. These functions measure how drastic the response will be and how much time is needed before the effect is neutralized.

Vector Autoregressive models come with advantages that make their usage preferable. All variables that are used within the system are considered endogenous and therefore the values of variables can be affected by not only by their own lags, but also by lags of other variables. However, VAR models can present some minor issues that require to be solved in order to proceed to the construction of the model. Firstly, all variables must be tested for stationarity and if they are not stationary, they must be converted, following the same procedure as the GARCH model. In addition, there is a large number of parameters to be calculated, taking into consideration that each equation has numerous variables, coefficients and lags. The latter is the reason that it is not entirely feasible to extract a conclusion out of the model itself. In order to extract a resolution, it is essential to perform the 2 specific tests that were previously mentioned.

The first method is the Granger causality test, created by Granger in 1969. It has been widely used in economics since then. By performing this test, it is possible to investigate whether causality exists between two or more variables in a time series. However, despite of the name of the test, it does not actually test for literal causality of the variables. A more appropriate description is that it tests for correlation between the current value of one variable and the past value of other variables, using empirical data. A multivariate VAR model that consists of 2 equations has the following structure:

$$y_{1t} = \alpha_{10} + \beta_{11}y_{1t-1} + \beta_{12}y_{2t-1} + \gamma_{11}y_{1t-2} + \gamma_{12}y_{2t-2} + \delta_{11}y_{1t-3} + \delta_{12}y_{2t-3} + u_{1t}$$

$$y_{2t} = \alpha_{20} + \beta_{21}y_{1t-1} + \beta_{22}y_{2t-1} + \gamma_{21}y_{1t-2} + \gamma_{22}y_{2t-2} + \delta_{21}y_{1t-3} + \delta_{22}y_{2t-3} + u_{2t}$$

In this bivariate formula, y denotes the maximum number of lagged observations. The null hypothesis of this test is that all regression coefficients of y_{1t} are null, meaning that they equal 0 and therefore no correlation can be assumed between them. This hypothesis can be interpreted as previous lags of observations do not explain the current observations and variables. The alternative hypothesis states that there is a correlation between the regression coefficients and as a result, previous observations have a causal link to the current ones. To reach the conclusion of rejection of the null hypothesis, there must be a p – value lower than 0.05 in a confidence level of 95%. This hypothesis is tested with the F – statistic, which has the following formula:

$$F = \frac{\frac{(ESS_R - ESS_{UR})}{q}}{\frac{ESS_{UR}}{n-k}}$$

If the null hypothesis is rejected and causality is accepted, it is safe to say that in the aforementioned equations of y_1 and y_2, if the first causes the latter, then the lags of y_1 should be significant in the second equation and vice versa. Bi – directional causality can also be a result. This method is especially useful in this current methodology, since it will allow to draw the conclusion if the financial markets indices are correlated during the crisis periods.

The second method that will be used to obtain the results from the VAR model is the Impulse Response Function. Impulse responses are used in dynamic systems by being the output when these systems are presented with an input signal or shock. By utilizing this method, it is possible to observe the responsiveness of the depended variable in a VAR model, when in each variable a shock is introduced. In order to study the behavior of each of the dependent variables, this unit shock is applied to the error of each variable separately. To better explain the impulse response procedure, a bivariate VAR model with 2 equations:

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \alpha_{11}y_{2t-1} + u_{1t}$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \alpha_{21}y_{1t-1} + u_{2t}$$

Then, if a unit shock is applied, for example, in the error u_{1t}, then this error will immediately alter the y_1 variable. This will also cause a chain effect on y_2 since this variable is linked to the first equation and it will also change y_1 again during the next lag. With impulse responses it is possible to examine the duration and intensity of the effects of a unit shock on all of the system's variables.

Furthermore, the last bivariate VAR model that is illustrated below, provides a clearer explanation for the specific methodology:

$$y_t = A_1 y_{t-1} + u_t$$

In this model, A_1 is the theoretical matrix $\begin{bmatrix} 0.2 & 0.4 \\ 0.0 & 0.1 \end{bmatrix}$. With this matrix in mind it is feasible now to write the VAR model analytically: $\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} 0.2 & 0.4 \\ 0.0 & 0.1 \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-2} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$. At time t = 0, a unit shock is applied to u_{1t} which can be written as $y_0 = \begin{bmatrix} u_{10} \\ u_{20} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$. It is clear now that in the second matrix of the above equation the unit shock that has been applied is displayed by the number 1. To examine how the whole system will transform under the effect of this unit shock, the next step is to multiply the values of the A_1 matrix with the matrix of shocks. Therefore, at time t=1:

$$y_1 = A_1 y_0 = \begin{bmatrix} 0.2 & 0.4 \\ 0.0 & 0.1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.2 \\ 0 \end{bmatrix}.$$

Multiplying the matrices, the conclusion is drawn that the unit shock applied to u_{1t} has an immediate effect only to the first variable. This happens because the 0.0 value in the A_1 matrix indicates that the second variable is not affected by the past values of the first variable. Consequently, it is not affected by the unit shock.

Moving on to time t=2, multiplying the A_1 matrix with the latest results obtained for the u_1: $y_2 = A_1 y_1 = \begin{bmatrix} 0.4 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix} 0.2 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.08 \\ 0 \end{bmatrix}$. It can be observed that the shock has a lower value of 0.08 instead of 0.2 that was the previous result. Gradually, as time t passes the shock will tend to equal 0. In this particular example the unit shock will not have any effect on the second variable whatsoever. Repeating the procedure, the effect a unit shock to y_{2t} at time t=0. Using the exact same formula, the only thing that changes is in the error matrix: $y_0 = \begin{bmatrix} u_{10} \\ u_{20} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$. Multiplying the matrixes again, at time t=1: $y_1 = A_1 y_0 = \begin{bmatrix} 0.2 & 0.4 \\ 0.0 & 0.1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.4 \\ 0.1 \end{bmatrix}$. It is now clear that a unit shock on the second variable will have an effect on both variables. At time t=2: $y_2 = A_1 y_1 = \begin{bmatrix} 0.2 & 0.4 \\ 0.0 & 0.1 \end{bmatrix} \begin{bmatrix} 0.4 \\ 0.1 \end{bmatrix} . = \begin{bmatrix} 0.48 \\ 0.1 \end{bmatrix}$. Since both variables are affected, it is confirmed that the first variable is tied to the past values of the second variable. Finally, it is worth noting that gradual decline of the shock values as time t moves forward is noticeable.

Chapter 5

Real data examination

In this chapter, 4 financial indices are thoroughly examined in order to understand the level of influence that the Subprime Mortgage Crisis of 2008, as well as the international health crisis of Covid – 19 had on these indices which represent the financial markets. The group of indices that are tested consist of BEL20, which is a financial market index from Belgium, the Hong Kong based Hang Seng Index or HSI, Mexico's largest financial index, MXX and finally USA's NASDAQ. As mentioned in the first chapter, the examination is split for the periods during the financial turbulence, as well as the period that precedes it. This 4 – period examination provides the ability to study the financial markets before the crisis, during a period without financial hardships, but also during the peak of the financial turmoil. Therefore, the data for these 4 indices stretch from 1/1/2005 to 31/12/2007 for the pre – crisis of 2008 and from 1/1/2008 to 31/12/2009 for the period regarding the crisis. Additionally, the pre – Covid era is studied between 1/1/2018 to 31/12/2019, while the last examination concerns the duration of the pandemic for a 2 – year period, ranging from 1/1/2020 to 31/12/2021. These 4 periods should provide an important overview of the financial markets situation that takes place during anxious times.
In order to begin the analysis, it is essential to mention that the first step is to convert the non – stationary data, which is the financial market values, into their logarithmic differences, which are essentially the returns. After creating the logarithmic differences, it is easy to perform some important statistical tests to obtain some insight about the quality of the specific market. First of all, a histogram is necessary to observe the indices' skewness and kurtosis, in order to understand the nature of the market. More specifically, the histogram can provide the means to check if a market is aimed for speculation or long – term investment. Secondly, to verify this result, a correlogram is built to check of the lags of the previous days are statistically significant. If this is the case, then autocorrelation is present among the variables. These statistical test aim to show the reaction of each different market during the periods of crisis, qualitatively.

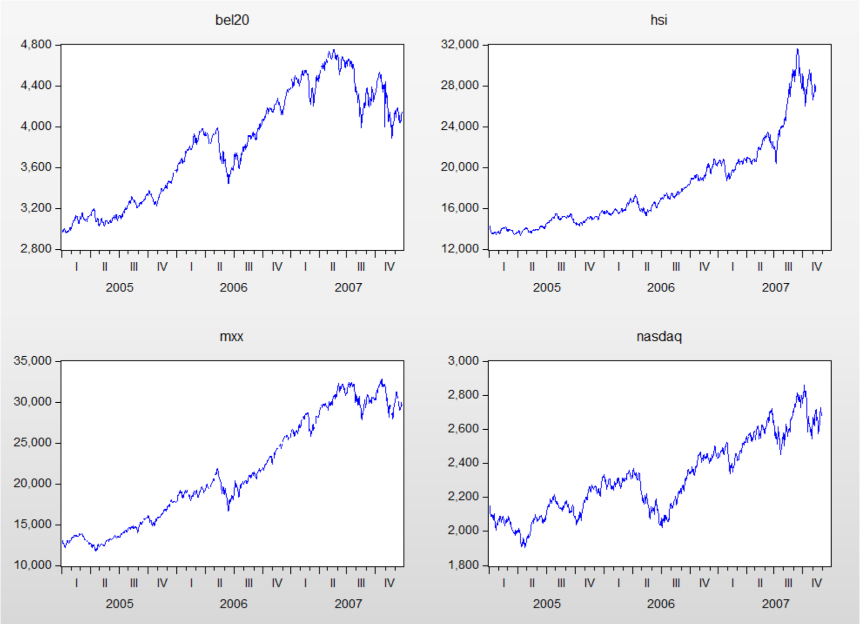
Furthermore, a TGARCH model is constructed for each of the 4 indices, for all the periods in question, to show if the indices had presented volatility clustering and / or leverage, in order to grasp the level of risk during such times. Finally, the correlations between all indices are given for all periods again.

It is also worth noting that since the 4 financial markets tested are from countries that have different currencies, their graphs also present different values regarding the height of each currency.

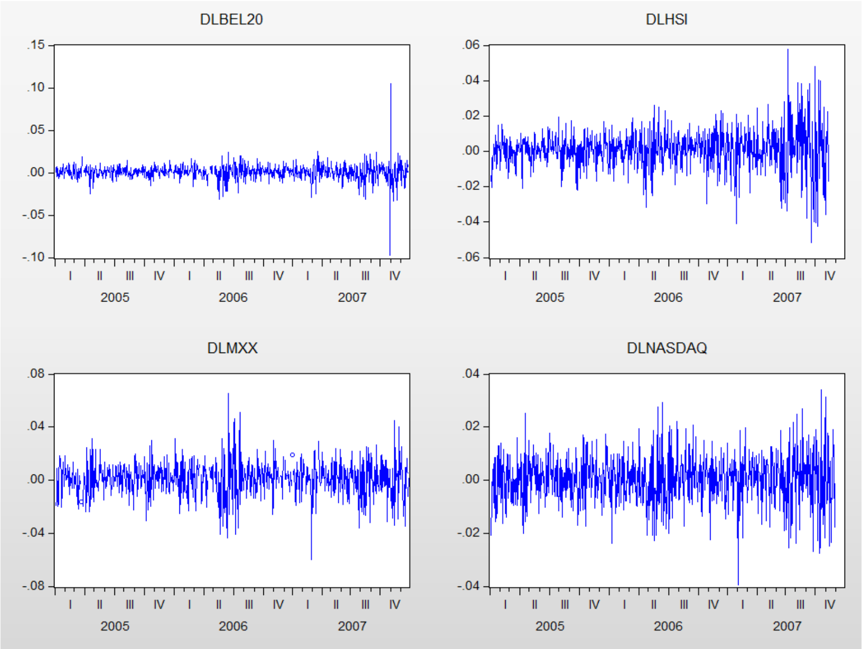
Descriptive statistics and TGARCH methodology

Pre – period of Subprime Mortgage Crisis, 1/1/2005 to 31/12/2007

The 4 indices show the following tables regarding their values during the pre – period of the Subprime Mortgage Crisis.



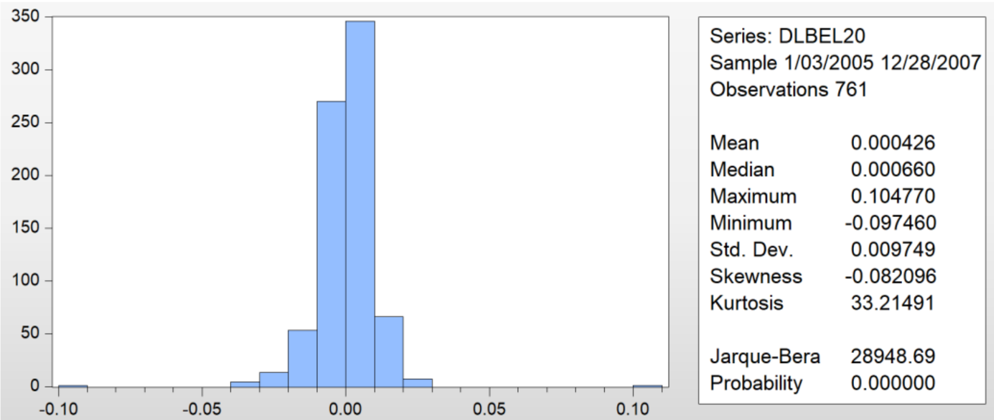
It is clear that the above tables do not represent stationary data. Non – stationarity does not allow for statistical testing and therefore it is essential to convert the data to stationary, as mentioned before. The following graphs present the aforementioned data converted into their logarithmic differences, meaning stationary ones.



DLBEL20

As can be seen by the graphs, during the pre – mortgage crisis period the financial markets returns do not present very extreme observations, with the exception of Belgium's BEL20 index, which shows a huge spike in the fourth quarter of 2007. This could be attributed to a number of reasons, or more specifically because of the rapid decline of BEL20's value, as seen in the first group of non – stationary tables. Moreover, a slight increase of volatility can be spotted on the Hang Seng index during late 2007, again in the final quarter.

Since the stationary data tables are established, it is feasible now to proceed to the statistical tests for all 4 indices during this period. Starting with the BEL20 index, the following histogram provides more useful information about the specific index.



First of all, it can be seen that BEL20 does not resemble a random distribution. This means that it is possible for investors to aim for speculation, as this histogram is not indicative of a large – cap index. Moreover, drawing more information from the above figure, Skewness has a value of -0.08, which is lower than 0, meaning that BEL20 is more likely to have negative returns instead of revenue. Finally, Kurtosis is much above the threshold of 3, with a value of 33.21, while Jarque – Bera value far exceeds the appropriate value of 5.99. Both values are clear indications that this index is of high risk, since it does not follow the normal distribution whatsoever.

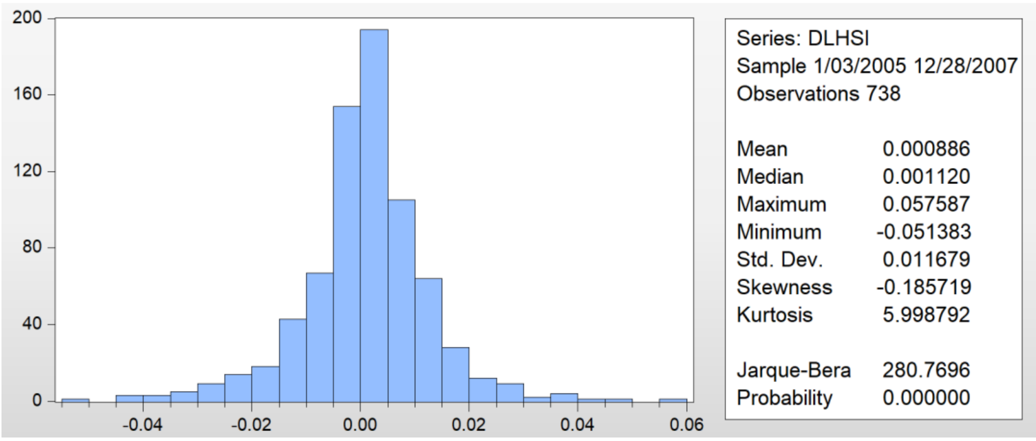
Sample: 1/03/2005 12/28/2007
Included observations: 761

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.141	-0.141	15.252	0.000
		2	0.003	-0.017	15.261	0.000
		3	-0.010	-0.012	15.340	0.002
		4	0.063	0.061	18.339	0.001
		5	-0.054	-0.038	20.619	0.001
		6	-0.012	-0.025	20.735	0.002
		7	-0.013	-0.019	20.867	0.004
		8	0.015	0.007	21.046	0.007
		9	0.033	0.042	21.862	0.009
		10	0.008	0.019	21.911	0.016
		11	0.005	0.010	21.934	0.025
		12	-0.019	-0.020	22.199	0.035
		13	-0.021	-0.030	22.527	0.048
		14	0.037	0.033	23.566	0.052
		15	-0.079	-0.069	28.375	0.019
		16	0.070	0.056	32.143	0.010
		17	-0.030	-0.014	32.857	0.012
		18	-0.015	-0.030	33.033	0.017
		19	0.017	0.020	33.251	0.022
		20	0.029	0.021	33.922	0.027
		21	-0.016	0.000	34.123	0.035
		22	0.028	0.030	34.744	0.041
		23	-0.046	-0.043	36.409	0.037
		24	-0.040	-0.053	37.667	0.037
		25	0.049	0.037	39.547	0.032
		26	-0.009	0.002	39.616	0.043
		27	-0.011	-0.004	39.717	0.054
		28	0.001	-0.001	39.718	0.070
		29	-0.031	-0.041	40.504	0.076
		30	0.045	0.027	42.121	0.070
		31	-0.001	0.020	42.121	0.088
		32	0.000	0.005	42.121	0.109
		33	-0.042	-0.037	43.520	0.104
		34	0.009	-0.008	43.580	0.126
		35	-0.042	-0.045	45.016	0.120
		36	0.018	0.000	45.290	0.138

The correlogram for the BEL20 index, presents 36 lags, most of which have a probability percentage less than 5%, meaning that the autocorrelations are statistically significant. This statistical significance can be interpreted as utilization of previous observations from the investors in order to negotiate present values. A clear indication of speculation again. However, it can be observed that the last observations are not statistically significant, therefore not all lags can be utilized for future predictions.

DLHSI

Moving to the histogram of the log differences of the Hang Seng Index, it is visible that this index has a much lower risk level than BEL20. Observing the histogram, there is indication of more normality and randomness. This time, Kurtosis has a value of 5.99, which is very close to 3. Moreover, the Jarque – Bera index is much higher than its theoretical threshold value of 5.99, with 280.76. Nevertheless, since real data are involved, it can be considered as very close to normality and randomness. This is a much larger capitalization index not targeted for speculation.



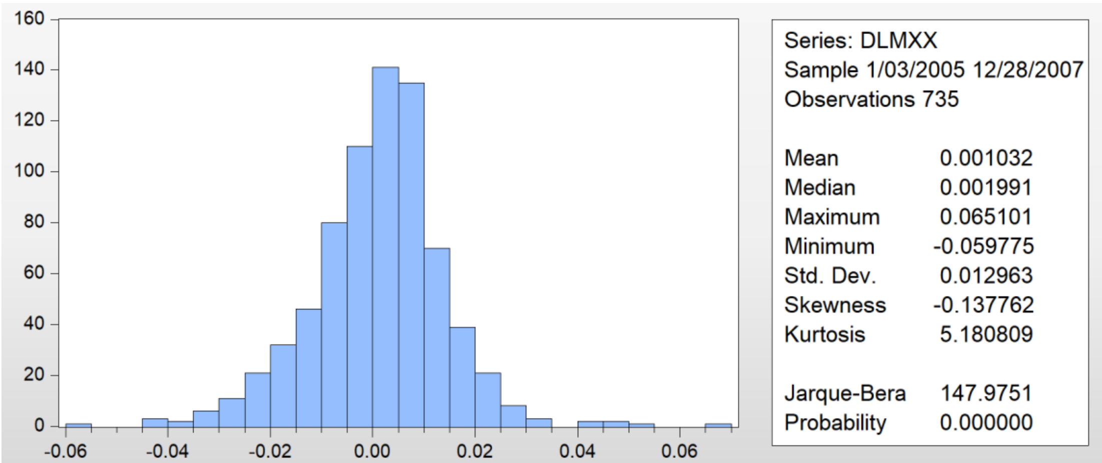
Sample: 1/03/2005 12/28/2007
Included observations: 738

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.007	0.007	0.0321	0.858
		2	-0.086	-0.086	5.4805	0.065
		3	0.122	0.124	16.508	0.001
		4	0.018	0.008	16.747	0.002
		5	-0.063	-0.043	19.681	0.001
		6	-0.092	-0.105	25.952	0.000
		7	0.028	0.020	26.557	0.000
		8	-0.042	-0.047	27.873	0.000
		9	0.043	0.077	29.281	0.001
		10	-0.032	-0.051	30.054	0.001
		11	0.031	0.046	30.766	0.001
		12	0.057	0.027	33.238	0.001
		13	0.024	0.042	33.663	0.001
		14	0.005	-0.003	33.685	0.002
		15	-0.029	-0.026	34.330	0.003
		16	0.004	-0.015	34.343	0.005
		17	-0.036	-0.023	35.311	0.006
		18	-0.059	-0.052	37.953	0.004
		19	0.020	0.032	38.249	0.006
		20	0.008	-0.000	38.300	0.008
		21	0.004	0.019	38.313	0.012
		22	0.003	-0.006	38.320	0.017
		23	-0.052	-0.069	40.374	0.014
		24	0.076	0.071	44.770	0.006
		25	-0.016	-0.031	44.977	0.008
		26	-0.033	-0.003	45.802	0.010
		27	0.012	-0.001	45.917	0.013
		28	-0.085	-0.098	51.527	0.004
		29	-0.008	0.008	51.580	0.006
		30	-0.031	-0.030	52.306	0.007
		31	0.031	0.044	53.071	0.008
		32	-0.029	-0.028	53.733	0.009
		33	-0.018	-0.031	53.978	0.012
		34	0.029	0.010	54.636	0.014
		35	-0.058	-0.060	57.241	0.010
		36	-0.015	-0.019	57.414	0.013

From Hang Seng's correlogram, it can be observed that the only first two autocorrelation lags have a probability of more than 5%, meaning that potential investors would take into account the lags referring to previous days in order to negotiate, except for the first 2. This means that this index also has some potential for speculation. However, before the 2008 Subprime Mortgage Crisis, the Hang Seng Index did not present extreme levels of risk.

DLMXX

The third examination for the pre – period of 2008 crisis concerns Mexico's financial index MXX. As can be seen from the following histogram, the logarithmic differences present a distribution that is very close to normality. The 5.18 value of Kurtosis is really close to the threshold of 3, showing a lesser level of risk that that of the previous index, the HSI. Jarque – Bera has a relatively low value of 147.97, which indicates that this index does not stray from normality substantially.



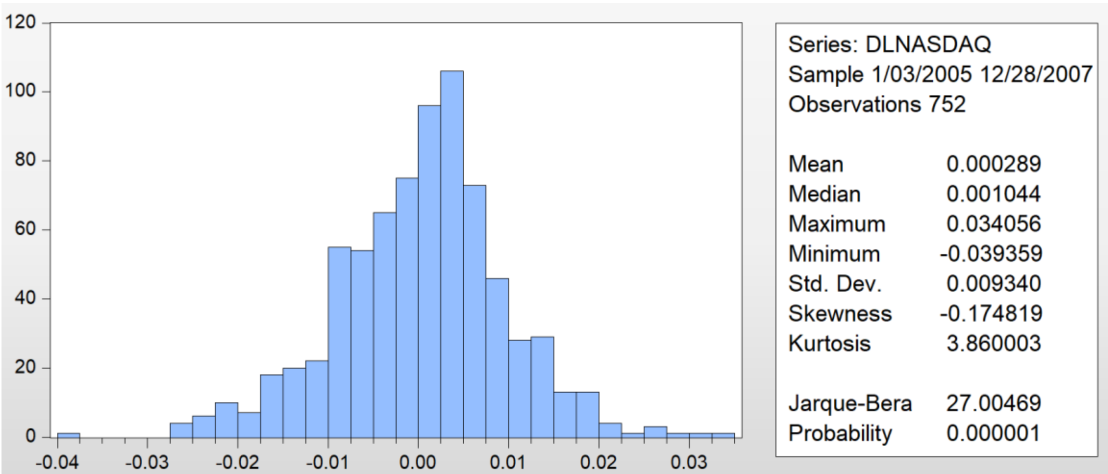
Sample: 1/03/2005 12/28/2007
Included observations: 735

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.074	0.074	4.0933	0.043
		2	-0.060	-0.066	6.7658	0.034
		3	-0.008	0.001	6.8160	0.078
		4	-0.037	-0.041	7.8492	0.097
		5	0.005	0.011	7.8654	0.164
		6	0.038	0.032	8.9510	0.176
		7	-0.056	-0.061	11.245	0.128
		8	-0.113	-0.102	20.797	0.008
		9	0.014	0.025	20.950	0.013
		10	0.024	0.011	21.385	0.019
		11	0.031	0.026	22.082	0.024
		12	0.051	0.041	24.060	0.020
		13	-0.029	-0.027	24.695	0.025
		14	-0.028	-0.013	25.278	0.032
		15	0.030	0.020	25.965	0.038
		16	-0.075	-0.092	30.236	0.017
		17	0.018	0.037	30.482	0.023
		18	-0.001	-0.013	30.482	0.033
		19	-0.015	0.003	30.648	0.044
		20	0.001	0.002	30.648	0.060
		21	-0.026	-0.039	31.154	0.071
		22	0.012	0.020	31.268	0.091
		23	-0.036	-0.049	32.245	0.095
		24	-0.009	-0.017	32.306	0.120
		25	-0.044	-0.039	33.769	0.113
		26	0.017	0.023	33.978	0.136
		27	-0.010	-0.021	34.050	0.165
		28	-0.041	-0.034	35.312	0.161
		29	-0.002	-0.009	35.315	0.194
		30	-0.056	-0.063	37.703	0.158
		31	-0.022	-0.016	38.087	0.178
		32	0.032	0.010	38.858	0.188
		33	0.020	0.017	39.169	0.213
		34	-0.023	-0.023	39.567	0.235
		35	-0.022	-0.022	39.946	0.260
		36	0.017	0.020	40.183	0.290

Also, the correlogram presents probabilities that are lower than 5%, meaning that they are statistically significant, notably at the first 2 autocorrelations and some of the middle ones. This can be explained since the MXX index approaches the normal distribution, but there is also a low level of risk and possibility for speculation involved. The previous days' pattern may prove significant for some investors, although this index can be characterized as high – cap index.

DLNASDAQ

The final index for examination for the pre mortgage crisis period is the United States' NASDAQ Composite index. As can be observed by its histogram, this is the closest to normality and randomness index out of all, for a period absent of financial turmoil. Its values indicate that this large capitalization index provides little risk and, therefore, speculation possibility. To be more specific, it is clear that Kurtosis has a value of 3.86, which is very close to 3, meaning that the returns of this index almost follow the normal distribution. Furthermore, Jarque – Bera has the lowest value, 27, of all the previous respective values, confirming the normality of this specific index. There is no doubt that NASDAQ offered little to no risk before the crisis.



Sample: 1/03/2005 12/28/2007
Included observations: 752

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.029	-0.029	0.6305	0.427
		2	-0.059	-0.060	3.3030	0.192
		3	0.021	0.017	3.6286	0.304
		4	-0.043	-0.045	4.9991	0.287
		5	-0.007	-0.007	5.0373	0.411
		6	-0.047	-0.053	6.7054	0.349
		7	-0.007	-0.009	6.7445	0.456
		8	-0.036	-0.045	7.7513	0.458
		9	-0.002	-0.005	7.7546	0.559
		10	0.086	0.077	13.448	0.200
		11	-0.002	0.002	13.450	0.265
		12	0.014	0.019	13.603	0.327
		13	-0.020	-0.024	13.899	0.381
		14	-0.042	-0.039	15.252	0.361
		15	-0.006	-0.012	15.284	0.431
		16	0.058	0.063	17.895	0.330
		17	0.020	0.025	18.204	0.376
		18	-0.025	-0.012	18.679	0.412
		19	0.015	0.011	18.845	0.467
		20	-0.008	-0.016	18.896	0.529
		21	0.013	0.014	19.019	0.584
		22	0.063	0.063	22.135	0.452
		23	-0.054	-0.042	24.424	0.381
		24	-0.043	-0.031	25.856	0.360
		25	0.031	0.026	26.584	0.377
		26	-0.004	-0.012	26.599	0.431
		27	-0.020	-0.022	26.913	0.469
		28	0.004	0.003	26.928	0.522
		29	-0.038	-0.043	28.032	0.516
		30	-0.024	-0.019	28.470	0.546
		31	0.004	-0.005	28.486	0.596
		32	-0.019	-0.039	28.778	0.630
		33	-0.018	-0.019	29.022	0.666
		34	-0.003	-0.004	29.027	0.710
		35	0.007	-0.001	29.066	0.749
		36	0.010	0.011	29.142	0.784

The aforementioned conclusion can be verified by the correlogram, since all probabilities of the autocorrelations present a value larger than 5%, indicating that previous days had no important part in current day's negotiations for the investors. This fact further proves the low risk that NASDAQ offered before the commence of the turbulent period.

TGARCH models

Before proceeding to build the TGARCH models for all 4 indices for the period before the 2008 financial crisis, it is essential to note again the TGARCH model formula:

$$R_t = \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_o + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + \cdots + a_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2 + \gamma_1\varepsilon_{t-1}^2 I_{(\varepsilon_{t-1}<0)}$$

The usefulness of this model comes from the fact that it is needed in order to understand the magnitude of the crisis impact on each index. During TGARCH examination, it must be considered that the z – Statistic is the factor that shows the statistical significance of each component of the model. If any component is found to have no statistical significance, then the model is reduced from TGARCH to its simpler form, TARCH, with the formula converted into the following:

$$R_t = \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_o + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + \cdots + a_p\varepsilon_{t-p}^2 + \gamma_1\varepsilon_{t-1}^2 I_{(\varepsilon_{t-1}<0)}.$$

However, the reduction process continues if no statistical significance is found once again, into the simplest ARCH model:

$$R_t = \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_o + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + \cdots + a_p\varepsilon_{t-p}^2.$$

It should be reminded that the TGARCH model can explain the leverage phenomenon, along with volatility clustering, which indicates that risk is highly variable and not constant.

Beginning with the DLBEL variable, the following full TGARCH model is presented:

TGARCH

Sample (adjusted): 1/03/2005 12/11/2007
Included observations: 761 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	5.15E-06	1.05E-06	4.918934	0.0000
RESID(-1)^2	-0.067555	0.031162	-2.167885	0.0302
RESID(-1)^2*(RESID(-1)<0)	0.353182	0.134581	2.624300	0.0087
GARCH(-1)	0.845614	0.028902	29.25782	0.0000

R-squared	-0.001914	Mean dependent var	0.000426
Adjusted R-squared	-0.000598	S.D. dependent var	0.009749
S.E. of regression	0.009752	Akaike info criterion	-6.793154
Sum squared resid	0.072372	Schwarz criterion	-6.768793
Log likelihood	2588.795	Hannan-Quinn criter.	-6.783774
Durbin-Watson stat	2.276992		

In this model, all coefficients are statistically significant, since they exceed the 1.96 threshold in 5% significance level, in absolute values. The a_1 coefficient represents the volatility clustering, meaning than the risk is concentrated on specific clusters, regarding time periods. However, in the case of BEL 20, this coefficient has a negative value. The negative value means that this specific TGARCH model must be reduced into a TARCH and examine the statistical significance of its coefficients.

TARCH

Dependent Variable: DLBEL20
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 03/19/22 Time: 11:56
Sample (adjusted): 1/03/2005 12/11/2007
Included observations: 761 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	7.29E-05	1.10E-06	66.38221	0.0000
RESID(-1)^2	0.008978	0.027780	0.323174	0.7466
RESID(-1)^2*(RESID(-1)<0)	0.231884	0.077148	3.005723	0.0026

R-squared	-0.001914	Mean dependent var	0.000426
Adjusted R-squared	-0.000598	S.D. dependent var	0.009749
S.E. of regression	0.009752	Akaike info criterion	-6.590001
Sum squared resid	0.072372	Schwarz criterion	-6.571731
Log likelihood	2510.495	Hannan-Quinn criter.	-6.582966
Durbin-Watson stat	2.276992		

ARCH

Dependent Variable: DLBEL20
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 03/19/22 Time: 12:04
Sample (adjusted): 1/03/2005 12/11/2007
Included observations: 761 after adjustments
Convergence achieved after 6 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	7.30E-05	1.12E-06	64.90420	0.0000
RESID(-1)^2	0.129390	0.028990	4.463307	0.0000

R-squared	-0.001914	Mean dependent var	0.000426
Adjusted R-squared	-0.000598	S.D. dependent var	0.009749
S.E. of regression	0.009752	Akaike info criterion	-6.575205
Sum squared resid	0.072372	Schwarz criterion	-6.563025
Log likelihood	2503.866	Hannan-Quinn criter.	-6.570515
Durbin-Watson stat	2.276992		

The TARCH model that is constructed shows a statistically significant γ_1 coefficient that represents leverage. However, the a_1 coefficient shows a z – Statistic lower than 1.96. The non – statistical significance of this coefficient indicates that the model must be transformed into a simple ARCH. As can be seen, the ARCH model shows a statistically significant α_1 coefficient that has a value of 0.12. This value represents the level of volatility clustering regarding the period before the 2008 crisis for the BEL20 index.

Continuing with DLHSI, the returns of the Hang Seng Index, the following models are built:

TGARCH

Sample (adjusted): 1/04/2005 11/09/2007
Included observations: 738 after adjustments
Convergence achieved after 27 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	1.34E-06	1.05E-06	1.278736	0.2010
RESID(-1)^2	0.058130	0.021050	2.761497	0.0058
RESID(-1)^2*(RESID(-1)<0)	0.015932	0.031215	0.510379	0.6098
GARCH(-1)	0.925685	0.022953	40.32992	0.0000

R-squared	-0.005758	Mean dependent var	0.000886
Adjusted R-squared	-0.004396	S.D. dependent var	0.011679
S.E. of regression	0.011704	Akaike info criterion	-6.340422
Sum squared resid	0.101099	Schwarz criterion	-6.315469
Log likelihood	2343.616	Hannan-Quinn criter.	-6.330800
Durbin-Watson stat	1.970201		

TARCH

Sample (adjusted): 1/04/2005 11/09/2007
Included observations: 738 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	0.000118	1.07E-05	10.99506	0.0000
RESID(-1)^2	0.047146	0.051154	0.921633	0.3567
RESID(-1)^2*(RESID(-1)<0)	0.213630	0.121527	1.757882	0.0788

R-squared	-0.005758	Mean dependent var	0.000886
Adjusted R-squared	-0.004396	S.D. dependent var	0.011679
S.E. of regression	0.011704	Akaike info criterion	-6.081423
Sum squared resid	0.101099	Schwarz criterion	-6.062708
Log likelihood	2247.045	Hannan-Quinn criter.	-6.074206
Durbin-Watson stat	1.970201		

It is obvious that in the TGARCH model the β_1 coefficient is not statistically significant, since its z – Statistic has a value of 0.51, which is much lower than 1.96. Moreover, the constant of this model seems of no statistical significance as well. The TGARCH model is transformed into a TARCH, where it can be seen that both the a_1 and γ_1 coefficients are not statistically significant, therefore the model is converted to a simple ARCH.

ARCH

Sample (adjusted): 1/04/2005 11/09/2007
Included observations: 738 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	0.000118	1.09E-05	10.77812	0.0000
RESID(-1)^2	0.148613	0.063502	2.340297	0.0193

R-squared	-0.005758	Mean dependent var	0.000886
Adjusted R-squared	-0.004396	S.D. dependent var	0.011679
S.E. of regression	0.011704	Akaike info criterion	-6.076570
Sum squared resid	0.101099	Schwarz criterion	-6.064093
Log likelihood	2244.254	Hannan-Quinn criter.	-6.071758
Durbin-Watson stat	1.970201		

In this particular ARCH model it is observed that the a_1 coefficient has a relatively low value, meaning that there is no notable volatility clustering in this financial index during the pre – 2008 crisis. The ARCH model confirms that there is no significant variable risk. It is also obvious that there is no leverage, since the TARCH model has been reduced.

The MXX financial index presents the following models:

TGARCH

Sample (adjusted): 1/03/2005 11/05/2007
Included observations: 735 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)
+ C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	1.11E-05	4.91E-06	2.255339	0.0241
RESID(-1)^2	-0.003119	0.050736	-0.061466	0.9510
RESID(-1)^2*(RESID(-1)<0)	0.240251	0.084781	2.833789	0.0046
GARCH(-1)	0.826906	0.050758	16.29117	0.0000

R-squared	-0.006350	Mean dependent var	0.001032
Adjusted R-squared	-0.004981	S.D. dependent var	0.012963
S.E. of regression	0.012996	Akaike info criterion	-6.006127
Sum squared resid	0.124133	Schwarz criterion	-5.981094
Log likelihood	2211.252	Hannan-Quinn criter.	-5.996472
Durbin-Watson stat	1.826629		

TARCH

Sample (adjusted): 1/03/2005 11/05/2007
Included observations: 735 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000158	1.30E-05	12.12750	0.0000
RESID(-1)^2	-0.019140	0.016609	-1.152358	0.2492
RESID(-1)^2*(RESID(-1)<0)	0.184260	0.088271	2.087439	0.0368

R-squared	-0.006350	Mean dependent var	0.001032
Adjusted R-squared	-0.004981	S.D. dependent var	0.012963
S.E. of regression	0.012996	Akaike info criterion	-5.854124
Sum squared resid	0.124133	Schwarz criterion	-5.835349
Log likelihood	2154.391	Hannan-Quinn criter.	-5.846883
Durbin-Watson stat	1.826629		

ARCH

Sample (adjusted): 1/03/2005 11/05/2007
Included observations: 735 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000159	1.31E-05	12.20784	0.0000
RESID(-1)^2	0.057983	0.048256	1.201576	0.2295

R-squared	-0.006350	Mean dependent var	0.001032
Adjusted R-squared	-0.004981	S.D. dependent var	0.012963
S.E. of regression	0.012996	Akaike info criterion	-5.846575
Sum squared resid	0.124133	Schwarz criterion	-5.834059
Log likelihood	2150.616	Hannan-Quinn criter.	-5.841748
Durbin-Watson stat	1.826629		

The procedure for the returns of Mexico's index MXX starts with the conversion of the TGARCH model into a TARCH, because of the lack of statistical significance of the a_1 coefficient of the initial model. Moreover, the same measure is taken once again due to the repeated insignificance of the same coefficient in the TARCH model, so eventually the simple ARCH shows that there is no volatility clustering or leverage in this index. This fact further confirms that before the crisis, the MXX index had no varying risk, but the risk was mostly random. This is expected from a large capitalization index.

Finally, concluding the analysis for the period before the mortgage crisis, the models for the largest index of the sample, NASDAQ Composite, are presented:

TGARCH

Sample (adjusted): 1/04/2005 11/29/2007
Included observations: 752 after adjustments
Convergence achieved after 29 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)
+ C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	4.51E-06	1.66E-06	2.714202	0.0066
RESID(-1)^2	-0.035137	0.022711	-1.547140	0.1218
RESID(-1)^2*(RESID(-1)<0)	0.154756	0.031761	4.872481	0.0000
GARCH(-1)	0.905084	0.029056	31.14914	0.0000

R-squared	-0.000958	Mean dependent var	0.000289
Adjusted R-squared	0.000373	S.D. dependent var	0.009340
S.E. of regression	0.009338	Akaike info criterion	-6.589285
Sum squared resid	0.065573	Schwarz criterion	-6.564696
Log likelihood	2481.571	Hannan-Quinn criter.	-6.579812
Durbin-Watson stat	2.049028		

TARCH

Sample (adjusted): 1/04/2005 11/29/2007
Included observations: 752 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	8.12E-05	5.80E-06	14.00917	0.0000
RESID(-1)^2	0.017891	0.046489	0.384841	0.7004
RESID(-1)^2*(RESID(-1)<0)	0.101989	0.075347	1.353593	0.1759

R-squared	-0.000958	Mean dependent var	0.000289
Adjusted R-squared	0.000373	S.D. dependent var	0.009340
S.E. of regression	0.009338	Akaike info criterion	-6.509208
Sum squared resid	0.065573	Schwarz criterion	-6.490767
Log likelihood	2450.462	Hannan-Quinn criter.	-6.502103
Durbin-Watson stat	2.049028		

ARCH

Sample (adjusted): 1/04/2005 11/29/2007
Included observations: 752 after adjustments
Convergence achieved after 8 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	8.07E-05	5.87E-06	13.74553	0.0000
RESID(-1)^2	0.076151	0.044478	1.712082	0.0869

R-squared	-0.000958	Mean dependent var	0.000289
Adjusted R-squared	0.000373	S.D. dependent var	0.009340
S.E. of regression	0.009338	Akaike info criterion	-6.509343
Sum squared resid	0.065573	Schwarz criterion	-6.497049
Log likelihood	2449.513	Hannan-Quinn criter.	-6.504606
Durbin-Watson stat	2.049028		

As with the previous index examination, NASDAQ's analysis follows the same steps that conclude in a simple ARCH model, where it is clear again that the phenomena of volatility clustering and, of course, leverage, are absent. Since this index has presented the lowest risk and the closest to normality distribution compared to all other indices, it is logical that it shows no volatility clustering.

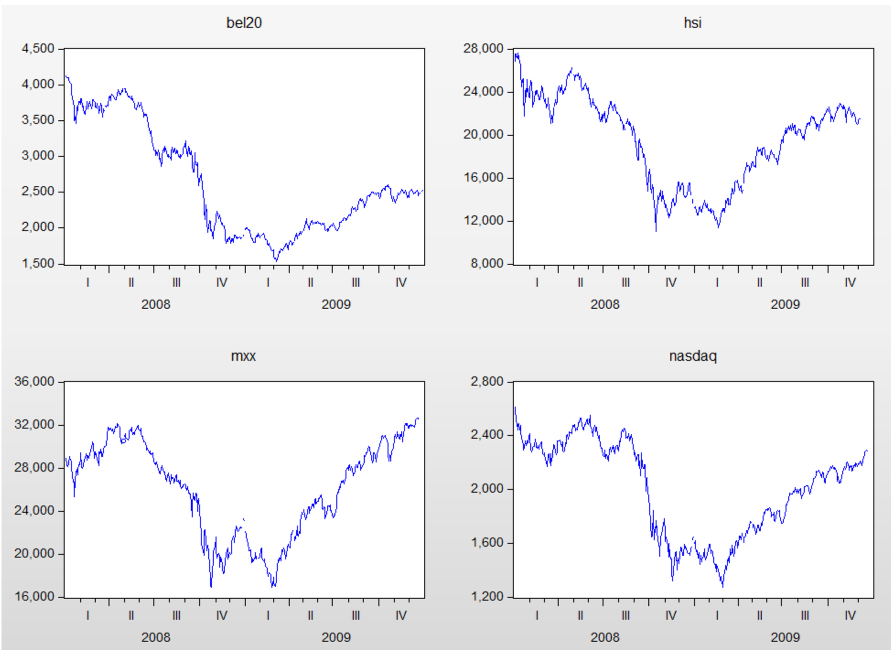
Correlation				
	DLBEL20	DLHSI	DLMXX	DLNASDAQ
DLBEL20	1.000000	-0.065953	-0.021736	0.024328
DLHSI	-0.065953	1.000000	-0.038573	0.028777
DLMXX	-0.021736	-0.038573	1.000000	-0.053503
DLNASDAQ	0.024328	0.028777	-0.053503	1.000000

Concluding the analysis for the years before the financial crisis of 2008, the above table provides information about the correlations between the indices during this period. It is clear that all indices have little to no correlations between them and even some of them present negative values.

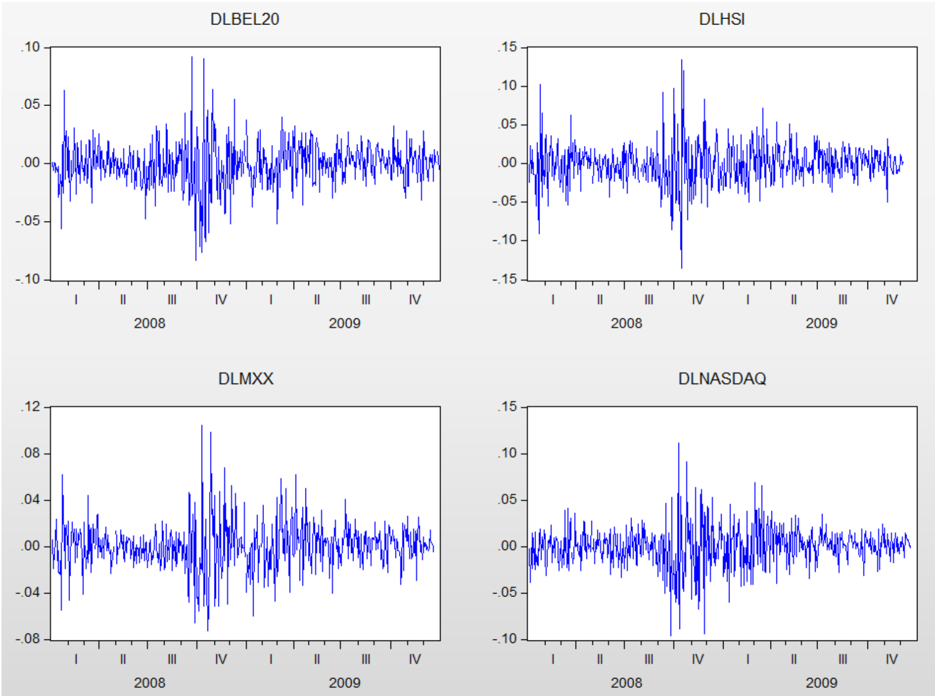
Subprime Mortgage Crisis, 1/1/2008 to 31/12/2009

The analysis that took place for the previous period are also be followed for the period for which the Subprime Mortgage Crisis began in the United States. The same procedure will shed light to the way that those aforementioned indices altered, following the financial turmoil.

The statistical test that were conducted in the preceding period are applied here as well. First and foremost, it is crucial to present the values of the 4 indices during these 2 years, as well as their logarithmic differences. The conversion of the values to logarithmic differences is essential, since stationarity is vital in order to proceed to testing.



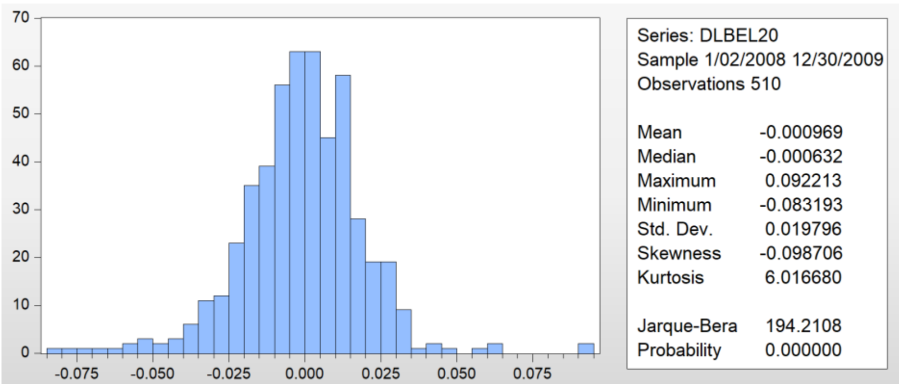
As can be seen from the above compilation of graphs, all 4 indices had a dramatic plunge before the fourth quarter of 2008 and during the first quarter of 2009. Inspecting the above graphs, one can observe that most if the indices start to recover sometime during early 2009. However, BEL20's recovery is nowhere near this significant, since it does not seem to reach similar value levels that had before the crisis. The rest of the indices seem to also not reach their previous levels, except Mexico's financial index that shows a miraculous recovery. This course of events will be thoroughly examined through the statistical tests and TGARCH models. As mentioned before, it is vital to convert the non – stationary data into stationary ones. The log differences of these values assist to this end.



The stationary observations reveal the times that volatility peaked between early 2008 and late 2009 and as can be seen, volatility patterns are very similar for each index. It is notable that the levels of volatility reached by the 3 indices corresponding to larger capitalization markers are very similar to those of BEL20. In some cases, more risk is also spotted. As noted by the values reached, it can be confirmed that the risk during this period skyrocketed to unprecedented heights.

DLBEL20

The below histogram presents a much more normal distribution than before. However, Skewness remains almost the same as before, with Kurtosis presenting a value that indicates randomness. It is also worth noting that Jarque – Bera has a value of 194.21, which is far lower than its last counterpart, which had a spectacular price of 28,948.69 that indicated no normality whatsoever. Since BEL20 is a high risk index, it seems that the financial turbulence does not add to this risk, but instead it normalizes the distribution.



Sample: 1/02/2008 12/30/2009
Included observations: 510

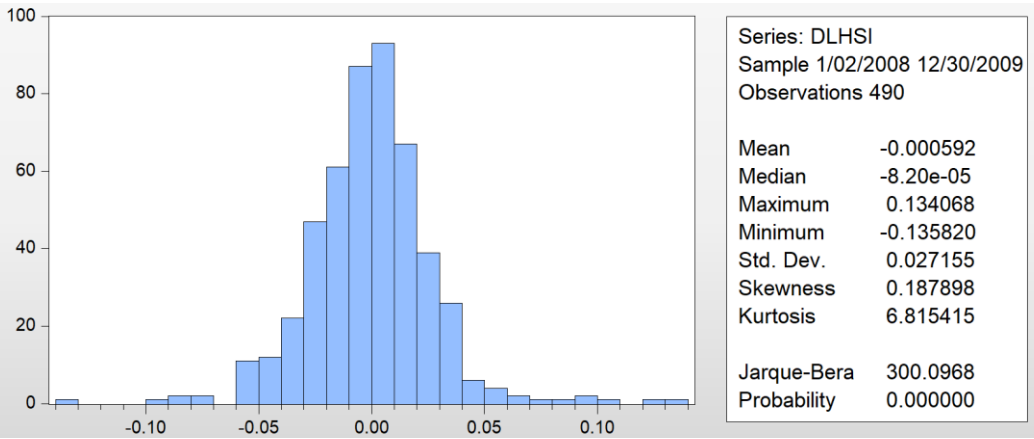
	AC	PAC	Q-Stat	Prob
1	0.038	0.038	0.7570	0.384
2	-0.026	-0.028	1.1044	0.576
3	-0.059	-0.057	2.9197	0.404
4	0.109	0.113	9.0442	0.060
5	0.001	-0.011	9.0450	0.107
6	-0.050	-0.049	10.361	0.110
7	0.047	0.066	11.515	0.118
8	0.122	0.104	19.232	0.014
9	0.021	0.008	19.464	0.022
10	-0.085	-0.067	23.257	0.010
11	-0.044	-0.035	24.252	0.012
12	0.082	0.062	27.761	0.006
13	-0.011	-0.026	27.821	0.010
14	-0.029	-0.009	28.254	0.013
15	-0.053	-0.047	29.759	0.013
16	0.072	0.041	32.491	0.009
17	0.066	0.067	34.831	0.007
18	-0.089	-0.074	38.994	0.003
19	-0.033	-0.009	39.586	0.004
20	0.050	0.033	40.905	0.004
21	0.081	0.053	44.395	0.002
22	-0.000	0.031	44.396	0.003
23	-0.031	-0.014	44.902	0.004
24	0.029	0.001	45.358	0.005
25	0.088	0.069	49.511	0.002
26	-0.005	0.009	49.525	0.004
27	-0.064	-0.038	51.760	0.003
28	0.022	0.002	52.012	0.004
29	0.070	0.027	54.656	0.003
30	0.020	0.028	54.870	0.004
31	-0.057	-0.030	56.662	0.003
32	0.060	0.060	58.638	0.003
33	0.050	0.001	59.998	0.003
34	-0.036	-0.041	60.728	0.003
35	-0.123	-0.070	69.104	0.001
36	0.086	0.088	73.152	0.000

(Columns Autocorrelation and Partial Correlation are bar graphics.)

The correlogram for BEL20 shows autocorrelations that are not statistically significant, at least for the first 7 lags, since their probabilities are larger than 5%. This fact shows that the risk does not allow investors to take into consideration the first 7 days in order to negotiate. This is a significant difference regarding the previous results where all lags were of statistical significance, except the very last ones.

DLHSI

The Hang Seng Index projects a random distribution, taking into consideration the histogram, but this time the values of the histogram indicate a very minor drift from the values of pre – crisis histogram. More specifically, Kurtosis' value of 6.81 is marginally greater than 5.99 that the previous respective histogram presented, though it still is considered as normal. Furthermore, the same applies for Jarque – Bera, which is 300 here. In the earlier examination, the same index had a similar value of 180.76, which is somewhat closer to the 5.99 normality threshold. Overall, there is no remarkable difference between these 2 periods.



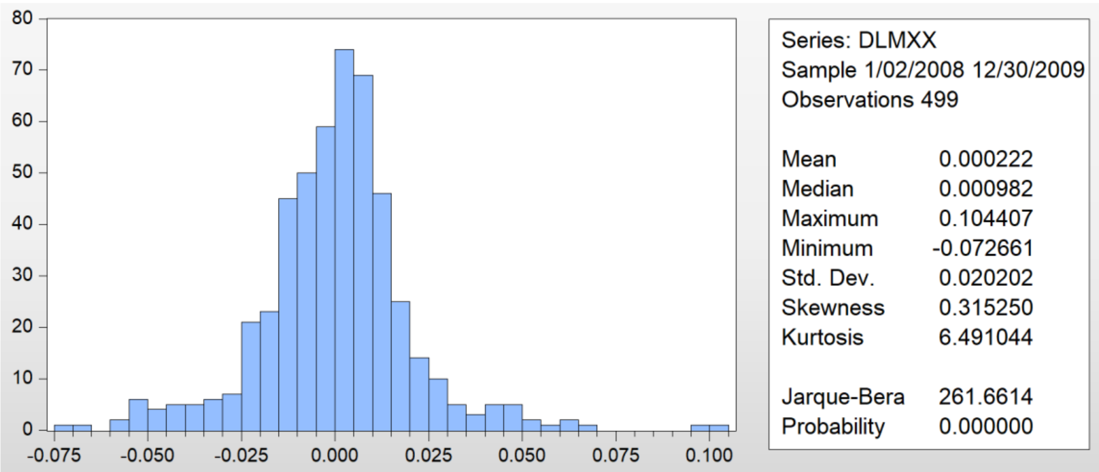
Sample: 1/02/2008 12/30/2009
Included observations: 490

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.051	-0.051	1.2753	0.259
		2	0.032	0.030	1.7928	0.408
		3	-0.102	-0.100	6.9756	0.073
		4	-0.055	-0.067	8.4853	0.075
		5	0.003	0.003	8.4912	0.131
		6	0.022	0.016	8.7430	0.189
		7	0.021	0.010	8.9608	0.255
		8	0.085	0.084	12.539	0.129
		9	-0.099	-0.089	17.487	0.042
		10	-0.090	-0.102	21.518	0.018
		11	0.040	0.057	22.325	0.022
		12	-0.001	0.000	22.326	0.034
		13	0.077	0.044	25.357	0.021
		14	-0.004	-0.000	25.366	0.031
		15	0.060	0.064	27.185	0.027
		16	0.007	0.024	27.209	0.039
		17	0.002	0.025	27.211	0.055
		18	0.008	0.025	27.241	0.075
		19	0.064	0.050	29.326	0.061
		20	0.006	0.014	29.345	0.081
		21	-0.012	-0.014	29.422	0.104
		22	-0.032	-0.014	29.947	0.120
		23	-0.019	-0.014	30.126	0.146
		24	0.000	0.000	30.127	0.181
		25	-0.043	-0.040	31.075	0.187
		26	0.121	0.109	38.702	0.052
		27	0.068	0.080	41.095	0.040
		28	-0.052	-0.061	42.500	0.039
		29	0.022	0.044	42.758	0.048
		30	-0.046	-0.020	43.861	0.049
		31	0.024	0.004	44.165	0.059
		32	-0.066	-0.084	46.447	0.048
		33	0.061	0.053	48.380	0.041
		34	0.018	-0.005	48.553	0.050
		35	0.054	0.043	50.073	0.047
		36	-0.052	0.002	51.503	0.045

It is also worth noting that the correlogram shows that the autocorrelations are not statistically significant, except from some lags in the middle of the month. Contrary to the previous correlogram that allowed predictions based on previous lags, this one shows that during the crisis periods it was not possible to aim for speculation. Despite the increased risk during this period, this index returned to normality quite fast.

DLMXX

The histogram of the log differences of Mexico's index is presented below:



The histogram shows again observations that seem to follow a normal distribution, as they did before, but upon further inspection, it can be observed that Kurtosis and Jarque – Bera have slightly inflated values. Kurtosis has an increased value of 6.49, which was 5.18 before the crisis, while Jarque – Bera measures at 261.66 instead of its previous value of 147.97. This low level increase shows that during the couple years of crisis the risk and volatility had risen to a certain degree.

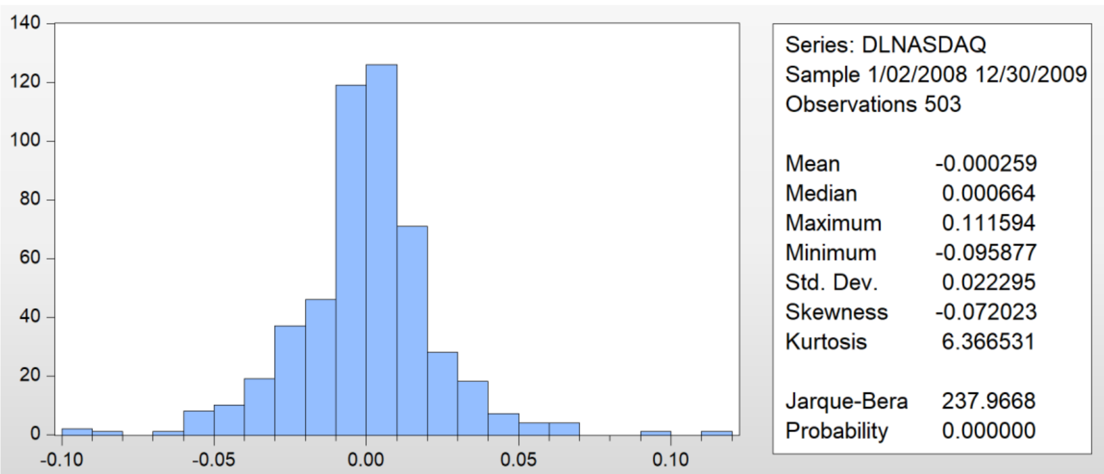
Sample: 1/02/2008 12/30/2009
Included observations: 499

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.105	0.105	5.5507	0.018
		2	-0.071	-0.083	8.0620	0.018
		3	-0.054	-0.038	9.5197	0.023
		4	0.006	0.010	9.5363	0.049
		5	0.005	-0.004	9.5476	0.089
		6	-0.023	-0.024	9.8113	0.133
		7	-0.104	-0.100	15.322	0.032
		8	0.045	0.066	16.354	0.038
		9	-0.027	-0.058	16.733	0.053
		10	-0.025	-0.017	17.042	0.073
		11	-0.022	-0.017	17.289	0.100
		12	0.080	0.080	20.611	0.056
		13	0.128	0.105	28.976	0.007
		14	-0.007	-0.035	29.003	0.010
		15	0.037	0.081	29.723	0.013
		16	0.094	0.080	34.251	0.005
		17	-0.058	-0.076	35.971	0.005
		18	-0.016	0.016	36.102	0.007
		19	-0.055	-0.040	37.696	0.006
		20	0.033	0.055	38.248	0.008
		21	-0.012	-0.045	38.321	0.012
		22	-0.052	-0.020	39.740	0.012
		23	-0.091	-0.067	44.103	0.005
		24	0.038	0.027	44.882	0.006
		25	0.042	0.018	45.809	0.007
		26	-0.009	-0.044	45.847	0.009
		27	0.031	0.066	46.363	0.012
		28	0.124	0.077	54.493	0.002
		29	0.033	0.000	55.076	0.002
		30	-0.055	-0.041	56.703	0.002
		31	-0.009	0.025	56.750	0.003
		32	0.090	0.096	61.127	0.001
		33	0.037	0.001	61.853	0.002
		34	-0.060	-0.032	63.765	0.001
		35	-0.044	0.021	64.801	0.002
		36	-0.019	-0.024	64.997	0.002

The correlogram for the MXX show that most of the probabilities have a percentage lower than 5%, indicating that information of the previous days counts towards predicting present day's value. However, this can be observed more on the later lags. Overall the correlogram does not show significant alterations from the results of the one that was calculated for before the 2008 crisis.

DLNASDAQ

The final analysis for the duration of the first 2 years of the financial crisis concerns the log differences of NASDAQ Composite. The following histogram shows a level of normality that has a significant distance from the previous one. There is higher Kurtosis than before, with 6.36 against 3.86 that was before. However, the most significant change comes in the Jarque – Bera value, which is much higher than before, equaling 237.97 against is previous value of 27. This is a clear indication of the decline in normality and randomness, while it also shows how the significant more risk affected this index.



Sample: 1/02/2008 12/30/2009
Included observations: 503

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.122	-0.122	7.5592	0.006
		2	-0.103	-0.119	12.888	0.002
		3	0.101	0.075	18.067	0.000
		4	-0.048	-0.038	19.234	0.001
		5	-0.010	-0.002	19.286	0.002
		6	0.033	0.016	19.856	0.003
		7	-0.008	0.004	19.891	0.006
		8	0.038	0.043	20.613	0.008
		9	-0.006	-0.001	20.630	0.014
		10	0.020	0.031	20.837	0.022
		11	-0.041	-0.044	21.709	0.027
		12	0.056	0.056	23.337	0.025
		13	-0.011	-0.011	23.402	0.037
		14	-0.032	-0.016	23.920	0.047
		15	-0.058	-0.082	25.661	0.042
		16	0.109	0.095	31.840	0.010
		17	0.016	0.033	31.974	0.015
		18	-0.102	-0.075	37.436	0.005
		19	0.038	0.004	38.192	0.006
		20	0.072	0.062	40.884	0.004
		21	-0.060	-0.016	42.766	0.003
		22	0.054	0.041	44.320	0.003
		23	0.001	0.005	44.321	0.005
		24	-0.060	-0.049	46.210	0.004
		25	0.083	0.067	49.840	0.002
		26	0.036	0.047	50.533	0.003
		27	0.040	0.090	51.382	0.003
		28	-0.008	-0.022	51.417	0.004
		29	-0.009	-0.005	51.456	0.006
		30	0.009	0.009	51.502	0.009
		31	0.014	0.038	51.606	0.012
		32	0.075	0.065	54.603	0.008
		33	0.025	0.032	54.933	0.010
		34	-0.127	-0.105	63.660	0.002
		35	0.080	0.051	67.142	0.001
		36	0.031	0.021	67.666	0.001

This time the correlogram shows that all probabilities have are statistically significant, a fact that clearly denotes increased risk and volatility levels. This is a strong departure from the previous correlogram for NASDAQ, since the former showed that autocorrelations had no significance. The conclusion can be drawn that this index was affected the most from the crisis, solely depending on the information given by the histogram and correlogram.

TGARCH models

As studied before, the TGARCH models will assist in estimating the level of change that took place in these 4 indices during the crisis years.

Starting with Belgium's BEL20 index, the models are presented below:

TGARCH

Sample (adjusted): 1/02/2008 12/29/2009
Included observations: 510 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	1.38E-05	4.52E-06	3.054251	0.0023
RESID(-1)^2	0.002625	0.036376	0.072170	0.9425
RESID(-1)^2*(RESID(-1)<0)	0.203785	0.066436	3.067405	0.0022
GARCH(-1)	0.850193	0.037492	22.67659	0.0000

R-squared	-0.002398	Mean dependent var	-0.000969
Adjusted R-squared	-0.000433	S.D. dependent var	0.019796
S.E. of regression	0.019800	Akaike info criterion	-5.315677
Sum squared resid	0.199949	Schwarz criterion	-5.282466
Log likelihood	1359.498	Hannan-Quinn criter.	-5.302656
Durbin-Watson stat	1.918426		

TARCH

Sample (adjusted): 1/02/2008 12/29/2009
Included observations: 510 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000273	3.92E-05	6.972930	0.0000
RESID(-1)^2	0.092343	0.067001	1.378234	0.1681
RESID(-1)^2*(RESID(-1)<0)	0.386346	0.161963	2.385400	0.0171

R-squared	-0.002398	Mean dependent var	-0.000969
Adjusted R-squared	-0.000433	S.D. dependent var	0.019796
S.E. of regression	0.019800	Akaike info criterion	-5.109587
Sum squared resid	0.199949	Schwarz criterion	-5.084679
Log likelihood	1305.945	Hannan-Quinn criter.	-5.099821
Durbin-Watson stat	1.918426		

ARCH

Sample (adjusted): 1/02/2008 12/29/2009
Included observations: 510 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	0.000264	4.23E-05	6.254039	0.0000
RESID(-1)^2	0.341103	0.116099	2.938036	0.0033

R-squared	-0.002398	Mean dependent var	-0.000969
Adjusted R-squared	-0.000433	S.D. dependent var	0.019796
S.E. of regression	0.019800	Akaike info criterion	-5.096708
Sum squared resid	0.199949	Schwarz criterion	-5.080102
Log likelihood	1301.660	Hannan-Quinn criter.	-5.090197
Durbin-Watson stat	1.918426		

The non - statistical significance of the TGARCH and TARCH models respectively pushes for reduction into a simple ARCH model, where can be seen that the a_1 coefficient has a value of 0.34, which is a sufficient number to assume that there is in fact some volatility clustering in this sample. This means that during this period there was increased variable risk.

Continuing the examination with the Hang Seng Index, the respective tables are seen below:

TGARCH

Sample (adjusted): 1/02/2008 11/30/2009
Included observations: 490 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	1.65E-05	8.64E-06	1.913786	0.0556
RESID(-1)^2	0.034521	0.028808	1.198292	0.2308
RESID(-1)^2*(RESID(-1)<0)	0.193916	0.064888	2.988498	0.0028
GARCH(-1)	0.841186	0.038615	21.78412	0.0000

R-squared	-0.000476	Mean dependent var	-0.000592
Adjusted R-squared	0.001566	S.D. dependent var	0.027155
S.E. of regression	0.027134	Akaike info criterion	-4.710384
Sum squared resid	0.360755	Schwarz criterion	-4.676144
Log likelihood	1158.044	Hannan-Quinn criter.	-4.696937
Durbin-Watson stat	2.097578		

TARCH

Sample (adjusted): 1/02/2008 11/30/2009
Included observations: 490 after adjustments
Convergence achieved after 21 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	0.000546	6.48E-05	8.423284	0.0000
RESID(-1)^2	0.000378	0.016623	0.022744	0.9819
RESID(-1)^2*(RESID(-1)<0)	0.377697	0.137135	2.754203	0.0059

R-squared	-0.000476	Mean dependent var	-0.000592
Adjusted R-squared	0.001566	S.D. dependent var	0.027155
S.E. of regression	0.027134	Akaike info criterion	-4.509328
Sum squared resid	0.360755	Schwarz criterion	-4.483648
Log likelihood	1107.785	Hannan-Quinn criter.	-4.499242
Durbin-Watson stat	2.097578		

ARCH

Sample (adjusted): 1/02/2008 11/30/2009
Included observations: 490 after adjustments
Convergence achieved after 7 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	0.000512	7.05E-05	7.260709	0.0000
RESID(-1)^2	0.270600	0.103628	2.611265	0.0090

R-squared	-0.000476	Mean dependent var	-0.000592
Adjusted R-squared	0.001566	S.D. dependent var	0.027155
S.E. of regression	0.027134	Akaike info criterion	-4.490425
Sum squared resid	0.360755	Schwarz criterion	-4.473305
Log likelihood	1102.154	Hannan-Quinn criter.	-4.483702
Durbin-Watson stat	2.097578		

As can be seen, there is no leverage on the Hang Seng Index during the crisis period, since the TGARCH and GARCH models are not statistically significant. However, there is a minor indication of volatility clustering. This is expected since the information drawn from the histogram showed a slight increase in risk and volatility, a fact that can also be confirmed by the ARCH model.

The third index for the examination of the 2008 crisis is the MXX, which is analyzed in the following models:

TGARCH

Sample (adjusted): 1/02/2008 12/11/2009
Included observations: 499 after adjustments
Convergence achieved after 28 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	4.98E-07	1.88E-06	0.265040	0.7910
RESID(-1)^2	-0.001366	0.017646	-0.077434	0.9383
RESID(-1)^2*(RESID(-1)<0)	0.147370	0.037064	3.976155	0.0001
GARCH(-1)	0.930378	0.020101	46.28449	0.0000

R-squared	-0.000121	Mean dependent var	0.000222
Adjusted R-squared	0.001884	S.D. dependent var	0.020202
S.E. of regression	0.020183	Akaike info criterion	-5.313271
Sum squared resid	0.203276	Schwarz criterion	-5.279502
Log likelihood	1329.661	Hannan-Quinn criter.	-5.300019
Durbin-Watson stat	1.789167		

TARCH

Sample (adjusted): 1/02/2008 12/11/2009
Included observations: 499 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000332	4.20E-05	7.906799	0.0000
RESID(-1)^2	0.036048	0.041260	0.873695	0.3823
RESID(-1)^2*(RESID(-1)<0)	0.310501	0.153676	2.020495	0.0433

R-squared	-0.000121	Mean dependent var	0.000222
Adjusted R-squared	0.001884	S.D. dependent var	0.020202
S.E. of regression	0.020183	Akaike info criterion	-5.013292
Sum squared resid	0.203276	Schwarz criterion	-4.987966
Log likelihood	1253.816	Hannan-Quinn criter.	-5.003354
Durbin-Watson stat	1.789167		

ARCH

Sample (adjusted): 1/02/2008 12/11/2009
Included observations: 499 after adjustments
Convergence achieved after 7 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000333	4.54E-05	7.324702	0.0000
RESID(-1)^2	0.190299	0.074167	2.565827	0.0103

R-squared	-0.000121	Mean dependent var	0.000222
Adjusted R-squared	0.001884	S.D. dependent var	0.020202
S.E. of regression	0.020183	Akaike info criterion	-5.001459
Sum squared resid	0.203276	Schwarz criterion	-4.984575
Log likelihood	1249.864	Hannan-Quinn criter.	-4.994833
Durbin-Watson stat	1.789167		

The same conclusion can be drawn also for the MXX, since the TGARCH model is eventually converted into a simple ARCH, where no leverage can be found, but there is a small indication for volatility clustering. Since there was no volatility clustering observed during the pre – crisis period, these new findings can be backed by the histogram, where a slight differentiation from normality is seen. However, the crisis has not affected this particular index in a large scale, but ultimately there is a minor increase in risk.

The last index to be tested again is the NASDAQ Composite, with its respective models:

TGARCH

Sample (adjusted): 1/02/2008 12/17/2009
Included observations: 503 after adjustments
Convergence achieved after 32 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	3.54E-06	2.21E-06	1.603276	0.1089
RESID(-1)^2	-0.013856	0.017090	-0.810796	0.4175
RESID(-1)^2*(RESID(-1)<0)	0.159498	0.041227	3.868803	0.0001
GARCH(-1)	0.923272	0.018129	50.92700	0.0000

R-squared	-0.000135	Mean dependent var	-0.000259
Adjusted R-squared	0.001853	S.D. dependent var	0.022295
S.E. of regression	0.022275	Akaike info criterion	-5.189044
Sum squared resid	0.249570	Schwarz criterion	-5.155481
Log likelihood	1309.045	Hannan-Quinn criter.	-5.175878
Durbin-Watson stat	2.244115		

TARCH

Sample (adjusted): 1/02/2008 12/17/2009
Included observations: 503 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000399	5.88E-05	6.781582	0.0000
RESID(-1)^2	0.065038	0.067314	0.966187	0.3340
RESID(-1)^2*(RESID(-1)<0)	0.255011	0.142998	1.783311	0.0745

R-squared	-0.000135	Mean dependent var	-0.000259
Adjusted R-squared	0.001853	S.D. dependent var	0.022295
S.E. of regression	0.022275	Akaike info criterion	-4.818048
Sum squared resid	0.249570	Schwarz criterion	-4.792875
Log likelihood	1214.739	Hannan-Quinn criter.	-4.808173
Durbin-Watson stat	2.244115		

ARCH

Sample (adjusted): 1/02/2008 12/17/2009
Included observations: 503 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000401	6.08E-05	6.595621	0.0000
RESID(-1)^2	0.191942	0.084993	2.258319	0.0239

R-squared	-0.000135	Mean dependent var	-0.000259
Adjusted R-squared	0.001853	S.D. dependent var	0.022295
S.E. of regression	0.022275	Akaike info criterion	-4.810610
Sum squared resid	0.249570	Schwarz criterion	-4.793828
Log likelihood	1211.868	Hannan-Quinn criter.	-4.804026
Durbin-Watson stat	2.244115		

Regarding the increased risk that was observed in the histogram of the NASDAQ index, the ARCH model verifies that indeed risk and volatility were present during the crisis. The a_1 coefficient shows a statistically significant value of 0.19, which is notably higher than the 0.076 value of the ARCH corresponding to the period before the crisis. There is no tremendous change to the point of leverage introduction, but the growth of risk indicates some level of volatility clustering even in this large capitalization index.

Concluding the analysis for the 2008 crisis, it is essential to present the correlations between those indices in order to spot if any increase is made during this period.

Correlation				
	DLBEL20	DLHSI	DLMXX	DLNASDAQ
DLBEL20	1.000000	-0.025186	0.043627	0.032077
DLHSI	-0.025186	1.000000	0.009386	-0.014569
DLMXX	0.043627	0.009386	1.000000	0.110934
DLNASDAQ	0.032077	-0.014569	0.110934	1.000000

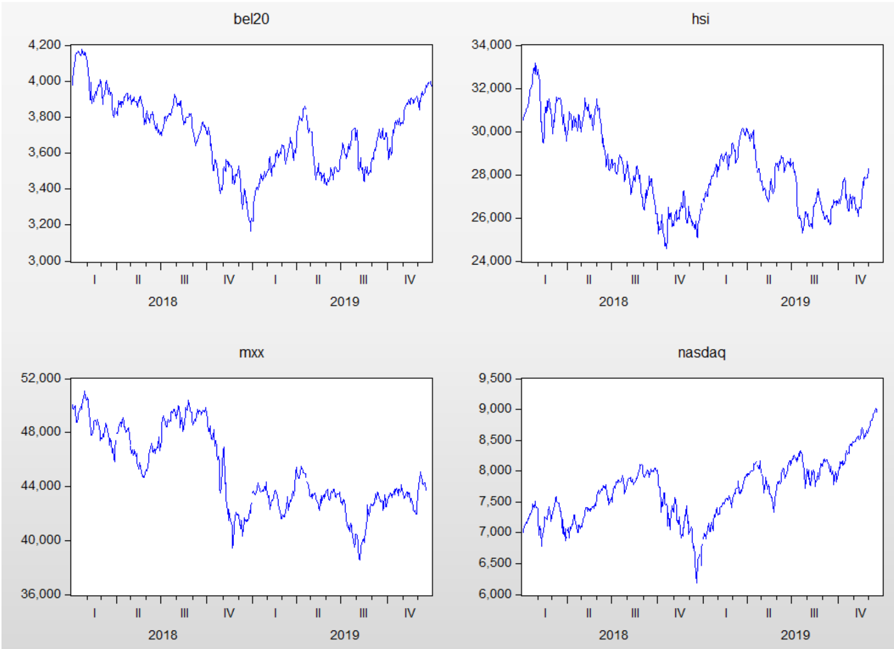
The most significant change that can be noted is the rise in correlation between MXX and NASDAQ from a former negative value of -0.05 to a positive 0.11. This can be justified since these 2 markets are of close proximity and therefore one can affect the other in a more impactful and direct way than others in geographically completely non – related markets.

Pre – period of Covid – 19 pandemic crisis, 1/1/2018 to 31/12/2019

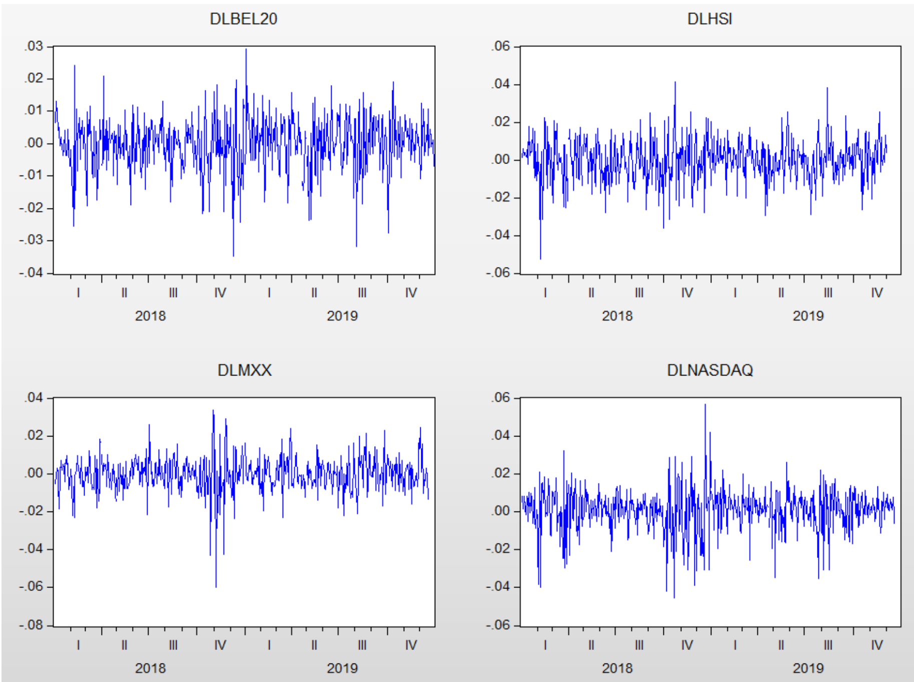
The case of the Covid – 19 pandemic is an especially peculiar case, since this health crisis that emerged in late 2019 in China and spread during early 2020 worldwide, impacted the financial markets globally. The procedures and tests conducted before are also applied for this period, in order to later reach a conclusion about the effect of this turbulence on the financial markets.

First and foremost, it is essential to start the statistical tests for each index again, following the same order. After this step, the TGARCH models are used again to confirm the results of the histograms and correlograms.

Before proceeding, it must be noted again that the observations must be converted into log differences in order to be stationary. The values of the indices during this period are shown in the following graph:

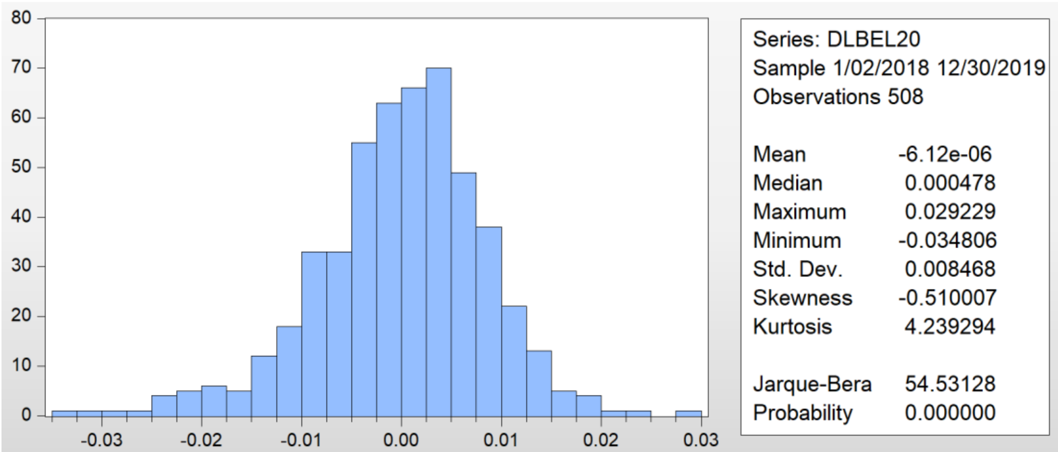


The non – stationary observations show inconsistent and unstable behavior, especially hsi, mxx and nasdaq. It seems that the HSI noted a severe drop during late 2008 and did not recover to the same level by the end of 2009. The same can also be said for MXX. However, BEL20 and NASDAQ follow a similar pattern, where they also face a huge decline during late 2018, but they present a clear recovery shortly after.



The converted stationary observations show that during this period BEL20 had the lowest volatility levels, while the other 3 had some periods of increased risk and volatility, but did not present extreme observations throughout the whole period of early 2018 to late 2019.

DLBEL



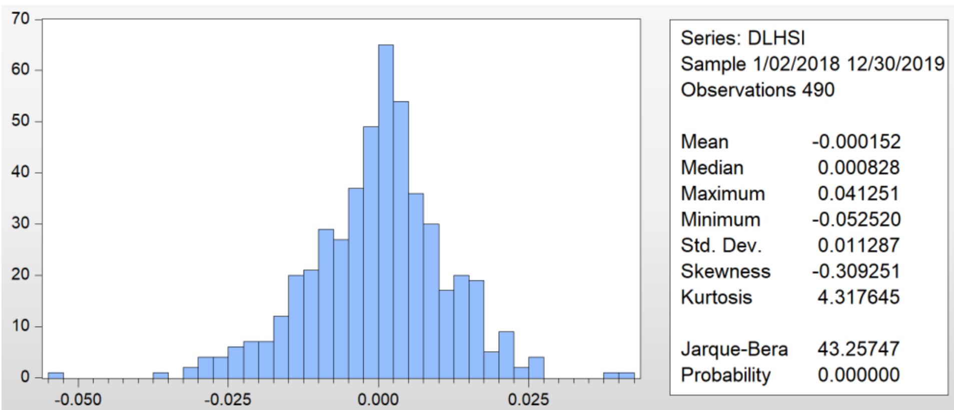
For BEL20, the descriptive tests show that during the pre – pandemic period it followed a very normal and random distribution. This is a very different result than the 2008 and prior periods where BEL20 was a highly volatile index. Kurtosis and Jarque – Bera have values that are clearly related to a normal distribution.

This histogram can be also backed by the correlogram, which shows that not a single autocorrelation is statistically significant, a characteristic of random distribution. This is an extraordinary shift from the volatile index that was during the previous examinations.

Sample: 1/02/2018 12/30/2019
Included observations: 508

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.077	0.077	3.0317	0.082
		2	0.034	0.028	3.6240	0.163
		3	0.032	0.028	4.1549	0.245
		4	-0.019	-0.025	4.3455	0.361
		5	-0.041	-0.040	5.1978	0.392
		6	-0.029	-0.022	5.6202	0.467
		7	-0.017	-0.009	5.7659	0.567
		8	-0.003	0.003	5.7691	0.673
		9	0.012	0.013	5.8468	0.755
		10	0.015	0.012	5.9655	0.818
		11	0.027	0.022	6.3514	0.849
		12	0.056	0.050	8.0125	0.784
		13	-0.035	-0.045	8.6419	0.799
		14	-0.042	-0.040	9.5657	0.793
		15	-0.031	-0.024	10.058	0.816
		16	-0.058	-0.046	11.858	0.754
		17	0.041	0.058	12.730	0.754
		18	0.010	0.007	12.784	0.804
		19	-0.061	-0.068	14.769	0.737
		20	0.038	0.037	15.537	0.745
		21	-0.050	-0.060	16.865	0.719
		22	-0.044	-0.035	17.877	0.713
		23	-0.092	-0.089	22.392	0.497
		24	-0.065	-0.051	24.635	0.426
		25	-0.032	-0.011	25.195	0.451
		26	-0.025	-0.014	25.526	0.489
		27	-0.040	-0.041	26.405	0.496
		28	-0.052	-0.058	27.877	0.471
		29	0.074	0.064	30.806	0.375
		30	0.036	0.026	31.513	0.391
		31	0.099	0.102	36.827	0.217
		32	0.032	0.003	37.400	0.235
		33	-0.066	-0.070	39.765	0.194
		34	0.030	0.043	40.267	0.213
		35	0.025	0.033	40.616	0.237
		36	0.007	0.026	40.645	0.273

DLHSI



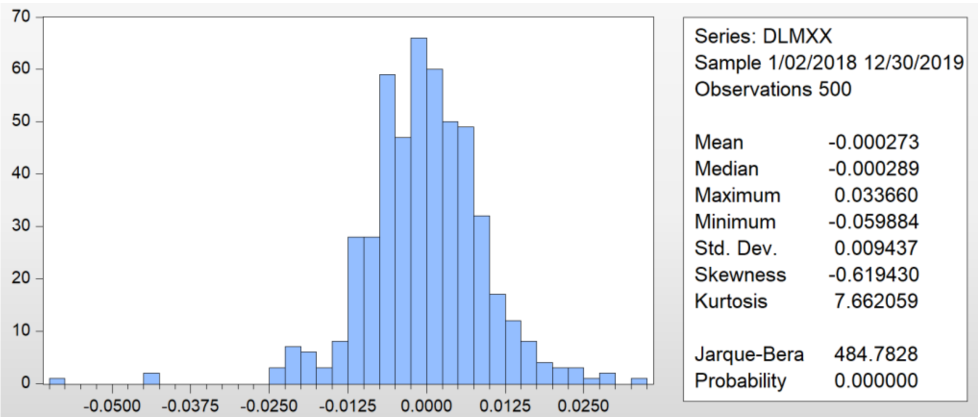
With very similar values with the previously tested histogram of BEL20, HSI follows the normal distribution as well. However, the distribution is even more normal than the period preceding the 2008 financial crisis.

Sample: 1/02/2018 12/30/2019
Included observations: 490

	AC	PAC	Q-Stat	Prob
1	0.016	0.016	0.1241	0.725
2	0.046	0.046	1.1667	0.558
3	0.044	0.043	2.1331	0.545
4	-0.048	-0.052	3.2971	0.509
5	-0.032	-0.034	3.7933	0.580
6	-0.089	-0.086	7.7119	0.260
7	0.026	0.036	8.0417	0.329
8	-0.010	-0.002	8.0905	0.425
9	-0.010	-0.008	8.1437	0.520
10	-0.064	-0.077	10.181	0.425
11	-0.013	-0.013	10.271	0.506
12	-0.047	-0.047	11.390	0.496
13	0.004	0.018	11.399	0.577
14	0.075	0.072	14.213	0.434
15	-0.025	-0.031	14.524	0.486
16	0.034	0.010	15.114	0.516
17	0.022	0.016	15.354	0.570
18	0.062	0.065	17.346	0.499
19	-0.062	-0.064	19.341	0.435
20	0.006	0.009	19.363	0.498
21	-0.023	-0.034	19.623	0.545
22	-0.074	-0.062	22.433	0.434
23	-0.041	-0.038	23.284	0.444
24	-0.111	-0.090	29.620	0.198
25	0.023	0.019	29.897	0.228
26	-0.068	-0.054	32.313	0.183
27	0.004	0.001	32.320	0.220
28	0.008	-0.008	32.355	0.260
29	0.013	0.013	32.450	0.300
30	-0.058	-0.082	34.192	0.273
31	0.017	0.013	34.342	0.311
32	0.041	0.019	35.230	0.318
33	-0.035	-0.027	35.885	0.335
34	0.028	-0.008	36.314	0.361
35	0.015	0.013	36.429	0.402
36	0.022	0.006	36.679	0.437

The same results are drawn from the correlogram, where it can be seen that the autocorrelations are not statistically significant, therefore no increased volatility can be observed.

DLMXX



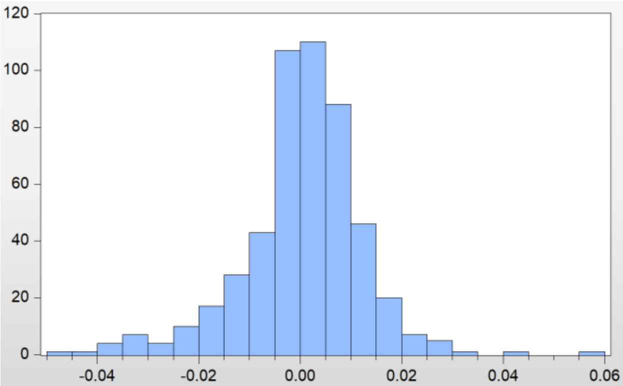
The histogram for the MXX shows a less normal distribution than of those 2 before and also less normal than its predecessor in pre – 2008 crisis, that had Kurtosis equaling 5.18 and Jarque – Bera 147.97. Instead, in this period's histogram Jarque – Bera has a value of 484.78, meaning that it strays more from the previous levels of randomness.

Sample: 1/02/2018 12/30/2019
Included observations: 500

	AC	PAC	Q-Stat	Prob
1	0.126	0.126	7.9571	0.005
2	-0.021	-0.038	8.1877	0.017
3	-0.056	-0.049	9.7664	0.021
4	-0.021	-0.009	9.9920	0.041
5	-0.018	-0.017	10.158	0.071
6	-0.092	-0.093	14.456	0.025
7	0.087	0.111	18.314	0.011
8	0.016	-0.017	18.449	0.018
9	0.007	0.001	18.472	0.030
10	-0.004	0.003	18.482	0.047
11	-0.008	-0.007	18.515	0.070
12	-0.059	-0.068	20.333	0.061
13	-0.014	0.024	20.430	0.085
14	0.065	0.053	22.621	0.067
15	-0.004	-0.029	22.631	0.092
16	0.005	0.011	22.644	0.124
17	0.131	0.141	31.549	0.017
18	0.090	0.044	35.813	0.007
19	0.001	0.001	35.813	0.011
20	-0.080	-0.052	39.180	0.006
21	-0.032	-0.021	39.731	0.008
22	-0.055	-0.052	41.344	0.007
23	-0.021	0.013	41.569	0.010
24	-0.031	-0.054	42.068	0.013
25	0.011	0.001	42.135	0.017
26	-0.008	-0.020	42.167	0.024
27	-0.002	0.006	42.170	0.032
28	-0.083	-0.103	45.853	0.018
29	-0.078	-0.031	49.118	0.011
30	0.011	0.022	49.183	0.015
31	0.029	0.005	49.642	0.018
32	0.012	-0.019	49.726	0.024
33	-0.005	0.004	49.741	0.031
34	0.008	-0.024	49.774	0.040
35	-0.013	-0.024	49.868	0.049
36	-0.063	-0.052	52.019	0.041

The correlogram indicates that almost all of the autocorrelations are statistically significant, except some of the middle ones. This means that during this period there was in fact increased volatility and risk. The results differ in a certain degree from the results given in the correlogram of the MXX before the start of the 2008 crisis, when the index followed a more normal distribution.

DLNASDAQ



Series: DLNASDAQ
Sample 1/02/2018 12/30/2019
Observations 501

Mean	0.000488
Median	0.000882
Maximum	0.056724
Minimum	-0.045263
Std. Dev.	0.011670
Skewness	-0.467504
Kurtosis	5.674618
Jarque-Bera	167.5807
Probability	0.000000

Sample: 1/02/2018 12/30/2019
Included observations: 501

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.047	-0.047	1.1221	0.289
		2	-0.073	-0.075	3.7827	0.151
		3	0.071	0.065	6.3511	0.096
		4	-0.001	-0.000	6.3519	0.174
		5	-0.062	-0.052	8.2749	0.142
		6	0.015	0.005	8.3876	0.211
		7	0.077	0.071	11.424	0.121
		8	-0.141	-0.128	21.554	0.006
		9	0.016	0.014	21.690	0.010
		10	0.000	-0.029	21.690	0.017
		11	-0.053	-0.036	23.150	0.017
		12	0.004	0.003	23.157	0.026
		13	0.017	-0.001	23.305	0.038
		14	-0.095	-0.094	27.938	0.014
		15	-0.033	-0.022	28.487	0.019
		16	0.076	0.039	31.518	0.012
		17	0.066	0.087	33.775	0.009
		18	0.023	0.043	34.042	0.012
		19	-0.027	-0.044	34.436	0.016
		20	-0.065	-0.079	36.657	0.013
		21	0.015	0.021	36.771	0.018
		22	0.003	-0.014	36.777	0.025
		23	0.021	0.024	37.007	0.032
		24	-0.066	-0.074	39.276	0.026
		25	0.007	0.002	39.302	0.034
		26	0.062	0.070	41.317	0.029
		27	-0.035	-0.011	41.953	0.033
		28	0.063	0.052	44.097	0.027
		29	-0.072	-0.089	46.885	0.019
		30	-0.008	-0.006	46.918	0.025
		31	-0.047	-0.031	48.105	0.026
		32	0.033	0.033	48.686	0.030
		33	0.062	0.048	50.758	0.025
		34	-0.052	-0.061	52.232	0.024
		35	0.021	-0.004	52.466	0.029
		36	-0.005	0.024	52.481	0.037

Upon first inspection, there is no deviation from the random distribution, but the values of Jarque – Bera and Kurtosis indicate that there is less normality than its previous counterpart tested for the pre – 2008 period.

Morevover, the correlogram shows no statistical significance for the first 5 autocorrelations, while the rest are significant. The difference from the pre – 2008 period is visible, because in that period no autocorrelations were significant. It seems that during 2018 to 2019 NASDAQ offered more risk than it did before a decade.

TGARCH models

The same procedure as before is followed, in order to understand the level of risk that each index presented during the pre – pandemic period.

Starting with BEL20, the models are shown below:

TGARCH

Sample (adjusted): 1/03/2018 12/30/2019
Included observations: 508 after adjustments
Convergence achieved after 21 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	9.10E-06	3.21E-06	2.838216	0.0045
RESID(-1)^2	-0.040063	0.026907	-1.488924	0.1365
RESID(-1)^2*(RESID(-1)<0)	0.266035	0.070624	3.766919	0.0002
GARCH(-1)	0.772070	0.071938	10.73251	0.0000

R-squared	-0.000001	Mean dependent var	-6.12E-06
Adjusted R-squared	0.001968	S.D. dependent var	0.008468
S.E. of regression	0.008460	Akaike info criterion	-6.797525
Sum squared resid	0.036358	Schwarz criterion	-6.764214
Log likelihood	1730.571	Hannan-Quinn criter.	-6.784463
Durbin-Watson stat	1.843299		

TARCH

Sample (adjusted): 1/03/2018 12/30/2019
Included observations: 508 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	5.89E-05	5.80E-06	10.16366	0.0000
RESID(-1)^2	0.061359	0.078020	0.786449	0.4316
RESID(-1)^2*(RESID(-1)<0)	0.237246	0.127699	1.857856	0.0632

R-squared	-0.000001	Mean dependent var	-6.12E-06
Adjusted R-squared	0.001968	S.D. dependent var	0.008468
S.E. of regression	0.008460	Akaike info criterion	-6.730962
Sum squared resid	0.036358	Schwarz criterion	-6.705979
Log likelihood	1712.664	Hannan-Quinn criter.	-6.721166
Durbin-Watson stat	1.843299		

ARCH

Sample (adjusted): 1/03/2018 12/30/2019
Included observations: 508 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	5.92E-05	5.74E-06	10.32652	0.0000
RESID(-1)^2	0.176589	0.069153	2.553601	0.0107

R-squared	-0.000001	Mean dependent var	-6.12E-06
Adjusted R-squared	0.001968	S.D. dependent var	0.008468
S.E. of regression	0.008460	Akaike info criterion	-6.726251
Sum squared resid	0.036358	Schwarz criterion	-6.709596
Log likelihood	1710.468	Hannan-Quinn criter.	-6.719720
Durbin-Watson stat	1.843299		

It is clear that with the activity of reduction of the models due to some components being statistically non – significant, BEL 20 is represented by a simple ARCH model that shows no notorious level of volatility clustering. This is to be expected since the previous histogram and correlogram showed that this index's logarithmic returns followed a normal distribution during 2018 to 2019.

Moving to the second index, HSI, the same methodology is applied:

TGARCH

Sample (adjusted): 1/03/2018 12/02/2019
Included observations: 490 after adjustments
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	1.02E-05	2.09E-06	4.866424	0.0000
RESID(-1)^2	-0.032270	0.018272	-1.766083	0.0774
RESID(-1)^2*(RESID(-1)<0)	0.097501	0.036977	2.636781	0.0084
GARCH(-1)	0.900386	0.026997	33.35119	0.0000

R-squared	-0.000183	Mean dependent var	-0.000152
Adjusted R-squared	0.001858	S.D. dependent var	0.011287
S.E. of regression	0.011277	Akaike info criterion	-6.146101
Sum squared resid	0.062312	Schwarz criterion	-6.111860
Log likelihood	1509.795	Hannan-Quinn criter.	-6.132653
Durbin-Watson stat	1.967667		

TARCH

Sample (adjusted): 1/03/2018 12/02/2019
Included observations: 490 after adjustments
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000126	7.68E-06	16.34991	0.0000
RESID(-1)^2	0.051124	0.059788	0.855080	0.3925
RESID(-1)^2*(RESID(-1)<0)	-0.070917	0.062920	-1.127087	0.2597

R-squared	-0.000183	Mean dependent var	-0.000152
Adjusted R-squared	0.001858	S.D. dependent var	0.011287
S.E. of regression	0.011277	Akaike info criterion	-6.122483
Sum squared resid	0.062312	Schwarz criterion	-6.096803
Log likelihood	1503.008	Hannan-Quinn criter.	-6.112398
Durbin-Watson stat	1.967667		

ARCH

Sample (adjusted): 1/03/2018 12/02/2019
Included observations: 490 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000127	7.81E-06	16.26245	0.0000
RESID(-1)^2	0.001008	0.033269	0.030305	0.9758

R-squared	-0.000183	Mean dependent var	-0.000152
Adjusted R-squared	0.001858	S.D. dependent var	0.011287
S.E. of regression	0.011277	Akaike info criterion	-6.123963
Sum squared resid	0.062312	Schwarz criterion	-6.106843
Log likelihood	1502.371	Hannan-Quinn criter.	-6.117239
Durbin-Watson stat	1.967667		

Once again, there is no significant risk or volatility clustering whatsoever associated with HSI and this ARCH model verifies the results provided by the histogram and the correlogram.

The next index is Mexico's MXX:

TGARCH

Sample (adjusted): 1/03/2018 12/16/2019
Included observations: 500 after adjustments
Convergence achieved after 22 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)
+ C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	6.90E-06	5.12E-06	1.348090	0.1776
RESID(-1)^2	0.094193	0.070631	1.333601	0.1823
RESID(-1)^2*(RESID(-1)<0)	0.064612	0.074936	0.862239	0.3886
GARCH(-1)	0.792632	0.093477	8.479437	0.0000

R-squared	-0.000836	Mean dependent var	-0.000273
Adjusted R-squared	0.001165	S.D. dependent var	0.009437
S.E. of regression	0.009432	Akaike info criterion	-6.634160
Sum squared resid	0.044481	Schwarz criterion	-6.600443
Log likelihood	1662.540	Hannan-Quinn criter.	-6.620929
Durbin-Watson stat	1.742401		

TARCH

Sample (adjusted): 1/03/2018 12/16/2019
Included observations: 500 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	7.07E-05	8.34E-06	8.484839	0.0000
RESID(-1)^2	0.403534	0.262922	1.534802	0.1248
RESID(-1)^2*(RESID(-1)<0)	-0.326854	0.265830	-1.229563	0.2189

R-squared	-0.000836	Mean dependent var	-0.000273
Adjusted R-squared	0.001165	S.D. dependent var	0.009437
S.E. of regression	0.009432	Akaike info criterion	-6.523613
Sum squared resid	0.044481	Schwarz criterion	-6.498325
Log likelihood	1633.903	Hannan-Quinn criter.	-6.513690
Durbin-Watson stat	1.742401		

ARCH

Sample (adjusted): 1/03/2018 12/16/2019
Included observations: 500 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	6.76E-05	8.07E-06	8.376325	0.0000
RESID(-1)^2	0.289838	0.135130	2.144877	0.0320

R-squared	-0.000836	Mean dependent var	-0.000273
Adjusted R-squared	0.001165	S.D. dependent var	0.009437
S.E. of regression	0.009432	Akaike info criterion	-6.517942
Sum squared resid	0.044481	Schwarz criterion	-6.501084
Log likelihood	1631.486	Hannan-Quinn criter.	-6.511327
Durbin-Watson stat	1.742401		

This time, the ARCH model shows that there is a substantial value for the a_1 coefficient, which is also statistically significant, in order to spot a level of volatility clustering. This can be backed by the histogram and also the correlogram, which both showed that during this period HSI had somewhat increased risk. Overall, there are no extreme levels of volatility, however, there are indications of a certain degree of risk involved during this time.

Finally, concluding this time period, the NASDAQ index is examined:

TGARCH

Sample (adjusted): 1/03/2018 12/17/2019
Included observations: 501 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)
+ C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	6.86E-06	2.70E-06	2.535082	0.0112
RESID(-1)^2	-0.020352	0.085393	-0.238327	0.8116
RESID(-1)^2*(RESID(-1)<0)	0.304999	0.119318	2.556191	0.0106
GARCH(-1)	0.817478	0.057688	14.17057	0.0000

R-squared	-0.001750	Mean dependent var	0.000488
Adjusted R-squared	0.000250	S.D. dependent var	0.011670
S.E. of regression	0.011668	Akaike info criterion	-6.341657
Sum squared resid	0.068208	Schwarz criterion	-6.307992
Log likelihood	1592.585	Hannan-Quinn criter.	-6.328448
Durbin-Watson stat	2.089039		

TARCH

Sample (adjusted): 1/03/2018 12/17/2019
Included observations: 501 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000101	1.18E-05	8.520872	0.0000
RESID(-1)^2	0.067056	0.081324	0.824555	0.4096
RESID(-1)^2*(RESID(-1)<0)	0.455985	0.171136	2.664464	0.0077

R-squared	-0.001750	Mean dependent var	0.000488
Adjusted R-squared	0.000250	S.D. dependent var	0.011670
S.E. of regression	0.011668	Akaike info criterion	-6.135963
Sum squared resid	0.068208	Schwarz criterion	-6.110714
Log likelihood	1540.059	Hannan-Quinn criter.	-6.126057
Durbin-Watson stat	2.089039		

ARCH

Sample (adjusted): 1/03/2018 12/17/2019
Included observations: 501 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Variance Equation		
C	0.000103	1.28E-05	8.048278	0.0000
RESID(-1)^2	0.259739	0.101452	2.560211	0.0105

R-squared	-0.001750	Mean dependent var	0.000488
Adjusted R-squared	0.000250	S.D. dependent var	0.011670
S.E. of regression	0.011668	Akaike info criterion	-6.115515
Sum squared resid	0.068208	Schwarz criterion	-6.098682
Log likelihood	1533.936	Hannan-Quinn criter.	-6.108910
Durbin-Watson stat	2.089039		

Again the ARCH for the pre – Covid period regarding the NASDAQ index shows that there is, in fact, a degree of volatility clustering and increased risk. It is not, however, significant to a concerning level, since the histogram showed a normal distribution altogether.

Concluding the analysis for the 2 years before the Covid – 19 pandemic, it is essential to show the correlations among the 4 indices.

Correlation				
	DLBEL20	DLHSI	DLMXX	DLNASDAQ
DLBEL20	1.000000	-0.009139	0.075447	-0.012667
DLHSI	-0.009139	1.000000	0.039910	0.091194
DLMXX	0.075447	0.039910	1.000000	0.209998
DLNASDAQ	-0.012667	0.091194	0.209998	1.000000

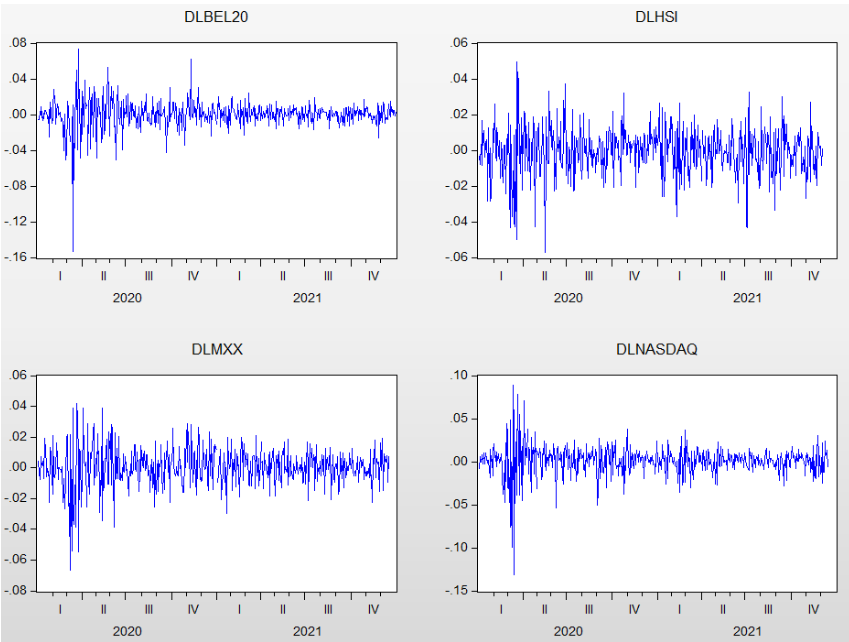
As can be observed, the most correlated indices are MXX and NASDAQ. This result was also given for the 2008 period of financial crisis. However, this time they are even more correlated, with a value of 0.209. It is clear that these 2 markets that exist in the same region are more correlated than others of different continents.

The Covid – 19 pandemic, 1/1/2020 to 31/12/2021

The last part of data analysis with this method concerns a two – year period from the start of 2020, when the Covid – 19 outbreak started spreading all over the world, to the end of 2021. It is a sufficient time period in order to distinguish the level of change of the financial markets behavior from the pre – pandemic period to some years later. Starting the analysis, descriptive statistics with histograms and correlograms take place, as well as TGARCH models that may gradually be converted into ARCH models if some components are found not to be statistically significant.

However, first and foremost, the values of the 4 indices need to be shown, as well as their log differences, in order to have a clear picture about the markets' course through time.

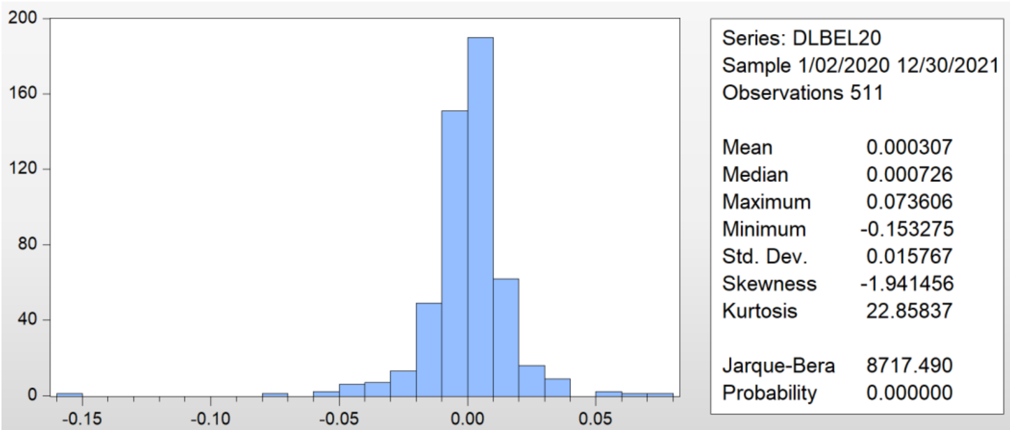
As can be seen from the above graphs, all indices showed a large fall during the first quarter of 2020, just when the pandemic transmitted globally. However, all indices seem to recover substantially during the later months, except HSI. This particular index notes a decline during early 2020 and rises right after, but at the closing months of 2021 it drops again to a similar rate of that of the pandemic spread.



The stationary observations show that the most dramatic volatility is generated in BEL20 and NASDAQ. The most extreme observations are a clear sign of the effect of the pandemic. Moreover, HSI appears to be the less affected from the pandemic, since its volatility seems relatively stable. Finally, MXX has the same effects with BEL20 and NASDAQ, but with nowhere near extreme observations.

DLBEL20

BEL20's histogram below makes it clear that this index had remarkably increased risk during the Covid – 19 period, since it appears to have a distance from the normal distribution, as can also be seen from Kurtosis and Jarque – Bera. The 22.85 and 8,717.49 values respectively show a transformation of a stable index, before the spread of the outbreak, to a volatile one in the last 2 years.



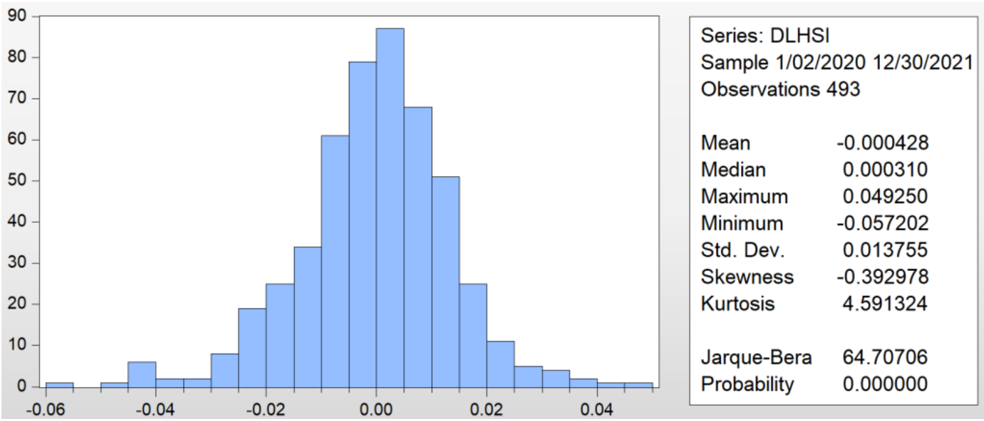
Sample: 1/02/2020 12/30/2021
Included observations: 511

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0009	0.976
		2	0.084	0.084	3.6753	0.159
		3	-0.066	-0.067	5.9211	0.116
		4	0.043	0.037	6.8766	0.143
		5	0.050	0.061	8.1548	0.148
		6	-0.127	-0.141	16.556	0.011
		7	0.101	0.104	21.843	0.003
		8	-0.140	-0.120	32.001	0.000
		9	0.032	-0.002	32.521	0.000
		10	-0.035	0.011	33.168	0.000
		11	0.103	0.089	38.693	0.000
		12	0.092	0.081	43.100	0.000
		13	-0.057	-0.045	44.819	0.000
		14	0.020	-0.020	45.032	0.000
		15	0.021	0.065	45.259	0.000
		16	-0.029	-0.087	45.694	0.000
		17	-0.188	-0.176	64.385	0.000
		18	-0.120	-0.101	71.992	0.000
		19	0.022	0.041	72.244	0.000
		20	0.068	0.105	74.721	0.000
		21	-0.034	-0.038	75.327	0.000
		22	0.038	0.039	76.107	0.000
		23	-0.033	-0.051	76.675	0.000
		24	-0.029	-0.064	77.139	0.000
		25	-0.015	-0.015	77.260	0.000
		26	0.090	0.073	81.685	0.000
		27	0.019	-0.003	81.888	0.000
		28	-0.115	-0.051	89.071	0.000
		29	-0.033	0.006	89.652	0.000
		30	-0.065	-0.051	91.971	0.000
		31	0.055	0.004	93.619	0.000
		32	-0.054	-0.026	95.197	0.000
		33	0.036	0.021	95.923	0.000
		34	0.048	0.021	97.202	0.000
		35	0.031	0.013	97.735	0.000
		36	-0.023	-0.044	98.033	0.000

The correlogram has statistically significant autocorrelations for all lags except the first 5. This is a significant turn for this index, since the correlogram for the 2 years prior did not show any significant autocorrelations whatsoever. The effect of the pandemic is clear in this occasion.

DLHSI

The descriptive tests for HSI exhibit an index that was not affected significantly by the pandemic. First of all, the histogram optically indicates a random distribution, while Kurtosis and Jarque – Bera have very similar values to those of the pre- pandemic period.

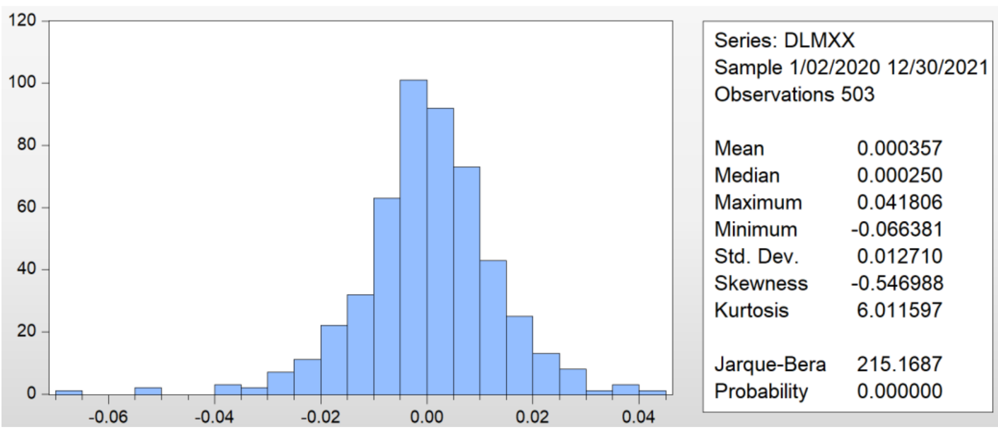


Sample: 1/02/2020 12/30/2021
Included observations: 493

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.065	-0.065	2.0847	0.149
		2	0.045	0.041	3.0710	0.215
		3	-0.041	-0.036	3.9263	0.270
		4	0.032	0.026	4.4506	0.348
		5	0.041	0.048	5.3030	0.380
		6	-0.055	-0.054	6.7954	0.340
		7	-0.023	-0.032	7.0692	0.422
		8	-0.047	-0.043	8.1586	0.418
		9	-0.064	-0.076	10.243	0.331
		10	0.001	-0.005	10.243	0.419
		11	0.026	0.035	10.583	0.479
		12	-0.062	-0.062	12.512	0.405
		13	-0.035	-0.041	13.150	0.436
		14	0.059	0.064	14.920	0.384
		15	-0.006	-0.013	14.936	0.456
		16	0.004	-0.010	14.945	0.529
		17	0.014	0.026	15.047	0.592
		18	0.017	0.008	15.201	0.648
		19	0.082	0.074	18.674	0.478
		20	-0.079	-0.066	21.890	0.346
		21	0.059	0.034	23.662	0.310
		22	0.001	0.017	23.663	0.365
		23	0.028	0.027	24.065	0.400
		24	-0.037	-0.035	24.760	0.419
		25	0.015	0.016	24.871	0.470
		26	-0.080	-0.074	28.202	0.349
		27	-0.057	-0.062	29.905	0.318
		28	0.011	0.016	29.971	0.365
		29	-0.018	-0.018	30.138	0.407
		30	-0.015	-0.017	30.249	0.453
		31	0.005	0.035	30.261	0.504
		32	0.054	0.047	31.813	0.476
		33	0.008	-0.013	31.845	0.525
		34	-0.012	-0.005	31.916	0.570
		35	0.029	0.016	32.366	0.596
		36	0.063	0.048	34.489	0.541

Also, the correlogram displays the exact same results with the previous non – crisis period, which also had 0 statistically significant autocorrelations. Both of these tests show the minimal effect of the pandemic to the Hong Kong financial market. This may be attributed to the measures taken early by the Chinese, in order to contain the pandemic and limit its consequences.

DLMXX



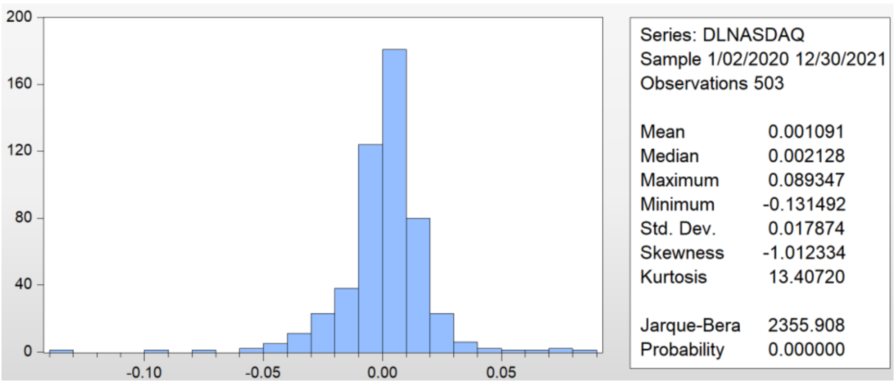
This time, the histogram for Mexico's index indicates that again it follows the normal distribution with Kurtosis and Jarque – Bera values that tend to normality eve more that the pre – Covid – 19 years.

Sample: 1/02/2020 12/30/2021
Included observations: 503

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.014	-0.014	0.1016	0.750
		2	-0.050	-0.050	1.3738	0.503
		3	0.003	0.001	1.3781	0.711
		4	0.006	0.004	1.3966	0.845
		5	0.002	0.002	1.3980	0.925
		6	0.022	0.022	1.6364	0.950
		7	0.047	0.048	2.7464	0.907
		8	0.052	0.056	4.1324	0.845
		9	0.044	0.051	5.1285	0.823
		10	0.053	0.061	6.5821	0.764
		11	-0.024	-0.018	6.8808	0.809
		12	-0.029	-0.026	7.3131	0.836
		13	-0.048	-0.056	8.5258	0.808
		14	-0.019	-0.031	8.7083	0.849
		15	0.124	0.112	16.741	0.335
		16	0.012	0.005	16.814	0.398
		17	-0.038	-0.035	17.562	0.417
		18	0.014	0.008	17.662	0.478
		19	0.035	0.034	18.308	0.502
		20	0.028	0.039	18.709	0.541
		21	-0.046	-0.034	19.805	0.534
		22	0.039	0.040	20.622	0.544
		23	0.010	0.002	20.675	0.601
		24	-0.063	-0.072	22.792	0.532
		25	0.033	0.015	23.388	0.555
		26	-0.053	-0.063	24.857	0.527
		27	-0.020	-0.018	25.067	0.571
		28	0.006	0.005	25.089	0.623
		29	-0.021	-0.025	25.321	0.661
		30	-0.011	-0.027	25.387	0.706
		31	0.009	0.013	25.431	0.748
		32	-0.074	-0.062	28.403	0.649
		33	-0.073	-0.067	31.316	0.551
		34	0.002	-0.004	31.318	0.600
		35	0.039	0.031	32.144	0.607
		36	0.081	0.110	35.726	0.482

Also, the correlogram gives no statistically significant autocorrelations, contrary to the previous correlogram that showed that some lags were significant. These descriptive statistics highly indicate that the MXX index was not severely affected by the pandemic, but refrained from the huge risk that affected other indices.

DLNASDAQ



Sample: 1/02/2020 12/30/2021
Included observations: 503

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.304	-0.304	46.610	0.000
		2	0.215	0.135	70.051	0.000
		3	-0.029	0.077	70.472	0.000
		4	-0.057	-0.084	72.105	0.000
		5	0.092	0.051	76.419	0.000
		6	-0.197	-0.150	96.247	0.000
		7	0.234	0.144	124.35	0.000
		8	-0.229	-0.101	151.27	0.000
		9	0.260	0.161	186.02	0.000
		10	-0.100	0.014	191.16	0.000
		11	0.020	-0.025	191.36	0.000
		12	0.086	0.041	195.18	0.000
		13	-0.160	-0.064	208.44	0.000
		14	0.159	0.021	221.57	0.000
		15	-0.135	0.026	230.99	0.000
		16	0.138	0.029	240.92	0.000
		17	-0.104	-0.025	246.61	0.000
		18	0.038	-0.026	247.35	0.000
		19	-0.016	-0.047	247.48	0.000
		20	-0.083	-0.031	251.11	0.000
		21	0.079	-0.018	254.43	0.000
		22	-0.144	-0.041	265.43	0.000
		23	0.033	-0.093	266.00	0.000
		24	-0.058	-0.017	267.80	0.000
		25	0.009	-0.020	267.84	0.000
		26	-0.111	-0.142	274.44	0.000
		27	0.050	0.038	275.77	0.000
		28	-0.002	0.011	275.77	0.000
		29	0.007	0.063	275.80	0.000
		30	0.031	-0.007	276.30	0.000
		31	-0.034	0.000	276.92	0.000
		32	0.037	0.011	277.65	0.000
		33	-0.047	0.003	278.83	0.000
		34	-0.031	-0.071	279.34	0.000
		35	-0.022	0.013	279.61	0.000
		36	0.056	0.063	281.31	0.000

Beginning with the histogram, it is observable that during the Covid – 19 pandemic, NASDAQ changed to a significant degree regarding the risk and volatility. Kurtosis and Jarque – Bera have higher values than those for 2 years prior, with Kurtosis equaling 13.40 against 5.67 that was before and Jarque – Bera equaling 2,355.90 against 167.58. Furthermore, the correlogram indicates that all autocorrelations are statistically significant, something that was not true before. This change shows the pandemic has seriously influenced the behavior of this market, significantly increasing its risk and volatility.

TGARCH models

The same methodology with TGARCH models is applied for a last time to estimate the level of risk and volatility that each index possessed during the outbreak period.

Starting with the BEL20 index:

TGARCH

Sample (adjusted): 1/02/2020 12/27/2021
Included observations: 511 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)
+ C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	2.28E-06	1.27E-06	1.804844	0.0711
RESID(-1)^2	-0.004312	0.019652	-0.219433	0.8263
RESID(-1)^2*(RESID(-1)<0)	0.195089	0.079176	2.464004	0.0137
GARCH(-1)	0.901526	0.027594	32.67069	0.0000

R-squared	-0.000379	Mean dependent var	0.000307
Adjusted R-squared	0.001579	S.D. dependent var	0.015767
S.E. of regression	0.015754	Akaike info criterion	-6.027080
Sum squared resid	0.126832	Schwarz criterion	-5.993918
Log likelihood	1543.919	Hannan-Quinn criter.	-6.014079
Durbin-Watson stat	1.994990		

TARCH

Sample (adjusted): 1/02/2020 12/27/2021
Included observations: 511 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000203	6.94E-05	2.919595	0.0035
RESID(-1)^2	0.219764	0.188647	1.164946	0.2440
RESID(-1)^2*(RESID(-1)<0)	0.026594	0.186873	0.142309	0.8868

R-squared	-0.000379	Mean dependent var	0.000307
Adjusted R-squared	0.001579	S.D. dependent var	0.015767
S.E. of regression	0.015754	Akaike info criterion	-5.493684
Sum squared resid	0.126832	Schwarz criterion	-5.468813
Log likelihood	1406.636	Hannan-Quinn criter.	-5.483934
Durbin-Watson stat	1.994990		

ARCH

Sample (adjusted): 1/02/2020 12/27/2021
Included observations: 511 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000203	6.92E-05	2.928351	0.0034
RESID(-1)^2	0.233106	0.156244	1.491934	0.1357

R-squared	-0.000379	Mean dependent var	0.000307
Adjusted R-squared	0.001579	S.D. dependent var	0.015767
S.E. of regression	0.015754	Akaike info criterion	-5.497529
Sum squared resid	0.126832	Schwarz criterion	-5.480949
Log likelihood	1406.619	Hannan-Quinn criter.	-5.491029
Durbin-Watson stat	1.994990		

Despite the data of histogram and correlogram, the ARCH model does not display any indication of volatility clustering, or in any case the phenomenon of leverage.

Continuing with the Hang Seng Index:

TGARCH

Sample (adjusted): 1/03/2020 12/02/2021
Included observations: 493 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)
+ C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	1.30E-05	7.18E-06	1.813996	0.0697
RESID(-1)^2	0.010955	0.039326	0.278579	0.7806
RESID(-1)^2*(RESID(-1)<0)	0.108486	0.054928	1.975074	0.0483
GARCH(-1)	0.856526	0.072401	11.83029	0.0000

R-squared	-0.000971	Mean dependent var	-0.000428
Adjusted R-squared	0.001060	S.D. dependent var	0.013755
S.E. of regression	0.013748	Akaike info criterion	-5.829128
Sum squared resid	0.093176	Schwarz criterion	-5.795046
Log likelihood	1440.880	Hannan-Quinn criter.	-5.815746
Durbin-Watson stat	2.127487		

TARCH

Sample (adjusted): 1/03/2020 12/02/2021
Included observations: 493 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML
sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000160	1.75E-05	9.141827	0.0000
RESID(-1)^2	0.115999	0.109940	1.055111	0.2914
RESID(-1)^2*(RESID(-1)<0)	0.048574	0.131418	0.369617	0.7117

R-squared	-0.000971	Mean dependent var	-0.000428
Adjusted R-squared	0.001060	S.D. dependent var	0.013755
S.E. of regression	0.013748	Akaike info criterion	-5.761827
Sum squared resid	0.093176	Schwarz criterion	-5.736266
Log likelihood	1423.290	Hannan-Quinn criter.	-5.751791
Durbin-Watson stat	2.127487		

ARCH

Sample (adjusted): 1/03/2020 12/02/2021
Included observations: 493 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000160	1.72E-05	9.305920	0.0000
RESID(-1)^2	0.140463	0.074142	1.894503	0.0582

R-squared	-0.000971	Mean dependent var	-0.000428
Adjusted R-squared	0.001060	S.D. dependent var	0.013755
S.E. of regression	0.013748	Akaike info criterion	-5.765300
Sum squared resid	0.093176	Schwarz criterion	-5.748259
Log likelihood	1423.146	Hannan-Quinn criter.	-5.758609
Durbin-Watson stat	2.127487		

The ARCH model for the HSI index again presents no volatility clustering. This is to be expected since the HSI initially did not manifest any extreme observations nor show any impactful risk increase during the pandemic.

Moving on to MXX:

TGARCH

Sample (adjusted): 1/03/2020 12/16/2021
Included observations: 503 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	5.92E-06	2.50E-06	2.366957	0.0179
RESID(-1)^2	0.064481	0.033680	1.914530	0.0556
RESID(-1)^2*(RESID(-1)<0)	0.104647	0.060491	1.729950	0.0836
GARCH(-1)	0.845295	0.039365	21.47318	0.0000

R-squared	-0.000790	Mean dependent var	0.000357
Adjusted R-squared	0.001200	S.D. dependent var	0.012710
S.E. of regression	0.012703	Akaike info criterion	-6.148165
Sum squared resid	0.081161	Schwarz criterion	-6.114602
Log likelihood	1550.263	Hannan-Quinn criter.	-6.134998
Durbin-Watson stat	2.025826		

TARCH

Sample (adjusted): 1/03/2020 12/16/2021
Included observations: 503 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000105	1.31E-05	7.975098	0.0000
RESID(-1)^2	0.169465	0.070390	2.407533	0.0161
RESID(-1)^2*(RESID(-1)<0)	0.389578	0.197461	1.972936	0.0485

R-squared	-0.000790	Mean dependent var	0.000357
Adjusted R-squared	0.001200	S.D. dependent var	0.012710
S.E. of regression	0.012703	Akaike info criterion	-6.017931
Sum squared resid	0.081161	Schwarz criterion	-5.992758
Log likelihood	1516.510	Hannan-Quinn criter.	-6.008056
Durbin-Watson stat	2.025826		

The results of the TARCH model for MXX point to the existence of leverage, although this is contrary to the descriptive statistics that took place before. The MXX did not appear to be influenced on this great degree at first.

The last examination concerns the NASDAQ index:

TGARCH

Sample (adjusted): 1/03/2020 12/16/2021
Included observations: 503 after adjustments
Convergence achieved after 22 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	1.35E-05	7.13E-06	1.892561	0.0584
RESID(-1)^2	0.078443	0.164581	0.476624	0.6336
RESID(-1)^2*(RESID(-1)<0)	0.181727	0.173026	1.050288	0.2936
GARCH(-1)	0.776274	0.104943	7.397072	0.0000

R-squared	-0.003735	Mean dependent var	0.001091
Adjusted R-squared	-0.001739	S.D. dependent var	0.017874
S.E. of regression	0.017890	Akaike info criterion	-5.767219
Sum squared resid	0.160978	Schwarz criterion	-5.733656
Log likelihood	1454.456	Hannan-Quinn criter.	-5.754052
Durbin-Watson stat	2.596763		

TARCH

Sample (adjusted): 1/03/2020 12/16/2021
Included observations: 503 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000177	2.90E-05	6.103852	0.0000
RESID(-1)^2	0.229676	0.147050	1.561896	0.1183
RESID(-1)^2*(RESID(-1)<0)	0.394156	0.252811	1.559095	0.1190

R-squared	-0.003735	Mean dependent var	0.001091
Adjusted R-squared	-0.001739	S.D. dependent var	0.017874
S.E. of regression	0.017890	Akaike info criterion	-5.473002
Sum squared resid	0.160978	Schwarz criterion	-5.447829
Log likelihood	1379.460	Hannan-Quinn criter.	-5.463126
Durbin-Watson stat	2.596763		

ARCH

Sample (adjusted): 1/03/2020 12/16/2021
Included observations: 503 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using Bollerslev-Wooldridge QML sandwich with expected Hessian
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.000183	2.91E-05	6.300305	0.0000
RESID(-1)^2	0.354999	0.125380	2.831392	0.0046

R-squared	-0.003735	Mean dependent var	0.001091
Adjusted R-squared	-0.001739	S.D. dependent var	0.017874
S.E. of regression	0.017890	Akaike info criterion	-5.464829
Sum squared resid	0.160978	Schwarz criterion	-5.448047
Log likelihood	1376.405	Hannan-Quinn criter.	-5.458246
Durbin-Watson stat	2.596763		

The ARCH model for NASDAQ clearly manifests a substantially significant coefficient regarding volatility clustering, a fact that can be backed from the previous descriptive statistics, since they showed increased risk and volatility. It must be noted, that this coefficient is higher than the previous one, meaning that the risk is adjectively greater.

Finalizing the analysis with the TGARCH models for the periods before both the crisis started and for the duration for all 4 indices, once again the correlations of the indices are given below, in order to observe which indices were correlated during the last period.

Correlation				
	DLBEL20	DLHSI	DLMXX	DLNASDAQ
DLBEL20	1.000000	0.076406	-0.020361	0.306771
DLHSI	0.076406	1.000000	0.101881	0.112789
DLMXX	-0.020361	0.101881	1.000000	0.031963
DLNASDAQ	0.306771	0.112789	0.031963	1.000000

This table of correlations shows that both NASDAQ and MXX were correlated with HSI during the pandemic period, to a greater degree than the years before. Furthermore, there is also a high correlation between NASDAQ and BEL20, while correlation between NASDAQ and MXX seems to decrease during this time.

VAR methodology

The research continues with the methodology that was mentioned in the previous chapter. A VAR model is built for each of the 4 periods tested before that includes all 4 indices for each period. The variables are tested for Granger causality in order to find if they are correlated during each period, while the impulse response methodology assists in illustrating the responsiveness of each variable when an external change or shock is introduced. As mentioned in Chapter 4, a unit shock is applied to the error term of each of the depended variables in order to see the reaction of the system.

Pre – period of Subprime Mortgage Crisis, 1/1/2005 to 31/12/2007

The examination begins yet again for the pre – 2008 financial crisis, with the data used previously. Before building the VAR model for this period, it is crucial to set the appropriate number of lags.

```
VAR system, maximum lag order 8

The asterisks below indicate the best (that is, minimized) values
of the respective information criteria, AIC = Akaike criterion,
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags        loglik    p(LR)       AIC          BIC          HQC

   1    8918.78305            -25.066994*  -24.938395*  -25.017316*
   2    8933.55374  0.02053  -25.063532   -24.832053   -24.974110
   3    8947.81533  0.02736  -25.058635   -24.724277   -24.929471
   4    8965.96257  0.00263  -25.064683   -24.627447   -24.895776
   5    8975.72784  0.24211  -25.047121   -24.507005   -24.838471
   6    8994.60763  0.00164  -25.055233   -24.412238   -24.806840
   7    9004.30587  0.24864  -25.037481   -24.291607   -24.749346
   8    9011.59345  0.55595  -25.012939   -24.164186   -24.685061
```

By setting the maximum lag order as 8, the Akaike (AIC), Schwarz Bayesian (BIC) and Hannah – Quinn criteria all point out that the optimum number of lags is 1.

```
VAR system, lag order 1
OLS estimates, observations 2005-01-05-2007-11-09 (T = 717)
Log-likelihood = 9009.5328
Determinant of covariance matrix = 1.4314097e-016
AIC = -25.0754
BIC = -24.9478
HQC = -25.0261
Portmanteau test: LB(48) = 943.423, df = 752 [0.0000]
```

The VAR model is constructed with lag order 1 since that is the value indicated by the criteria. It should be noted that the variables are inserted into the VAR system by order of significance. To be more specific, equation 1 and 2 consist of the log differences of NASDAQ and MXX respectively, since the United States are the place that the 2008 crisis started from. The third and fourth equation represent the BEL20 index and the Hang Seng Index respectively. It should also be noted that the F – tests define Granger causality, meaning that if they display a p – value that is lower than 0.1, the null hypothesis of no correlation between present and past lags of Granger causality is rejected and it is assumed that there is, in fact correlation between them.

```
Equation 1: ld_nasdaq

               coefficient    std. error    t-ratio   p-value
  ---------------------------------------------------------
  const         0.000387202   0.000350700    1.104    0.2699
  ld_nasdaq_1  -0.0426941     0.0373317     -1.144    0.2532
  ld_mxx_1      0.0155276     0.0290353      0.5348   0.5930
  ld_bel20_1   -0.0188303     0.0380108     -0.4954   0.6205
  ld_hsi_1     -0.0364038     0.0294415     -1.236    0.2167

Mean dependent var    0.000348   S.D. dependent var    0.009309
Sum squared resid     0.061753   S.E. of regression    0.009313
R-squared             0.004770   Adjusted R-squared   -0.000821
F(4, 712)             0.853110   P-value(F)            0.491839
rho                  -0.003976   Durbin-Watson         2.006516

F-tests of zero restrictions:

All lags of ld_nasdaq       F(1, 712) =    1.3079 [0.2532]
All lags of ld_mxx          F(1, 712) =   0.28600 [0.5930]
All lags of ld_bel20        F(1, 712) =   0.24541 [0.6205]
All lags of ld_hsi          F(1, 712) =    1.5289 [0.2167]
```

As can be seen from the table regarding Equation 1, no Granger causality exists between the variables of the other indices that affect the lags of NASDAQ during this period. However, for the same time frame it can be observed that BEL20 had a causal relationship with the MXX index, meaning that previous lags of BEL20 affected the behavior of MXX. No other variable affected Mexico’s index for the examined years before 2008.

Equation 2: ld_mxx

	coefficient	std. error	t-ratio	p-value	
const	0.000997767	0.000468228	2.131	0.0334	**
ld_nasdaq_1	−0.0139971	0.0498425	−0.2808	0.7789	
ld_mxx_1	0.0444956	0.0387657	1.148	0.2514	
ld_bel20_1	0.252032	0.0507492	4.966	8.55e-07	***
ld_hsi_1	−0.00735844	0.0393081	−0.1872	0.8516	

Mean dependent var	0.001151	S.D. dependent var	0.012688
Sum squared resid	0.110078	S.E. of regression	0.012434
R-squared	0.045032	Adjusted R-squared	0.039667
F(4, 712)	8.393745	P-value(F)	1.28e-06
rho	0.002266	Durbin-Watson	1.992826

F-tests of zero restrictions:

All lags of ld_nasdaq	F(1, 712) = 0.078864	[0.7789]
All lags of ld_mxx	F(1, 712) = 1.3175	[0.2514]
All lags of ld_bel20	F(1, 712) = 24.663	[0.0000]
All lags of ld_hsi	F(1, 712) = 0.035043	[0.8516]

Equation 3: ld_bel20

	coefficient	std. error	t-ratio	p-value	
const	0.000393785	0.000359177	1.096	0.2733	
ld_nasdaq_1	0.0431362	0.0382342	1.128	0.2596	
ld_mxx_1	0.102298	0.0297372	3.440	0.0006	***
ld_bel20_1	−0.187148	0.0389297	−4.807	1.87e-06	***
ld_hsi_1	−0.0154696	0.0301533	−0.5130	0.6081	

Mean dependent var	0.000424	S.D. dependent var	0.009701
Sum squared resid	0.064774	S.E. of regression	0.009538
R-squared	0.038633	Adjusted R-squared	0.033232
F(4, 712)	7.152977	P-value(F)	0.000012
rho	−0.005563	Durbin-Watson	2.004217

F-tests of zero restrictions:

All lags of ld_nasdaq	F(1, 712) = 1.2729	[0.2596]
All lags of ld_mxx	F(1, 712) = 11.834	[0.0006]
All lags of ld_bel20	F(1, 712) = 23.110	[0.0000]
All lags of ld_hsi	F(1, 712) = 0.26320	[0.6081]

Equation 4: ld_hsi

	coefficient	std. error	t-ratio	p-value	
const	0.000937183	0.000446657	2.098	0.0362	**
ld_nasdaq_1	−0.0683200	0.0475464	−1.437	0.1512	
ld_mxx_1	0.0128287	0.0369799	0.3469	0.7288	
ld_bel20_1	−0.0285839	0.0484113	−0.5904	0.5551	
ld_hsi_1	0.0145807	0.0374973	0.3888	0.6975	

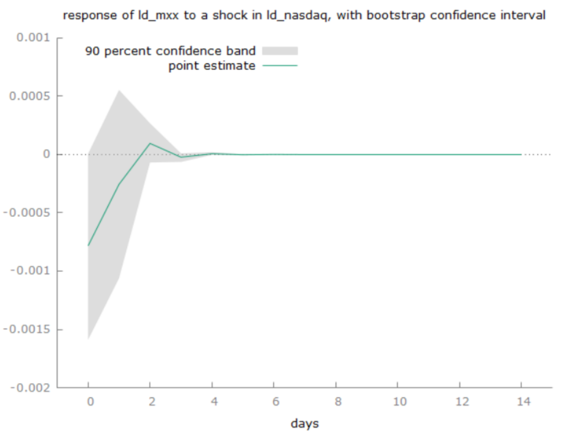
Mean dependent var	0.000930	S.D. dependent var	0.011849
Sum squared resid	0.100169	S.E. of regression	0.011861
R-squared	0.003584	Adjusted R-squared	−0.002014
F(4, 712)	0.640200	P-value(F)	0.633962
rho	0.002300	Durbin-Watson	1.987480

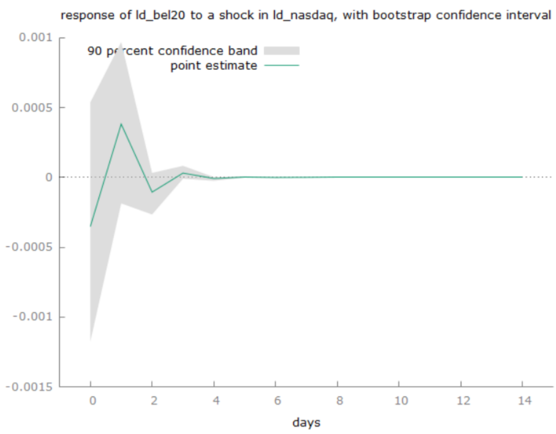
F-tests of zero restrictions:

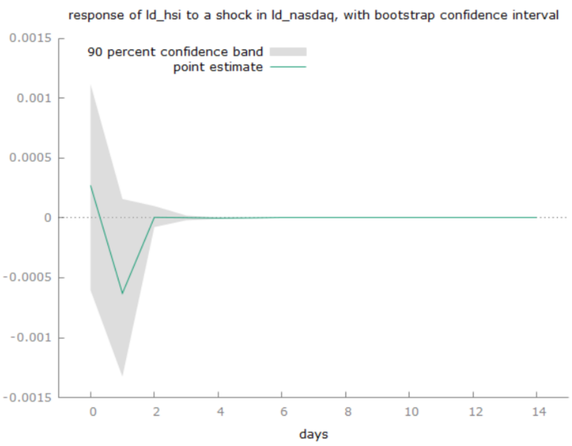
All lags of ld_nasdaq	F(1, 712) = 2.0647	[0.1512]
All lags of ld_mxx	F(1, 712) = 0.12035	[0.7288]
All lags of ld_bel20	F(1, 712) = 0.34862	[0.5551]
All lags of ld_hsi	F(1, 712) = 0.15120	[0.6975]

Regarding Belgium's BEL20 index, it is clear that it is affected by previous lags of itself and also by MXX. The correlogram for BEL20 for the 3 years prior to 2008 showed that indeed the lags were statistically significant, therefore it verifies the Granger causality result. Finally, the equation for the Hang Seng Index in the table below shows that HSI is not Granger – caused by any other index.

Continuing with the Impulse Response methodology, the results of shocks applied to NASDAQ index are analyzed, regarding the reactions of the other indices. This particular index is considered a priority, since the source of the financial Subprime Mortgage Crisis was the United States.







As can be seen from the graphs of impulse responses, during the 3 years before the 2008 financial crisis, a unit shock on NASDAQ would have different results in each index. First of all, it is noticeable that a unit shock applied on NASDAQ has a negative effect on MXX that turns into a positive one during the third day, creating a reaction that is equalized during the first 5, almost, days. Moreover, a different result is observed for the BEL20 index, since a shock on the first index initially produces a negative result that continues to positive values and then goes back to 0 in a matter of 5 days, the same time period with the previous large – capitalization index. Finally, a negative result is also observed on the Hang Seng Index, but this time it takes much less in order for the shock effects to be eliminated. It should be noted, however, that in 90% confidence band, none of the responses to the shock are statistically significant.

<u>Subprime Mortgage Crisis, 1/1/2008 to 31/12/2009</u>

Continuing with the next period, the examination now focuses on the years of the financial crisis, for the couple of years 2008 to the end of 2009. First of all, the lag selection for the VAR model takes place, giving the table seen below.

```
VAR system, maximum lag order 8

The asterisks below indicate the best (that is, minimized) values
of the respective information criteria, AIC = Akaike criterion,
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags        loglik    p(LR)        AIC          BIC          HQC

   1    4692.49845            -19.387960   -19.214602   -19.319829
   2    4750.22700  0.00000  -19.561108   -19.249062*  -19.438471
   3    4776.33760  0.00001  -19.603061   -19.152328   -19.425918
   4    4815.33787  0.00000  -19.698497   -19.109078   -19.466850*
   5    4827.74864  0.07303  -19.683604   -18.955498   -19.397452
   6    4849.65452  0.00021  -19.708110   -18.841317   -19.367452
   7    4871.71145  0.00019  -19.733243*  -18.727762   -19.338079
   8    4885.96468  0.02748  -19.725995   -18.581827   -19.276326
```

According to the Schwarz Bayesian criterion, the proper lag order should equal 2. This lag order number is applied on the VAR model.

```
VAR system, lag order 2
OLS estimates, observations 2008-01-07-2009-12-07 (T = 488)
Log-likelihood = 4816.5739
Determinant of covariance matrix = 3.1412666e-014
AIC = -19.5925
BIC = -19.2834
HQC = -19.4711
Portmanteau test: LB(48) = 1049.57, df = 736 [0.0000]
```

The variables are once again added in order of significance and since the 2008 crisis source was the United States, the log – differences of NASDAQ are used first.

The F – tests for the first equation regarding NASDAQ show that this specific index is Granger caused by previous lags of itself, as well as by lags of MXX for this specific crisis period, since their respective p – values are lower than 0.1. The other 2 indices, BEL20 and HSI had no effect on NASDAQ during this time. The correlogram for this index that was analyzed before showed statistically significant autocorrelations with previous lags, confirming the results of VAR's Granger causality examination.

```
Equation 1: ld_nasdaq

                 coefficient    std. error    t-ratio    p-value
  ---------------------------------------------------------------
  const         -0.000422032    0.00100334    -0.4206    0.6742
  ld_nasdaq_1   -0.136183       0.0455199     -2.992     0.0029   ***
  ld_nasdaq_2   -0.157215       0.0542771     -2.897     0.0039   ***
  ld_mxx_1       0.0438046      0.0602230      0.7274    0.4674
  ld_mxx_2       0.150220       0.0498230      3.015     0.0027   ***
  ld_bel20_1    -0.0549730      0.0503366     -1.092     0.2753
  ld_bel20_2     0.0630588      0.0503391      1.253     0.2109
  ld_hsi_1      -0.0506417      0.0369172     -1.372     0.1708
  ld_hsi_2      -0.0107447      0.0369603     -0.2907    0.7714

Mean dependent var  -0.000259   S.D. dependent var   0.022543
Sum squared resid    0.233819   S.E. of regression   0.022094
R-squared            0.055251   Adjusted R-squared   0.039473
F(8, 479)            3.501637   P-value(F)           0.000604
rho                  0.002577   Durbin-Watson        1.994592

F-tests of zero restrictions:

All lags of ld_nasdaq       F(2, 479) =   7.2471 [0.0008]
All lags of ld_mxx          F(2, 479) =   4.9976 [0.0071]
All lags of ld_bel20        F(2, 479) =   1.3231 [0.2673]
All lags of ld_hsi          F(2, 479) =  0.96402 [0.3821]
```

Below the 3 next equations can be seen, that reflect the results of the VAR models for MXX, BEL20 and HSI respectively. First and foremost, during the crisis period, MXX is clearly Granger caused by NASDAQ and by previous lags of itself. This is expected, since these 2 markets are behaving similarly most of the time examined in this thesis. Moreover, the influence of MXX's previous lags to itself can be also confirmed in the correlogram examined before for this time period.

Equation 2: ld_mxx

	coefficient	std. error	t-ratio	p-value	
const	0.000436706	0.000752150	0.5806	0.5618	
ld_nasdaq_1	0.524212	0.0341237	15.36	1.37e-043	***
ld_nasdaq_2	0.209991	0.0406885	5.161	3.61e-07	***
ld_mxx_1	−0.0724929	0.0451458	−1.606	0.1090	
ld_mxx_2	−0.0525973	0.0373495	−1.408	0.1597	
ld_bel20_1	−0.0791129	0.0377345	−2.097	0.0366	**
ld_bel20_2	0.00130327	0.0377364	0.03454	0.9725	
ld_hsi_1	−0.00424317	0.0276748	−0.1533	0.8782	
ld_hsi_2	−0.0191224	0.0277071	−0.6902	0.4904	

Mean dependent var	0.000248	S.D. dependent var	0.020393
Sum squared resid	0.131399	S.E. of regression	0.016563
R-squared	0.351196	Adjusted R-squared	0.340360
F(8, 479)	32.41020	P-value(F)	1.04e-40
rho	−0.019821	Durbin-Watson	2.038419

F-tests of zero restrictions:

All lags of ld_nasdaq	F(2, 479) =	120.38	[0.0000]
All lags of ld_mxx	F(2, 479) =	2.4599	[0.0865]
All lags of ld_bel20	F(2, 479) =	2.1995	[0.1120]
All lags of ld_hsi	F(2, 479) =	0.24481	[0.7829]

Equation 3: ld_bel20

	coefficient	std. error	t-ratio	p-value	
const	−0.00102021	0.000860003	−1.186	0.2361	
ld_nasdaq_1	−0.0625075	0.0390168	−1.602	0.1098	
ld_nasdaq_2	−0.0551459	0.0465230	−1.185	0.2365	
ld_mxx_1	0.0725320	0.0516194	1.405	0.1606	
ld_mxx_2	0.306481	0.0427052	7.177	2.74e-012	***
ld_bel20_1	0.0153389	0.0431454	0.3555	0.7224	
ld_bel20_2	0.00653349	0.0431475	0.1514	0.8797	
ld_hsi_1	0.0441379	0.0316431	1.395	0.1637	
ld_hsi_2	0.0876687	0.0316801	2.767	0.0059	***

Mean dependent var	−0.000983	S.D. dependent var	0.020121
Sum squared resid	0.171784	S.E. of regression	0.018938
R-squared	0.128717	Adjusted R-squared	0.114165
F(8, 479)	8.845483	P-value(F)	2.54e-11
rho	−0.064127	Durbin-Watson	2.128239

F-tests of zero restrictions:

All lags of ld_nasdaq	F(2, 479) =	1.6774	[0.1879]
All lags of ld_mxx	F(2, 479) =	27.628	[0.0000]
All lags of ld_bel20	F(2, 479) =	0.077192	[0.9257]
All lags of ld_hsi	F(2, 479) =	4.6024	[0.0105]

Equation 4: ld_hsi

	coefficient	std. error	t-ratio	p-value
const	−0.000481877	0.00123781	−0.3893	0.6972
ld_nasdaq_1	0.0193077	0.0561573	0.3438	0.7311
ld_nasdaq_2	0.0345863	0.0669609	0.5165	0.6057
ld_mxx_1	0.0662166	0.0742963	0.8913	0.3732
ld_mxx_2	−0.0623277	0.0614659	−1.014	0.3111
ld_bel20_1	−0.0271250	0.0620995	−0.4368	0.6625
ld_bel20_2	0.0341731	0.0621027	0.5503	0.5824
ld_hsi_1	−0.0493622	0.0455442	−1.084	0.2790
ld_hsi_2	0.0409206	0.0455975	0.8974	0.3699

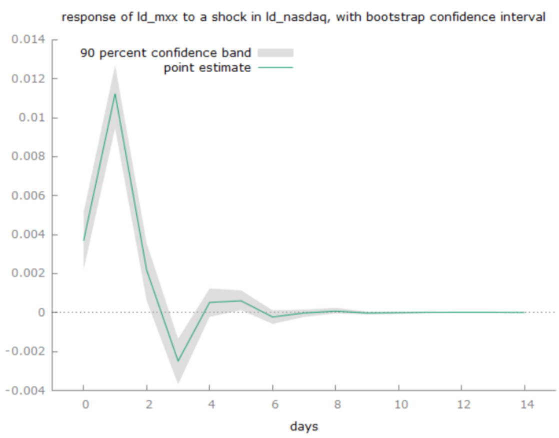
Mean dependent var	−0.000506	S.D. dependent var	0.027201
Sum squared resid	0.355869	S.E. of regression	0.027257
R-squared	0.012401	Adjusted R-squared	−0.004093
F(8, 479)	0.751850	P-value(F)	0.645587
rho	0.001182	Durbin-Watson	1.997476

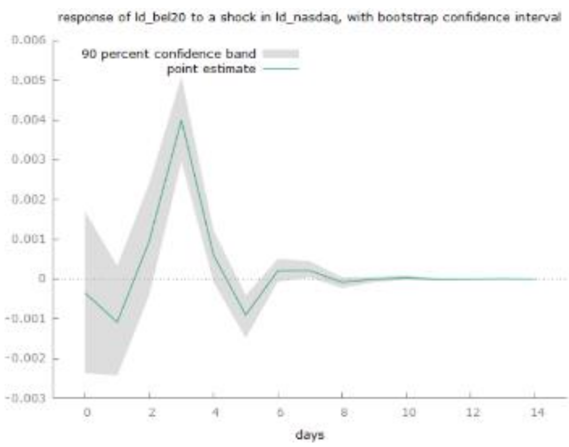
F-tests of zero restrictions:

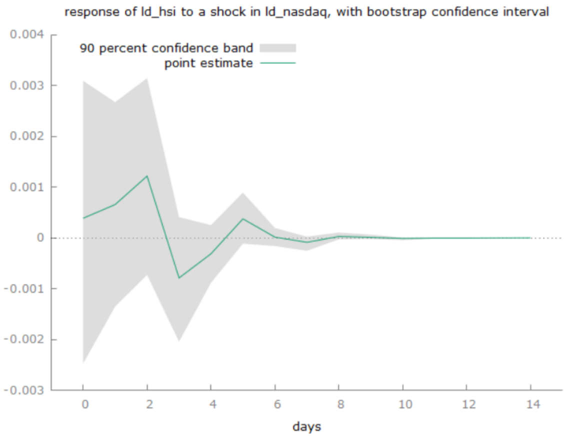
All lags of ld_nasdaq	F(2, 479) =	0.16393	[0.8488]
All lags of ld_mxx	F(2, 479) =	0.84956	[0.4282]
All lags of ld_bel20	F(2, 479) =	0.23663	[0.7894]
All lags of ld_hsi	F(2, 479) =	1.0470	[0.3518]

BEL20 is highly affected by lags of MXX and HSI, but is clearly not Granger caused by itself, as well as by NASDAQ. This is especially peculiar, since this highly volatile index could be expected to be Granger caused by NASDAQ during such times. The respective correlogram also showed that at least the first 7 lags were of no statistical significance. Finally, HSI is not Granger caused by any other index, including itself.

The impulse response for the MXX index shows the reaction of Mexico's index to a shock applied in NASDAQ during the 200 crisis. As can be seen from the impulse response graph, MXX is affected by a shock on NASDAQ in a much more impactful way than before. This time, the response reaches a much higher value that also takes considerable more time to normalize again. It should also be noted that the response is also statistically significant.The same can be also noted for the for the BEL20 index, where a spike is observed that is gradually reduced to 0 completely almost after 8 days. The time that the response needs to return to normal is doubled that that of the period before the crisis. This response is also statistically significant.







This is not the case for HSI, as it is observed that the response to the shock does not seem that extreme as in the previous cases and it also is of no statistical significance. However, the response is much more intense than the 3 years before the financial turbulence.

Overall, during these couple years the impulse responses are much more volatile. This is to be expected considering the severity of the crisis.

<u>Pre – period of Covid – 19 pandemic crisis, 1/1/2018 to 31/12/2019</u>

For the examination of this specific period the order of the equations is shifting, prioritizing HSI since China was the source of the pandemic. For this reason, HSI is inserted first into the VAR model and the other indices follow as well. All 3 criteria point out that the optimal lag selection is lag order 1.

```
VAR system, maximum lag order 8

The asterisks below indicate the best (that is, minimized) values
of the respective information criteria, AIC = Akaike criterion,
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags        loglik    p(LR)       AIC          BIC          HQC

   1    8918.78305            -25.066994*  -24.938395*  -25.017316*
   2    8933.55374  0.02053  -25.063532   -24.832053   -24.974110
   3    8947.81533  0.02736  -25.058635   -24.724277   -24.929471
   4    8965.96257  0.00263  -25.064683   -24.627447   -24.895776
   5    8975.72784  0.24211  -25.047121   -24.507005   -24.838471
   6    8994.60763  0.00164  -25.055233   -24.412238   -24.806840
   7    9004.30587  0.24864  -25.037481   -24.291607   -24.749346
   8    9011.59345  0.55595  -25.012939   -24.164186   -24.685061
```

```
VAR system, lag order 1
OLS estimates, observations 2018-01-04-2019-12-02 (T = 489)
Log-likelihood = 6227.9923
Determinant of covariance matrix = 1.0176459e-016
AIC = -25.3906
BIC = -25.2191
HQC = -25.3232
Portmanteau test: LB(48) = 947.582, df = 752 [0.0000]
```

Equation 1 represents the logarithmic differences of HSI inside the VAR system, where it can be seen that during the pre – pandemic period HSI was not Granger caused by any index. This result can be verified by the descriptive statistics that took place earlier during this chapter.

```
Equation 1: ld_hsi

                 coefficient   std. error   t-ratio   p-value
  -----------------------------------------------------------
  const           0.000937183  0.000446657   2.098    0.0362  **
  ld_hsi_1        0.0145807    0.0374973     0.3888   0.6975
  ld_bel20_1     -0.0285839    0.0484113    -0.5904   0.5551
  ld_nasdaq_1    -0.0683200    0.0475464    -1.437    0.1512
  ld_mxx_1        0.0128287    0.0369799     0.3469   0.7288

Mean dependent var   0.000930   S.D. dependent var   0.011849
Sum squared resid    0.100169   S.E. of regression   0.011861
R-squared            0.003584   Adjusted R-squared  -0.002014
F(4, 712)            0.640200   P-value(F)           0.633962
rho                  0.002300   Durbin-Watson        1.987480

F-tests of zero restrictions:

All lags of ld_hsi          F(1, 712) =  0.15120 [0.6975]
All lags of ld_bel20        F(1, 712) =  0.34862 [0.5551]
All lags of ld_nasdaq       F(1, 712) =   2.0647 [0.1512]
All lags of ld_mxx          F(1, 712) =  0.12035 [0.7288]
```

```
Equation 2: ld_bel20

                 coefficient   std. error   t-ratio   p-value
  -----------------------------------------------------------
  const           0.000393785  0.000359177   1.096    0.2733
  ld_hsi_1       -0.0154696    0.0301533    -0.5130   0.6081
  ld_bel20_1     -0.187148     0.0389297    -4.807    1.87e-06 ***
  ld_nasdaq_1     0.0431362    0.0382342     1.128    0.2596
  ld_mxx_1        0.102298     0.0297372     3.440    0.0006   ***

Mean dependent var   0.000424   S.D. dependent var   0.009701
Sum squared resid    0.064774   S.E. of regression   0.009538
R-squared            0.038633   Adjusted R-squared   0.033232
F(4, 712)            7.152977   P-value(F)           0.000012
rho                 -0.005563   Durbin-Watson        2.004217

F-tests of zero restrictions:

All lags of ld_hsi          F(1, 712) =  0.26320 [0.6081]
All lags of ld_bel20        F(1, 712) =   23.110 [0.0000]
All lags of ld_nasdaq       F(1, 712) =   1.2729 [0.2596]
All lags of ld_mxx          F(1, 712) =   11.834 [0.0006]
```

However, equation 2 shows that BEL20 is in fact Granger caused by previous lags of itself and by MXX. The first conclusion is contrary to the respective descriptive statistics of the same period, where it was evident that there was no autocorrelation among the lags.

Equation 3: ld_nasdaq

	coefficient	std. error	t-ratio	p-value
const	0.000387202	0.000350700	1.104	0.2699
ld_hsi_1	−0.0364038	0.0294415	−1.236	0.2167
ld_bel20_1	−0.0188303	0.0380108	−0.4954	0.6205
ld_nasdaq_1	−0.0426941	0.0373317	−1.144	0.2532
ld_mxx_1	0.0155276	0.0290353	0.5348	0.5930

Mean dependent var	0.000348	S.D. dependent var	0.009309
Sum squared resid	0.061753	S.E. of regression	0.009313
R-squared	0.004770	Adjusted R-squared	−0.000821
F(4, 712)	0.853110	P-value(F)	0.491839
rho	−0.003976	Durbin-Watson	2.006516

F-tests of zero restrictions:

All lags of ld_hsi	F(1, 712) = 1.5289	[0.2167]
All lags of ld_bel20	F(1, 712) = 0.24541	[0.6205]
All lags of ld_nasdaq	F(1, 712) = 1.3079	[0.2532]
All lags of ld_mxx	F(1, 712) = 0.28600	[0.5930]

Equation 4: ld_mxx

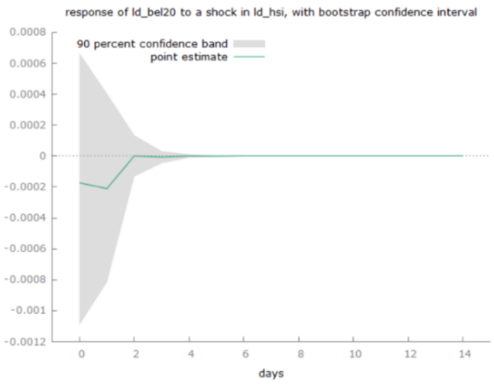
	coefficient	std. error	t-ratio	p-value	
const	0.000997767	0.000468228	2.131	0.0334	**
ld_hsi_1	−0.00735844	0.0393081	−0.1872	0.8516	
ld_bel20_1	0.252032	0.0507492	4.966	8.55e-07	***
ld_nasdaq_1	−0.0139971	0.0498425	−0.2808	0.7789	
ld_mxx_1	0.0444956	0.0387657	1.148	0.2514	

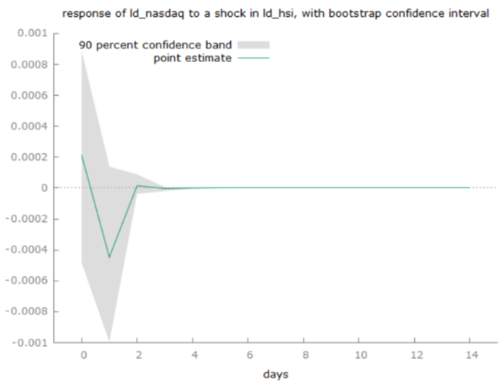
Mean dependent var	0.001151	S.D. dependent var	0.012688
Sum squared resid	0.110078	S.E. of regression	0.012434
R-squared	0.045032	Adjusted R-squared	0.039667
F(4, 712)	8.393745	P-value(F)	1.28e-06
rho	0.002266	Durbin-Watson	1.992826

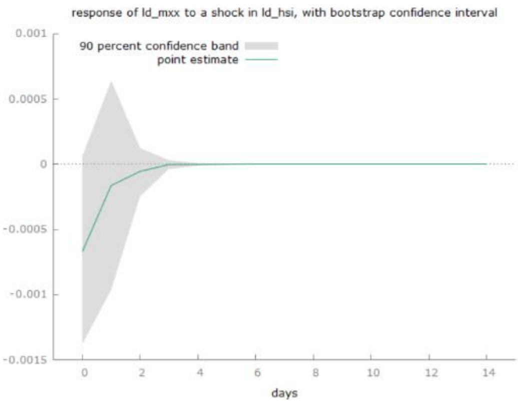
F-tests of zero restrictions:

All lags of ld_hsi	F(1, 712) = 0.035043	[0.8516]
All lags of ld_bel20	F(1, 712) = 24.663	[0.0000]
All lags of ld_nasdaq	F(1, 712) = 0.078864	[0.7789]
All lags of ld_mxx	F(1, 712) = 1.3175	[0.2514]

Observing equation 3, NASDAQ is not Granger caused by any index, but MXX is Granger caused only by BEL20.







The impulse responses of BEL20, NASDAQ and MXX to the shock applied in HSI greatly resemble the responses presented during the pre – crisis period before 2008. As a matter of fact, the shock has mild responses from all indices that are also not statistically significant. Furthermore, the responses take up to 3 days to be neutralized.

<u>The Covid – 19 pandemic, 1/1/2020 to 31/12/2021</u>

Regarding the final period for testing, before commencing the construction of the VAR model, it is essential to select the proper number of lag order. As seen below, the Schwarz Bayesian criterion shows that the optimal lag order is 2.

```
VAR system, maximum lag order 8

The asterisks below indicate the best (that is, minimized) values
of the respective information criteria, AIC = Akaike criterion,
BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags        loglik    p(LR)       AIC          BIC          HQC

   1    5477.42142            -22.551328   -22.378515   -22.483423
   2    5548.33267  0.00000   -22.778234   -22.467170*  -22.656004*
   3    5561.23348  0.05688   -22.765428   -22.316113   -22.588874
   4    5570.81423  0.26038   -22.738902   -22.151336   -22.508023
   5    5588.98582  0.00259   -22.747875   -22.022059   -22.462673
   6    5616.69607  0.00000   -22.796265*  -21.932198   -22.456738
   7    5627.01265  0.19305   -22.772780   -21.770462   -22.378928
   8    5637.49398  0.17995   -22.749975   -21.609407   -22.301799
```

Proceeding to the VAR model, the lag order is set to 2, while the variables are inserted into the system by the same order they were inserted for the previous period as well, as HSI is prioritized.

```
VAR system, lag order 2
OLS estimates, observations 2020-01-07-2021-12-02 (T = 490)
Log-likelihood = 5626.7264
Determinant of covariance matrix = 1.2473708e-015
AIC = -22.8193
BIC = -22.5111
HQC = -22.6983
Portmanteau test: LB(48) = 948.458, df = 736 [0.0000]
```

The F – tests of the first equation that represents the HSI show that this index was Granger caused by itself and MXX, while BEL20 seems to be Granger caused by every other index except from itself. This is a significant change since for the pre – Covid period BEL20 presented Granger causality with itself.

```
Equation 1: ld_hsi

               coefficient    std. error    t-ratio   p-value
  -----------------------------------------------------------
  const        -0.000486295   0.000613157   -0.7931   0.4281
  ld_hsi_1     -0.0901210     0.0459875     -1.960    0.0506   *
  ld_hsi_2      0.0554142     0.0451533      1.227    0.2203
  ld_bel20_1    0.0420084     0.0402619      1.043    0.2973
  ld_bel20_2    0.0370424     0.0398570      0.9294   0.3532
  ld_nasdaq_1   0.0226651     0.0392647      0.5772   0.5640
  ld_nasdaq_2  -0.0160462     0.0394366     -0.4069   0.6843
  ld_mxx_1      0.244917      0.0498825      4.910    1.25e-06 ***
  ld_mxx_2     -0.0603223     0.0511043     -1.180    0.2384

Mean dependent var  -0.000408   S.D. dependent var   0.013827
Sum squared resid    0.087232   S.E. of regression   0.013467
R-squared            0.066990   Adjusted R-squared   0.051472
F(8, 481)            4.316965   P-value(F)           0.000049
rho                  0.004018   Durbin-Watson        1.991692

F-tests of zero restrictions:

All lags of ld_hsi         F(2, 481) =   2.9555 [0.0530]
All lags of ld_bel20       F(2, 481) =   1.0348 [0.3561]
All lags of ld_nasdaq      F(2, 481) =  0.39170 [0.6761]
All lags of ld_mxx         F(2, 481) =   13.077 [0.0000]
```

```
Equation 2: ld_bel20

               coefficient    std. error    t-ratio    p-value
  ------------------------------------------------------------
  const        -0.000200468   0.000658542   -0.3044    0.7609
  ld_hsi_1     -0.0254042     0.0493914     -0.5143    0.6072
  ld_hsi_2      0.250058      0.0484955      5.156     3.69e-07 ***
  ld_bel20_1   -0.00675728    0.0432420     -0.1563    0.8759
  ld_bel20_2    0.0642009     0.0428071      1.500     0.1343
  ld_nasdaq_1   0.00198170    0.0421710      0.04699   0.9625
  ld_nasdaq_2   0.236183      0.0423556      5.576     4.11e-08 ***
  ld_mxx_1      0.176046      0.0535747      3.286     0.0011   ***
  ld_mxx_2      0.271384      0.0548869      4.944     1.06e-06 ***

Mean dependent var   0.000094   S.D. dependent var   0.016489
Sum squared resid    0.100623   S.E. of regression   0.014464
R-squared            0.243140   Adjusted R-squared   0.230551
F(8, 481)            19.31501   P-value(F)           2.84e-25
rho                 -0.034409   Durbin-Watson        2.068508

F-tests of zero restrictions:

All lags of ld_hsi         F(2, 481) =   13.852 [0.0000]
All lags of ld_bel20       F(2, 481) =   1.1272 [0.3248]
All lags of ld_nasdaq      F(2, 481) =   17.954 [0.0000]
All lags of ld_mxx         F(2, 481) =   16.844 [0.0000]
```

Moving to the last 2 equations, both are Granger caused by some indices with NASDAQ being affected by HSI, MXX and itself, while MXX is Granger caused by BEL20 and NASDAQ. However, it is notable that MXX is not affected by HSI during this period, especially when every other index is.

Equation 3: ld_nasdaq

	coefficient	std. error	t-ratio	p-value	
const	0.00122032	0.000734009	1.663	0.0971	*
ld_hsi_1	−0.0345850	0.0550516	−0.6282	0.5302	
ld_hsi_2	0.226806	0.0540529	4.196	3.24e-05	***
ld_bel20_1	−0.0161554	0.0481974	−0.3352	0.7376	
ld_bel20_2	0.0277089	0.0477127	0.5807	0.5617	
ld_nasdaq_1	−0.292374	0.0470037	−6.220	1.08e-09	***
ld_nasdaq_2	0.179566	0.0472095	3.804	0.0002	***
ld_mxx_1	0.256582	0.0597142	4.297	2.10e-05	***
ld_mxx_2	0.0305490	0.0611768	0.4994	0.6178	

Mean dependent var	0.001102	S.D. dependent var	0.018538
Sum squared resid	0.125007	S.E. of regression	0.016121
R-squared	0.256122	Adjusted R-squared	0.243750
F(8, 481)	20.70146	P-value(F)	5.17e-27
rho	0.005272	Durbin-Watson	1.986654

F-tests of zero restrictions:

All lags of ld_hsi	F(2, 481) =	9.3764 [0.0001]
All lags of ld_bel20	F(2, 481) =	0.21441 [0.8071]
All lags of ld_nasdaq	F(2, 481) =	41.152 [0.0000]
All lags of ld_mxx	F(2, 481) =	9.2712 [0.0001]

Equation 4: ld_mxx

	coefficient	std. error	t-ratio	p-value	
const	0.000142539	0.000559920	0.2546	0.7992	
ld_hsi_1	0.0137546	0.0419947	0.3275	0.7434	
ld_hsi_2	0.0518424	0.0412328	1.257	0.2093	
ld_bel20_1	0.00147095	0.0367661	0.04001	0.9681	
ld_bel20_2	0.114688	0.0363964	3.151	0.0017	***
ld_nasdaq_1	0.180881	0.0358555	5.045	6.45e-07	***
ld_nasdaq_2	0.00328707	0.0360125	0.09128	0.9273	
ld_mxx_1	−0.0272720	0.0455514	−0.5987	0.5496	
ld_mxx_2	−0.0568441	0.0466671	−1.218	0.2238	

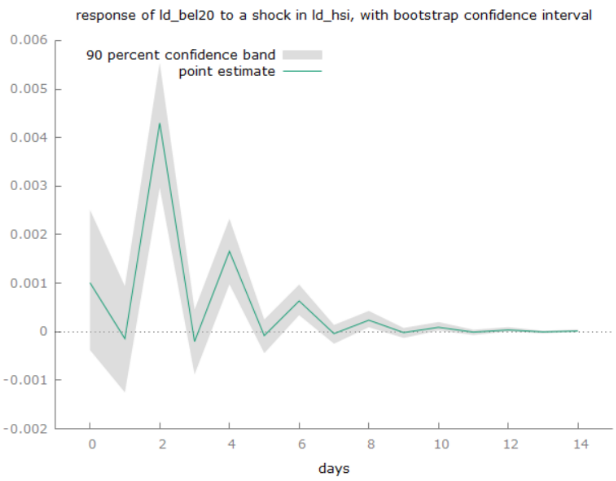
Mean dependent var	0.000294	S.D. dependent var	0.012725
Sum squared resid	0.072741	S.E. of regression	0.012298
R-squared	0.081370	Adjusted R-squared	0.066091
F(8, 481)	5.325723	P-value(F)	2.02e-06
rho	−0.002445	Durbin-Watson	2.003224

F-tests of zero restrictions:

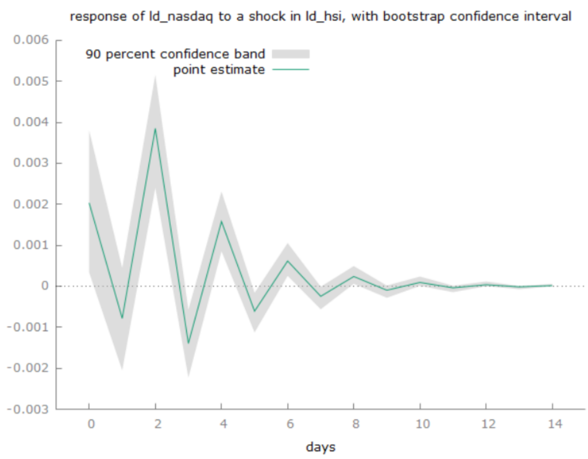
All lags of ld_hsi	F(2, 481) =	0.80997 [0.4455]
All lags of ld_bel20	F(2, 481) =	4.9889 [0.0072]
All lags of ld_nasdaq	F(2, 481) =	14.591 [0.0000]
All lags of ld_mxx	F(2, 481) =	0.88645 [0.4128]

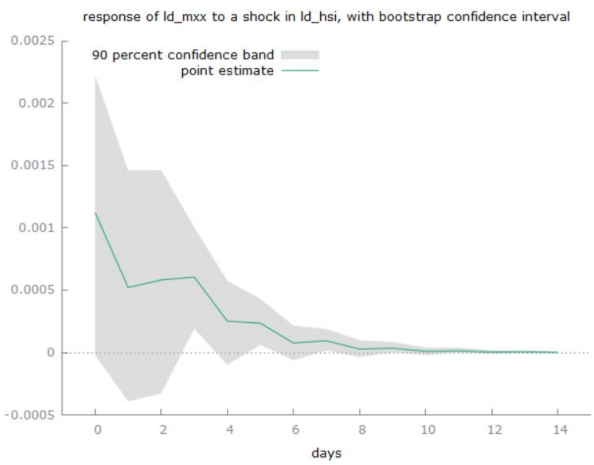
Concluding the data analysis with VAR methodology, the last procedure concerns the impulse responses of the 4 indices for 2020 to the end of 2021.

As can be seen from the impulse response of BEL20 to a shock in HSI, the results are notable. On a 90% confidence band, the statistically significant results indicate a large spike as a reaction to the shock that eventually requires almost 12 days to be normalized. This effect is much more serious than the effect that the previous shock to NASDAQ had on BEL20 during the 2008 financial crisis.



The almost same results are observed for the case of the reaction of NASDAQ to a shock applied to HSI, as it almost requires the same number of days to be neutralized.





However, the impulse response of MXX is quite different, with the shock affecting the index to present a more aggressive value that is eventually ironed out, without mimicking the inconsistent behavior of the previous 2 indices. Despite this being also statistically significant, the reaction requires less days in order to be zeroed. It is clear that the reactions to an HSI shock has much more severe reactions of the other indices during the pandemic period.

Chapter 6

Results

The examination of the 4 indices showed the effects that the 2 crises had on some of the financial markets of the United States, Mexico, Belgium and finally China and to be more specific, Hong Kong. In order to better understand the consequences of each crisis, the samples were divided into 4 periods in total. The first period concerned the 3 years before the start of the 2008 Subprime Mortgage Crisis, ranging from early 2005 to the end of 2007. The second period was the immediate continuation of the aforementioned, starting from 2008 until the closing month of 2009, including data for 2 years in total. Each of the 4 indices was analyzed individually in order to observe its behavior during both periods. During the earlier stages of the examination, a TGARCH model was built for each index, presenting the nature of the risk involved in each index, along with the descriptive statistics that included histograms and correlograms.

Interestingly enough, during the first part of the analysis that focused on the periods before and during the 2008 crisis, the behavior of each index changed in different ways. First of all, before turning the non – stationary observations into stationary, all 4 indices showed an almost completely increasing in value course, with a minor drop during early 2005. Later, the stationary observations indicated that BEL20 presented the most extreme values, while the other indices were less volatile. This fact was confirmed shortly after since the histogram, correlogram and TGARCH model for BEL20 also indicated a risky and highly volatile index. However, the financial crisis seemingly normalized the distribution, eventually showing that BEL20 did not become more volatile during such turbulent time.

Mexico's financial index, MXX along with HSI and NASDAQ, appeared to be much more stable indices before the crisis, with the descriptive statistics displaying distributions that were following normality and randomness. This was also backed by the ARCH models that had no evidence of volatility clustering or leverage. Nonetheless, all 3 indices appeared more volatile during the crisis, but not by a large margin. NASDAQ's descriptive statistics showed an inflated risk factor, but the changes were of no great significance. Overall, the first part of the analysis showed that the larger capitalization indices had, in fact, somewhat increased risk that did not reach notable levels, while BEL20 seemed to have reduced volatility.

The pre – crisis period of Covid – 19 showed an inconsistent course of the 4 indices, while their stationary observations suggested low volatility for all 4 of them. Furthermore, the descriptive statistics along with the ARCH models were also in accordance with this result. However, the pandemic severely impacted NASDAQ and BEL20, since all examinations displayed significantly increased risk, while their histograms revealed that they drifted away from normality.

The second part of the examination focused on the VAR methodology and especially on the analysis of the 4 periods for all indices regarding Granger causality and impulse responses. For the 2005 – 2007 timespan, MXX was Granger caused by BEL20, while the latter was Granger caused by MXX and by itself. Moreover, the impulse responses showed that a shock on NASDAQ had different effects on the other 3 indices that needed almost 5 days to be neutralized. The 2008 crisis, however, indicated that all the indices were Granger caused by one another, except HSI which suggested no such causality once again. This time, the impulse responses were statistically significant, with the exception of HSI. It is notable that all responses require considerably more days in order to nullify.

Concluding this chapter, for the pre – pandemic period the VAR model showed that BEL20 and MXX were Granger caused by each other, while the effects of the impulse responses were very similar to those of the period before 2008. Finally, the effects of the pandemic are remarkable, since Granger causality is much more evident among the equations, while the impulse responses the HSI shock are severely more aggressive. This VAR analysis displayed the significant effects that a financial crisis may have upon the indices.

Chapter 7

Conclusions

Financial turbulences have taken place numerous times during the last century, effectively influencing the course of the economy. The first most notable modern financial crisis happened in 1987 with the occurrence of Black Monday, when leading stock markets of the United States plunged and lost great percentages of their value in a matter of days, eventually spreading the crisis overseas. This event was followed by the Russian crisis in 1998, eleven years later when Russia entered a period of decline since it was affected by the Chechen war, while the Asian crisis of 1997 fueled this decline by reducing the imports from Russia. Later, in 2001 the burst of the dot – com bubble along with the shocking terrorist attack in the United States caused USA's markets to crash, again spreading the volatility and risk abroad. However, the focus of this thesis remains on the 2008 Subprime Mortgage Crisis, an event that was created by the subprime mortgages that dominated the market during that time, and the effects of the pandemic crisis of Covid – 19 on the economy.

For an overview of the aforementioned anxious times, except the latest turbulence of the pandemic, the Random Matrix Theory was utilized by Sandoval & Franca (2012), where each crisis period was examined in order to calculate the correlations that existed between the international financial markets around the world. This analysis showed that a financial turbulence drives the international markets to be significantly more volatile, as well as more correlated in their movements. This result was drawn for all the aforementioned crises studied by Sandoval & Franca (2012).

The increased volatility and correlation eventually escape the financial market sector and transmit to the real economy, creating the worldwide consequences. Of course, this transmission is enhanced by the fact of financial globalization that has rapidly grown in the last decades, providing the ease of uncertainty and destabilization transmission. As examined in the previous chapters, it is clear that the markets tend to move together during hard times affecting one another. However, from the GARCH, VAR models, as well as from the descriptive statistics it is observed that the larger – capitalization indices were not affected in a standard way each time. While the smaller BEL20 index was prone to the events of both 2008 and 2020, the other 3 indices were not affected in the same degree whatsoever, with the exception on NASDAQ during the Covid – 19 outbreak. It is noted though, that during the crises the existence of increased volatility and risk were present for all indices, even if not on a great and significant level.

Concluding this thesis, it must be noted that it adds to the still growing literature and extensive research for the effects of the financial turbulences on the global markets. The descriptive statistics and the GARCH models for BEL20, HSI, MXX and NASDAQ provided a clear picture about the nature of the indices before the anxious times, as well as about their transformation that took place during the years of setbacks. Moreover, the second part of the analysis with the VAR methodology, targeting Granger causality and impulse responses also showed how each index was affected.

The examination of the financial crises in total is an essential procedure in order to better understand how the hardships of the financial markets eventually spill to the real economy and how a greater calamity can be prevented, setting as example the previously tested Hong Kong index, HSI, which was not significantly affected by the pandemic, since the measures taken were successful.

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