THE FEAR OF COVID-19 ON INDONESIA CAPITAL MARKET VOLATILITY

Andrew Young Hengsaputra* and Bona Christanto Siahaan

Faculty of Economics and Business, Universitas Indonesia Jakarta, Indonesia

E-mail address: andrew.young91@ui.ac.id

***Abstract*—COVID-19 has caused a pervasive impact on human life and business operations, leading to investor fear and capital market volatility. This research aims to understand whether COVID-19 affecting Indonesia's capital market (IDX) volatility by analyzing the daily and weekly volatility from intraday stock data, the daily positive case of COVID-19 in Indonesia, and utilizing Google search volume index for some negative words related to the COVID-19 to understand the investor fear. This research adopted a simplified heterogeneous autoregressive model and covering the first case of COVID-19 in Indonesia until a day before the first vaccine was injected in Indonesia (March 2, 2020 - January 12, 2021) in all sectors on the IDX. The results showed the daily volatility, weekly volatility, and the daily positive case of COVID-19 in Indonesia can predict future volatility in almost all sectors on the IDX. We also found the global investor fear can predict future volatility in the property sector. However, we did not find evidence that investor fear in Indonesia could predict future volatility on sectoral indices on the IDX.**

Keywords—capital market, COVID-19, google trends, investor fear, volatility

I. INTRODUCTION

The novel coronavirus (COVID-19) outbreak in China at the end of 2019 has spread widely to 191 countries and infected more than 107 million people by February 12, 2021 [1]. The COVID-19 also causes several impacts on global socio-economic, including unemployment and poverty rates, lower oil prices, altered education sectors, changes in the nature of work, and lower GDPs, and heightened risks to health care workers [2]. Subsequently, the COVID-19 also harmed the US stock market in March 2020, with the US crash, stock markets in Europe and Asia have also plunged [3].

Financial markets have seen dramatic moves on an unprecedented scale, and the global financial market risks increase substantially in response to the pandemic. Stock market reactions are related to the magnitude of the outbreak in each region, which necessitates a policy response to the pandemic's immense uncertainty and associated economic losses, causing markets to become highly volatile and unpredictable [3]. The stock exchanges in Asia are among the worst affected by the COVID-19 pandemic [4]. However, the research also found the Asian stock markets respond more quickly to the outbreak than the other countries. Some of them recovering slightly in the later stages of the pandemic, and investor's fear sentiment are proved to be a complete mediator and transmission channel for the COVID-19 outbreak's effect on stock markets.

The negative sentiment of investors during the COVID-19 outbreak also has a diverse impact on the sectoral indices on the stock market. Reference [5] shows the COVID-19 impact on G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) the healthcare sector and consumer services sector was the most severely affected, while the technology sector was the least severe compared to the other sectors. However, the technology sectors in the United Kingdom's stock market have outperformed the others by a large margin, while the consumer discretionary sector performed substantially worse than the economy [6]. In Indonesia, almost all sectoral indices on the Indonesian Stock Exchange (IDX) had a rapid downturn during the early stage of the COVID-19 spread in Indonesia, except for the property sector that is relatively stable during the COVID-19 pandemic [7]. After some months of the virus spread in Indonesia, the sectoral indices in Indonesia also gradually recover, reflecting on the sectoral performance during the third quarter of 2020 until early 2021. However, the recovery speed between sectoral indices in Indonesia varies from one sector to another. The mining sector had recovered faster than the other sectors in early 2021, while the property sector is still stagnant when most sectoral indices are growing. Hence it is interesting to see the COVID-19 impact on sectoral indices on the IDX during the pandemic.

Although COVID-19 is not the first health-threatening epidemic globally, such as the MERS Virus, Avian Flu, SARS, Ebola, which have occurred before and harm human health, it is interesting to look back at what happened to previous epidemics and pandemics. One of the examples is SARS which emerged in late 2002 lead to the great concern of stakeholders, as the virus rapidly spread to some countries and infected more than 10,000 people in 2003, with 10% of them dying, the overall health effect was much less severe than initially expected [8]. SARS also harmed the economy in many countries, as European markets saw higher negative returns than other markets. The downturn in the market may be due to increased media attention during the pandemic, which resulted in pessimistic emotions, causing stocks to fall and volatility to grow [9].

Hence, it is believed that the COVID-19 pandemic caused fear for investors and provided a negative paradigm that causes stock market volatility because investors are very sensitive and do not like uncertainty. The level of this fear is measured by Google Search Volume Index (GSVI), and this fear has significant predictive power for the uncertainty of the future stock market [10]. The previous research believed the outbreak of the COVID-19 pandemic, markets around the world, lost a large amount of value in a short period and severely affected society negatively. This is also caused by short-term investor sentiment caused by the fear of the coronavirus. Unlike previous studies, this research tries to emphasize the impact of the fear of COVID-19 and the occurrence of volatility on the Indonesia Stock Exchange

ISBN*: 978-623-92201-2-9*

sectoral indices. A daily positive case of COVID-19 also used in this research [11]. Furthermore, A simplified version of the heterogeneous autoregressive (HAR) model is used in this research [12].

This research is expected to give investors insight into making investment decisions in the stock market, especially on the IDX during the current crisis caused by the COVID-19 pandemic that will be beneficial for the investor in mitigating the investment losses due to the unexpected volatility. The COVID-19 variable is also used in this research to see the impact on each sectoral indices on the IDX, as the daily positive case of COVID-19 is related to the Government's regulation in Indonesia in restricting the business operations that presumably trigger the investor reaction on the stock market that caused volatility.

II. Literature Review

A. Behavioral Finance

Behavioral finance as how psychological aspects influence people, markets, and organizations [13]. Researchers in psychology discovered that people often behave in odd ways while making decisions where money is involved, and economic decisions are often made in a seemingly irrational manner. One example is the January Effect, an anomaly in the financial market where a security increase in January without fundamental reasons [14].

Traditionally people are portrayed as rational beings who always want to maximize their utility, which results in many factors, including rational and irrational thinking which drive investor behavior [15]. The traditional finance theory relies heavily on three fundamental assumptions, such as perfect rationality, perfect self-interest and perfect information [16]. However, we are not living in ideal circumstances where we got all information that we need ideally, and most markets are inefficient. Reference [17] said that, because no one has access to all of the knowledge required to maximize their expected utility, no individual can be said to have "perfect information" at all times. Hence it will create an anomaly in the market in that speculative actions, overreaction, and underreaction to new information occur. This means that there is more to the financial decision-making process than a calculative rational agent.

The application of behavioral finance in the financial markets assists practitioners in identifying their own mistakes as well as those of others and understand the reasons behind these mistakes. Such an application assists practitioners in being more vigilant of market trends while also protecting them from the consequences of poor decisions [18]. The improvement in the quality of a decision can occur if the decision-maker gets good information to help determine the decision [19].

Behavioral finance evolved as a subdiscipline of social psychology that incorporates rational decision-making and subjective experience [18]. Reference [20] said behavioral finance is a finance component that studies how economic markets are impacted by individuals' inherent psychological processes while making financial decisions. Similarly, understanding the psychology of financial decision-making also includes learning about the most popular topics when talking about the greed and fear that drive the stock market [21]. Those psychosocial issues significantly impacted how people weighed their options and sought to maximize their usefulness. Reference [22] also claims that behavioral finance can be defined as relating to the psychological effects on financial practitioners' behavior, affecting the stock market.

Generally, people are more optimistic in their choices and judgments in good moods than those in bad moods [23]. Bad moods are associated with more detailed and critical evaluation strategies [24]. Hence, moods tend to affect relatively abstract judgments more than specific ones about which people have concrete information. In response to that, prices will react violently to short-term fundamental news, resulting in a positive correlation between short-term return movements and long-term return movements [25]. This issue subsequently causes the asset's value to have no long-term relationships with other asset prices, triggering herd behavior.

B. Investor Fear

People's emotions are related to their previous experiences, which subsequently impacting their decision-making process [26]. Two predominant emotions are frequently associated with financial markets: fear and greed [27]. Fear plays a role; the majority of investors respond less to greed and more to hope. Fear induces an investor to concentrate on highly unfavorable events. In contrast, hope induces him or her to concentrate on favorable events [28].

Fear encourages investors to expect poor, high-risk returns, whereas hope inclines them to expect high returns with low risk [29]. Hope and fear impact the way investors evaluate alternatives. Fear causes investors to look from the bottom up at possibilities. At the same time, hope encourages investors to look from the top down at options [28]. Investors usually tend to invest in the company and sectors that have performed better in recent times to avoid any regret or risk of losing money that might happen in the future from the investment made. Fear is usually dominated by people with risk-averse characteristics, while the risk-taker generally dominates the hope.

During the crisis, the decision-making process will need to balance the level of security by considering the potential consequences and the level of potential or probability that benefit the people. When people are not keeping the balance between safety and the potential outcomes, it will result in a gamble that might cause regret in the future. Anticipated emotions (e.g., regret and disappointment) are happening in the future and not at the time of decision making [26]. Even though regret and disappointment are similar, regret implies a sense of responsibility for the outcome. These two factors are dependent on the degree to which people can picture a different (more desirable) conclusion and the importance placed on that alternative conclusion in their minds.

In measuring the investor fear or sentiment, the Google Search Volume Index (GSVI) from the internet can be utilized to evaluate investors' interest in studying financial contagion in the currency market [30]. The investor attention gained from the GSVI index has proven to be a significant predictor of financial market performance. Further, the amount of time retail investors spend researching the stock market is characterized by how often they search for keywords on the internet, and this has been shown to be positively correlated with and is a causative factor, the actual realization of the volatility of the index [31][32]. Reference [33] said the increase of google searches could predict future volatility in the stock market. In addition, the google search volume index generated from a particular geographical region and

ISBN*: 978-623-92201-2-9*

worldwide is also necessary to reflect search intensity in countries other than the given market [10]. Hence, the following hypotheses are established to see whether the investor fear able to predict the future volatility on certain sectoral indices in the IDX:

H1: The investor fear in Indonesia able to predict the future volatility on certain sectoral indices on the IDX.

H2: The investor fear in the Global able to predict the future volatility on certain sectoral indices on the IDX.

C. Volatility

Volatility defined as a measure of how quickly the market is moving [34]. In contrast to markets that move slowly, low-volatility markets have a steadier price flow, but swift-moving markets have more dramatic price fluctuations, by taking note of the volatility's occurrence, we can observe from the mean, and standard deviation, which forms a complete picture of a normal distribution curve An estimator of daily or weekly price changes from annual volatility is required because volatility is one of the inputs into a theoretical pricing model that cannot be directly observed.

An accurate estimation of volatility is an essential aspect of option pricing, portfolio analysis and risk management [35]. Hence, having a proper estimation method or method is needed that can explain the volatility behavior. In measuring the volatility, some types of measurement can be used, such as realized volatility, model volatility, implied volatility and stochastic volatility models, despite the classical way of measuring financial market volatility through calculating sample standard deviation [36].

Investors frequently rely on and closely monitor historical stock prices to spot patterns in otherwise random time series, which has caused them to misinterpret series of rises and falls in stock prices as a trend, even though even relatively long strings of similar observations could be coincidental [25]. Reference [37] state that in the best possible approximation, the conditional variance of fixed-period data can be calculated, and it can be done rather accurately using a sum of squared realizations even when data is available at high sampling frequencies. The classic methods that use squared returns use the realized volatility theory to overcome many of its problems.

Realized Variance (RV), or historical volatility, measures the standard deviation of the logarithmic returns of a financial time series [38]. Realized volatility is the average variance of stock returns that can be measured after the stock has moved between time t and time T, after which a static methodology may be used. When dealing with past data, real-life realized variables are known as historical data. Implied variables, on the other hand, are identified as present and possible future information. Historical volatility also can be described as volatility, which is a measure of volatility, represented as an average over a specified time period. This includes merely how much price volatility has shifted in the past without considering the possibility of future price volatility [39].

The realized volatility might be estimated using squared intraday returns to have an unbiased and efficient estimator of the variance [40]. Utilizing intraday squared returns of no shorter than five-minute periods, a method that gives a reliable assessment of the latent process that determines volatility might be determined [41]. In the context of not having an empirically superior proved alternative regarding modelling day or intraday volatility using high-frequency data, the standard practice remained the same, using the traditional modelling tools to obtain relatively good estimates of daily values, although intraday data was available. Reference [42] also found realized volatility that utilizes a high frequency realized returns is a simple and accurate technique that may forecast volatility and assess volatility.

RV is believed as an effective method of efficiently summarizing intraday variance to daily variance used for modeling [43]. Reference [40] also said the RV is a popular empirical measure of volatility. This method gives a reliable assessment of the latent process that determines volatility might be determined. Reference [34] suggests using an estimator of daily or weekly price changes from annual volatility is required because volatility is one of the inputs into a theoretical pricing model that cannot be directly observed. Reference [12] also differentiated some kinds of investors; some are short-term traders with daily or higher trading frequency and medium-term investors who typically rebalance their positions weekly. There is also evidence that the RV method can measure the capital market volatility during the COVID-19 pandemic [10]. They found that the method helps understand the market uncertainty. Therefore, the following hypotheses are established to see whether daily and weekly volatility measured by RV can predict future volatility on certain sectoral indices in the IDX:

H3: The daily volatility able to predict the future volatility on certain sectoral indices on the IDX.

H4: The weekly volatility able to predict the future volatility on certain sectoral indices on the IDX.

D. COVID-19

COVID-19, which started in Wuhan, China, at the end of 2019 and becoming a pandemic on March 11, 2020, has emerged as a bane for the financial markets with unexpected uncertainty levels and high volatility [44]. Reference [45] also said COVID-19 had had a broad impact, causing investors, regulators, and the public at large that natural disasters can inflict economic damage on a previously authentic scale. Those impacts are caused because countries worldwide have implemented extensive measures, such as city lockdowns and border closings, which have led to economic shutdowns in many places [46].

In addition, the COVID-19 is also subsequently affecting the volatility in the capital market. Reference [11] shows the increase in COVID-19 confirmed cases are one of the factors that cause volatility in the capital markets. There is also evidence that the COVID-19 confirmed case also harmed the stock market, as it caused investors pessimistic sentiment on future returns and fear of uncertainties [4]. Hence, the following hypothesis is established to see whether the daily positive case of COVID-19 in Indonesia is able to predict the future volatility on certain sectoral indices in the IDX:

H5: The daily positive case of COVID-19 in Indonesia able to predict the future volatility on certain sectoral indices on the IDX.

ISBN*: 978-623-92201-2-9*

III. METHODOLOGY

This research aims to determine the relationship between COVID-19 and volatility in sectoral indices on the IDX. Therefore, the research was limited to the COVID-19 period from March 2, 2020, to January 12, 2021. March 2, 2020, was used as the start of the research period because it reflected the onset of COVID-19 cases in Indonesia. Meanwhile, January 12, 2021, is one day before the first COVID-19 vaccine is injected in Indonesia.

This research uses secondary data such as the daily and intraday 5-minutes stocks data obtained from the IDX. The price variation data is gathered for all sectoral indices of the IDX, which cover the following sectors: agriculture, basic industry, consumer goods, finance, infrastructure, mining, miscellaneous, manufacture, property, and trading sectors. The data gathered from these sectors then be calculated by using the RV method to understand the volatility.

In addition, to capture the fear of the COVID-19 both in Indonesia (local) and Global levels, this research uses data from Google Trends. Google makes the Google Search Volume Index (GSVI) of search terms public via Google Trends' product, http://www.google.com/trends [47]. This research took the normalized daily individual search volume index to a range from 0 to 100 for the following terms: corona, World Health Organization, virus, COVID-19, SARS, MERS, epidemic, pandemic, symptom, infected, spread, outbreak, social distancing, restriction, quarantine, suspends, travel, lockdown and postpone [10]. These terms are related to the COVID-19 outbreak situation and are therefore unlikely to predict past market uncertainties in Indonesia and Global.

The daily positive case of COVID-19 in Indonesia is also used in this research to see whether the fluctuation of the COVID-19 case in Indonesia also affects the stock market volatility. The COVID-19 data in Indonesia is obtained from https://kawalcovid19.id/, an Indonesian trusted source that provides the information about COVID-19 in Indonesia.

A. *Variable Definitions and Measurement*

1) *Volatility*

Daily volatility in each sectoral index is calculated using the annualized daily RV model as shown in the following equation [10]:

$$Daily\ Volatility\ = trading\ days\ in\ a\ year\ x\left(j_t^2 + \sum_{i=1}^{M} r_{t,i}^2\right) \tag{1}$$

The daily volatility computed by considering the j_t notation, which represents the return between the closing value of the index on day t-1 ($lnP_{t-1,M}$) and the opening value on day t ($lnP_{t,M}$) that represents the overnight price variation and reflected by the following equation:

$$j_t = 100\% \times (lnP_{t,M} - lnP_{t-1,M}) \tag{2}$$

While the $r_{t,i}$ represents the continuous intraday return that can be measured by considering the value of a sectoral index on day t at the intraday time i ($lnP_{t,i}$) and the previous tick ($lnP_{t-1,i}$). The following equation reflects the intraday return:

$$r_{t,i} = 100\% \times (lnP_{t,i} - lnP_{t-1,i}) \tag{3}$$

We also calculate the weekly volatility by adopting the following formula [10]:

$$Weekly\ Volatility\ = 4^{-1} \sum_{s=t-1}^{t-4} RV_s \tag{4}$$

Equation (4) is to ensure that the daily and weekly components do not overlap. Further, we also add the future volatility as the dependent variable, which can be calculated by $lnRV_{t+1}$ that represents the next day's volatility on sectoral indices [10].

2) *Investor fear*

Fear of COVID-19 data gathered from Google Trends, http://www.google.com/trends that shows how frequently a particular search term is searched over a given date range that the user inputs compared to the overall search volume worldwide. This is quantified by the Google Search Volume Index (GSVI), which is first measured using regular search interest and then normalized to control the total increase in the number of searches. Search interest is indexed on a relative scale to values ranging from 0-100, allowing us to see the relative changes in search interest over that period.

The following equation shows the formula that can be used in measuring the investor fear [47]:

$$Investor\ Fear\ =\ In\left(\frac{ASVI_t}{median\{ASVI_{t-1}, \ldots, ASVI_{t-5}\}}\right) \tag{5}$$

Where, $ASVI_t$ represents the Average Search Volume Index from each keyword generated from the Google Trends, and median $\{ASVI_{t-1}, \ldots, ASVI_{t-5}\}$ represents the five-day historical average of GSVI from all related keywords generated from Google Trends. This research will use the above formula to measure investor fear in Indonesia and investor fear in Global.

3) *Daily positive case of COVID-19*

Daily data of COVID-19 case in Indonesia are gathered from KawalCOVID19 that shows the daily confirmed case of COVID-19 in Indonesia. This research considers the following formula in calculating the growth rate of COVID-19 cases [11]:

$$Daily\ Positive\ Case\ of\ COVID-19\ in\ Indonesia\ =\ In\left(\frac{Case_t}{Case_{t-1}}\right) \tag{6}$$

Daily positive case of COVID-19 in Indonesia is calculated by using the natural logarithm of the changes on the daily positive case of COVID-19. $Case_t$ described the daily COVID-19 case at day t, while the $Case_{t-1}$ represents the daily COVID-19 case on the previous day.

B. *Research Model*

The variables used in this research are all sectoral index on the IDX, the fear index obtained from Google trends to analyze the investor fear of COVID-19 in Indonesia and global, and the daily positive case of COVID-19 in Indonesia. Hence, the model used in this research is shown below [10][11]:

$$\begin{aligned} &Future\ Volatility \\ &\quad = \beta_0 + \beta_1 Daily\ Volatility + \beta_2 Weekly\ Volatility \\ &\quad + \beta_3 Investor\ Fear\ in\ Indonesia + \beta_4 \text{Investor Fear in Global} \\ &\quad + \beta_5 Daily\ Positive\ Case\ of\ COVID-19\ in\ Indonesia + \varepsilon \end{aligned} \tag{7}$$

ISBN*: 978-623-92201-2-9*

IV. RESULTS

Based on Table I below, we found that daily volatility that utilizes the 5-minutes intraday data on the IDX can predict future volatility in all sectoral indices on the IDX during the COVID-19 pandemic Indonesia except for the finance sector. The weekly volatility also has a quite similar ability to predict future volatility in almost all sectoral indices on the IDX during the COVID-19 pandemic, except for the agriculture, finance, miscellaneous, and manufacturing sectors. Therefore, the RV method that utilizes the historical intraday data gathered from the sectoral indices on the IDX during the COVID-19 pandemic can predict the pattern of the future fluctuation of the sectoral indices on the IDX. Reference [42] also shows a consistent result, which stated that utilizing a high frequency RV from the stock price could be an adequate and straightforward technique in predicting the volatility. In addition, we also found that the RV is one of the methods that we can use to predict the occurrence of volatility on the IDX. It is also consistent with the previous research, which stated that the RV method is one of the effective methods of efficiently summarizing intraday variance to daily variance, which is used for modeling [43]. Our research findings also contribute to the previous study, where the analysis is performed on the sectoral indices level able to capture daily and weekly volatility measured by the RV method in predicting the future volatility on each sectoral indices during the COVID-19 pandemic.

Further, Table I also shows the impact of investor fear on future volatility on sectoral indices in Indonesia. We found that investor fear in Indonesia cannot predict future volatility on all sectoral indices in Indonesia during the COVID-19 pandemic. In contrast, the future volatility in the property sector on the IDX can be predicted by the global investor fear during the pandemic. The situation that happened in the property sector is also consistent with the sectoral indices performance published by IDX, which mentioned that during the COVID-19 pandemic, the property sector faces the highest downturn, which has decreased by 11.51% from February 28, 2020, to February 28, 2021 [7]. Therefore, for most sectoral indices on the IDX, we found that the investor fear might not directly affect the future volatility during this research period. The investor sentiment might only affect the capital market for a shorter period or during certain conditions, for example, when the Government announced a lockdown or business restrictions that might affect business operations. It is also supported by the previous research, which found that the lockdown or the government interventions might be caused uncertainty and resulting in negative sentiment and as a primary factor for the capital market to hit the circuit breaker several times [3]. Thus, our findings will give valuable insights for the investor in taking care of the emerging issues on the global that can be used as a signal for the occurrence of future volatility on certain sectors on the IDX.

We also found that the daily positive case of COVID-19 in Indonesia was able to predict future volatility on some sectors on the IDX, such as agriculture, basic industry, consumer goods, infrastructure, miscellaneous, manufacture, property, and trading sectors. These findings were also consistent with the previous research, which also found evidence that the COVID-19 confirmed case also harmed the stock market [4]. It caused investors pessimistic sentiment on future returns and fear of uncertainties, subsequently affecting the stock market. However, we also found that the impact caused by the COVID-19 in Indonesia is not similar between one sector to another sector on the capital market in Indonesia. Reference [48] also stated that the COVID-19 impact in Vietnam also varies from one sector to another sector. They also stated the financial sector was the most affected sector in Vietnam during the COVID-19 outbreak. Hence, the selection of investment types is not enough in making the investment decision during the COVID-19, selecting which sector to invest in is also an essential aspect that the investor or potential investor needs to consider before taking action. Our research findings also fill the current knowledge gaps, where currently, most of the research performed is seeing the COVID-19 impact on countries' stock markets as a whole. In comparison, our research findings contribute to giving more detailed information about which sector or industry is affected the most by the COVID-19 that influences the volatility.

TABLE I. REGRESSION RESULTS

Independent Variables	Agriculture	Basic Industry	Consumer Goods	Finance	Infrastructure	Mining	Miscellaneous	Manufacture	Property	Trading
Constant	0.0280	0.0182	0.0033	0.0072	0.0129	0.0201	0.0674	0.0032	0.0286	0.0156
	0.0043	0.0027	0.0013	0.0035	0.0030	0.0035	0.0069	0.0015	0.0056	0.0017
	0.0000	0.0000	0.0101	0.0430	0.0000	0.0000	0.0000	0.0320	0.0000	0.0000
Daily Volatility	0.1881	0.2418	0.4341	0.0859	0.4326	0.1910	0.2586	0.5349	0.2404	0.1622
	0.0287	0.0152	0.0065	0.2673	0.0155	0.0321	0.0255	0.0092	0.0308	0.0329
	0.0000	0.0000	0.0000	0.7480	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Weekly Volatility	0.0477	0.0820	0.1297	0.3474	0.1206	0.2296	0.0233	0.0185	0.1365	0.0873
	0.0379	0.0165	0.0074	0.2207	0.0171	0.0401	0.0318	0.0103	0.0420	0.0421
	0.2084	0.0000	0.0000	0.1170	0.0000	0.0000	0.4632	0.0737	0.0012	0.0381
Investor Fear in Indonesia	0.0014	0.0187	0.0029	0.0094	0.0018	0.0108	-0.0037	0.0009	0.0255	0.0019
	0.0148	0.0122	0.0062	0.0224	0.0138	0.0130	0.0275	0.0073	0.0180	0.0059
	0.9246	0.1248	0.6392	0.6750	0.8960	0.4032	0.8940	0.9052	0.1563	0.7482
Investor Fear in Global	-0.0006	-0.0282	-0.0079	0.0286	-0.0270	-0.0213	-0.0858	-0.0213	0.1736	-0.0166
	0.0240	0.0200	0.0104	0.0869	0.0229	0.0212	0.0454	0.0120	0.0300	0.0096
	0.9790	0.1579	0.4433	0.7420	0.2373	0.3153	0.0584	0.0763	0.0000	0.0847
Daily Positive Case of COVID-19 in Indonesia	0.4330	0.5895	0.3420	-0.0098	0.4386	0.0260	0.3305	0.3602	0.1951	0.0837
	0.0262	0.0224	0.0111	0.1100	0.0250	0.0221	0.0492	0.0132	0.0304	0.0102
	0.0000	0.0000	0.0000	0.9290	0.0000	0.2388	0.0000	0.0000	0.0000	0.0000

We use robust method for the analysis as there is a heteroskedasticity problem on the dataset. Reference [49] stated robust standard errors could be used as a corrector of heteroskedasticity when there is a heteroskedasticity issue. The first row on the regression results represents the coefficient, followed by the standard error and the P-value (z-test).

ISBN*: 978-623-92201-2-9*

V. Conclusion and Recommendation

A. Conclusion

Based on the research and analysis performed, we found evidence that investor fear in Indonesia cannot predict future volatility on all sectoral indices on the IDX during the COVID-19 pandemic. However, we found evidence that the global investor fear can predict the future volatility of the property sector on the IDX during the COVID-19 pandemic. Hence, there is evidence that the investor's negative sentiment or fear might also impact the stock market performance. Generally, the investor tends to shift their investment to a safer instrument during the uncertain period to minimize the potential loss that might occur.

Our research also found evidence that the daily volatility from intraday stock data could predict future volatility on almost all sectoral indices on the IDX during the COVID-19 pandemic, except for the finance sector. Furthermore, we also found evidence that the weekly volatility can also predict future volatility in the basic industry, consumer goods, infrastructure, mining, property, and trading sectors during the COVID-19 pandemic in Indonesia. Therefore, we found evidence that the historical stock market data gives the investor valuable insight in predicting the capital market volatility.

Furthermore, the daily positive case of COVID-19 in Indonesia can predict future volatility in some sectors on the IDX, such as agriculture, basic industry, consumer goods, infrastructure, miscellaneous, manufacture, property, and trading sectors. It is also concluded the current COVID-19 outbreak is also impacting Indonesia's capital market, where the increase of positive cases of COVID-19 is usually related to the Government action to restrict the people's movement and business operations that give operational uncertainty. The operational uncertainty and disruptions are subsequently affecting the capital market.

B. Recommendation

Recommendations that authors think might be considered in future research are analyzing the impact of COVID-19 on the capital market by using the blue-chip company (at the company's level) as the sample and also considering some fundamental factors. Because the sectoral analysis that includes some entities might have a different trading pattern. We also suggest that future research can compare the severity of the current crisis caused by the COVID-19 with the previous crisis globally, such as the Global Financial Crisis (GFC) or previous epidemic or pandemic. The comparison is expected to understand the severe impact caused by each crisis in the world and as an evaluation factor for the adequacy of the current crisis prevention plan in mitigating the potential crisis from time to time.

References

[1] John Hopkins University. (2021). *COVID-19 Dashboard by the Center for Systems Science and Engineering*. https://coronavirus.jhu.edu/map.html

[2] Mofijur, M., Fattah, I. M. R., Alam, M. A., Islam, A. B. M. S., Ong, H. C., Rahman, S. M. A., Najafi, G., Ahmed, S. F., Uddin, M. A., and Mahlia, T. M. I. (2021). Impact of COVID-19 on the social, economic, environmental and energy domains: Lessons learnt from a global pandemic. *Sustainable Production and Consumption*, 26(September 2020), 343–359. https://doi.org/10.1016/j.spc.2020.10.016

[3] Zhang, D., Hu, M., and Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 36(April). https://doi.org/10.1016/j.frl.2020.101528

[4] Liu, H.Y., Manzoor, A., Wang, C.Y., Zhang, L., and Manzoor, Z. (2020). The COVID-19 Outbreak and Affected Countries Stock Markets Response. *International Journal of Environment Research and Public Health*, 17, 2800.

[5] Izzeldin, M., Muradoglu, Y. G., Pappas, V., and Sivaprasad, S. (2021). The Impact of Covid-19 on G7 Stock Markets Volatility: Evidence from a ST-HAR Model. *International Review of Financial Analysis*, 74, 101671.

[6] Sherif, M. (2020). The Impact of Coronavirus (COVID-19) Outbreak on Faith-based Investments: An Original Analysis. *Journal of Behavioral and Experimental Finance*, 28, 100403.

[7] IDX. (2021). *IDX Monthly Statistics*. Retrieved March 17, 2021, from https://www.idx.co.id/media/9729/idx-monthly-february-2021.pdf

[8] Keogh-Brown, M. R., and Smith, R. D. (2008). The economic impact of SARS: How does the reality match the predictions? *Health Policy*, 88(1), 110–120. https://doi.org/10.1016/j.healthpol.2008.03.003

[9] Engelberg, J. E., and Parsons, C. A. (2011). The Causal Impact of Media in Financial Markets. *Journal of Finance*, 66(1), 67–97. https://doi.org/10.1111/j.1540-6261.2010.01626.x

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

[11] Baig, A. S., Butt, H. A., Haroon, O., and Rizvi, S. A. R. (2021). Death, Panic, Lockdowns and US Equity Markets: The Case of COVID-19 Pandemic. *Finance Research Letters*, 38, 101701

[12] Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7(2), 174–196. https://doi.org/10.1093/jjfinec/nbp001

[13] De Bondt, W., Muradoglu, G., Shefrin, H., and Staikouras, S. K. (2008) Behavioral finance: Quo vadis? *Journal of Applied Finance*, 18, 7-21.

[14] Rozeff, M. S., and Kinney, W. J. (1976). Capital Market Seasonality: The case of stock returns. *Journal of Financial Economics*, 3(4), 379 – 402.

[15] Mushinada, V. N. C. (2020). Are individual investors irrational or adaptive to market dynamics? *Journal of Behavioral and Experimental Finance*, 25. https://doi.org/10.1016/j.jbef.2019.100243

[16] Pompian, M. (2011). Behavioural Finance and Wealth Management: How to Build Optimal Portfolios That Account for Investor Biases (2nd ed.). New Jersey: Wiley Finance Publications.

[17] Keynes, J. M. (1967). The General Theory of Employment, Interest, and Money. London: McMillan.

[18] Prosad, J. M., Kapoor, S., and Sengupta, J. (2015). Theory of Behavioral Finance. In Z. Copur, (Ed.), *Behavioral Finance and Investment Strategies* (pp. 1-24). USA, IGI Global. DOI: 10.4018/978-1-4666-7484-4.ch001.

[19] Altman, M. (2012). Implications of Behavioural Economics for Financial Literacy and Public Policy. *Journal of Socio-Economics*, 41(5), 677–690. doi: 10.1016/j.socec.2012.06.002

[20] Kishore, R. (2006). Theory of Behavioural Finance and Its Application to Property Market: A Change in Paradigm. *Paper presented at the Twelfth Annual Pacific Rim Real Estate Society Conference*, Auckland, New Zealand.

[21] Kasemsap, K. (2015). The Role of Psychological Factors in Behavioral Finance. In Z. Copur, (Ed.), *Behavioral Finance and Investment Strategies* (pp. 94-115). USA, IGI Global. DOI: 10.4018/978-1-4666-7484-4.ch001.

[22] Sewell, M. (2008). Behavioural Finance. University of College London.

[23] Wright, W. F., and Bower, G. (1992). Mood Effects on Subjective Probability Assessment. *Organizational Behavior and Human Decision Processes*, 52, 2, 276-291. https://doi.org/10.1016/0749-5978(92)90039-A

[24] Petty, R. E., Gleicher, F., and Baker, S. M. (1991). Multiple Roles for Affect in Persuasion. *J. Forgas, (Ed.), Emotion and Social Judgments* (pp. 181-200). Oxford, Pergamon.

[25] Szyszka, A. (2013). Behavioral Finance and Capital Markets: How Psychology Influences Investors and Corporations. New York: Palgrave Macmillan. DOI: 10.1057/9781137366290.

[26] Loewenstein, G. (2003). Emotions in Economic Theory and Economic Behavior. *American Economic Review*, 90, 426-432.

[27] Ackert, L. F., and Deaves, R. (2010). Behavioral Finance: Psychology, Decision-Making and Markets (Vol. 4, Issue 3). South-Western Cengage Learning.

[28] Shefrin, H. (2002). *Beyond greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*. Oxford University Press. https://doi.org/10.5860/choice.37-5212

[29] Statman, M. (2019). *Behavioral finance. CFA Institute Research Foundation*. https://doi.org/10.1016/S0927-538X(03)00048-9

[30] Wu, Y., Han, L., and Yin, L. (2018). Our Currency, Your Attention: Contagion Spillovers of Investor Attention on Currency Returns. *Econ. Model, in press.*

[31] Dimpfl, T., and Jank, S. (2016). Can Internet Search Queries Help to Predict Stock Market Volatility? *Eur. Financial Manag*, 22 (2), pp. 171–192.

[32] Hamid, A., and Heiden, M. (2015). Forecasting Volatility with Empirical Similarity and Google Trends. J. *Econ. Behav. Organ*. 117, pp. 62–81.

[33] Kim, N., Lučivjanská, K., Molnár, P., and Villa, R. (2019). Google Searches and Stock Market Activity: Evidence from Norway. *Finance Research Letters*, 28, 208–220.

[34] Natenberg, S. (1994). Option Volatility and Pricing: Advanced Trading Strategies and Techniques. USA: McGraw-Hill.

[35] Fleming, Jeff, Kirby, C., and Ostdiek, B. (2001). The Economic Value of Volatility Timing. *Journal of Finance*, 56, 1.

[36] Dacorogna, M. M., Gençay, R., Müller, U. A., Olsen, R. B., and Pictet, O. V. (2001). An Introduction to High-Frequency Finance. *Academic Press*. https://doi.org/https://doi.org/10.1016/B978-0-12-279671-5.X5000-X

[37] Merton, R. C. (1980). On Estimating the Expected Return on the Market: An Exploratory Investigation. *Journal of Financial Economics*, 8, 323-361.

[38] Hilpisch, Y. J. (2017). *Listed Volatility and Variance Derivatives: A Python-Based Guide*. United Kingdom: John Wiley & Sons Ltd.

[39] Keene, A. (2013). Keene on the Market: Trade to Win Using Unusual Options Activity, Volatility, and Earnings. New Jersey: John Wiley & Sons

[40] Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics* (Vol. 61, Issue 1). https://doi.org/10.1016/S0304-405X(01)00055-1

[41] Andersen, T.G., Bollerslev, T., and Lange, S. (1999). Forecasting Financial Market Volatility: Sample Frequency vis-à-vis Forecast Horizon. *Journal of Empirical Finance*, 6(5), pp. 457-477. https://doi.org/10.1016/S0927-5398(99)00013-4

[42] Barndorff-Nielsen, O. E., and Shephard, N. (2002). Econometric Analysis of Realized Volatility and Its Use in Estimating Stochastic Volatility Models. *Journal of the Royal Statistical Society*, 64 (2), pp. 253-280

[43] Frijns, B. and Margaritis, D. (2008). Forecasting Daily Volatility with Intraday Data. *The European Journal of Finance*, 14, 6, 523-540, https://doi.org/10.1080/13518470802187644

[44] Ali, M., Alam, N., and Rizvi, S.A.R. (2020). Coronavirus (COVID-19) - An Epidemic or Pandemic for Financial Markets. *Journal of Behavioral and Experimental Finance*, 27, 100341.

[45] Goodell, J.W. (2020). COVID-19 and Finance: Agendas for Future Research. *Finance Research Letters*, 35, 101512

[46] Hayakawa, K., and Mukunoki, H. (2021). The Impact of COVID-19 on International Trade: Evidence from the First Shock. *Journal of the Japanese and International Economies*, 60, 101135.

[47] Da. Z., Engelberg. J., and Gao, P. (2011). In Search of Attention. *The Journal of Finance*, 66, 5, 1461-1499.

[48] Anh, D. L. T., and Gan, C. (2020). The Impact of the COVID-19 Lockdown on Stock Market Performance: Evidence from Vietnam. *Journal of Economic Studies*. https://doi.org/10.1108/JES-06-2020-0312

[49] Gujarati, D. N. (2011). *Econometrics by Example*. Basingstoke: Palgrave Macmillan. ISBN 978-0-230-29039-6.