NEWS IMPACT CURVE ANALYSIS AND SPILLOVERS DURING COVID-19 PANDEMIC CASE STUDIES: PHARMACEUTICAL INDUSTRY, TECH COMPANIES (FAANG) & AIRLINE INDUSTRY

GÜLŞAH ALCAN

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BY

GÜLŞAH ALCAN

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PLAGIARISM

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

GÜLŞAH ALCAN

23.08.2021

ABSTRACT

The Covid-19 pandemic, which has gained momentum since the day it started, has taken the whole world under its influence. In this thesis, how the Covid-19 pandemic affected three sectors, namely the pharmaceutical industry, technology companies, and the airline industry, was investigated in three separate chapters. Sectors have been affected by the discovery of the vaccine as well as by the pandemic. In this context, in the first chapter, an analysis was made using the EGARCH Model and news impact curves to examine the effects on the returns of pharmaceutical and biotechnology companies. As a result of the measures and restrictions taken to prevent the pandemic from progressing, people started to work from home. People have had to start meeting many of their needs online because restaurants only offer takeaway, shopping malls are closed, etc. Therefore, the need for technology has increased even more in this period. Individuals, being locked at home, have turned to online broadcasts such as Netflix. In this context, in the second chapter, how the stock returns of Facebook, Apple, Amazon, Netflix, and Alphabet (FAANG) are affected by using the DCC GARCH model was examined. In some periods, travel has been imposed restrictions due to the increasing number of cases. With the discovery of the vaccine, restrictions have also changed. In the last chapter, an analysis has made using the Granger Causality Tests and Diagonal BEKK Model to examine long-term spillover effects among the two crude oil prices (Brent, WTI) and three US Airlines Stock prices (American Airlines Group, Southwest Airlines Company, and Delta Air Lines). By expanding the data set used in the study, more comprehensive results can be obtained and may guide future research.

Key words: *Covid-19, pharmaceutical industry, tech companies, airline industry*

ÖZET

Başladığı günden itibaren ivme kazanan Covid-19 pandemisi tüm dünyayı etkisi altına aldı. Bu tezde Covid-19 pandemisinin ilaç endüstrisi, teknoloji şirketleri ve havayolu endüstrisi olmak üzere üç sektörü nasıl etkilediği üç ayrı bölümde incelenmektedir. Sektörler salgının yanı sıra aşının bulunmasından da etkilendiler. Bu bağlamda birinci bölümde, ilaç ve biyoteknoloji şirketlerinin getirileri üzerindeki etkileri incelemek için EGARCH Modeli ve haber etki eğrileri kullanılarak bir analiz yapılmıştır. Salgının ilerlememesi için alınan önlemler ve kısıtlamalar sonucunda insanlar evden çalışmaya başladı. Restoranların sadece paket servis hizmeti sunması, alışveriş merkezlerinin kapalı olması vb. nedenlerle insanlar birçok ihtiyacını internet üzerinden karşılamaya başlamak zorunda kaldılar. Dolayısıyla, bu dönemde teknolojiye ihtiyaç daha da artmıştır. Evde kilitli kalan bireyler, Netflix gibi çevrimiçi yayınlara yöneldi. Bu kapsamda ikinci bölümde DCC GARCH modeli kullanılarak Facebook, Apple, Amazon, Netflix ve Alphabet (FAANG) hisse senedi getirilerinin nasıl etkilendiği incelenmiştir. Bazı dönemlerde artan vaka sayısı nedeniyle seyahat kısıtlamaları getirildi. Aşının bulunmasıyla birlikte kısıtlamalar da değişti. Son bölümde, iki ham petrol fiyatı (Brent, WTI) ve üç ABD havayolları (American Airlines Group, Southwest Airlines Company, Delta Air Lines) hisse senedi fiyatı arasındaki uzun vadeli yayılma etkilerini incelemek için Granger Nedensellik Testleri ve Çapraz BEKK Modeli kullanılarak bir analiz yapılmıştır. Çalışmada kullanılan veri seti genişletilerek daha kapsamlı sonuçlar elde edilebilir ve ileride yapılacak araştırmalara yön verebilir.

Anahtar kelimeler: *Covid-19, ilaç endüstrisi, teknoloji şirketleri, havayolu endüstrisi*

To my parents…

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ABSTRACT

Since the breakout, investor mood is mainly driven by coronavirus alerts and news on globally dangerous diseases. On 28th of February the Dow Jones Industrial dropped nearly 1,200 points marking the worst intraday point decline in the history of the Dow. The reason of this collapse was a growing consensus that Covid-19 has landed on U.S. shores and will likely have a stronger impact on the economy than the investors initially predicted. In this paper, we examine whether Covid-19 related news trigger investment to pharmacy companies. We investigate the news impact of pandemic on global pharmaceuticals and biotechnology industry stock returns by utilizing EGARCH models and News Impact Curves.

Key words: *Covid-19, stock returns, pharmaceuticals, biotechnology*

1. INTRODUCTION

Many epidemic diseases have occurred worldwide in history. There is abundant literature as regards the social, political, and economic effects of diseases. The literature review shows us that many epidemics have resulted in the deaths of millions of people around the world for centuries.

Some of the most socially and economically affected epidemics are namely; the Black Death, known as the Pestilence, between 75 and 100 million people who died between 1346 and 1352; the Viral hemorrhagic fever, in which about 50% of the population in Mexico between 1545-1548 died and 2-25 million people died; the Cholera epidemic, in which approximately 1 million people died in Russia between 1852-1860 and a total of 800 thousand people in the continents of Europe Asia and Africa between 1899-1923; HIV AIDS, which is the first seen in the Congo basin, where approximately 30 million people have died since 1960, Spanish Flu, in which about 75 million people died in the worldwide between 1918-1920 years, SARS(Coronavirus) from 2002 to 2003, and epidemic diseases like Swine influenza, Avian flu, and Ebola (Sherman, 2016).

In December 2019, pneumonia was observed in various patients that developed for no specific reason and did not respond to treatment and vaccines. A respiratory disease outbreak caused by a new coronavirus, called Covid-19, was first detected in Wuhan, China's Hubei Province. With the virus detected in tens of thousands of people in a short time in China, Chinese health officials stated that the infection spread from person to person. Covid-19 was declared as a global epidemic by the World Health Organization on 11 March 2020, after reporting virus cases in several countries in Europe, North America and Asia-Pacific in January and February. As of April 10, 2020, the total number of patients in 212 countries worldwide is 1 million 619 thousand, the total number of deaths is 97,056[1].

After the Covid-19, the Chinese economy slowed down with production cuts, disrupted the functioning of global supply chains, and gave the first warning of a global depression. Since China has both a producer and consumer role, it has seriously affected the real sectors and the stock market as well as its economy. Depending on the inputs from China, companies' production started to shrink regardless of their size. After the transportation has to limited among countries, global economic activities slowed down even more. High-risk industries such as manufacturing, tourism, travel, transportation, and automotive sectors have been among the sectors most struggling and most affected by the epidemic.

According to the Organization for Economic Cooperation and Development (OECD), it has stated that the world economy will face the lowest growth rate since 2009 due to the coronavirus outbreak this year. Especially with the expansion of the epidemic in China, the closure of factories in the Wuhan region and the dismissal of a significant number of workers to reduce the dangerous effect of the virus harmed the Chinese economy. Along with the decrease in production in China, the shrinkage in raw material and energy demand has affected the world trade volume dramatically. Along with the decrease in production in China, the shrinkage in raw material and energy demand has affected the world trade volume dramatically. Afterward, the spread of the virus to Europe and America caused similar effects to being seen in these economies as well. For instance, in the USA, unemployment applications reached 10 million people in two weeks. The transition to partial quarantine after the outbreak caused demand shock. Supply shock has occurred due to the breakage of chains in the

[1] (https://www.worldometers.info/coronavirus/)

supply channel. On the other hand, the demand for many various sectors mentioned above decreased drastically. As a result, inevitably, the reduction in world trade volume and critical disruptions in production will adversely affect the world economy. As a consequence of all these, it is expected that negative growth figures dominate many countries. While the demand for sectors such as automotive, tourism, and financial services decreased, medical supply services, e-commerce, food sectors' demand increased excessively.

Some panic among consumers and companies in all markets disrupted their usual consumption habits and created market anomalies. Global financial markets also responded to changes, and global stock indices diminished. The evolution of the disease and the uncertainty of its economic impact make it difficult for policymakers to formulate an appropriate macroeconomic policy response. All this proves that even an epidemic can significantly affect the global economy in the short term. Almost all economists address the importance of investing more in public health systems in all economies, especially in less developed economies where health systems are less developed, and the population density is high. The decisions taken by investors in line with the bad news spread reveal a financial contagion just like in infectious diseases. Contagion in financial sectors is the spread of the reaction of several sectors and regions to a shock in an economy to all financial sectors or countries with a strong financial structure. As can be seen from the previous global financial crises, financial sectors are sensitive to shocks. (Tiryaki and Ekinci, 2015).

Of course, the developments in this real economy will inevitably increase the volatility in the financial markets and decrease the risk appetite. Thus, the S&P 500 index, which is the best indicator of US stock markets, decreased by 35 percent even though there was a slight recovery afterward. Decreasing appetite for taking risks in the markets and increasing willingness to avoid risky investments led to a drop in asset prices in financial markets. The destruction in asset prices decreased the collateral values as a result of the mainly leveraged transactions in the financial markets and increased the collateral completion requests called Margin-Call. That exceedingly increased the need for liquidity in financial markets, and central banks of developed countries, especially the Fed, had to infuse tremendous amounts of liquidity into the markets by increasing their purchases. These significant changes in exchanges can affect many investments. After the Covid-19 outbreak, FTSE, Dow Jones Industrial Average, and Nikkei have seen massive drops. Dow and FTSE have recently seen their most prominent daily decline since 1987.

All these volatility impacts are closely related to the business of global pharmaceutical and biotechnology deeply related to infectious diseases. In this sense, it is essential to measure how infectious disease outbreaks influence the market behavior and stock performance of the companies operating in these sectors. In this period, GlaxoSmithKline decided to invest $250m in San Francisco-based start-up Vir Biotechnology to develop antibodies that could be used to treat coronavirus. Due to this announcement, Vir share hiked up almost 20 percent to $34.75 in mid-morning trading in New York. In addition, Pfizer Inc. informed about its plans to support the development and distribution of BioNTech SE’s BNTX Covid-19 vaccine candidate. BioNTech targets to start the clinical trials across the US and Germany in late April 2020.

Moreover, three drugs with the potential to treat Covid-19 have received the most public attention. Gilead's remdesivir, which was originally developed to treat the Ebola virus, is in late-stage clinical studies and could be the most promising treatment. Finally, the biopharmaceutical company Dynavax Technologies decided to allow usage of its adjuvant technology by partnering with companies that develop Covid-19 vaccines, alongside working on the vaccine development with the University of Queensland. In this context, we investigated whether news related to Covid-19 triggered investment in pharmaceutical companies, namely Abb Vie Inc, Bristol Myers Squibb, Chinext, Dynavax Technologies, Gilead Sciences, and Pfizer by utilizing volatility models and new impact curves. Finally, this paper is a preliminary study for upcoming research papers after the impact of Covid-19 on financial markets, pharmaceuticals and biotechnology companies becomes more visible.

2. LITERATURE REVIEW

Zeren and Hızarcı have exposed the potential effects of coronavirus pandemic on stock exchanges that were reviewed with Maki (2012) cointegration test by using Covid-19 daily total death, and also Covid-19 daily total case. Research results show that all stock markets considered with total death act in unison over the long term. Furthermore, after the investigations, it can be said that even though total cases of Covid-19 have a cointegration association with SSE, KOSPI, and IBEX35, have no cointegration association with FTSE MIB, CAC40, and DAX30. In these circumstances, it is suggested that investors tend to derivative markets, which are seen as more reliable than the stock market, and to stock markets of other less risky countries (Zeren, and Hızarcı, 2020).

Spectral causality and the well-known Granger causality model have tested to see the effects of the Covid-19 on the stock markets, such as Shanghai Se A Share, France Cac 40, Dax 30, etc. These countries' stocks rank as the world's leading markets. Moreover, Covid-19 has interpreted as a "black swan" event for the financial markets.

As a result of the analysis, it has seen that the Shanghai Se A index had a short-term effect on global markets at the beginning of the epidemic (Morales, and Andresosso, 2020).

Researchers, who predict that Covid-19 will become a dangerous global pandemic before being declared an epidemic by the World Health Organization, have analyzed the effects of various situations on macroeconomic results, and financial markets in a global dynamic stochastic general equilibrium (DSGE), and computable general equilibrium (CGE) models. These models demonstrate that the global economy has dramatically influenced in the short term (McKibbin, and Fernando, 2020).

Event study analysis and regression-based methods have implemented in another research that investigated the investor's impression on the stocks of pharmaceutical companies in the USA, which was steered by media news about global pandemics. In this examination, 102 drug companies listed on the New York Stock Exchange (NYSE) or NASDAQ, and S&P500 Drug index American Deposit Receipts (ADR) have analyzed. After the results of the research, it is clear that disease-related news (DRN) has a positive and substantial impact on the stock returns of pharmaceutical companies. Besides, these impacts of the disease news last several days. The news about the disease caused fear and anxiety among investors. The index, which is affected by the fear of investors, affects to pharmaceutical companies and returns of the stocks tremendously negatively (Donadelli et al, YEAR?). Besides, in another research, they also analyzed the financial returns of the top 10 pharmaceutical companies in the USA, using all historical data on serious infectious diseases considered epidemic by the World Health Organization. In this study, its negative impacts have also mentioned (Donadelli et al, 2017).

In this study analyzing the consequences of the SARS outbreak, the association between the Chinese and Asian (Hong Kong, Taiwan, Singapore, Japan) exchanges have examined using the cointegration model. According to the consequences of the research, it has observed that the co-integration relationship that changed over time in the total stock price indices between China and Asian countries weakened. Consequently, investors can have achieved arbitrage gains by portfolio diversification amongst the mentioned countries during disruptive pandemic infections (Chen, M. P. et al, 2018).

Taiwan, officially the Republic of China, is so essential country for this researches since it has faced several epidemics, such as dengue fever, enter virus 71, H1N1, and SARS in the decade. In this analysis, a total of 75 observation numbers from 38 biotechnology companies have examined, and the expected return has acquired from the ordinary least squares (OLS) method. When the relationship between biotechnology companies' financial reports and abnormal returns is analyzed, it can be said to have a significant effect (Wang Y. et al, 2013).

Another article investigating the impacts of the SARS outbreak, one of the various pandemic diseases, has studied its effects on the Taiwan stock exchange. In this article, it has concluded that unlike the other sectors, such as tourism, and retail, the biotechnology sector received positive shocks from the effects of the SARS crisis by using the GARCH method. Moreover, investors can buy stocks, especially of the biotechnology sectors, and gain investment profit during the SARS crisis. (Chen, C. D. et al, 2009)

The event study methodology (ESM), and ARCH, GARCH, and also EGARCH models have used in a study investigating the impact of the SARS outbreak on the

Taiwan Stock Exchange and hotels' stock prices. The findings of the study demonstrated that hotel share prices are sensitive and respond to outbreaks. Moreover, most of the sectors, especially the tourism sector, have damaged along with the SARS (Chen M.H. et al, 2007). Moreover, Keogh-Brown et al emphasized the fact that countries' economies are extremely sensitive to the strategies and macroeconomic policies implemented in response to a pandemic (Keogh-Brown et al, 2010).

In 2004, unlike other similar studies, the SARS virus, which negatively affects China, and Vietnam stocks, has been found to have no negative impression on the stock markets of other infected countries such as Canada, Indonesia, the Philippines, Singapore, and Thailand. In this study, pioneer stock indices, non-SARS period indices, and S&P 1200 global index have compared. Besides, conventional t-tests and non-parametric Whitney tests have used (Nippani, and Washer, 2004).

In a study looking at the effect of swine flu (H1N1), panel data analysis and Monte Carlo simulation have implemented. The tourism industry has a substantial contribution to Sarawak's economy and it's GDP. Thus, 10 major markets in Sarawak tourism have used in this research. Furthermore, it can be said that shocks are not permanent in the short term. Even though these markets had faced lots of shocks, they recovered themselves quickly over and over (Solarin, 2015).

The MONASH-Health model was applied to analyze the economic impacts of swine influenza (H1N1) pandemic on the Australian macroeconomy. This also analysis supports that there is a notable effect of the H1N1 pandemic in the short term. However, the critical point is that the order of stationarity of physical capital and labor (Verikios et al, 2012).

All these literature reviews show us that pandemic diseases have serious effects not only on health but also on the world economy.

3. METHODOLOGY

One model that allows for the asymmetric effect of news is the EGARCH model. One problem with a standard GARCH model is that it is necessary to ensure that all of the estimated coefficients are positive. Nelson (1991) proposed a specification that does not require non-negativity constrains.

Consider:

$$\ln(h_t) = \alpha_0 + \alpha_1 \left(\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right) + \lambda_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}} \right| + \beta_1 \ln(h_{t-1}) \qquad [3.1]$$

Equation (3.1) is called the exponential-GARCH or EGARCH model. There are three interesting features to notice about EGARCH model:

1. The equation for the conditional variance is in log-linear form. Regardless of the magnitude of $ln(h_t)$, the implied value of h_t can never be negative. Hence, it is permissible for the coefficients to be negative.
2. Instead of using the value of ε_{t-1}^2, the EGARCH model uses the level of standardized value of ε_{t-1}^2 [i.e., ε_{t-1}^2 divided by $(h_{t-1})^{0.5}$]. Nelson argues that this standardization allows for a more natural interpretation of the size and persistence of shocks. After all, the standardized value of ε_{t-1}^2 is a unit-free measure.
3. The EGARCH model allows the leverage effects. If $\varepsilon_{t-1}^2 / (h_{t-1})^{0.5}$ is positive, the effect of the shock on the log of conditional variance is

$\alpha_1 + \lambda_1$. If ${\varepsilon_{t-1}^2}/{(h_{t-1})^{0.5}}$ is negative, the effect of the shock on the log of the conditional variance is - $\alpha_1 + \lambda_1$.

The trade-off between future risks and asset returns are the essence of most financial decisions. Risk mainly composes two factors such as volatilities and correlations of financial assets. Since the economy changes frequently and new information is distributed in the markets second moments evolve over-time. Consequently, if methods are not carefully established to update estimates rapidly then volatilities and correlations measured using historical data may not be able to catch differentiation in risk (Cappiello et. al, 2006).

If we consider EGARCH models, the news impact curve has its minimum at $\varepsilon_{t-1} = 0$ and is exponentially increasing in both directions but with different parameters. The news impact curves are made up by using the estimated conditional variances equation for the related model as such the given coefficient estimates and with the lagged conditional variance set to the unconditional variance.

Consider EGARCH (1, 1)

$$\ln(h_t) = \alpha_0 + \beta \ln(h_{t-1}) + \alpha_1 z_{t-1} + \gamma(|z_{t-1}|) - E(|z_{t-1}|) \quad [3.2]$$

where $z_t = {\varepsilon_t}/{\sigma_t}$. The news impact curve is

$$h_t = \begin{cases} A exp\left[\frac{\alpha_1 + \gamma}{\sqrt{h_t}}\right] & for\ \varepsilon_{t-1} > 0 \\ A exp\left[\frac{\alpha_1 - \gamma}{\sqrt{h_t}}\right] & for\ \varepsilon_{t-1} < 0 \end{cases} \quad [3.3]$$

$$A \equiv h_t^{\beta} exp\left[\alpha_0 - \gamma\sqrt{2/\pi}\right] \quad [3.4]$$

$$\alpha_1 < 0 \qquad \alpha_1 + \gamma > 0 \quad [3.5]$$

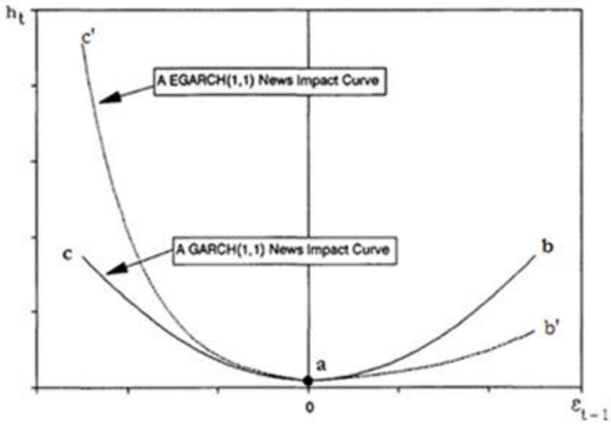
An important characteristic of asset prices is that “bad” news has a more persistent impact on volatility than “good” news has. Most of the stocks have a strong negative correlation between the current return and future volatility. In this context, we can define leverage effect as such volatility tends to decrease when returns increase and to increase when returns decrease.

The idea of the leverage effect is exhibited in the figure below, where “new information” is defined and measured by the size of ε_{t-1} . If $\varepsilon_{t-1} = 0$, expected volatility (h_t) is 0. Actually, any news increases volatility but if the news is “good” (i.e., if ε_t is positive), volatility rises from point ***a*** to point ***b*** along ab curve (or abꞌ for EGARCH model). However, if the news is “bad”, volatility rises from point ***a*** to point ***c*** along ac curve (or acꞌ for EGARCH model). Since ac and acꞌ are steeper than ab and abꞌ, a positive ε_t shock will have a lower impact on volatility than a negative shock of these same magnitudes (Figure 1).

Asymmetric volatility models are the most interesting approaches in the literature since good news and bad news have different predictability for future volatility. Overall, Chen and Ghysels (2010) found that partly good (intra-daily) news decreases volatility (the next day), while both very good news which is unusual high intra-daily positive returns, and bad news which is negative returns increase volatility. However, the latter has a more severe impact over longer horizons the asymmetries fade away.

The news impact curve illustrates the impact of previous return shocks on the return volatility which is implicit in a volatility model.

Figure 1: News Impact Curves



4. DATA AND PRELIMINARY ANALYSIS

The study covers daily closing prices for AbbVie Inc[2] **(ABBV)**, Bristol Myers Squibb[3] **(BMY)**, Chinext[4] **(CHINEXT)**, Dynavax Technologies[5] **(DVAX)**, Gilead Sciences[6] **(GILD)**, and Pfizer **(PFE)**. Daily data for all assets have been taken from Thompson Reuters Eikon. The time span for the study runs from 01 January 2015 to 30 March 2020.

[2] AbbVie is an American publicly traded biopharmaceutical company founded in 2013. It originated as a spin-off of Abbott Laboratories

[3] Bristol Myers Squibb Company is an American pharmaceutical company, headquartered in New York City. Bristol Myers Squibb manufactures prescription pharmaceuticals and biologics in several therapeutic areas, including cancer, HIV/AIDS, cardiovascular disease, diabetes, hepatitis, rheumatoid arthritis and psychiatric disorders.

[4] ChiNext is a NASDAQ-style subsidiary of the Shenzhen Stock Exchange. The first batch of firms started trading on ChiNext on October 30, 2009. As of June 2015, there were 464 firms listed on ChiNext. ChiNext aims to attract innovative and fast-growing enterprises, especially high-tech firms

[5] Dynavax Technologies Corporation (Nasdaq: DVAX) is a fully-integrated biopharmaceutical company focused on leveraging the power of the body's innate and adaptive immune responses through Toll-like Receptor (TLR) stimulation. Dynavax develops, and commercializes novel vaccines.

[6] Gilead Sciences, Inc., is an American biotechnology company that researches, develops and commercializes drugs. The company focuses primarily on antiviral drugs used in the treatment of HIV, hepatitis B, hepatitis C, and influenza, including Harvoni and Sovaldi.

Figure 2: Closing Price Graph of the Dataset

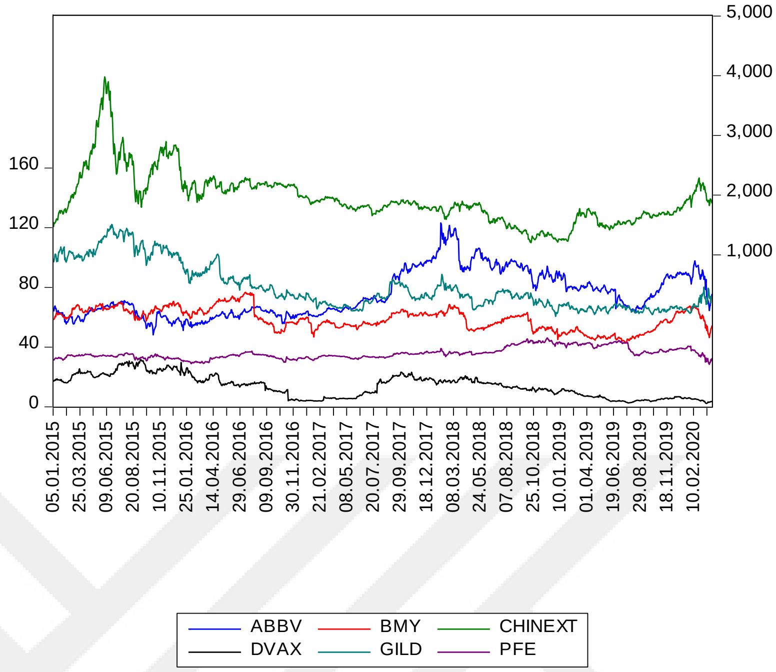


Table 1 illustrates the descriptive statistics of the return of the series. As evident from Table 1, returns of all series are negatively skewed and the kurtosis is much higher than 3 for all the cases. This is indicative of the deviation of series from the normal distribution which is also supported with Jarque-Bera statistics. Further, the stationary of the variables has been examined using the Augmented Dickey-Fuller (ADF) unit root test. The null hypothesis of the unit root is rejected for all return series.

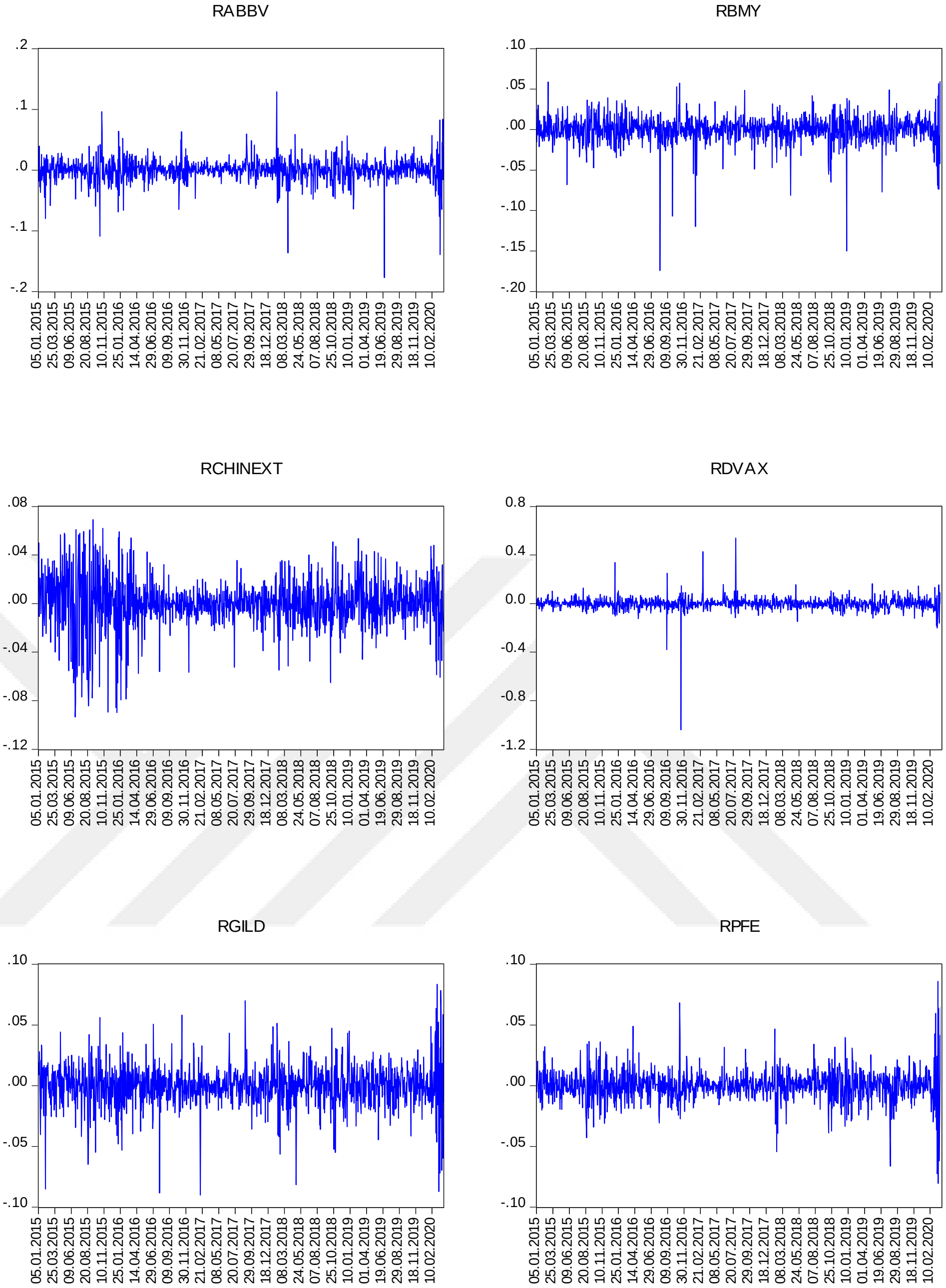
Table 1 : Descriptive Statistics

	RABBV	RBMY	RCHINEXT	RDVAX	RGILD
Mean	6.72E-05	-0.000192	0.000161	-0.000983	-0.000174
Median	0.000946	0.000815	0.000000	0.000000	0.000306
Maximum	0.128985	0.059407	0.06914	0.538546	0.083497
Minimum	-0.177363	-0.174176	-0.093319	-1.040018	-0.090087
Std. Dev.	0.01941	0.017185	0.020966	0.055971	0.017102
Skewness	-1.077872	-2.175612	-0.584761	-4.082499	-0.351434
Kurtosis	16.34614	20.58435	5.818517	110.6006	7.545792
Jarque-Bera	9404.863	16885.67	479.1707	599209.1	1088.768
Probability	0	0	0	0	0
ADF Tests (Level)	-34.91	-36.65	-33.58	-39.13	-36.74

Notes: Between parenthesis: p-values. The number of observations for first period is 1235
JB are the empirical statistics for Jarque Bera tests for normality based on skewness and kurtosis
ADF Tests refer to Augemented Dickey Fuller test for the presence of unit root for long differences (returns)

Returns of all series are calculated by taking the first differences of the logarithm of the two successive prices i.e. $r_t = \log\left({}^{P_t}/_{P_{t-1}}\right)$ which are RABBV, RBMY, RCHINEXT, RDVAX, RGILD, and RPFE. Time-series graphs of the returns have been illustrated which exhibits vividly how volatility has varied in the last three months in Figure 3. It is also visible that industry index Chinext experienced huge volatility clustering in 2015 due to the Chinese stock market bubble burst. A dummy variable for the Covid-19 outbreak is also created and included into the models. The period after the first case was announced by the Chinese government takes the value of “1” till the end of the dataset period and “0” before the announcement back to 01 January 2015.

Figure 3: Time Series Graphs of the Returns



5. EMPIRICAL RESULTS

Having performed unit root tests the next step is to run different versions of EGARCH models for all selected companies. In Table 2 the results of multivariate EGARCH models indicate that coefficients of the Covid-19 dummy variable are positive and significant at %1 significance level in the mean equation of Chinext while it is negative and significant at %1 significance level in the mean equation of Dynavax. On 22nd of February 2020, Shenzhen's technology-focused ChiNext index increased 22 percent which was the most among more than 300 leading benchmarks tracked by Bloomberg. Technology and internet companies, which are set to benefit from higher spending by consumers forced to stay indoors because of the viral outbreak were the main drivers of this hike. However, what is more important for our study is healthcare and biotechnology stocks which have also rallied on hopes that these companies will develop coronavirus treatments or get more business owing to the epidemic.

Table 2: EGARCH MODELS

	RCHINEXT				RGILD				RDVAX			
	Mean Equation		**Variance Equation**		**Mean Equation**		**Variance Equation**		**Mean Equation**		**Variance Equation**	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
C	-0.7796	-0.0004			0.0892	0.0892			0.0002	0.2159		
RGILD	4.9369	0.1134							0.1617	3.4512	-10.9079	-7.6186
RABBV												
RCHINEXT					0.1016	0.1016	-1.6152	-4.0556	0.1448	4.4927		
RDVAX					0.0180	0.0180						
RBMY							-2.1525	-4.8664	0.2746	5.9438	0.0685	2.5689
RPFE									0.1476	1.5158	-24.0989	-14.7944
COV19	1.3744	0.0029	0.0245	3.0877			0.0481	6.0816	-0.0072	-1.9431	0.2490	4.3727
α_0			-0.1204	-6.3153			0.1692	-2.8023			-2.1743	-13.7551
$\boldsymbol{\alpha_1}$			**-0.0161**	**-1.8935**			**0.0541**	**5.1276**			**0.1848**	**8.6462**
λ_1			0.0928	7.2087			0.0503	4.4253			0.8666	22.1568
$\boldsymbol{\beta_1}$			**0.9938**	**597.1417**			**0.9843**	**148.8343**			**0.7411**	**33.3894**
Observations	1235				1235				1235			
R^2	0.0160				0.0178				0.0231			
DW	1.9221				2.1881				2.2449			

	RABBV				RBMY				RPFE			
	Mean Equation		**Variance Equation**		**Mean Equation**		**Variance Equation**		**Mean Equation**		**Variance Equation**	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
C	0.0005	1.2866			0.0028	7.2701			0.0000	0.1962		
RGILD					0.2041	16.8851			0.0490	3.4316	-3.7563	-2.4818
RABBV									0.1557	16.4996	3.9763	3.8843
RCHINEXT					0.0721	4.8970	2.4410	4.5589				
RDVAX	0.0136	2.3627	-0.9916	-2.4221								
RBMY	0.3871	23.4960	-12.7331	-14.4177			-17.9676	-29.1097	0.2466	20.9511	-7.0298	-5.7251
RPFE	0.4147	13.6764	1.9380	2.4671	0.4256	16.7840	4.7112	3.5582				
COV19											0.1590	2.2555
α_0			-1.6089	-10.9871			-0.9208	-10.8398			-2.2217	-8.3934
$\boldsymbol{\alpha_1}$			**0.0093**	**0.4590**			**0.1820**	**10.3454**			**-0.0859**	**-3.2006**
λ_1			0.4716	14.2694			-0.0817	-4.6271			0.4981	11.6877
$\boldsymbol{\beta_1}$			**0.8472**	**50.1501**			**0.8868**	**85.7061**			**0.8040**	**30.8188**
Observations	1235				1235				1235			
R^2	0.2824				0.2359				0.3137			
DW	1.9797				1.9753				2.1119			

Dynavax stocks experienced a fall in contrast with the major stock indices in the global financial markets just after the announcement of the outbreak. However, the biopharmaceutical company's stocks rebounded very quickly since Dynavax, as a commercial-stage vaccine company, which is providing CpG 1018, the adjuvant contained in U.S. FDA-approved HEPLISAV-B vaccine, to support the rapid development of Clover's Covid-19 vaccine, can play a vital role in the fight against this pandemic.

For the variance equation, the Covid-19 dummy variable is valid and significant at %1 level for Chinext, Gilead[7], Dynamax, and Pfizer and has volatility increasing impact. Considering its unique contribution to the hassle with Covid-19, α_1 in RDVAX model is one of the highest levels observed among all other models which refers that short-term shock has a more significant impact on Dynavax stock returns. The level of α_1 is also high in RBMY model compared to other models Bristol-Myers Squibb's stock has declined due to the Coronavirus/Oil Price War crisis however, it could bounce back strongly as the crisis winds down. Covid-19 dummy is not significant in both mean and variance equation in the RBMY model so we can conclude that short term shocks for Bristol-Myers is due to the major market indices trend, not a specific reaction to pandemic itself but a reaction the overall falling trend of financial markets. The sum of the coefficients of the lagged squared error and the lagged conditional variance are close to unity (0.99) for Chinext, Gilead, Dynamax, and Bristol-Myers Squibb, implying that shocks to conditional variance are highly persistent. For Pfizer and Abbvie the impact of persistency is lower compared to Chinext, Gilead, Dynamax, and Bristol-Myers Squibb.

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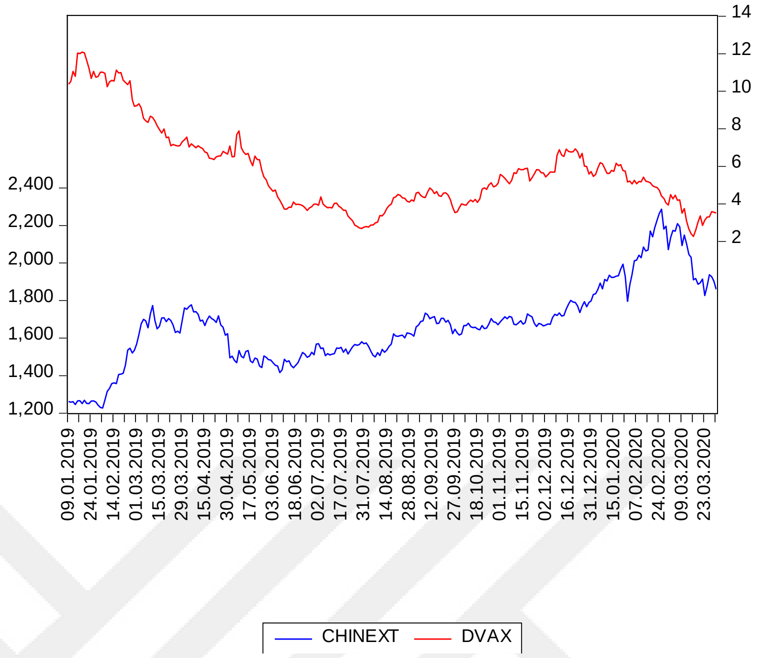
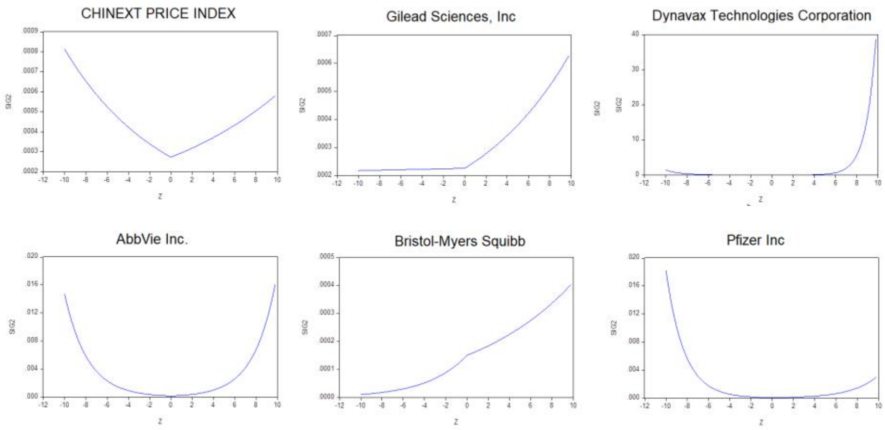
[7] Gilead has been working in consultation with regulatory authorities to establish additional expanded access programs for remdesivir, our investigational medicine for COVID-19. The programs enable hospitals or physicians to apply for emergency use of remdesivir for multiple severely ill patients at a time.

Figure 4: Chinext and Dynavax Price Graph after Covid-19 Outbreak



Hence EGARCH models are important for us to obtain News Impact Curves (NICs) and test the leverage effect (Figure 5). Any news increases volatility however if the news is "good" volatility increases along the right side of the curve. If the news is "bad" volatility increases along the left side of the curve.

Figure 5: News Impact Curves



Since Gilead and Dynamax's right side of the NICs is steeper than the left side, a positive ε_t shock will have a bigger effect on volatility than a negative shock of the same magnitude. For Abbvie the NIC is nearly symmetric which suggests that any news good or bad has the same impact on the volatility of returns. Finally, Chinext and Pfizer since the left side of the curve are steeper than the right side, a negative ε_t shock will have a bigger effect on volatility than a negative shock of the same magnitude which is quite consistent with an approach that Chinext and one the major players of the pharma industry, which is not specifically related with the fight against this pandemic, represents a more general market. In this context, we can also conclude that companies like Gilead and Dynavax which have more to the point roles in the outbreak period compared to other global pharmaceutical companies react to good news more intensely. Gilead is a longtime drugmaker best known for developing the first major cure for hepatitis-C in Sovaldi while Dynavax's adjuvant technology can help provide an increased immune response to a vaccine that makes them usual suspected solution providers for the pandemic.

6. CONCLUSION

Financial markets in the time of the coronavirus pandemic hard to predict due to the noise in the markets. Dow Jones Industrial dropped nearly 1,200 points marking the worst intraday point decline in the history of the Dow. The reason for this collapse was a growing consensus that Covid-19 has landed on U.S. shores and will likely have a stronger impact on the economy than the investors initially predicted. Covid-19 is a once-in-a-lifetime business opportunity for most of the pharmaceutical and biotech companies. However, due to the news impact curves, we claim that the impact of Covid-19 is not a de facto for all related industry companies. There are outstanding companies such as Gilead with its remdesivir which was originally developed to treat the Ebola virus and Dynavax partnering with vaccine developer companies to use its technology. The asymmetry in the NICs for the favor of good news suggests that companies like Gilead and Dynavax are priced by the market with an expectation to find the cure or play an important part in this process. Companies like Gilead and Dynavax which have more to the point roles in the outbreak period compared to other global pharmaceutical companies react to good news more intensely. Finally, this paper is a preliminary study for upcoming research papers after the impact of Covid-19 on financial markets, pharmaceuticals and biotechnology companies becomes more visible.

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CHAPTER 2: IS "THE RETURN OF THE TECH BUBBLE" NEXT DYSTOPIAN MOVIE OF NETFLIX? A DCC-GARCH ANALYSIS

ABSTRACT

On-demand streaming is the most distributive development in the entertainment market for the traditional cinema business. Netflix the pioneer of streaming revolution is assessed with big tech company stocks; Facebook, Apple, Amazon, Netflix, and Alphabet; namely FAANG stocks. However, businesswise the priority of the competition for streaming business is (or should be) with cinema, TV, and streaming business players. In this context, first we analyzed the interaction between Netflix and cinema, TV, and streaming business stocks by utilizing conditional correlation (DCC) multivariate GARCH models. Secondly, we compared our results to FAANG and FAAMG model results to find the best fit. Third, we tested FAANG models for a longer overall period and Covid-19 period separately to see if any bubble effect exists in the model results. According to our results we cannot strongly claim that Netflix belongs to the cinema, TV, and streaming business instead of big tech company stocks. We also checked whether Microsoft is a better alternative to Netflix stocks, but we concluded that neither Netflix nor Microsoft is significantly a better match to FAAG stocks which is interesting since Microsoft is obviously a tech innovator. Especially in the pandemic period the increasing cointegration of big tech companies and their behavior as if all these stocks belong to one company drives us to comment that FAANG and Microsoft stocks are treated as if they are commodities rather than company stocks in the pandemic period which makes us to be cautious about a second dotcom crisis since %26 of S&P 500 market cap is driven by FAANG and Microsoft stocks.

Key words: *Netflix, dotcom crisis, tech stocks, DCC-GARCH, FAANG*

7. INTRODUCTION

Over the past 20 years, big tech company stocks have recovered. They are now essentials of the society since it is hard to find someone who does not own a smartphone or have an email account. The FAANG stocks (Facebook, Amazon, Apple, Netflix, and Google) have driven the markets to fuel all-time highs. Since March 2020, big tech companies have outperformed all other sectors, making many investors and academicians suspect that there is a new dotcom-like bubble brewing. In this context, it is worth looking back to the 2000s to ask what led to this bubble, and whether it could pop again. Even though these companies recreated the rules of business, their valuations became detached from any rational financial underpinnings.

There have been technological developments in the world since the middle of the 20th century. Further, these developments have enabled the world to progress in the field of communication.

The boundaries between local and global have eliminated via the internet. The interactions installed have led to the availability of new and various channels. Internet technologies have been improving for more than 50 years, and we see that the time needed for these improvements has declined over time.

Media, which is the plural word of the medium, which means a device in Latin, has received the name of “new media” in the age of communication. As stated by Karaismailoğlu, new media is a diversified media strategy that permits the communication of many sounds, shades, and ideas all over the world. (Karaismailoğlu, 2014: 302) According to Aktaş (2007), the unique features of the new media are transmission lines, differentiated content, direction, and interaction. The concept of digital cinema has created a name for itself with computer technology started to advance since the 1990s. The developing technology has not only created new concepts but has also led to the establishment of various digital platforms. With the improvement of technology, traditional mass media have also evolved, and both the media and functions of media have also gained new meanings. The cinema and film industry have been digitally affected by these media technologies, which have also taken an active role in film production processes. There have been substantial changes in broadcasting, thanks to digitalization. While the movies are shown in movie theaters traditionally, in addition to this, the online broadcasting opportunity has been offered to the audience. Besides, after the digitalization in the cinema sector, new and diverse film production models have been started to produce. In this environment, digital stages such as Netflix and Amazon have managed to reach a large number of people. Netflix, which entered digital broadcasting 10 years after its establishment, was originally founded in 1997 as a DVD rental service company. In 2000, an agreement was made with CineMatch. The members evaluated the films and started to give them points. In this way, it is easier for them to direct their services. It achieved rapid growth in this field, gaining an overwhelming power over its rivals, and then turned its publications entirely digital. We can say that the demands of such digital stages are pretty intense because individuals have the opportunity to watch them wherever and whenever they want. The latest reports show that the number of Netflix subscribers is more than 183 million worldwide. Even after coronavirus restrictions, it added 16 million new members in its first quarter of the year.[8] As Erkek R. said (2019), the absence of advertising in such channels with monthly membership also led to a rise in the number of users and members. Strategy Analytics

[8] https://www.dw.com/tr/netflixin-abone-say%C4%B1s%C4%B1-183-milyona-%C3%A7%C4%B1kt%C4%B1/a-53206573

foresees more than 450 million houses to pay digital platforms in 2022 (Mercer, 2018).

As Ramkumar said that, individual investors are interested in well-liked technology stocks at even economic darkness and risk arising from the pandemic period (2020). Some individual investors prefer to use internet stocks to hedge funds. Also, institutional investors may prefer to use these stocks if institutional investors expect a significant growth rate. Ramkumar also stated, in the pandemic period, some of the tech stocks are overvalued and worried about the shares of the stock damaged.

As declared by Muralidharan (2018), Apple touched 1 trillion a market value on August 2, not far behind Amazon and Google. After fluctuations until 2020, Microsoft Corp was the only US Company to hold the value at 13 digits.[9] In its May 2020 report, Netflix is ranked as the third most valuable company in the world with a market value of $ 1.286 billion. Microsoft is in second place on this list, Amazon is in 4th place, Alphabet Inc is in 5th place, and Facebook is in 6th place.[10]

On any given day, the transactions in FAANG companies' stocks expose several estimations of their potential of earnings. FAANG valuations are about future growth expectations, not about the current earnings. Although Netflix positions itself as a technology company (even within FAANG), is its business-wise competitor Time Warner, ACM, CJ CGV, or technology companies? This study seeks to answer this question.

[9] https://www.bloomberght.com/apple-in-piyasa-degeri-1-trilyon-dolarin-altina-geriledi-2250808
[10] https://tr.fxssi.com/dunyanin-en-degerli-sirketleri

8. LITERATURE REVIEW

Many changes occurred during the coronavirus pandemic in the world. One of these is the rate of change and views in broadcast streams. For instance, Roku (NASDAQ: ROKU) published that its expectations in the first division reports reach approximately 13 billion, with an extension of 50% compared to the past year.[11] Of course, there are other companies like Roku. For example, Walt Disney's (NYSE: DIS) latest report demonstrates that Disney + subscriptions have touched almost 50 million shortly after launch. Also, Hulu, which is the broadcasting service presently majority-owned by Disney, has encountered a more raised audience. According to streaming aggregator Reelgood, US' flowing times duplicated in the first week of April compared to the previous month. Thus, Netflix had taken the lion's share with 41.3%. In the second place is Amazon Prime Video (NASDAQ: AMZN) with a share of 22.1%. This shows us that the video broadcasting giant Netflix remains to be a strong opponent.

If we look at the first dealing week of 2020, we can observe that Netflix had the most high-grade performance among the FAANG group, which is also known as the best technology group. This November, Disney, and Apple started its video streaming services, which names are Disney + and Apple TV +. WarnerMedia HBO Max showed in May, and NBCUniversal, Comcast (NASDAQ: CMCSA), is getting ready to launch the USA-based Peacock on July 15. In a report by analyst Nat Schindler, it is clear that the interaction Disney+ has reached is far backward compared to Netflix. This strengthens the idea that Disney+ is not an alternative. Besides, the prevalent

[11] https://www.nasdaq.com/articles/why-streaming-stocks-could-be-the-big-winners-in-the-bear-market-2020-04-15

belief of analysts is that Netflix can recompense for its weakness in the regional market by swiftly developing its global occupation.

As Shattuc wrote in the book chapter Amazon is not only a retail company, it has also web services, Cloud, and games. However, it can be said that, compared with Netflix, Amazon does not focus on video streaming (2020). It is also mentioned that Netflix has evolved television and movie by making TV further complicated and global in this book chapter.

In this article, where Martinez and his friends worked, a system improved to forecast what the Nasdaq Index will be. This system covered by tweets about Facebook, Apple, Amazon, Netflix, and Alphabet Google companies known as FAANG (Martinez et al, 2019). Positive and negative news or tweets have influenced the positions to be taken. Whereas negative tweets about the FAANG lead to the short position (sell), positive tweets cause to a long position (buy).

After this article, also, it can be said that the impression of investor behavior is so substantial in the stock market analysis and its understanding. Furthermore, using the Back Testing methodology, they tried to estimate the future from history. Different back testing had worked to several open position time periods in steps of 30 minutes and it has been seen that the optimum open position time was 60 minutes.

In another article about FAANG Companies, linear and nonlinear methods were implemented the next day to evaluate the closing price of each stock. Ingredient series methodologies were established using the time series wavelet method. After that, for the linear functions Autoregressive Integrated Moving Average Model (ARIMA), and Long Short Term Memory (LSTM) network to all series to create following day forecasts. Thanks to this wavelet analysis, motions to be interpreted on the time domain. Oner et al stated that low-frequency information at a long time interval and also high-frequency information in a short time interval can be specified (2017). In this study, models have established on daily closing prices of FB, AAPL, AMZN, NFLX, and GOOG shares between 2010 and 2017. ARIMA model's principal presumption is constant variance and volatility. Although this is not the case in the actual scenario, the ARIMA (ARIMAX) or General Autoregressive Conditional Heteroskedasticity (GARCH) model can properly determine this action.

Goldman Sachs neologized the abbreviation FAAMG, which is Facebook, Amazon, Apple, Microsoft, and Google in 2017. In 2019, Jim Cramer offered that Netflix is excluded from FANG, and replaced with Microsoft. Also, he suggested that the name should be called FAAM.[12]

On the other a significant portion of S&P500 Index market cap is driven by big tech companies. This high impact makes us cautious about the existence of a possible bubble and a second dotcom crisis possibility.

According to Mills (2001), although capital markets have achieved an excellent function in shifting money to the new industry sector described by dotcoms, they have failed to decide which initiatives to promote. Dot-coms are built on new business models, not on proprietary technologies or products. For this reason, traditional plans and strategies have not been implemented.

In Ljungqvist and Wilhelm's article on IPO Pricing, they examined the businesses that were observed to be affected by the dotcom balloon. Then, they computed high technology, internet, and bubble dummies to the simple regression model they settled. After that, they compared the estimated coefficients. They see that the high-tech and

[12] https://www.investors.com/news/technology/what-are-fang-stocks-faang-stocks/

Internet dummy variables' coefficients are statistically significant at % 5 level. As a result of the data used in the article, it has been found that the abnormal price behaviors occurring during the dotcom bubble can be partially explained by the important changes in the ownership structure before IPO (Ljungqvist and Wilhelm, 2003).

The subject of the stock market and its valuation was also a favorite topic during the dot-com bubble of the 1990s. Morris and Alam have examined the correlation between market valuation and traditional accounting techniques. They also verified that the former studies that document a slump between the market value and traditional accounting techniques until the bubble era. On the other, they also recognize that after the 2000 bubble burst, it changed conversely (Morris and Alam, 2012).

NASDAQ Composite Index's multiple changes in resolution in the dividend price and price-earnings ratio have analyzed by Leone and Medeiros. Recent Time Series methods have used in this research. This analysis shows that methods capable of choosing up warning signals of the derivation of a bubble could be extremely beneficial (Leone, and Medeiros, 2015).

Another article where bubbles formed in 1997 and 2007 in the Hong Kong stock exchange and the characteristics of NASDAQ related to 2000 dot-com have investigated, technical analysis strategies giving trading signals have examined. As a result of the researches, taking buy or sell positions during the bubble configuration, and also short strategy after the bubble burst leads to produces returns even greater wealth. Moreover, according to McAleer and team workers, bubble assignation signs advise investors to create more comprehensive wealth from implementing moving average (MA) strategies (McAleer et al, 2016).

In the article, which examines the correlation between temporary investor networks and volumes for Nokia stock, the differences around the dotcom bubble were analyzed in addition to the studies. These analysis were carried out separately for households, financial and non-financial institutions. The results show that it reflects the crisis for the household. Furthermore, it can see that the upward trend in the bull market when the bubble was building up (Ranganathan et al, 2018).

In this context, first we analyzed the interaction between Netflix and cinema, TV and streaming business stocks by utilizing conditional correlation (DCC) multivariate GARCH models. Secondly, we compared our results to FAANG and FAAMG model results to find the best fit. Third, we tested FAANG models for a longer overall period and Covid-19 period separately to see if any bubble effect exists in the model results.

9. METHODOLOGY

Firstly, we used GARCH instruments to model the volatility behavior of big tech stocks. The major advantage of the model is that, instead of considering heteroskedasticity as a problem to be corrected, ARCH and GARCH models treat it as a variance to be modeled. Usually, financial data suggests that some periods are riskier than others; that is, the expected value of the magnitude of error terms sometimes is greater than at others. The goal of such models is to provide a volatility measure, like a standard deviation, then can be used in financial decisions related to risk analysis, portfolio selection, and derivative pricing (Engle 1982, 1993 and 2001).

ARCH model assumes that the variance of t $u_t$in period t, σ_t^2 depends on the square of the error term in t-1 period, u_{t-1}.

In this context, ARCH(q) and GARCH(q) models are as follows.

$\alpha_0 > 0$, $\alpha_i > 0$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}{}^2 + \alpha_2 \varepsilon_{t-2}{}^2 + ... + \alpha_q \varepsilon_{t-q}{}^2 + \nu_t \qquad [10.1]$$

GARCH models which express the generalized form of ARCH models were developed by Engle (1982) and Bollerslev (1986) to provide reliable estimations and predictions. GARCH models consist of conditional variance, in equation (2) in addition to conditional mean in the equation [10.1].

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i r^2{}_{t-i} + \sum_{i=!}^{p} \beta_j h_{t-j} \qquad [10.2]$$

In this context, restrictions of variance model are as follows.

for $\alpha_i \geq 0$ and $\beta_i \geq 0$, $\alpha_i + \beta_i < 1$

If $\alpha_i + \beta_i \geq 1$ it is termed as non-stationary invariance. For non-stationary in variance, the conditional variance forecasts will not converge on their unconditional value as the horizon increases (Brooks 2008). In this context ARCH and GARCH models have become very popular as they enable the econometrician to estimate the variance of a series at a point in time. Clearly, asset pricing models indicate that the risk premium will depend on the expected return and the variance of that return (Enders 2004).

The coefficient α_i refers to the ARCH process in the residuals from asset i which depicts the fluctuations of the assets reflecting the impact of external shocks on fluctuations. The ARCH effects measure short-term persistence while the GARCH effect measures long-term persistence which is represented by β_i.

9.1. DCC – GARCH

The Dynamic Conditional Correlation (DCC-) GARCH belongs to the class" Models of conditional variances and correlations. It was introduced by f and Sheppard in 2001. The idea of the models in this class is that the covariance matrix, H_t, can be decomposed into conditional standard deviations, D_t, and a correlation matrix, R_t. In the DCC-GARCH model both D_t and R_t are designed to be time-varying.

Suppose we have returns, at, from n assets with expected value 0 and covariance matrix H_t. Then the Dynamic Conditional Correlation (DCC-) GARCH model is defined as:

$$r_t = \mu_t + \alpha_t$$
$$\alpha_t = H_t^{1/2} z_t$$
$$H_t = D_t R_t D_t$$

r_t: n×1 vector of log returns of n assets at time t.,

α_t: $E[\alpha_t]=0$ and $Cov[\alpha_t]=H_t$ n×1 vector of mean-corrected returns of n assets at time t, i.e.,

μ_t: n×1 vector of the expected value of the conditional r_t

H_t: n×n matrix of conditional variances of α_t at time t.

$H_t^{1/2}$: Any n×n matrix at time t such that H_t is the conditional variance matrix of at. $H_t^{1/2}$ may be obtained by a Cholesky factorization of H_t.

D_t: n×n, diagonal matrix of conditional standard deviations of α_t at time t

R_t: n×n conditional correlation matrix of α_t at time t

Z_t: n×1 vector of iid errors such that $E[Z_t]=0$ and $E[Z^T{}_t]$

In addition, Q_0, the starting value of Q_t, has to be positive definite to guarantee H_t to be positive definite. The correlation structure can be extended to the general DCC (M, N)-GARCH model:

$$R_t = \varrho_t^{*1} \varrho_t \varrho_t^{*1}$$

$$\varrho_t = (1 - \varrho_1 - \varrho_2)\bar{\varrho} + \varrho_1 \varepsilon_{t-1} \varepsilon_{t-1}^T + \varrho_2 \varrho_{t-1}$$

In this context ϱ_t can be estimated as mentioned below:

$$\varrho_t = \frac{1}{T} \sum_{t=1}^{T} \varepsilon_t \varepsilon_t^T$$

There are imposed some conditions on the parameters ϱ_1 and ϱ_2 to guarantee H_t to be positive definite. In addition to the conditions for the univariate GARCH model to ensure positive unconditional variances, the scalars a, and b must satisfy: $\varrho_1 \geq 0$, $\varrho_2 \geq 0$ and $\varrho_1 + \varrho_2 < 1$.

10. ECONOMETRIC DATA DESCRIPTION

On-demand streaming is the most distributive development in the entertainment market for the traditional cinema business. Although console games and e-sports challenged the interest of consumers to traditional cinema, on-demand streaming is an excellent substitute for movie watchers. Disney+ for 6.99$ a month, which is slightly less than the cost of a cinema ticket, is now available for America, Canada, and the Netherlands. Even in a few hours, the algorithm hoovered up enough data to suggest personalized content to the brand-new subscribers of Disney+. Yet, Netflix the pioneer of streaming revolution is assessed with the tech stocks Facebook, Apple, Amazon, Netflix, and Alphabet, namely FAANG stocks. However, businesswise the priority of the competition for streaming business is (or should be) with the traditional cinema chains.

In this context, our dataset contains daily Facebook (FACEBOOK) Alphabet-Google (ALPHABET), Apple (APPLE), Amazon (AMAZON), Netflix (NETFLIX) and Microsoft (MICROSOFT) between June 24, 2016, and July 6, 2020, for FAANG and FAAMG analysis. We also narrowed the period between December 31, 2019, and July 6, 2020, to analyze the impact of Covid-19 on technology stock performance. We will construct our FAANG and FAAMG GARCH models separately for both periods based on this dataset. For cinema, TV, and streaming business analysis we included AMC Theatres (AMC), The Walt Disney Company (Disney), Cineworld (CINEWORLD), The IMAX Corporation (IMAX), and Comcast Corporation (COMCAST) between June 24, 2016, and July 6, 2020. We again narrowed the period between December 31, 2019, and July 6, 2020, to analyze the impact of Covid-19 cinema, TV, and streaming business.

Descriptive statistics and distributional characteristics of returns have reported in Table 3 and Table 4. The normal distribution has a skewness of zero, however financial data can be perfectly symmetric rarely. In such cases to understand the skewness of the data series shows either mean deviates from the mean positively or negatively. Amazon, Netflix, AMC, Cineworld, and IMAX are negatively skewed which means that the mass of the distribution is concentrated on the right side of the figure. The others are positively skewed which means that the mass of the distribution is concentrated on the left side.

The kurtosis of any univariate normal distribution is 3 and distributions with kurtosis less than 3 are said to be platykurtic which has thinner tails. It means the distribution produces fewer and less extreme outliers than does the normal distribution. Distributions with kurtosis greater than 3 are said to be leptokurtic. All the series in our dataset are highly leptokurtic which has fatter tails which are expected for financial assets. Since all the series in our dataset are highly leptokurtic, we chose to use t-distribution in our GARCH models.

Table 3: Descriptive Statistics-Overall Period

	RALPHABET	RAMAZON	RAPPLE	RFACEBOOK	RMICROSOFT	RNETFLIX
Mean	-7.78E-04	-1.46E-03	-1.39E-03	-7.67E-04	-1.43E-03	-1.72E-03
Median	-0.001188	-0.001668	-0.001035	-0.001141	-0.0013	-0.000603
Maximum	0.123685	0.082535	0.137708	0.210239	0.159453	0.140714
Minimum	-0.091852	-0.124131	-0.113157	-0.102704	-0.132929	-0.174189
Std. Dev.	0.016846	0.018325	0.018572	0.020554	0.017477	0.025065
Skewness	0.429607	-0.220505	0.423698	1.521923	0.313839	-0.146888
Kurtosis	10.72785	8.969102	11.98841	19.93432	16.93407	8.70745
Jarque-Bera	2514.041	1489.709	3389.441	12310.17	8090.134	1358.165
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ADF Tests (Level)	-6.790811***	-6.705609***	-5.793534***	-5.946681***	-7.748591***	-6.934488***

	RAMC	RCINEWORLD	RCOMCAST	RDISNEY	RIMAX
Mean	1.88E-03	1.42E-03	-7.78E-04	-1.86E-04	9.52E-04
Median	0.000807	0.000000	-0.001188	-0.000185	0.000000
Maximum	0.313412	0.562152	0.123685	0.139085	0.297541
Minimum	-0.310695	-0.922818	-0.091852	-0.134639	-0.465654
Std. Dev.	0.042655	0.052781	0.016846	0.017158	0.030803
Skewness	-0.162953	-3.866434	0.429607	0.072737	-1.928767
Kurtosis	17.75713	119.1527	10.72785	18.54962	69.26816
Jarque-Bera	9060.143	563506	2514.041	10055.34	183230.7
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
ADF Tests (Level)	-10.74278***	-6.819627***	-6.790811***	-6.683788***	-7.05201***

Notes: Between parenthesis: p-values. The number of observations for first period is 998.
JB are the empirical statistics for Jarque Bera tests for normality based on skewness and kurtosis
ADF Tests refer to Augemented Dickey Fuller test for the presence of unit root for long differences (returns).
Maximum lag number (12) is applied for the tests
*denotes rejection for the presence of unit root at %10 level
**denotes rejection for the presence of unit root at %5 level
***denotes rejection for the presence of unit root at %1 level

In Table 4, descriptive statistics are exhibited for the Covid-19 period. Distribution form of the series is similar to overall period however ADF test either fail to reject the presence of unit root for maximum lag length or we can reject H0 hypothesis weakly at 5% level for Amazon and at 10% level for Netflix, Cineworld, AMC, and IMAX which leads us to suspect that we may face a cointegration problem for Covid-19 models.

Table 4: Descriptive Statistics-Covid-19 Period

	RALPHABET	RAMAZON	RAPPLE	RFACEBOOK	RMICROSOFT	RNETFLIX
Mean	-8.40E-04	-3.82E-03	-1.88E-03	-1.26E-03	-2.19E-03	-3.32E-03
Median	-0.003522	-0.004788	-0.000707	-0.003487	-0.005581	-0.00099
Maximum	0.123685	0.082535	0.137708	0.153769	0.159453	0.118095
Minimum	-0.088388	-0.111329	-0.113157	-0.097444	-0.132929	-0.109331
Std. Dev.	0.029731	0.026813	0.033569	0.033508	0.034249	0.031633
Skewness	0.440086	-0.17035	0.319232	0.79948	0.424484	0.173878
Kurtosis	5.956503	5.653921	6.551191	6.703603	8.037369	5.422175
Jarque-Bera	50.35346	37.88503	68.89007	86.11316	138.0904	31.68578
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ADF Tests (Level)	-2.0327	-2.8839**	-2.2678	-2.0430	-2.5323	-3.3081**

	RAMC	RCINEWORLD	RCOMCAST	RDISNEY	RIMAX
Mean	4.42E-03	1.05E-02	-8.40E-04	1.79E-03	4.75E-03
Median	0.010794	0.007843	-0.003522	0.001451	0.000000
Maximum	0.238411	0.562152	0.123685	0.139085	0.297541
Minimum	-0.310695	-0.922818	-0.088388	-0.134639	-0.465654
Std. Dev.	0.092896	0.13936	0.029731	0.036599	0.067573
Skewness	-0.511174	-1.894435	0.440086	0.128754	-1.523008
Kurtosis	5.070393	19.94255	5.956503	5.977712	23.69301
Jarque-Bera	28.2137	1594.938	50.35346	47.27087	2314.992
Probability	0.000001	0.000000	0.000000	0.000000	0.000000
ADF Tests (Level)	-2.6682*	-2.6668*	-2.0327	-2.1160	-2.6244*

ADF Tests refer to Augemented Dickey Fuller test for the presence of unit root for long differences (returns).
Maximum lag number (12) is applied for the tests.
However, for lag number (6) all the variables are non-stationary
*denotes rejection for the presence of unit root at %10 level
**denotes rejection for the presence of unit root at %5 level
***denotes rejection for the presence of unit root at %1 level

Figure 6 exhibits daily value of S&P 500 and NASDAQ indices, Figure 7 exhibits daily prices for FAANG and Microsoft stocks, while Figure 8 exhibits daily prices of Cinema, TV, and Streaming Business during the pandemic period. The S&P 500 stands at 3,231 on December 31st, 20219 dropped to 2,237 on March 23 due to the

2020 Covid-19 crash and as of July 6th, 2020 it rebounded all the way to 3,179. The index was down 31% as of 23rd of March compared to the first announced corona cased in December 2019, but as of 6th of July 2020 index is 42% higher than the March lows. Quite a staggering rebounded, driven mainly by Tech stocks like Facebook, Amazon, Apple, Netflix, Google, Microsoft, etc. which fueled the V-Shape recovery in financial markets.

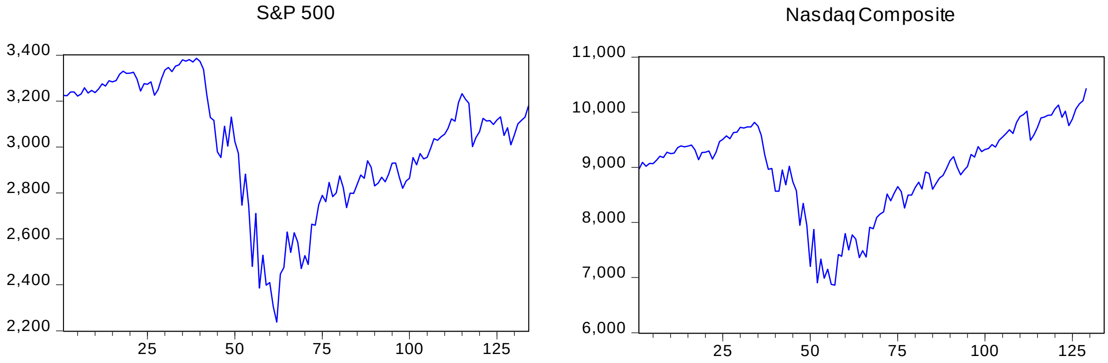
Table 5: FAANMG Market Cap Shares in S&P 500

Company/Index	Mcap (bln $)	Company/S&P 500
Facebook	686.43	3%
Amazon	1500	6%
Apple	1670	7%
Netflix	213.95	1%
Alphabet (Google)	1040	4%
Microsoft	1550	6%
FAANMG	**6660.4**	**26%**
S&P 500	25640	

Table 5 confirms that the S&P 500 has six companies (FAANGM) responsible for over 26% of the index's rebound worse even than the dot com bubble[13] of 1999/2000. The rush to buy FAANMG is a broader bet that the pandemic has only increased society's reliance on technology. Big Tech companies have the financial flexibility to get through the crisis not only with mountains of cash that they have saved but they can easily enter the capital markets to provide more financial resources.

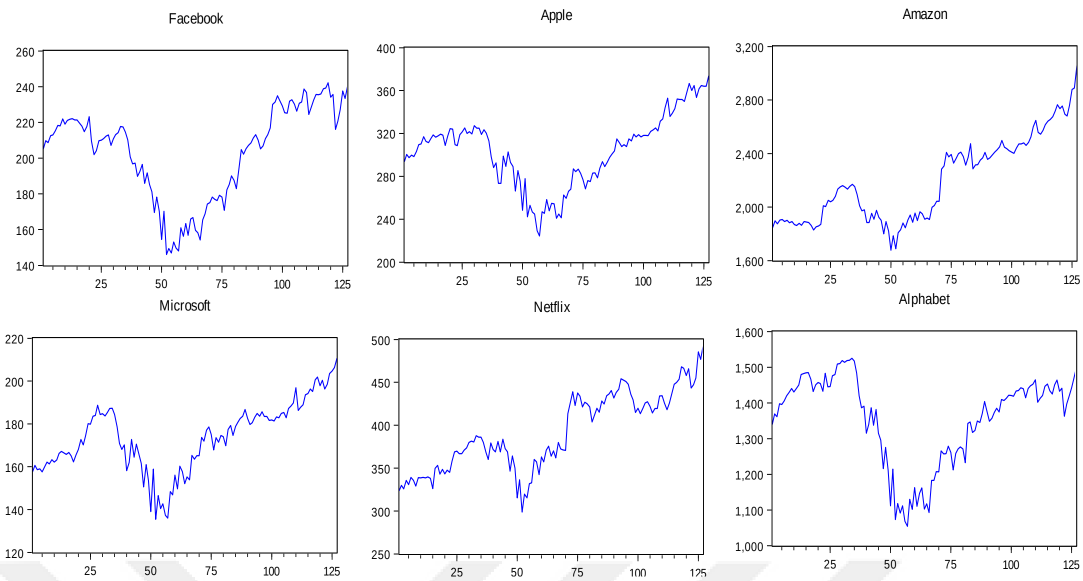
[13] The dot-com bubble is also known as the tech bubble. This balloon was a stock market bubble created by extreme speculation in Internet-related businesses in the late 1990s.Although Dotcom Balloon was largely referred to as the internet companies' shares were destroyed in the stock market, one of the factors that actually inflated the bubble was the dreams of smart devices that did not exist at that time.

Figure 6: S&P 500 and NASDAQ Daily Closing- Covid 19 Period



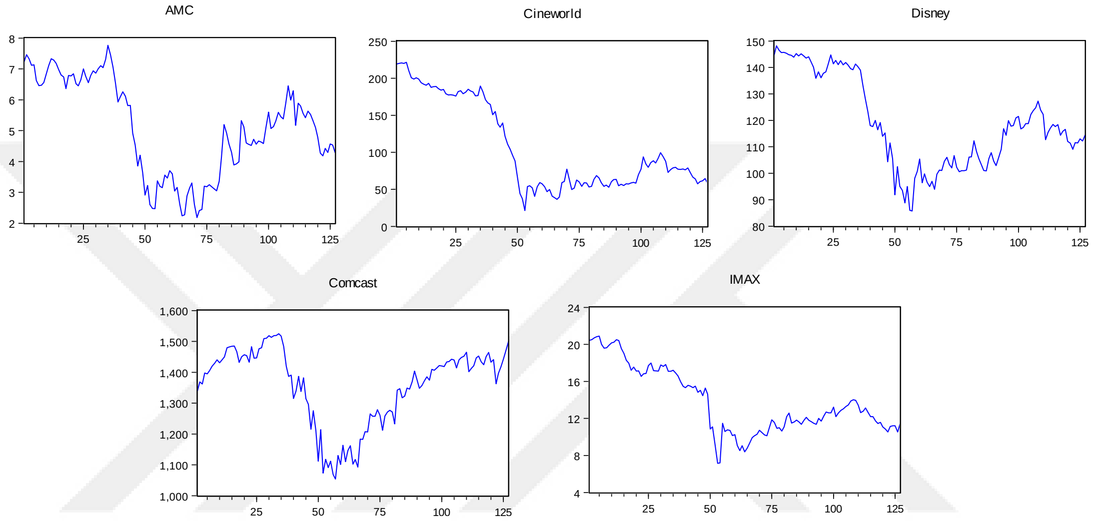
At its peak in April 2020, the pandemic forced an estimated 3 billion people worldwide to be in lockdown. This situation made businesses and consumers have little choice but to use online services. Consequently, stocks of Apple, Netflix, Microsoft, and Amazon all trading at, or near record highs in the Covid-19 pandemic period. Investors believe the business models of these companies can not only weather this downturn but also thrive in it, so they rushed into these stocks. Microsoft, Netflix, and Amazon have subscription-based services driving recurring revenue thus, a strong balance sheet and recurring revenue are what makes these companies attractive. Stay-at-home orders have accelerated the shift away from malls and shopping centers which fueled Amazon sales. Moreover, most of the employees working at home-offices are relying on the cloud-computing platforms provided by Amazon, Microsoft, and other tech companies. Likewise, people who are stuck at home and with no live sports to watch became a natural catalyzer for Netflix subscribers to increase. Apple suffered during pandemic since it scrambled its supply chains in Asia and demand for pricey iPhones and other gadgets decreased. Finally, Alphabet and Facebook are hurting from a sharp drop in advertising which shows that not all the big tech companies are affected in positively from the pandemic.

Figure 7: FAANG and Microsoft Daily Prices-Covid19 Period



The pandemic has fundamentally affected the entertainment industry and forced it to evolve. Movie theater owners fear that studios will start to shift away from the theatrical model and toward the in-home market in case crowds do not return to the theaters. Although the pandemic helped Comcast to drive record performance on one cable metric, its NBCUniversal and Sky businesses suffered due to the closures of theme parks and movie theaters. In 2020, AMC's stock performed down around %50 on the year as most of the company's 11,000 screens around the world remain shuttered. However, AMC has the ability to divest operations, reduce capex and salvage and newly established debt restructuring for the company seems to be appreciated by the investors and the stock begin to recover. Besides Disney Company and Disney Plus, Disney owns a myriad of other media companies including 12 colossal theme parks and the second-biggest streaming service in the world, in this context, Covid-19 has clobbered Disney's core businesses and the pandemic has closed theme park and prevented Disney from releasing new films into theaters. However, the assets like Star Wars, Marvel, and Disney characters made Disney leverage these intangible assets via Disney Plus which generated cash for the company and made it to balance its losses due to pandemic. Finally, IMAX announced a loss of $49.4 million in the first quarter of 2020 due to the coronavirus pandemic. IMAX felt the impact of closed theaters before other exhibition companies since the company is heavily dependent on China.

Figure 8: Cinema, TV and Streaming Business Daily Prices-Covid19 Period



11. APPLICATION AND FINDINGS

In Table 6 FAANG GARCH models for the overall period are exhibited. Most of the big tech stock returns have a positive impact on the returns of other tech stocks, and they are statistically significant. FAANG models differentiate from each other based on their volatility structure. Only Facebook stock returns are statistically not significant to explain the return changes of Amazon stocks as well as Netflix is statistically not significant to explain the return changes of Alphabet-Google stocks in the overall period. Based on the variance equations of the Facebook model we see that the parameter β is 0, 9779 and significant at a 1% level. The sum of α and β is 0.99 very close to 1 which shows the persistence of news impact on Facebook stock volatility is very strong. In the Apple variance equation, we see that the parameter β is 0, 7737 and highly significant. The sum of α and β is 0.9100 which shows the persistence of news impact on Apple stock volatility is strong. Moreover, short term persistence is significantly higher for Apple compared to Facebook. For Amazon, Netflix, and Alphabet, the persistence of news impact is not as strong as Facebook and Apple. The sum of α and β for Amazon, Netflix, and Alphabet are 0.8304, 0.7614 and 0.7241, respectively. Furthermore, the value of αs of Amazon, Netflix and Alphabet are significantly higher than Facebook and Apple which are 0.2523, 0.1529, and 0.1858 respectfully. These results show that short term shocks have more impact on the volatility of Amazon, Netflix and Alphabet compared to Facebook and Amazon.

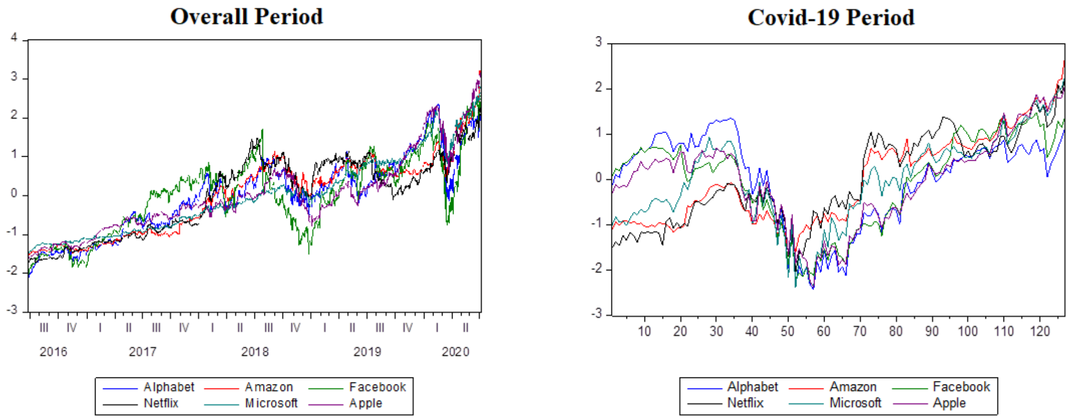
In Table 7 FAAMG GARCH models for the overall period are exhibited. Most of the big tech stock returns have a positive impact on the returns of other tech stocks and they are statistically significant. Only lagged variables of Facebook and Microsoft stock returns are expected to have a negative impact on Facebook and Microsoft returns. FAAMG models differentiate from each other due to their volatility structure. Based on the variance equations of the Facebook model, we see that the parameter β is statistically not significant and α is negative. In the Apple variance equation, we see that the parameter β is 0, 7481 and highly significant. The sum of α and β is 0.8900, which shows the persistence of news impact on Apple stock volatility is strong. Moreover, again short-term persistence is significantly higher for Apple compared to Facebook. For Amazon, Microsoft, and Alphabet, the persistence of news impact is not as strong as Apple. The sum of α and β for Amazon, Microsoft, and Alphabet are 0.8494, 0.8578, and 0.6246, respectively. Furthermore, the value of αs of Amazon, and Microsoft is significantly higher than Facebook, Apple, and Alphabet which are

0.2466 and 0.1874 respectfully. These results show that short term shocks have more impact on the volatility of Amazon and Microsoft compared to Facebook, Amazon, and Alphabet. In this context, we can conclude that FAANG and FAAMG GARCH models have similar returns and volatility structures which shows that either including Netflix or Microsoft to big tech (FAAG) stocks group does not have a significant difference.

In Table 8, instead of tech companies, we combined Netflix with cinema, TV, and streaming business company stocks such as ACM, Cineworld, Comcast, IMAX, and Disney. Our main hypothesis was to test whether combining Netflix with companies which has more similar business definition and share the same industry and the market with Netflix to see whether we can construct better models compared to FAANG models. However, both the mean equation and variance equation structure do not differentiate from FAANG models significantly. Also, models exhibited in Table 8 are not significantly better than the FAANG models exhibited in Table 6. As a result, we can claim that Netflix positions itself as a tech company and the markets accepts this classification as it is. Business descriptions and operational fundamentals do not create a considerable difference in the assessment of these companies for investment.

Finally, in Table 9 FAANG models for the Covid-19 period are exhibited. We found interesting results. In the pandemic period, the GARCH term became statistically insignificant for all models except Facebook. Also, we detected unit root in the dataset and cointegration relationship among the stocks. Both situations did not exist in the overall period models. In Figure 9, normalized daily stock prices of Facebook, Apple, Amazon, Alphabet, Netflix, and Microsoft are exhibited. In the Covid-19 period, we can see the FAANG stocks and Microsoft stocks behave and move as if they are all one stock. Their movement is very identical. There has probably never been as big a divergence between markets and economies as there is in the pandemic period. Even the International Monetary Fund (IMF) warned of a worrying “disconnect” between markets and the real economy. The feature of the current market dynamic is passive investing, whereby investors or funds buy indices rather than individual stocks. This may be distorting the current cycle. The FAANG stocks are seemingly sucking in a level of investment that bears little relation to their inherent value or projected future earnings.

Figure 9: FAANG and Microsoft Normalized Daily Stock Prices



In Table 10 and Table 11 ϱ_1 and ϱ_2 dynamic conditional correlation coefficients are exhibited for all GARCH models in every period. A DCC model really should only be applied to a set of series which are relatively similar since the cross-correlations are all governed by just two parameters. If ϱ_2 is very close to 1, then the process is closer to being a CC. The "dynamic" part comes from ϱ_1. However, in practice, a "large" value for DCC ϱ_1 is something like .1 to .2, with ϱ_2 being relatively close to 1-ϱ_2. If both ϱ_1 and ϱ_2 are small, it means that there appears to be no systematic correlation among the variables. According to Francq and Zakoian (2010), there are two definitions regarding the GARCH process. The first one is called semi-strong, where there exists the coefficient of the constant, arch and garch (no need to be positive, but must be significant). The second one is called a strong GARCH process, where the coefficient of arch and garch are nonnegative while the coefficient of the constant must be positive. According to FAANG models for the overall period, Facebook-Netflix garch process is semi-strong while Amazon-Netflix garch process is strong and ϱ_1 is 0.1160 and ϱ_2 is 0.6253. Apple-Netflix and Alphabet-Netflix garch processes are not significant. For the pandemic period FAANG models, Facebook-Netflix garch process is still semi-strong as well as Alphabet -Netflix model. But in Alphabet-Netflix model ϱ_2 is 0.9967 which shows that the process is not dynamic but a CC process. Moreover, Apple-Netflix and Amazon-Netflix garch processes are not significant in the Covid-19 period.

Based on FAAMG models, we can claim that Apple-Microsoft and Alphabet-Microsoft garch processes are statistically significant. ϱ_1 is 0.0265 and ϱ_2 is 0.9651 for Appel-Microsoft and ϱ_1 is 0.0109 and ϱ_2 is 0.9666 in Alphabet which refers to CC processes, not dynamic. Furthermore, only ϱ_2 is significant in the Facebook-Microsoft and ϱ_1 is significant in the Amazon-Microsoft model. Finally, according to the models results of Cinema, TV and streaming business models, Comcast-Netflix has a semi-strong garch process. ϱ_2 is significant in Cineworld-Netflix model while Disney-Netflix and AMC-Netflix garch processes are insignificant.

Movement of conditional correlation of FAANG, FAAMG and cinema, TV and streaming business stock returns are depicted in Figure 5. For FAANG models, graphs show that in the overall period correlations between Apple-Netflix and Amazon-Netflix are highly volatile and vary substantially over time. The correlation goes through several troughs and peaks and a reverse sign recurs. For Facebook-Netflix and Alphabet-Netflix we see one-time spikes and in the overall period, the volatility is low for mentioned pairs. Time-varying conditional correlations exhibit a relatively higher level of co-movement between Facebook-Netflix and Alphabet-Netflix pairs. The dynamic correlation coefficients between Facebook-Netflix and Alphabet-Netflix remain around 0.0 and 0.1 for all periods. In the Covid-19 period all pairs are highly volatile however in the last month we observe that the correlation series overall appear to have a ragged declining trend except Facebook-Netflix pair, there we observe an increasing trend. For FAAMG models, graphs show that in the overall period correlations between Amazon-Microsoft are highly volatile and vary substantially over time. The correlation goes through several troughs and peaks and a reverse sign recurs. Time-varying conditional correlations exhibit a relatively higher level of co-movement between Facebook-Microsoft. The dynamic correlation coefficients between Facebook-Microsoft mostly remain around 0.1 for all periods if we exclude three times spikes in the timeline. For cinema, TV and streaming business models, in the overall period correlations between AMC-Netflix, Cineworld-Netflix and Disney-Netflix are highly volatile and vary substantially over time. The correlation goes through several troughs and peaks and a reverse sign recurs. Only time- varying conditional correlations exhibit a relatively higher level of co-movement between Comcast-Netflix by remaining around 0.4 for all periods if we exclude onetime big spikes in the timeline.

In summary, Microsoft and Netflix are two pairs that are combined with FAAG stocks frequently in financial markets. The marketing for FAANG, FAAMG, and relevant big tech stocks drive the S&P 500, especially in the pandemic period. According to the GARCH models and DCC results we concluded that neither Netflix nor Microsoft is significantly a better match to FAAG stocks which is interesting since Microsoft is obviously a tech innovator, Netflix is much more a content provide rather than a tech pioneer. Based on this hypothesis we tested models that we combined Netflix with cinema, TV and streaming business company stocks such as AMC, Comcast, Cineworld, and Disney. When we compare FAANG models with cinema, TV and streaming business we cannot clearly state that Netflix belong to one of these classifications based on econometric models and its market performance. Especially in the pandemic period the increasing cointegration of big tech companies and their behavior as if all these stocks belong to one company drives us to comment that FAANG and Microsoft stocks are treated as if they are commodities rather than company stocks in the pandemic period.

Table 6: Panel A: FAANG GARCH Models for Overall Period

Panel A-FAANG GARCH Models												
	RFACEBOOK				**RAPPLE**				**RAMAZON**			
	Mean Equation		**Variance Equation**		**Mean Equation**		**Variance Equation**		**Mean Equation**		**Variance Equation**	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
c	-0.0001	-0.4816			-0.0007	-2.1911			0.00015	0.58212		
RALPHABET	0.5055	18.7133			0.4048	15.2592			0.37726	13.99043		
RAMAZON	0.2176	10.0448			0.2208	9.3244					-0.00054	-2.32287
RNETFLIX	0.0646	5.2493			0.0146	1.0486			0.15050	12.59738		
RAPPLE	0.1221	5.7578	0.0003	2.1082					0.16870	8.15087		
$RFACEBOOK_{t-1}$	-0.0496	-3.1480										
$RAMAZON_{t-1}$									0.16917	8.99807		
RFACEBOOK					0.0654	3.4783						
α_0			0.0000	1.9802			0.0000	2.8422			0.0000	3.6135
$\boldsymbol{\alpha_1}$			**0.0221**	**3.1366**			**0.1363**	**3.2466**			**0.2523**	**3.7144**
$\boldsymbol{\beta_1}$			**0.9779**	**165.7**			**0.7737**	**13.3403**			**0.5781**	**7.2105**
Observations				997				998				998
R^2				0.539				0.528				0.582
DW				1.883				1.957				2.072

	RNETFLIX				**RALPHABET**			
	Mean Equation		**Variance Equation**		**Mean Equation**		**Variance Equation**	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
c	-0.0001	-0.1639			0.00012	0.55191		
RALPHABET	0.2290	4.9020						
RAMAZON	0.4996	13.6169	-0.00256	-2.98492	0.25782	15.38988		
RNETFLIX					0.03721	0.03721		
RAPPLE	0.1174	3.3260	0.00244	2.25857	0.24305	15.26508		
$RFACEBOOK_{t-1}$								
$RAMAZON_{t-1}$								
RFACEBOOK	0.1479	4.8472			0.3141	21.1668		
α_0			0.0001	3.2960			0.0000	3.3380
$\boldsymbol{\alpha_1}$			**0.1529**	**2.8175**			**0.1858**	**3.1801**
$\boldsymbol{\beta_1}$			**0.6085**	**6.2371**			**0.5383**	**4.8248**
Observations				998				998
R^2				0.406				0.671
DW				1.970				2.052

Table 7: Panel B: FAAMG GARCH Models for Overall Period

Panel B-FAAMG GARCH Models												
	RFACEBOOK				RAPPLE				RAMAZON			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
c	-0.0001	-0.4630			-0.0004	-1.5200			0.00016	0.57760		
RFACEBOOK$_{t-1}$	-0.0432	-2.9962										
RFACEBOOK												
RAMAZON	0.1637	7.2678			0.1391	6.2024					-0.00039	-1.87217
RAMAZONt-1									0.06024	3.32754		
RAPPLE	0.0833	3.6316	0.0007	1.0326					0.13081	5.83567		
RALPHABET	0.5582	17.4893			0.2643	9.5406			0.40945	14.93010		
RMICROSOFT$_{t-1}$	0.1188	3.7568										
RMICROSOFT					0.4097	13.3482			0.33455	11.47395		
α_0			0.0001	0.9492			0.0000	2.8074			2.62E-05	3.749622
α_1			**-0.0053**	**-2.3241**			**0.1419**	**3.0958**			**0.24666**	**3.9768**
β_1			**0.4459**	**0.7776**			**0.7481**	**11.1575**			**0.60284**	**8.2910**
Observations				997				998				998
R^2				0.541				0.591				0.555
DW				1.894				1.870				2.130

	RMICROSOFT				RALPHABET			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
c	0.0004	-1.9006			0.00031	1.47452		
RFACEBOOK$_{t-1}$								
RFACEBOOK					0.26541	17.90088		
RAMAZON	0.2354	13.9682			0.14134	8.72316		
RAMAZONt-1								
RAPPLE	0.2144	11.6224			0.12278	7.32355		
RALPHABET	0.3793	18.7716						
RMICROSOFT$_{t-1}$	-0.1141	-6.9854						
RMICROSOFT								
α_0			0.0000	3.3026			0.0000	2.5342
α_1			**0.1874**	**3.7981**			**0.0993**	**2.1083**
β_1			**0.6704**	**9.1320**			**0.5253**	**3.1284**
Observations				997				998
R^2				0.738				0.720
DW				2.153				2.030

Table 8: Panel C: Cinema, TV and Streaming Business GARCH Models for Overall Period

Panel C-Cinema, TV and Streaming Business GARCH Models

	RAMC				RDISNEY				RCINEWORLD			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
c	0.0009	1.2567			0.0002	0.6710			0.0009	-1.8294		
RCINEWORLD	0.0174	0.9341	0.0029	2.3256	0.0398	3.8403					0.0013	2.5874
RDISNEY	0.4119	8.8245										
RIMAX	0.5745	21.8645	-0.0038	-1.9106	0.0614	4.2663						
RNETFLIX	0.0851	2.7720	0.0085	2.4322	0.0389	3.0740						
RAMC					0.6710	4.8310			0.0418	0.0418		
RCOMCAST					0.2524	11.5792			0.1398	4.1163		
RAMAZON												
RAPPLE												
RALPHABET												
$RMICROSOFT_{t-1}$												
α_0			0.0007	1.8463			0.0000	3.1100			0.0000	3.4843
$\boldsymbol{\alpha_1}$			**0.0353**	**1.6969**			**0.1744**	**4.3228**			**0.1547**	**4.7025**
$\boldsymbol{\beta_1}$			**0.5471**	**3.5241**			**0.7757**	**18.3371**			**0.8189**	**30.5116**
Observations				998				998				998
R^2				0.350				0.336				0.019
DW				1.881				2.226				2.154

	RNETFLIX				RCOMCAST				RIMAX			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
c	-0.0002	-0.4430			-0.0004	-1.4001			0.0004	0.9327		
RCINEWORLD	-0.0429	-5.1944			0.0324	3.8528			0.0511	2.8917		
RDISNEY					0.2715	12.4373			0.2134	5.2109		
RIMAX	0.0647	3.4922										
RNETFLIX					0.2680	21.9984						
RAMC					0.0172	1.8629			0.2698	16.8260		
RCOMCAST	-5.1944	9.3197							0.1025	2.8205		
RAMAZON	0.5986	17.4336										
RAPPLE												
RALPHABET												
$RMICROSOFT_{t-1}$												
α_0			0.0001	2.4867			0.0000	2.4943			0.0000	2.3956
$\boldsymbol{\alpha_1}$			**0.1169**	**2.3319**			**0.1069**	**3.2515**			**0.0321**	**3.2659**
$\boldsymbol{\beta_1}$			**0.6392**	**5.2231**			**0.8119**	**14.8609**			**0.9452**	**59.8265**
Observations				998				997				998
R^2				0.416				0.446				0.346
DW				1.958				2.130				2.025

Table 9: Panel D: FAANG GARCH Models for Covid-19 Period

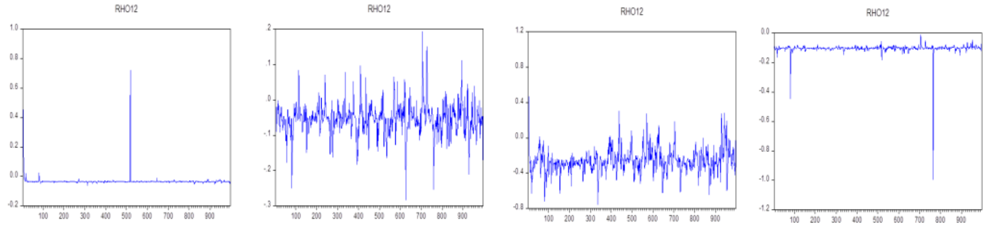
Panel D-FAANG GARCH Models												
	RFACEBOOK				**RAPPLE**				**RAMAZON**			
	Mean Equation		**Variance Equation**		**Mean Equation**		**Variance Equation**		**Mean Equation**		**Variance Equation**	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
c	-0.0002	-0.1994			-0.0007	-0.7537			0.0000	0.0241		
RALPHABET	0.6200	7.1656			0.8083	11.2267						
RAPPLE	0.3288	4.6636							0.1988	4.6053		
RFACEBOOK					0.2015	3.1851			0.1974	4.2530		
RAMAZON												
RNETFLIX					0.1286	2.6104	-0.0016	-3.2911	0.3510	10.6283		
$RAPPLE_{(t-1)}$					0.0711	2.1257						
$RALPHABET_{(t-1)}$												
α_0			0.0000	1.7773			0.0001	1.6000			0.0004	0.9585
$\boldsymbol{\alpha_1}$			**0.0047**	**0.1399**			**-0.0633**	**-2.0160**			**0.1322**	**0.5985**
$\boldsymbol{\beta_1}$			**0.9702**	**35.8**			**0.5368**	**1.6115**			**-0.3343**	**-0.6517**
Observations				127				127				127
R^2				0.779				0.809				0.648
DW				1.874				1.934				1.911

	RNETFLIX				**RALPHABET**			
	Mean Equation		**Variance Equation**		**Mean Equation**		**Variance Equation**	
	coefficient	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**	**coefficient**	**z-stats**
c	-0.0004	-0.2735			0.0017	0.0245		2.24931
RALPHABET								
RAPPLE					0.3900	9.0517		
RFACEBOOK	0.3075	7.1363			0.3633	9.0211		
RAMAZON	0.7547	12.9719			0.1440	2.9882		
RNETFLIX								
$RAPPLE_{(t-1)}$								
$RALPHABET_{(t-1)}$					-0.0614	-1.9783		
α_0			0.0002	2.0565			0.0000	0.7753
$\boldsymbol{\alpha_1}$			**0.7197**	**2.7343**			**0.1579**	**1.0108**
$\boldsymbol{\beta_1}$			**0.0416**	**0.2079**			**0.5272**	**0.9994**
Observations				127				127
R^2				0.591				0.869
DW				2.229				2.530

Figure 10: DCC Graphs

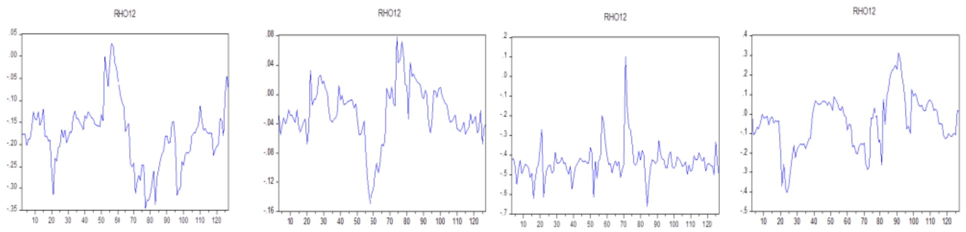
FAANG-Overall Period Conditional Correlations

Facebook-Netflix | Apple-Netflix | Amazon-Netflix | Alphabet (Google)-Netflix



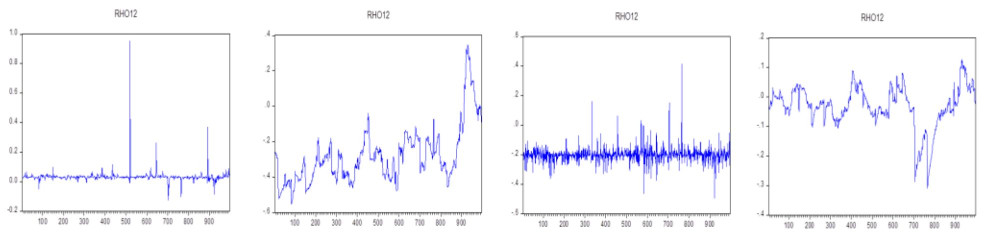
FAANG-Covid 19 Period Conditional Correlations

Facebook-Netflix | Apple-Netflix | Amazon-Netflix | Alphabet (Google)-Netflix



FAAMG-Overall Period Conditional Correlations

Facebook-Microsoft | Apple-Microsoft | Amazon-Microsoft | Alphabet (Google)-Microsoft



Cinema and Streaming -Overall Period Conditional Correlations

AMC-Netflix | Cineworld-Netflix | Disney-Netflix | Comcast-Netflix

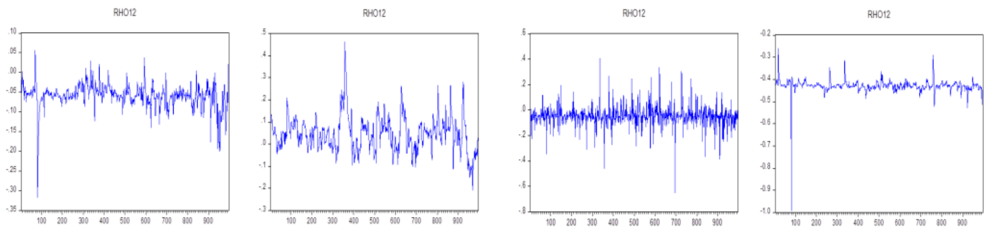


Table 10: FAANG DCC GARCH Tables

FAANG Models-DCC GARCH Tables (Overall Period)					FAANG Models-DCC GARCH Tables (Covid-19 Period)				
Facebook-Netflix	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**Facebook-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	-0.0031	-24097.8600	0.0000	6.0263	ρ_1	-0.011	-199.606	0.0000	5.5702
ρ_2	0.5873	7.7565	0.0000		ρ_2	0.7661	4.2222	0.0000	
Observations	997				Observations	127			
Apple-Netflix	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**Apple-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	0.0344	1.0458	0.2957	5.7742	ρ_1	0.0228	0.3360	0.7368	5.7311
ρ_2	0.6495	1.5774	0.1147		ρ_2	0.8180	1.4488	0.1474	
Observations	998				Observations	127			
Alphabet-Netflix	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**Alphabet-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	-0.0088	-3659.6670	0.0000	5.8724	ρ_1	-0.0583	-2.0542	0.0400	5.680
ρ_2	0.5818	0.4693	0.6388		ρ_2	0.9967	37.3617	0.0000	
Observations					Observations	127			
Amazon-Netflix	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**Amazon-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	0.1160	3.6703	0.0002	5.6959	ρ_1	0.1009	0.8328	0.4049	5.564
ρ_2	0.6153	5.8653	0.0000		ρ_2	0.3327	0.5812	0.5611	
Observations	998				Observations	127			

Table 11: FAAMG and Cinema, TV, Streaming Business DCC GARCH Tables

FAAMG Models-DCC GARCH Tables (Overall Period)					Cinema, TV and Streaming Business Models DCC GARCH Graphs				
Facebook-Microsoft	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**Cineworld-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	-0.0102	-1.2835	0.1993	5.8432	ρ_1	0.0382	1.5960	0.1105	5.7322
ρ_2	0.5948	3.3130	0.0009		ρ_2	0.8777	9.1601	0	
Observations	998				Observations	997			
Apple-Microsoft	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**Comcast-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	0.0265	3.7510	0.0002	5.5665	ρ_1	-0.0113	-199.6059	0.0000	5.5702
ρ_2	0.9651	80.483	0.0000		ρ_2	0.7661	4.2222	0.0000	
Observations	998				Observations	998			
Amazon-Microsoft	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**Disney-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	0.0595	2.0838	0.0372	5.6437	ρ_1	0.0843	1.8249	0.0680	5.7736
ρ_2	-0.0399	-0.1025	0.9183		ρ_2	0.1446	0.3642	0.7157	
Observations	998				Observations	997			
Alphabet-Microsoft	**Coefficients**	**Z-statistics**	**Probability**	**AIC**	**AMC-Netflix**	**Coefficients**	**Z-statistics**	**Probability**	**AIC**
ρ_1	0.0109	2.2062	0.0274	5.7519	ρ_1	0.0238	0.6773	0.4982	5.5233
ρ_2	0.9666	51.295	0.0000		ρ_2	0.7652	1.7594	0.0785	
Observations	998				Observations	997			

12. CONCLUSION

On-demand streaming is the most distributive development in the entertainment market for the traditional cinema business. Although console games and e-sports challenged the interest of consumers to traditional cinema, on-demand streaming is an excellent substitute for movie watchers. Disney+ for 6.99$ a month, which is slightly less than the cost of a cinema ticket, is now available for America, Canada, and the Netherlands. Even in a few hours, the algorithm hoovered up enough data to suggest personalized content to the brand-new subscribers of Disney+. Yet, Netflix the pioneer of streaming revolution is assessed with the tech stocks Facebook, Apple, Amazon, Netflix, and Alphabet, namely FAANG stocks. However, businesswise the priority of the competition for streaming business is (or should be) with the traditional cinema chains. At its peak in April 2020, the pandemic forced an estimated 3 billion people worldwide to be in lockdown. This situation made businesses and consumers have little choice but to use online services. Consequently, stocks of Apple, Netflix, Microsoft, and Amazon all trading at, or near record highs in the Covid-19 pandemic period. Investors believe the business models of these companies can not only weather this downturn but also thrive in it, so they rushed into these stocks. Microsoft, Netflix, and Amazon have subscription-based services driving recurring revenue thus, a strong balance sheet and recurring revenue are what make~~s~~ these companies attractive

When we compare FAANG models with cinema, TV and streaming business, we cannot clearly state that Netflix belongs to one of these classifications based on econometric models and its market performance. Especially in the pandemic period, the increasing cointegration of big tech companies and their behavior as if all these stocks belong to one company. The returns of FAANG stocks lose their stationarity in the pandemic period and cointegration exists among them as well. As a result, we conclude that FAANG and Microsoft stocks are treated as if they are commodities rather than company stocks in the pandemic period.

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CHAPTER 3: CRUDE OIL PRICE VARIATIONS AND UNITED STATES AERONAUTICAL INDUSTRY: AN EMPIRICAL STUDY

ABSTRACT

The objective of this research is to investigate how the association between selected US airline stock prices and crude oil prices is. Three airline companies, namely American Airlines (AAL), Southwest Airlines (LUV), and Delta Airlines (DAL), which are among the world's largest airlines, and also two crude oil markets, Brent crude oil futures (Brent), and Crude Oil Contract (WTI) were chosen for this research. According to studies in the literature, stock returns are generally expected to experience fluctuations due to crude oil prices. Whereby our empirical studies, we will conclude whether the chosen three airline stock returns are correlated with crude oil prices. Besides, it will be investigated whether there is a statistically significant relationship between the stock returns of these three airlines and crude oil prices, and also how they interact during the Covid-19 period will be examined.

Keywords: Airlines, Crude Oil, Granger Causality Test, VAR Diagonal BEKK, Spillover

13. INTRODUCTION

Crude oil is substantial for developing countries (Huang et al. 1996). In the list of total liquids consumption (in thousands of barrels per day) by countries, the United States ranks first with 20.3% world share and 934.3 gallons per capita per year[14]. The oil consumption of the United States between 2014 and 2019, its growth rate, and share in 2019 are shown in Table 13. Moreover, it is seen in the oil consumption (thousand barrels daily) that United States' share in 2019 is 19.7%, and the growth rate in 2019 is -0.14%. As follows some selected countries' oil consumption growth rates are listed in Table 12.

As Huang et al. stated in 1996, crude oil was regarded as a significant economic sign. Previous studies show that it is clear that there is a strong relationship between crude oil and economic activities. As Hamilton mentioned in his studies in 1983 and 2003, the volatility in crude oil prices has a negative effect on economic activities. Besides, Huang et al emphasized (1996) that cash flows are also affected by the effect of crude oil prices, which will directly affect production costs, and therefore stock prices are also affected. Kathiravan et al (2019) represented that crude oil price influences the stock prices through cash flows, discount rate, and commodity prices.

[14] https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2020-full-report.pdf

Table 12: Oil Consumption Growth Rate (2019) by the chosen countries

Countries	Oil Consumption Growth Rate,2019
Argentina	-1.96%
Belgium	-2.74%
Bulgaria	5.21%
Canada	-1.67%
China	5.09%
Germany	0.94%
Japan	-1.10%
Malaysia	2.06%
United States	**-0.14%**
Venezuela	-11.60%

Source: Data obtained from BP Statistical Review of World Energy June 2020 (www.BP.com)

Table 13: United States Oil Consumption (Thousand barrels daily)

2014	2015	2016	2017	2018	2019	Growth Rate 2019	Share 2019
18136	18523	18617.6	18883.3	19427.6	19399.9	-0.14%	19.7%

Source: Data obtained from BP Statistical Review of World Energy June 2020 (www.BP.com)

13.1. UNITED STATES AERONAUTICAL INDUSTRY

According to the Table 14, American Airlines Group is the best performer with the 19.6% market share. Two other airlines that follow it are Southwest Airlines and Delta Air Lines with the respectively 18.1% and 14.7% market share.

Table 14: Best Performers in the United States Aeronautical Industry

Airlines	Market Share (%)
American Airlines Group	19.6
Southwest Airlines	18.1
Delta Air Lines	14.7

Source: Data obtained from Bureau of Transportation Statistics, March 2020 February 2021, https://www.transtats.bts.gov/

American Airlines was founded in 1926 under the name American Airways in the US state of Texas. It was formed in 2013 by the merger of AMR Corporation and US Airways Group, which were the principal companies of American Airlines and US Airways respectively[15].

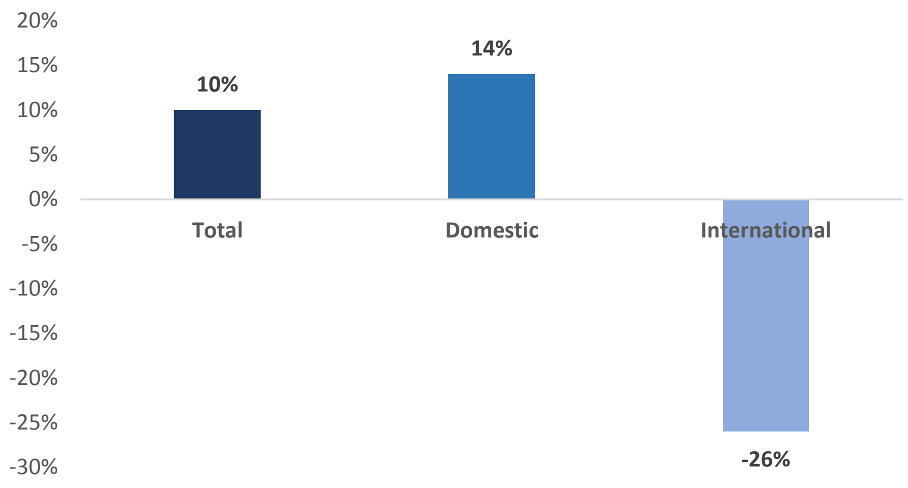
Southwest Airlines Corporation was founded in 1967 under the name Air Southwest in Texas. In addition to being the second in terms of market share in the United States, its most notable characteristic is that it is the world's biggest cost-efficient airway company[16].

Delta Air Lines was founded in Georgia in 1925. In addition to being the second-largest airline in the world in terms of traveler numbers and fleet capacity, it is also 59th according to the Fortune 500[17].

The purpose of this study is that the causal linkages and long-term spillover effects among the two crude oil prices (Brent, and WTI) and three Airlines Stock prices (American Airlines Group, Southwest Airlines, and Delta Air Lines) in the US.

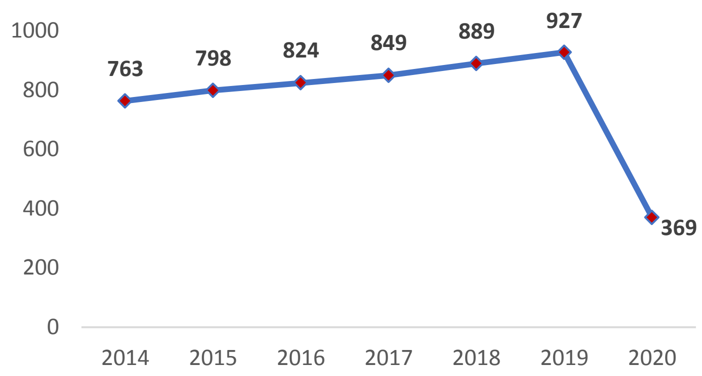
[15] https://en.wikipedia.org/wiki/American_Airlines
[16] https://simpleflying.com/southwest-lcc-model/
[17] https://web.archive.org/web/20190721014954/https://fortune.com/fortune500/delta-air-lines/

Figure 11: US Airline Passengers March 2021 vs. 2020 Change[18]



According to the Bureau of Transportation Statistics data in Figure 11, we see the March2021 -2020 changes in US airline passengers. Compared to March 2020, US airlines carried approximately 10% more programmed service customers. The reason for the increase in the general situation is due to the 14% increase in the number of domestic passengers. In this period, the decrease in the number of international passengers was recorded as 26%. In addition, due to Covid-19, March 2020 was observed as the initial month when airline travels decreased.

Figure 12: Passengers (in millions) on US Airlines (Jan-Dec) 2014-2020[19]



[18] *Data obtained from* https://www.bts.gov/newsroom/figure-1-january-december-passengers-us-airlines-2003-2020

[19] *Data obtained from* https://www.bts.gov/newsroom/figure-1-january-december-passengers-us-airlines-2003-2020

Figure 12 shows the changes in annual passenger numbers of US airlines between 2014 and 2020. As can be seen from this graph, while there was a consecutive expansion until 2019, a very serious contraction was reported in 2020. The lowest number of passengers was reported in 2020 with 369 million in the last seven years. It is seen that air travel is also affected by various precautions and restrictions due to the rapid spread of the Covid-19 virus around the world.

Figure 13: Domestic Revenue Passenger Miles (billions)[20]

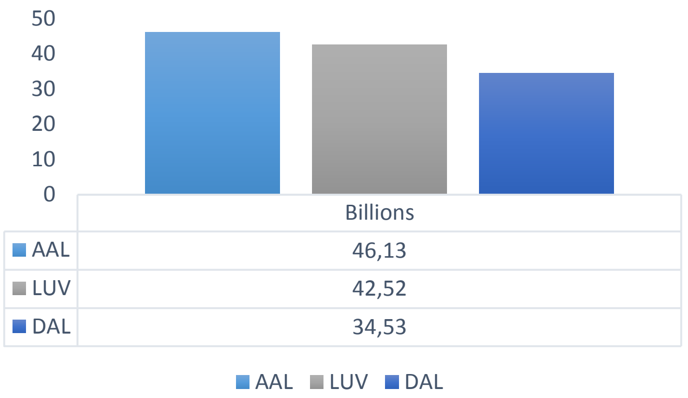


Figure 13 shows the domestic revenue passenger miles of the three American airlines used in the analysis. American Airlines Group (AAL) ranks first with 46.13 billion. It is followed by Southwest Airlines (LUV) and Delta Airlines (DAL) with 42.52 and 34.53 billion respectively.

The purpose of this study is that the causal linkages and long-term spillover effects among the two crude oil prices (Brent, and WTI) and three Airlines Stock prices (American Airlines Group, Southwest Airlines, and Delta Air Lines) in the US.

[20] *Data obtained from Bureau of Transportation Statistics, March 2020 – February 2021, https://www.transtats.bts.gov/*

14. LITERATURE REVIEW

In the literature, there are lots of researches about the association between price of crude oil and returns of stocks because crude oil is one the most substantial activator for economics.

Chen et al. (1986) tried to explain the changes in stock prices with macroeconomic variables, but could not provide any proof. However, Ferson and Harvey, in their study in 1995, instantiated that the return of eighteen stocks is significant influenced by the price of crude oil. Huang et al. (1996), analyzing the connection between US stock returns and changes in crude oil prices, explained that the move in the oil stock index was affected by the changes in crude oil prices. In another study, the relationship between oil price and Australian stock returns was examined by Faff and Brailsford (1999). Until 1996, a thirteen-year data set was used in this study. And as a result of this research, it has been concluded that oil prices have a positive impression on some sectors, such as transportation. In Mohanty et al study, in which they examined the effect of crude oil prices on some sectors of the United States in the period of 2008-2009, it was concluded that profits of the airline stocks were adversely affected. According to Shaeri et al. (2016), the airline industry had been more affected by fluctuations in crude oil prices compared to other industries. Yashodha et al. conducted a study in 2016 that supports the adverse repercussions of volatility in crude oil prices on the airline business, namely Cathay Pacific and China. Kristjanpoller and Concha designed a GARCH model using the price returns of 56 airlines, WTI and Jet Fuel. According to this model, results confirmed that there was a positive effect. Yun and Yoon (2018) designed the VAR GARCH model to examine the relationship between the prices of WTI, Brent, and Dubai and the prices of their four chosen airline businesses. As a result of this model they designed, they achieved that there is a negative association between them. In another study, UK data were used for analyzing the connection between prices of petrol, excise tax, and crude oil prices. A co-integration method was applied and after the necessary adjustments were made, it was concluded that there was no asymmetry (Manning, 1991). In the study of Mohanty and Nandha (2011), the asset pricing model was used and the risks of US oil and gas prices were modeled. According to the results of this study, it has been exposed that different effects are depending on whether being a crude oil producer or being a purchaser. Unlike other studies, Uddin et al. (2020) investigated the spillover effect between the US stock market, precious metals, and oil. They also showed how the US stock market was changed in diverse scenarios (such as bad, normal, extreme).

15. ECONOMETRIC METHODOLOGY

By examining financial data, we can observe that some stages include more risk compared to other periods. The purpose of the established models is to make the risk analysis correctly and thus to help in obtaining the crucial decisions.

15.1. Diagonal BEKK Model

The Diagonal BEKK model, created by Engle and Kroner in 1995, is a multivariate GARCH model. Besides, conditional covariance can be parameterized dynamically in this model. Constraints on the diagonal of the matrix of each parameter also prevent the increase in the number of estimated parameters. So this matrix will always be positive. Furthermore, part of the VECH-related challenge is that it does not allow the conditional covariance matrix to be negative.

The common Diagonal BEKK Model Equation does present as:

$$H_t = C'C + A'(\Xi_{t-1}\Xi'_{t-1})A + B'(H_{t-1})B \qquad [1]$$

Where H_t represents nxn conditional variance – covariance matrix, C represents parameters' upper triangle matrix, Ξ_{t-1} represent nx1 disturbance vector, and A, and B represent nxn diagonal parameter matrices.

$$\Omega = C'C$$

$$= \begin{bmatrix} c_{11} & 0 & 0 \\ c_{12} & c_{22} & 0 \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ 0 & c_{22} & c_{23} \\ 0 & 0 & c_{33} \end{bmatrix}$$

$$= \begin{bmatrix} c_{11}^2 & c_{11}c_{12} & c_{11}c_{13} \\ c_{11}c_{12} & c_{12}^2 c_{22}^2 & c_{12}c_{13} + c_{22}c_{23} \\ c_{11}c_{13} & c_{12}c_{13} + c_{22}c_{23} & c_{13}^2 + c_{23}^2 + c_{33}^2 \end{bmatrix} \qquad [2]$$

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix} \qquad [3]$$

Subsequently, this equation displays:

Since therefore, all conditional variance equations and covariance equations can be shown as:

$$h_{11,t} = \Omega_{11} + a_{11}^2 u_{1,t-1}^2 + b_{11}^2 h_{11,t-1} \qquad [5]$$

$$h_{12,t} = \Omega_{12} + a_{11}a_{12}u_{1,t-1}u_{2,t-1} + b_{11}b_{22}h_{12,t-1} \qquad [6]$$

$$h_{13,t} = \Omega_{13} + a_{11}a_{33}u_{1,t-1}u_{3,t-1} + b_{11}b_{33}h_{13,t-1} \qquad [7]$$

$$h_{22,t} = \Omega_{22} + a_{22}^2 u_{2,t-1}^2 + b_{22}^2 h_{22,t-1} \qquad [8]$$

$$h_{23,t} = \Omega_{23} + a_{22}a_{33}u_{2,t-1}u_{3,t-1} + b_{22}b_{33}h_{23,t-1} \qquad [9]$$

$$h_{33,t} = \Omega_{33} + a_{33}^2 u_{3,t-1}^2 + b_{33}^2 h_{33,t-1} \qquad [10]$$

The multivariate GARCH representation predicts the parameters by maximizing the log-likelihood function shown below.

$$\ln(\theta) = -{}^{TN}/_{2} - {}^{1}/_{2} \sum_{t=1}^{T} (log|H_t| + \Xi_t H_{t-1}^{-1} \Xi_t) \qquad [11]$$

16. DATA

In this study, two crude oil prices (Brent, and WTI) and three Airlines Stock prices (American Airlines Group, Southwest Airlines, and Delta Air Lines) in the US were selected. Firstly, we investigated the Granger Causality Tests and after that analyzed the long-term spillover effects among them. The data set, obtained from investing.com[21], is daily and includes approximately seven years between 28.04.2014 and 12.03.2021. The Covid-19 virus, which was first encountered in Wuhan, China on December 31st, spread rapidly all over the world. For this reason, we describe it as the Covid-19 pandemic period from 31.12.2019 to 12.03.2021. After that, each market's return is computed as the following:

$$ln(P_t) - ln(P_{t-1}) \qquad [12]$$

where RBRENT, RWTI, RAAL, RDAL, and RLUV belongs to the returns of relevant series.

In Figure 1, the daily prices of Brent, WTI, American Airlines Group (AAL), Southwest Airlines (LUV), and Delta Air Lines (DAL) are shown. Like many industries, the airline industry has been seriously affected since the day the coronavirus pandemic started. It is envisaged that these influences will not begin to remove and overcome in a short time, and there will be a gradual progression.

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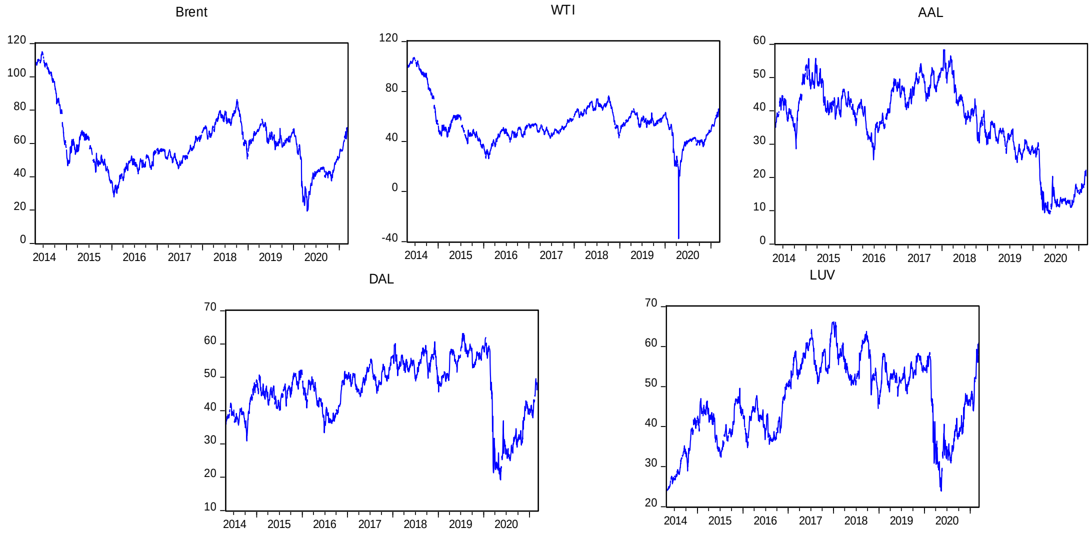
[21] https://www.investing.com/

Figure 14: Daily Prices of Brent, WTI, DAL, LUV, and AAL



In the charts in Figure 14, it is seen that the WTI from the oil market is negative for the first time in its history. One of the reasons for this is that there is an imbalance of supply and demand in oil. In addition, it can be said that WTI has its factors. The first OPEC+ meeting after June 2019 took place in early March. Russia did not accept this offer, opposing some countries that offered to reduce the supply, as the serious decrease in demand also lowered prices. The fact that an agreement could not be reached as a result of this meeting also affected the markets. From the first month after the meeting, there has been a percentage reduction in world oil consumption.

Table 15: Descriptive Statistics

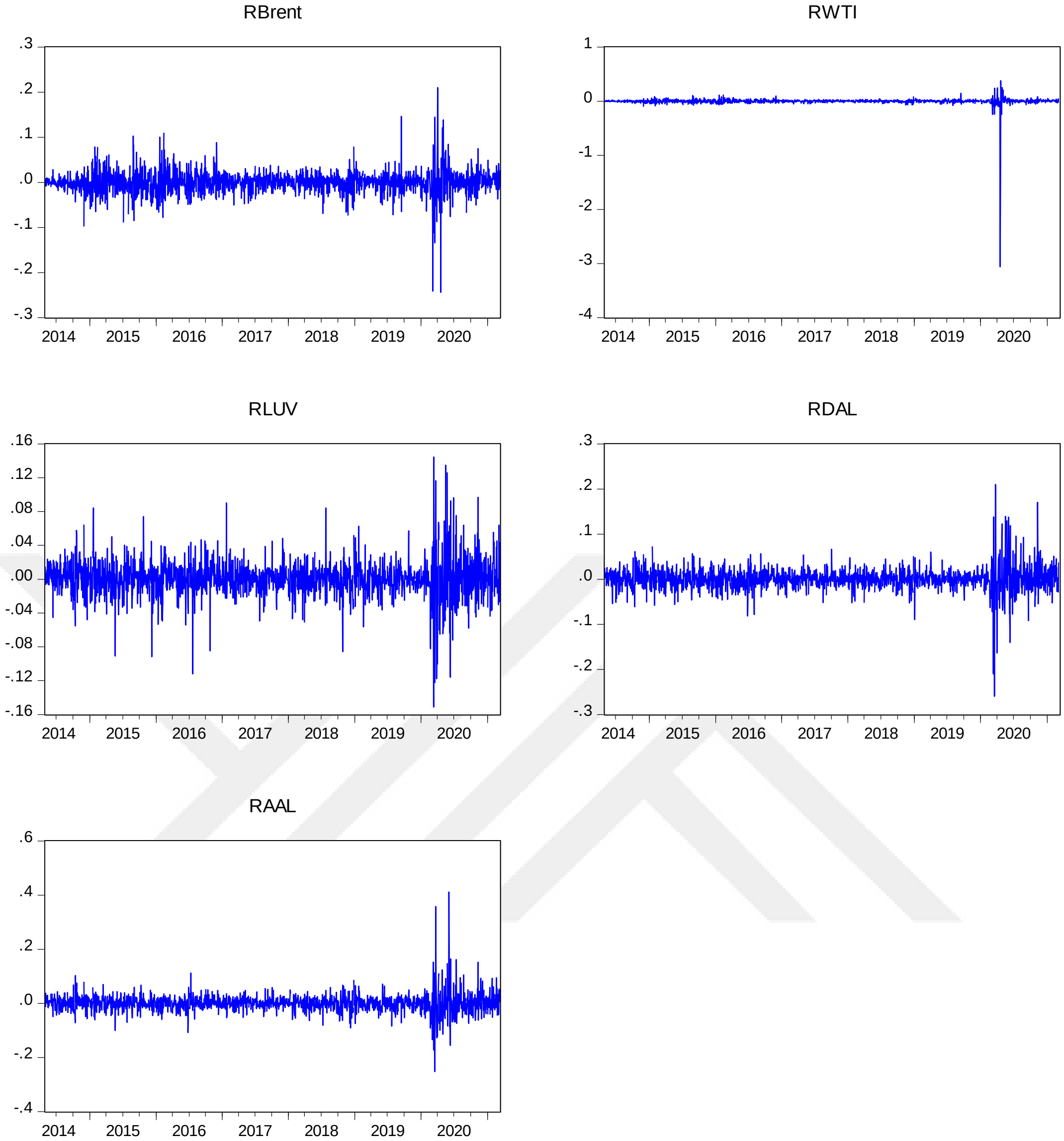
	Crude Oil		Airlines		
	RBRENT	RWTI	RLUV	RDAL	RAAL
Mean	9.21E-05	-0.00192	0.000794	0.000521	0.000299
Median	0.000745	0.000605	0.000789	0.000759	0.00000
Maximum	0.210186	0.376623	0.144441	0.210171	0.41097
Minimum	-0.24404	-3.05966	-0.15109	-0.25992	-0.25225
Std. Dev.	0.026326	0.08562	0.022305	0.025575	0.033131
Skewness	-0.29906	-28.1769	-0.09266	-0.21595	1.679682
Kurtosis	16.78257	971.1001	10.23064	20.08658	28.74158
Jarque-Bera	13694.9	67669155	3764.611	21021.74	48493.76
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
ADF Test Level	-8.1844	-9.5464	-10.7412	-15.9294	-12.6033
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	1727	1727	1727	1727	1727

Notes: Between parenthesis: p-values. ADF Tests indicate to the Augmented Dickey-Fuller test for the existence of unit root

Table 15 explains the descriptive statistics of the returns of two crude oil (Brent, WTI), and returns of three US Airline companies (American Airlines Group, Southwest Airlines, Delta Air Lines) during the research time from April 28, 2014, to March 11, 2021. The mean values of the returns of both crude oils and airlines are near zero. RWTI has a maximum value within the crude oils with the 0.376623, and also RAAL has a maximum value within the airlines with the 0.41097. It is perceived that the RWTI and RAAL showed the highest standard deviation of 0.08562 and 0.033131 sequentially, while RBRENT and RLUV showed the lowest standard deviation with values of 0.026326 and 0.022305 sequentially. It is certainly seen from the Skewness test that all variables derived negative value except RAAL through the research time. It is noteworthy that all returns' kurtosis values are higher than three, which presented that fat-tail and leptokurtic. Due to the nature of the financial time series, they have a fat tail and show leptokurtosis features. The point that draws our attention in all data Jarque-Bera statistics do not provide the assumption of normality for all series. The probability of all variables less than 0.05 indicates that the series are not distributed normally. Moreover, according to the unit root test, all variables' results (with constant, with constant & trend, without constant & trends) are significant both at the level and at the first difference. Through the unit root test (ADF), it can be seen that the variables are stationary or not. It is obvious that the null hypothesis, which has a unit root, of all variables is rejected.

Figure 15 displays the daily returns of Brent and WTI crude oils, and also daily returns of American Airlines (AAL), Southwest Airlines (LUV), and Delta Air (DAL). During the pandemic stage, the highest inconstancies in returns of Brent and WTI crude oils have been observed in the last seven years. Demand shocks occurred due to travel restrictions and other precautions during the pandemic period. Besides, clumps and comparatively high return inconstancies are observed for AAL, LUV, and DAL in the pandemic period.

Figure 15: Daily Returns of Brent, WTI, AAL, DAL and LUV



17. EMPIRICAL RESULTS

17.1. Granger Causality Results

In this part, the Granger Causality for the two crude oil prices' returns and three US Airline companies' returns was investigated. It is shown in Table 16, and Table 17. One lag was chosen in these Pairwise Granger Causality tests.

The results of Granger Causality, for testing the causal linkages between Brent's return and three US airlines stock returns are displayed in Table 16. Also as it can be seen in Table 16, all null hypotheses cannot be rejected. Consequently, according to the Pairwise Granger Causality results, all US airline returns used in this study have no causal relation with Brent's return. In Table 17, in which the relationship with the return of WTI is examined, only one hypothesis was rejected. While RWTI does not granger cause RDAL, RDAL granger causes RWTI. It can be said that there is a unidirectional relationship between them. Furthermore, all other hypotheses cannot be rejected because of the probabilities less than 0.05. In addition to the whole period, Granger Causality was also investigated for two crude oil price returns and three US Airline returns during the Covid-19 period (from 31.12.2019 to 12.03.2021), which is shown in Table 18 and Table 19. In Table 18, in which the relationship with the return of Brent is examined, only one hypothesis was rejected. While RBRENT does not granger cause RDAL, RDAL granger causes RBRENT. It can be mentioned that there is a unidirectional relationship between them. Furthermore, all other hypotheses cannot be rejected because of the probabilities less than 0.05. It can be said that there is no Granger causality between RAAL and RBRENT, and also between RLUV and RBRENT. It is seen in Table 19 that the results of the analysis of causality links between the return of WTI and the returns of three US airlines are shown, that all null hypotheses cannot be rejected. In conclusion, according to the Pairwise Granger Causality results, RAAL, RLUV, and also RDAL do not have a causal relationship with the return of WTI.

Table 16: Pairwise Granger Causality Tests for the Returns of Brent and Three Airlines Stock Returns - Overall Period

Null Hypothesis (H_0):	F-Statistic	Prob.	Result
RBRENT does not Granger Cause RAAL	1.09841	0.2948	do not reject H_0
RAAL does not Granger Cause RBRENT	0.05007	0.823	do not reject H_0
RBRENT does not Granger Cause RDAL	0.59291	0.4414	do not reject H_0
RDAL does not Granger Cause RBRENT	2.01174	0.1563	do not reject H_0
RBRENT does not Granger Cause RLUV	0.08116	0.7758	do not reject H_0
RLUV does not Granger Cause RBRENT	1.39853	0.2371	do not reject H_0

Table 17: Pairwise Granger Causality Tests for the Returns of WTI and Three Airlines Stock Returns - Overall Period

Null Hypothesis (H_0):	F-Statistic	Prob.	Result
RWTI does not Granger Cause RAAL	0.07101	0.7899	do not reject H_0
RAAL does not Granger Cause RWTI	2.05382	0.152	do not reject H_0
RWTI does not Granger Cause RDAL	0.48866	0.4846	do not reject H_0
RDAL does not Granger Cause RWTI	10.3158	**0.0013**	**reject H_0**
RWTI does not Granger Cause RLUV	2.79082	0.095	do not reject H_0
RLUV does not Granger Cause RWTI	2.48129	0.1154	do not reject H_0

Table 18: Pairwise Granger Causality Tests for the Returns of Brent and Three Airlines Stock Returns - Covid19 Period

Null Hypothesis (H_0):	F-Statistic	Prob.	Result
RAAL does not Granger Cause RBRENT	0.52025	0.4713	do not reject H_0
RBRENT does not Granger Cause RAAL	1.04209	0.3082	do not reject H_0
RDAL does not Granger Cause RBRENT	5.56315	**0.019**	**reject H_0**
RBRENT does not Granger Cause RDAL	0.38555	0.5351	do not reject H_0
RLUV does not Granger Cause RBRENT	3.72214	0.0546	do not reject H_0
RBRENT does not Granger Cause RLUV	0.00499	0.9438	do not reject H_0

Table 19: Pairwise Granger Causality Tests for the Returns of WTI and Three Airlines Stock Returns - Covid19 Period

Null Hypothesis (H_0):	F-Statistic	Prob.	Result
RAAL does not Granger Cause RWTI	0.78933	0.375	do not reject H_0
RWTI does not Granger Cause RAAL	0.00019	0.9891	do not reject H_0
RDAL does not Granger Cause RWTI	3.67308	0.0563	do not reject H_0
RWTI does not Granger Cause RDAL	0.0697	0.792	do not reject H_0
RLUV does not Granger Cause RWTI	0.8909	0.346	do not reject H_0
RWTI does not Granger Cause RLUV	0.84185	0.3596	do not reject H_0

17.2. VAR Specification Models

VAR System Specification for Model 1:

[13]

$$RAAL = \boldsymbol{C(1)} * RAAL(-1) + C(2) * RDAL(-1) + C(3) * RLUV(-1) + C(4) * RBRENT(-1) + C(5)$$

$$RDAL = C(6) * RAAL(-1) + C(7) * RDAL(-1) + C(8) * RLUV(-1) + C(9) * RBRENT(-1) + C(10)$$

$$RLUV = C(11) * RAAL(-1) + C(12) * RDAL(-1) + C(13) * RLUV(-1) + C(14) * RBRENT(-1) + \boldsymbol{C(15)}$$

$$RBRENT = C(16) * RAAL(-1) + C(17) * RDAL(-1) + C(18) * RLUV(-1) + \boldsymbol{C(19)} * RBRENT(-1) + C(20)$$

VAR System Specification for Model 2:

[14]

$$RAAL = \boldsymbol{C(1)} * RAAL(-1) + C(2) * RDAL(-1) + \boldsymbol{C(3)} * RLUV(-1) + C(4) * RWTI(-1) + C(5)$$

$$RDAL = C(6) * RAAL(-1) + C(7) * RDAL(-1) + C(8) * RLUV(-1) + C(9) * RWTI(-1) + C(10)$$

$$RLUV = C(11) * RAAL(-1) + C(12) * RDAL(-1) + C(13) * RLUV(-1) + C(14) * RWTI(-1) + \boldsymbol{C(15)}$$

$$RWTI = C(16) * RAAL(-1) + C(17) * RDAL(-1) + C(18) * RLUV(-1) + C(19) * RWTI(-1) + C(20)$$

Tables 20 and 21 display the Diagonal BEKK Model results for equations 13 and 14. In addition, the Diagonal BEKK Model results of these equations for the Covid-19 period are also displayed in Tables 22 and 23. In the overall period (Table 20), Model 1; C (1), C (15) and C (19), in Model 2; C (1), C (3), C (15) are significant statistically accordance with the 5% significance level. According to the consequences of restricted mean return equalizations for Model 1, returns of AAL, and Brent are reliant at first lags. The mean spillover of AAL's first lag is positive, however, the mean spillover of Brent's first lag is negative. That means showing a descending motion. Furthermore, diagonal coefficients C7 and C13 are not significant in the process of RDAL and RLUV, explicating that returns of them are independent of their own preceding returns. According to the consequences of restricted mean return equalizations for Model 2, returns of AAL is reliant at first lag. The mean spillover of AAL's first lag is positive, showing that an upward motion in this. Moreover, cross - means spillovers are not significant in all equations in all models, except for C (3) in Model 2, RLUV to RAAL, with -0.08153 coefficient.

Table 20: Estimation Results for Conditional Mean Returns - Diagonal BEKK Models – Overall Period

Model 1	Coefficient	z-Statistic	P-value	Model 2	Coefficient	z-Statistic	P-value
C(1)	0.098314	2.849664	**0.0044***	**C(1)**	0.089671	2.580437	**0.0099***
C(2)	-0.030351	-0.65408	0.5131	**C(2)**	-0.01494	-0.31979	0.7491
C(3)	-0.073639	-1.89973	0.0575	**C(3)**	**-0.08153**	-2.08861	**0.0367***
C(4)	-0.006551	-0.30407	0.7611	**C(4)**	0.005429	0.318586	0.75
C(5)	0.000122	0.241142	0.8094	**C(5)**	0.000203	0.400654	0.6887
C(6)	0.02335	0.884818	0.3763	**C(6)**	0.015861	0.595639	0.5514
C(7)	-0.021706	-0.5712	0.5679	**C(7)**	-0.00727	-0.19074	0.8487
C(8)	-0.028252	-0.86422	0.3875	**C(8)**	-0.03553	-1.09317	0.2743
C(9)	-0.023614	-1.34977	0.1771	**C(9)**	0.000656	0.047825	0.9619
C(10)	0.000456	1.155326	0.248	**C(10)**	0.000519	1.317074	0.1878
C(11)	-0.003024	-0.12618	0.8996	**C(11)**	-0.0086	-0.35638	0.7216
C(12)	-0.00288	-0.08656	0.931	**C(12)**	0.00836	0.24808	0.8041
C(13)	-0.021199	-0.70229	0.4825	**C(13)**	-0.02698	-0.88913	0.3739
C(14)	-0.009458	-0.57882	0.5627	**C(14)**	0.005014	0.384174	0.7008
C(15)	0.000819	2.215744	**0.0267***	**C(15)**	0.000916	2.479596	**0.0132***
C(16)	0.031841	1.072012	0.2837	**C(16)**	0.01227	0.388898	0.6974
C(17)	-0.00158	-0.03637	0.971	**C(17)**	0.038607	0.853301	0.3935
C(18)	-0.014445	-0.36422	0.7157	**C(18)**	-0.04771	-1.1463	0.2517
C(19)	-0.05291	-2.30298	**0.0213***	**C(19)**	-0.03515	-1.4581	0.1448
C(20)	0.000696	1.739115	0.082	**C(20)**	0.000744	1.717836	0.0858

Notes: * denote the rejection of null hypothesis at 5% significance level. The coefficients are represented in Equation 13-14

Table 21: Transformed Variance – Overall Period

Model 1	Coefficient	z-Stat.	P-value	Model 2	Coefficient	z-Stat.	P-value
M(1,1)	1.55E-05	5.540358	**0.0000***	**M(1,1)**	1.52E-05	5.583215	**0.0000***
M(1,2)	9.83E-06	6.331321	**0.0000***	**M(1,2)**	9.74E-06	6.363924	**0.0000***
M(1,3)	7.97E-06	6.026584	**0.0000***	**M(1,3)**	7.94E-06	6.046969	**0.0000***
M(1,4)	2.36E-08	0.026825	0.9786	**M(1,4)**	3.93E-07	0.20151	0.8403
M(2,2)	9.93E-06	6.368602	**0.0000***	**M(2,2)**	9.96E-06	6.331439	**0.0000***
M(2,3)	6.63E-06	6.385713	**0.0000***	**M(2,3)**	6.67E-06	6.359636	**0.0000***
M(2,4)	2.13E-08	0.030304	0.9758	**M(2,4)**	5.68E-08	0.035865	0.9714
M(3,3)	7.64E-06	5.396768	**0.0000***	**M(3,3)**	7.74E-06	5.367785	**0.0000***
M(3,4)	7.77E-08	0.122146	0.9028	**M(3,4)**	5.51E-07	0.374332	0.7082
M(4,4)	1.01E-05	3.852376	**0.0001***	**M(4,4)**	4.67E-05	6.43306	**0.0000***
A1(1,1)	0.154295	13.72787	**0.0000***	**A1(1,1)**	0.150629	13.76667	**0.0000***
A1(2,2)	0.147993	14.20447	**0.0000***	**A1(2,2)**	0.150177	14.16723	**0.0000***
A1(3,3)	0.153318	13.67529	**0.0000***	**A1(3,3)**	0.154723	13.64755	**0.0000***
A1(4,4)	0.271624	12.90651	**0.0000***	**A1(4,4)**	0.396996	13.95053	**0.0000***
B1(1,1)	0.97709	326.9626	**0.0000***	**B1(1,1)**	0.977686	337.2546	**0.0000***
B1(2,2)	0.977542	366.8933	**0.0000***	**B1(2,2)**	0.977111	358.4345	**0.0000***
B1(3,3)	0.977902	329.7085	**0.0000***	**B1(3,3)**	0.977548	324.9962	**0.0000***
B1(4,4)	0.958836	165.6839	**0.0000***	**B1(4,4)**	0.89245	83.9172	**0.0000***

Notes: * denote the rejection of null hypothesis at 5% significance level.

Table 22: Estimation Results for Conditional Mean Returns - Diagonal BEKK Models - Covid 19 Period

Model 1	Coefficient	z-Statistic	P-value	Model 2	Coefficient	z-Statistic	P-value
C(1)	**0.23741**	2.674086	**0.0075***	**C(1)**	**0.22712**	2.515546	**0.0119***
C(2)	-0.0532	-0.76235	0.4459	**C(2)**	-0.21203	-1.44461	0.1486
C(3)	-0.25113	-1.72717	0.0841	**C(3)**	-0.12222	-0.97131	0.3314
C(4)	-0.06785	-0.53274	0.5942	**C(4)**	0.001016	0.031754	0.9747
C(5)	-0.0007	-0.30092	0.7635	**C(5)**	-0.00058	-0.25849	0.796
C(6)	0.052674	1.04978	0.2938	**C(6)**	0.102996	1.518353	0.1289
C(7)	0.060915	0.95207	0.3411	**C(7)**	-0.0392	-0.30913	0.7572
C(8)	-0.03456	-0.32788	0.743	**C(8)**	-0.12221	-1.192	0.2333
C(9)	-0.02001	-0.22886	0.819	**C(9)**	0.003688	0.115468	0.9081
C(10)	0.00212	1.790713	0.0733	**C(10)**	0.000332	0.203107	0.8391
C(11)	0.101006	1.472703	0.1408	**C(11)**	-0.04059	-0.69062	0.4898
C(12)	-0.05371	-0.87577	0.3812	**C(12)**	0.138498	1.323883	0.1855
C(13)	-0.06236	-0.48409	0.6283	**C(13)**	-0.15089	-1.62557	0.104
C(14)	-0.07421	-0.71215	0.4764	**C(14)**	0.007483	0.265664	0.7905
C(15)	0.000173	0.10436	0.9169	**C(15)**	0.000504	0.363909	0.7159
C(16)	-0.04446	-0.74524	0.4561	**C(16)**	0.056536	1.431291	0.1523
C(17)	-0.02737	-0.56322	0.5733	**C(17)**	-0.05947	-0.57222	0.5672
C(18)	0.126209	1.236318	0.2163	**C(18)**	-0.0159	-0.17648	0.8599
C(19)	-0.11449	-1.24233	0.2141	**C(19)**	0.046812	0.79178	0.4285
C(20)	0.000363	0.258331	0.7962	**C(20)**	0.00253	1.989269	**0.0467***

Notes: * denote the rejection of null hypothesis at 5% significance level. The coefficients are represented in Equation 13-14

Table 23: Transformed Variance - Covid 19 Period

Model 1	Coefficient	z-Stat.	P-value	Model 2	Coefficient	z-Stat.	P-value
M(1,1)	1.35E-04	2.491802	**0.0127***	**M(1,1)**	1.56E-04	2.257347	**0.024***
M(1,2)	1.85E-05	1.740709	0.0817	**M(1,2)**	9.37E-05	2.610962	**0.009***
M(1,3)	8.23E-05	2.860043	**0.0042***	**M(1,3)**	6.84E-05	2.593365	**0.0095***
M(1,4)	6.09E-05	2.756893	**0.0058***	**M(1,4)**	5.82E-05	1.865226	0.0621
M(2,2)	4.13E-05	2.462415	**0.0138***	**M(2,2)**	7.49E-05	2.829057	**0.0047***
M(2,3)	1.48E-05	1.755612	0.0792	**M(2,3)**	5.21E-05	2.740283	**0.0061***
M(2,4)	1.06E-05	1.462154	0.1437	**M(2,4)**	5.66E-05	2.340135	**0.0193***
M(3,3)	6.66E-05	2.975426	**0.0029***	**M(3,3)**	5.14E-05	2.496731	**0.0125***
M(3,4)	4.64E-05	2.815609	**0.0049***	**M(3,4)**	4.62E-05	2.090879	**0.0365***
M(4,4)	4.53E-05	2.506957	**0.0122***	**M(4,4)**	2.39E-04	3.353842	**0.0008***
A1(1,1)	0.18455	5.348035	**0.0000***	**A1(1,1)**	0.183745	4.735983	**0.0000***
A1(2,2)	0.303953	5.350136	**0.0000***	**A1(2,2)**	0.239444	5.633067	**0.0000***
A1(3,3)	0.242059	6.330625	**0.0000***	**A1(3,3)**	0.261635	5.382409	**0.0000***
A1(4,4)	0.273535	5.883635	**0.0000***	**A1(4,4)**	0.545303	6.449095	**0.0000***
B1(1,1)	0.959633	81.75908	**0.0000***	**B1(1,1)**	0.961659	76.3811	**0.0000***
B1(2,2)	0.942096	54.91128	**0.0000***	**B1(2,2)**	0.958204	92.45917	**0.0000***
B1(3,3)	0.954114	87.82155	**0.0000***	**B1(3,3)**	0.960083	88.04621	**0.0000***
B1(4,4)	0.95424	79.73264	**0.0000***	**B1(4,4)**	0.791621	23.19538	**0.0000***

Notes: * denote the rejection of null hypothesis at 5% significance level.

As can be seen in Table 22, which Equations 13 and 14 have the results of the Diagonal BEKK Model for the Covid-19 period, while it was statistically significant for Model 1 only as C (1), Model 2 was also statistically significant as C(1) and C(20). According to the consequences of restricted mean return equalizations for Model 1 in Table 22, returns of AAL is reliant at first lag. The mean spillover of AAL's first lag is positive with the 0.23741 coefficient. That means showing an upward motion. Furthermore, diagonal coefficients C (7), C (13), and C (19) are not significant in the process of RDAL, RLUV, and RBRENT, explicating that returns of them are independent of their own preceding returns. According to the consequences of restricted mean return equalizations for Model 2 in Covid-19 period, returns of AAL is reliant at first lag. The mean spillover of AAL's first lag is positive with 0.22712 coefficient, showing that an upward motion in this. Moreover, cross - means spillovers are not significant in all equations in all models in Model 2 for Covid-19 period.

As it can be seen in Table 21 and Table 23, most coefficients are meaningful statistically, which shows that the volatilization and cross volatilization between the variables can be determined by the equations of conditional variance and covariance. We achieved that strong proof of the GARCH impact and the existence of a strong effect of ARCH, based on the empirical results.

In Model 1, the association between RAAL, RDAL, RLUV, and RBRENT has been investigated. As it is shown in Table 21 and Table 23, the conditional ARCH effect, all A1 matrices, is statistically significant at %5 critical level. According to analysis demonstrate that these three airlines and Brent crude oil are impacted by the volatilization of their own marketplaces. In addition to that, it can be said that there exist volatility spillover effects among them in the short period. Besides, the effects of conditional GARCH, all B1 matrices are statistically significant at %5 critical level in Model 1. Consequently, it is obvious that a long period spillover effect between RAAL, RDAL, RLUV, and RBRENT exists. In addition to all these interpretations, we can say that there is powerful volatility spread among the mentioned markets in the long run. This result is also in line with the conclusion in economic theory that any shock in the financial markets influences the real economy by a lag.

In Model 2, the association between RAAL, RDAL, RLUV, and RWTI has been investigated. As it is shown in Table 21 and Table 23, the conditional ARCH effect, all A1 matrices, is statistically significant at %5 critical level. Results illustrate that these three airlines and WTI crude oil are influenced by the volatilization of their own marketplaces. Also, it can be said that there exist volatility spillover effects among them in the short period. Further, the influences of conditional GARCH, all B1 matrices are statistically meaningful at %5 critical level in Model 2. Eventually, a long period of spillover effect between RAAL, RDAL, RLUV, and RBRENT subsists. Additionally, it can be mentioned that there is powerful volatility spread among the mentioned markets in the long run.

It can be shown that conditional covariance in Figure 16 (for Model 1), and in Figure 18 (for Model 2) and conditional correlation coefficients in Figure 17 (for Model 1), and Figure 19 (for Model 2). It is also seen in Model 1 and also Model 2 that the fluctuation in correlation coefficients was very high after Covid-19 was declared.

Figure 16: Conditional Covariance for Model 1

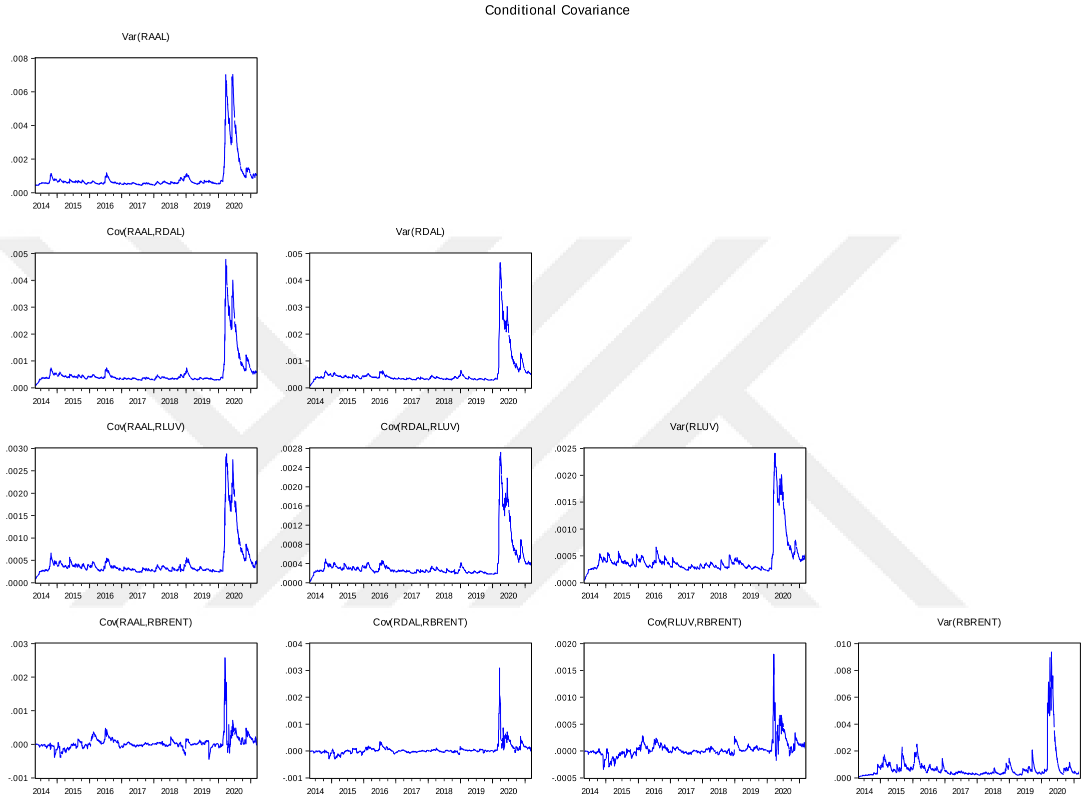


Figure 17: Conditional Correlation for Model 1

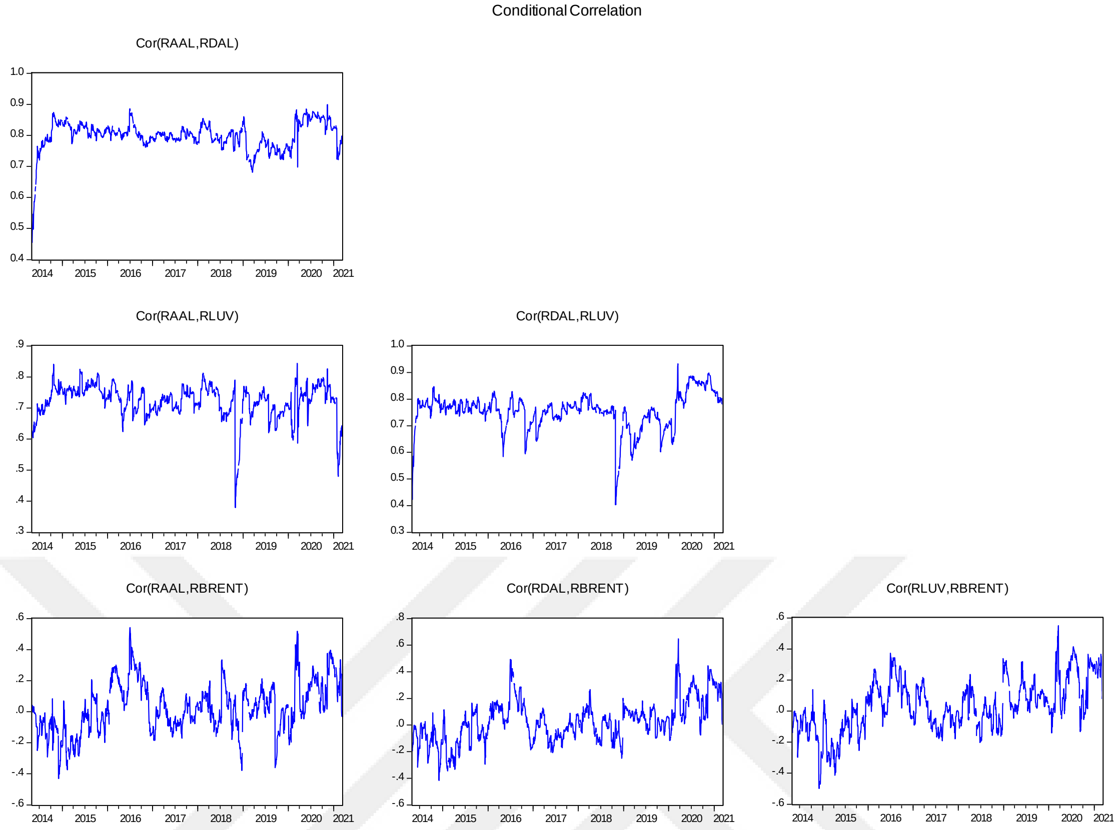


Figure 18: Conditional Covariance for Model 2

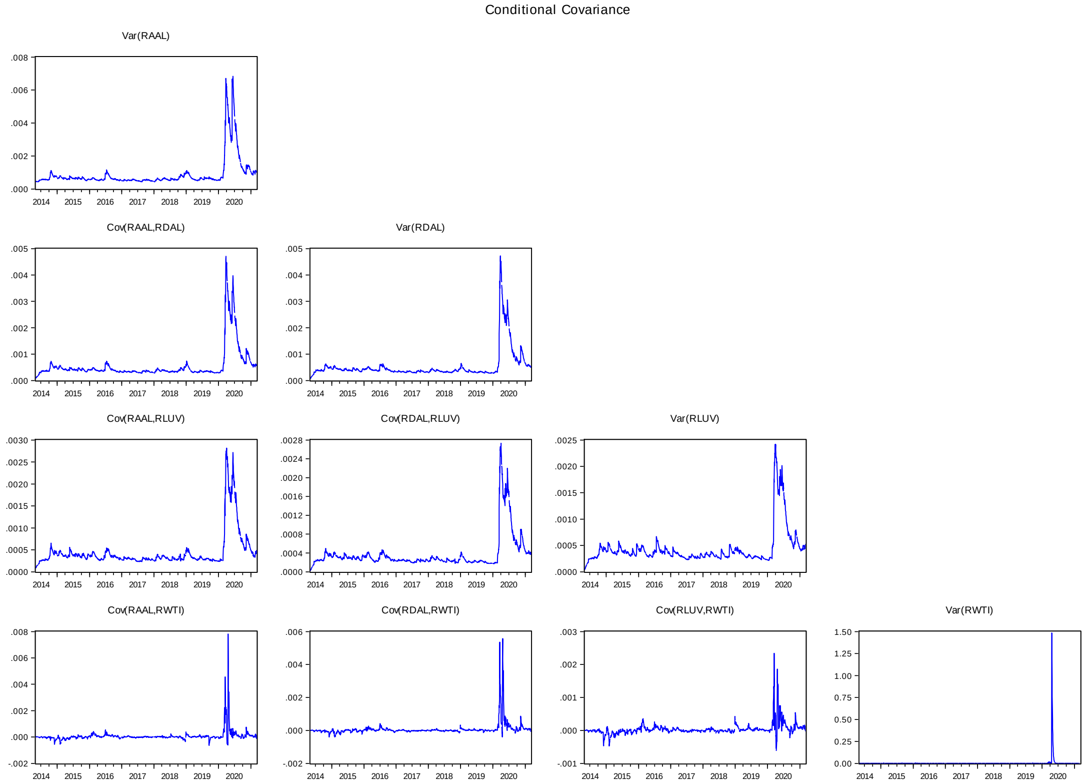
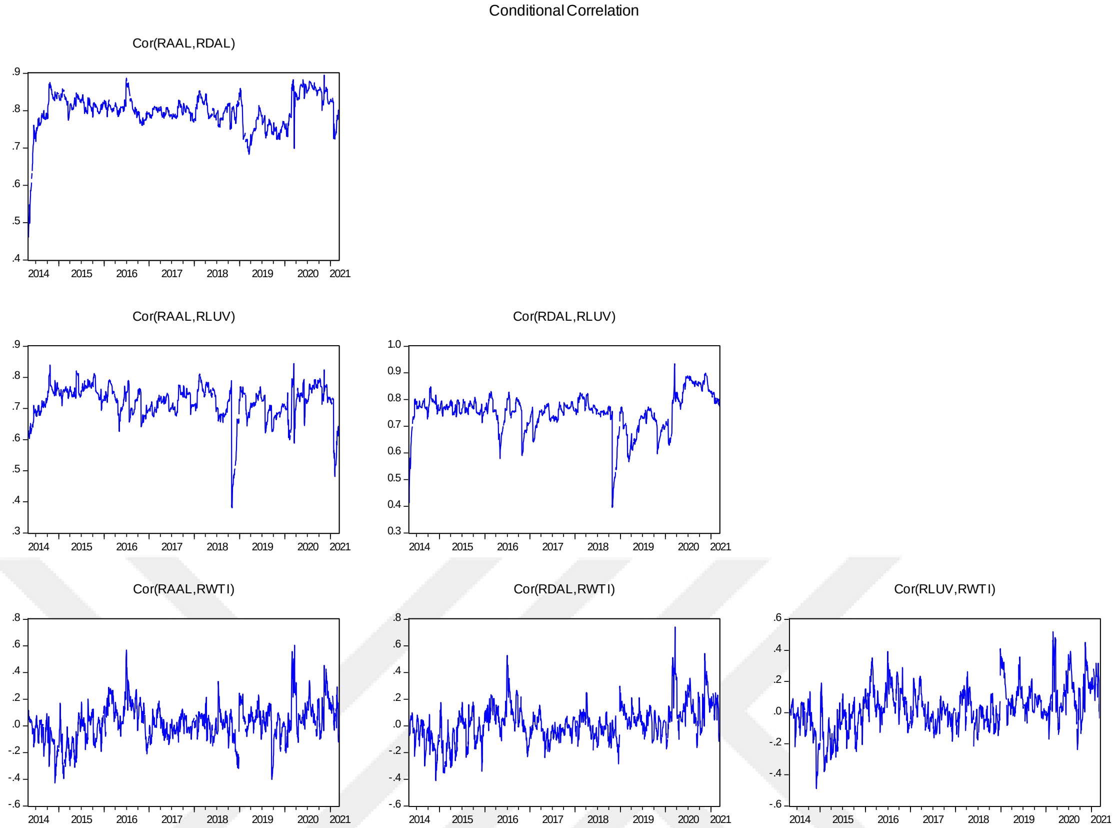


Figure 19: Conditional Correlation for Model 2



18. CONCLUSION

In this research, firstly, the Pairwise Granger causality analysis between three US airlines (RAAL, RDAL, and RLUV) and two crude oil markets (Brent and WTI) was examined. The analysis was applied for the whole period covering the period 28.04.2014 and 12.03.2021 and for the dates 31.12.2019 - 12.03.2021 covering the Covid-19 period. According to results of Pairwise Granger Causality tests for the returns of Brent and three airlines stock returns (overall period), these three stock returns do not granger cause RBRENT, and also RBRENT does not granger cause for all these three stocks. However, if this analysis is investigated for the covid-19 period, it can be concluded that RDAL granger causes RBRENT. According to results of Pairwise Granger Causality tests for the returns of WTI and three airlines stock returns (overall period), RAAL and RLUV do not granger cause RWTI, except RDAL. However, if this analysis is investigated for the covid-19 period, we can say that there is no granger cause between them.

Secondly, mean return spillover and volatility spillover was investigated via Diagonal BEKK Models for both overall and covid-19 period. Ticket prices, which may change in connection with demand, are not expected to reduce due to the measures to be taken, especially during the pandemic period. In addition to the increasing costs of airline companies, fluctuations in crude oil prices have also been added. Hence, the airway corporations' financial situations are compatibly the high covariance variations during the pandemic. It is deduced from the model consequences that volatility spillover influence is more meaningful in comparison with the influence of return spillover.

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APPENDIX A: LIST OF ABBREVIATION

ADR: American Deposit Receipts
DRN: Disease-Related News
OLS: Ordinary Least Squares
ESM: Event Study Methodology
ARCH: AutoRegressive Conditional Heteroskedasticity
GARCH: Generalized AutoRegressive Conditional Heteroskedasticity
EGARCH: Exponential Generalized AutoRegressive Conditional Heteroskedasticity
GDP: Gross Domestic Product
ABBV: AbbVie Inc
BMY: Bristol Myers Squibb
CHINEXT: Chinext
DVAX: Dynavax Technologies
GILD: Gilead Sciences
PFE: Pfizer
ADF: Augmented Dickey - Fuller
RABBV: Return of AbbVie Inc
RBMY: Return of Bristol Myers Squibb
RCHINEXT: Return of Chinext
RDVAX: Return of Dynavax Technologies
RGILD: Return of Gilead Sciences
RPFE: Return of Pfizer
NICs: News Impact Curves
DCC GARCH: Dynamic Conditional Correlation multivariate GARCH Model
FAANG: Facebook, Amazon, Apple, Netflix, and Google
ARIMA: Autoregressive Integrated Moving Average Model
AMC: AMC Theatres
Disney: The Walt Disney Company
CINEWORLD: Cineworld
IMAX: The IMAX Corporation
COMCAST: Comcast Corporation
FB: FACEBOOK
AAPL: APPLE
AMZN: AMAZON
NFLX: NETFLIX
GOOG: Alphabet-Google
AAL: American Airlines
LUV: Southwest Airlines
DAL: Delta Airlines
BRENT: Brent crude oil futures
WTI: Crude Oil Contract
RAAL: Return of American Airlines
RLUV: Return of Southwest Airlines
RDAL: Return of Delta Airlines
RBRENT: Return of Brent crude oil futures
RWTI: Return of Crude Oil Contract