CHAPTER III
Data and Methodology

3.1 Hypothesis Development

Based on the research objectives and research gaps identified from the background and literature review, this thesis the following hypotheses:

1. The US financial crisis rapidly spread to the rest of the world's economies due to the interconnectedness of international financial systems, and interconnectedness that is enhanced by the increased levels of market globalization. (Morales & Andreosso-O'callaghan, n.d.) used the Forbes and Rigobon (2002) the contagion approach and two other research methodologies; they also included an extra variable to measure for regional effects to investigate the existence of contagion in a broad sample consisting of the stock markets of 58 countries. The authors used the three different models to test for the contagion effects and found that two of their models showed little evidence of contagion effects from the US stock market affecting the countries under study (Kong et al., 2014). Using network analysis, (Zhang et al., 2020) analyzes the impact of COVID-19 on the stock markets of the ten countries with the most COVID-19 cases. The authors report that the European stock markets remain connected during this pandemic and the USA stock market failed to take the leading role before and during the outbreak (Aslam et al., 2020). The decline in the U.S stock market began in late 2007, which was quickly followed by declines in both the emerging and frontier markets. There exits important bi-directional, yet asymmetric, the interdependence and contagion between the U.S. and the emerging markets, with the important regional variations. The interdependence is driven more by the U.S. shocks than by the emerging market shocks, whereas the contagion is driven more by emerging market shocks than by the U.S. shocks. Another example is the work of (Bekaert et al., 2011) that analyzes the equity market transmission of the 2007-2009 GFC to country-industry equity portfolios in 55 countries. They find evidence of contagion from the US markets and the global financial sector, but the effects are economically small (Kenourgios & Dimitriou, 2014).

   From the explanation above, the hypotheses created

   Hypothesis 1 (H0) = DJIA significant effect on JKFINA

2. The Chinese stocks fell on Monday as the coronavirus infections and deaths spiked beyond mainland China, offsetting the assurances from Beijing that it would step up the policy adjustments to help cushion the blow to its epidemic-hit economy. At the midday break, the Shanghai Composite index edged down 0.3% to 3,029.22 points, while the blue-chip CSI300 index fell 0.5%. "the sentiment was hurt as the coronavirus outbreak spread outside China", said Linus Yip, the analyst with the First Shanghai Securities. The U.S. and China stock markets giving up some of their recent strong gains could also add pressure on the Hong Kong market[1].

[1]https://www.indopremier.com/ipotnews/newsDetail.php?jdl=China_stocks_fall_amid_fears_of_global_coronavirus_contagion&news_id=116166&group_news=IPOTNEWS&news_date=&taging_subtype=Emerging Market&name=&search=y_general&q=china stocks, shanghai composite, CSI300,&halaman=1

(Yang et al., 2003) used a vector autoregressive (VAR) approach to examine long-run and short-run the dynamic causal linkages among ten Asian emerging stock markets (Hong Kong, Singapore, Korea, Taiwan, India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand) and two the developed markets (Japan and the US). The comparative analyses of the pre-crisis, crisis and post-crisis periods were conducted by the authors to understand the market behavior during times of stability, turmoil, and recovery. The markets became significantly more responsive to innovations implemented in the Hong Kong market during the crisis. When the European financial markets started to show major losses after the Chinese stock market had crashed, the coverage for the crisis in China increased significantly in the Western media. The crisis in China was now being perceived as a potential threat to financial markets all over the world due to possible contagion[2][3].

From the explanation above, the hypotheses created

Hypothesis 2 (H0) = SSCE significant effect on JKFINA

3. The COVID-19 virus was first recorded in Europe and the Americas around late February 2020. The speed at which the virus spread across these continents rapidly increased through March. As more and more cases were diagnosed and the reality of lockdowns in the countries around the world set-in, the investors became wary about the unusual uncertainty surrounding the financial markets. The most remarkable event was a steep drop in March 2020, resulting from the investors aiming to protect their investments and therefore hastily sell-off their assets. This sell-off occurred concerning the more global spread of the virus and a large amount of uncertainty about the actual impact of the virus on our economies. All three indexes across the globe were similarly affected during this period of panic, where the S&P 500 and EURONEXT 100 index dropped by about 30% - 38%. It can also be seen that the HANG SENG index reacted to China's virus situation sooner than the other markets in late - January 2020. As the cases in China were contained, the HANG SENG's drop was relatively small, with a YTD low of 24% in March and a relatively flat continuation thereafter[4]. So far, the countries with the largest number of confirmed cases in the world include the People's Republic of China, Italy, South Korea, France, Spain, Germany, Japan, and the United States of America. The outbreak center has been gradually shifted from China to Europe and the USA (He et al., 2020). (Ashraf, 2020) finds that the stock market returns declined as the number of COVID-19 confirmed cases increased. On the Chinese stock market, (Al-Awadhi et al., 2020) confirm that the daily growth in the total confirmed cases and the total cases of death caused by the COVID-19 both have significant negative effects on the stock returns across all companies. (Zhang et al., 2020) measured the general pattern of country-specific risk and systematic risk across the world financial markets in the presence of COVID-19 outbreak fear. They documented that the global markets have become highly volatile and financial market risk has increased in response to the uncertainty of market conditions. In the case of the USA, they suggested that the non-conventional policy interventions (quantitative easing) could increase more problems for the economy.

[2] https://financialpost.com/investing/global-investor/markets-tumble-in-global-rout-after-china-plunge-halts-trading-minutes-after-opening/wcm/f8a7d0ba-b146-43e6-9376-85f847fa74f1
[3] https://financialpost.com/investing/global-investor/markets-tumble-in-global-rout-after-china-plunge-halts-trading-minutes-after-opening/wcm/f8a7d0ba-b146-43e6-9376-85f847fa74f1
[4] https://www.europeandataportal.eu/en/impact-studies/covid-19/thunder-financial-markets-retrospective-view

From the explanation above, the hypotheses created

Hypothesis 3 (H0) = USAC significant effect on JKFINA

Hypothesis 4 (H0) = CHINAAC significant effect on JKFINA

The order of the hypotheses between independent and dependent variables is illustrated as well.

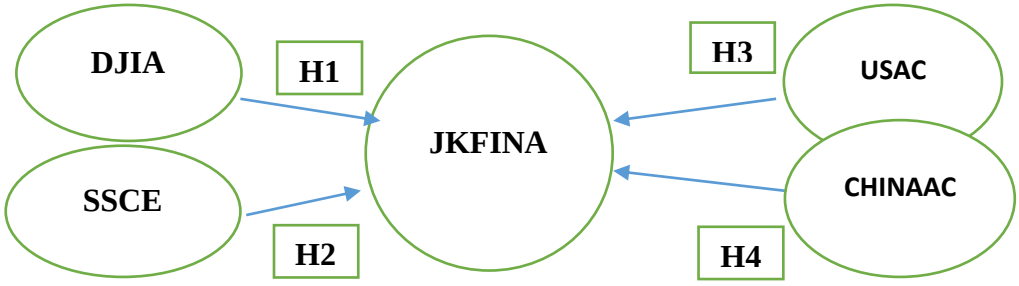

Figure 1 Hypothesis

This research is explanatory, using an econometric method (Koutsoyiannis, 1977; Intriligator et al., 1996; Desfiandi et al., 2019). The main purpose of explanatory research design is to allow the connection of thoughts to apprehend reason and effect. This thesis will explain how the covid-19 pandemic effects on the Financial Market Index of Indonesia on The Indonesia Stock Exchange during the coronaviruses pandemic. The variables of research are DJIA, SSCE, USAC, CHINAAC, JKFINA.

3.2 Empirical Model

This research uses Vector Autoregressive (VAR) model to analyze the contagion effect of the Covid-19 pandemic on The Financial Market Index on The Indonesia Stock Exchange during the coronaviruses pandemic. The VAR model in this research is then given by the following system of the equation:

$$JKFINA_{it} = \Sigma_{i=1}^{p}{}_{\alpha_1} DJIA_{it} + \Sigma_{i=1}^{p}\alpha_2\, SSCE_{it} + \Sigma_{i=1}^{p}\alpha_3\, USAC_{it} + \Sigma_{i=1}^{p}\alpha_4 CHINAAC_{it} + \varepsilon_{it} \quad \dots Eq\ (1)$$

The formulation above is VAR models used inside this Research. Where the period is denoted by the subscript t (t=1,…..,t); Country subscript i (i = 1,…..n); α_0 represents constant term; and i_t is the random error term. Daily data on stock market Index consists of DJIA, SSCE, Total Active Cases of United States (USAC) and Total Active Cases of China (CHINAAC), Financial Market stock of Indonesia (JKFINA).

3.3 Estimation Strategy

The estimation strategy used in this study are as follows:

Table 1 Estimation Strategy

No	Variable	Code	Unit	Time Series of Resp*
1	US Index	DJIA	Point	225 Days observation
2	China Index	SSCE	Point	225 Days observation
3	Finance Index Of Indonesia	JKFINA	Point	225 Days observation
4	Total Active Cases of Covid-19 in the US	USAC	Case	225 Days observation
5	Total Active Cases of Covid-19 in China	CHINAAC	Case	225 Days observation

Note : 01/January/2020 – 30/October/2020 (5 days reports)*

3.4 Data Collection

This study used daily data from January 1, 2020, to October 30, 2020, obtained from Yahoo Finance, Worldmeters web, and other websites supported this thesis to be well. The variables represented in the collected data are consist of the United States Stock Index (DJIA), Shanghai Stock Index (SSCE), The Number of Active Cases in the United States (USAC), The Number of Active Cases in China (CHINAAC), and The Financial Market Index (JKFINA) on The Indonesia Stock Exchange during the coronaviruses pandemic.

3.5 Data Processing

3.5.1 Unit Root Test

According to (WINARTO, 2011), before analyzing data, we must know in advance whether the time series data is stationary or not (Pranyoto, 2016). This test is part of the study the stationarity/non – stationarity test of variables. This test uses the Augmented Dickey-Fuller (ADF). The unit root test has purposes to test for the stationarity of the variables in a time series. The Augmented Dickey-Fuller test allows for the higher-order autoregressive processes by including $\Delta y_{t-p} \Delta y_{t-p}$ in the model. But our test is still if $\gamma=0\gamma=0$.

$$\Delta y_t=\alpha+\beta t+\gamma y_{t-1}+\delta 1\Delta y_{t-1}+\delta 2\Delta y_{t-2}+\ldots \quad \textit{Eq (2)}$$

The null hypothesis for both tests is that the data are non-stationary. The test wants to REJECT the null hypothesis for this test, so the test wants a p-value of less than 0.05 (or smaller)[5].

[5] (*5.3 Dickey-Fuller and Augmented Dickey-Fuller Tests | Applied Time Series Analysis for Fisheries and Environmental Sciences*, n.d.)

While the stationary test hypothesis is as follows:

$H_o = \emptyset = 1$ (There are root units or data not stationary)
$H_1 |\emptyset| =< 1$ (No root units or data not stationary)

H_o is rejected if the statistical value of the ADF test calculates less than the critical value of the ADF 5% table or the ADF probability value is less than the residual value of the output. If H_o rejected, then the data is stationary (Febrianti et al., 2020)

3.5.2 Lag Length Determination

Estimates using the vector autoregression (VAR) requires the variable of data to be in the stationary condition. Therefore, the variable data is stationary at the level of Difference, so the estimate is expected to produce a valid model output, so the researcher's' conclusions will have a high level of validity as well. The best model is the model that has the smallest Akaike Information Criterion (AIC) value. The criteria is formulated as follows (Febrianti et al., 2020)

$$\text{AIC (k)} = T \ln\left(\frac{SSR\ (k)}{t}\right) + 2n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textit{Eq (4)}$$

Whereas

T = Number of observations used
k = Lag length
SSR = Residual Sum of Square
n = Estimated number of parameters

3.5.3 Stability Test

To interpret the different results from the bivariate VAR (1) model, it is necessary to test its econometric robustness (Saïdane & Abdallah, n.d.). This thesis will apply the stability condition of the eigenvalue. The stability test is a requirement to continue on the next method namely is the Impulse Response Function (IRF) and the Variance Decomposition (VD)[6]. If the data is unstable then IRF and VD cannot be trusted, and vice versa.

3.5.4 Vector Autoregressive (VAR) Models

The vector autoregression (VAR) time series model is an econometric model used to capture the evolution and the inter-dependencies between multiple time series[7]. The VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. In addition to the data description and the forecasting, the VAR model is also used for structural inference and policy analysis. In the structural analysis, certain assumptions about the causal structure of the data under the investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with the impulse response functions

[6] Centia Sari, N., & Azhar Jurusan Ilmu Ekonomi Fakultas Ekonomi Universitas Negeri Padang Jl Hamka Air Tawar Padang, Z. (2019). Analisis Kausalitas Kriminalitas, Pendidikan Dan Kemiskinan Di Indonesia. In *Jurnal Kajian Ekonomi dan Pembangunan* (Vol. 1, Issue 2). https://doi.org/10.24036/JKEP.V1I2.6288

[7] https://towardsdatascience.com/vector-autoregressive-for-forecasting-time-series-a60e6f168c70

and the forecast error variance decompositions[8]. Vector Autoregression (VAR) is used to project a system of time series variables and aims to analyze the dynamic impact of interference factors contained in those variable systems. However, the inclusion of fixed effects presents an estimation challenge, which arises in any model that includes the lag of the dependent variable: the effect remains correlated with the repressor and, therefore, the usual difference in the mean procedure used to eliminate the fixed effects creates a coefficient of bias.

3.5.5 Causality Granger Test

This method is based on the Granger's Causality and Error Correction Model Causality estimates of a set of equations and provides the Pairwise Granger Causality Test for each variable in the time series data. In this test, the basis of decision making to look at the causal relationship on each variable can be known by looking at the probability value. The criterion is if the probability value is less than 5%, that is means there is a causal relationship.

The hypothesis and formulation of the Causality Granger Test as follows (Febrianti et al., 2020)

The following is the hypothesis of this test

H_0 : $\emptyset_{1p}$ or $y_{2p} = 0$ (variable 0 does not effect on the variable γ and vice versa)

H_0: $\emptyset_{1p}$ or $y_{2p} \neq 0$ (variable 0 does not affect the variable γ and vice versa)

The test statistics of this test as follows

$$F = \frac{(RSS_R - RSS_{UR})/p}{RSS_{UR}/(n-b)} \quad \text{..... Eq (5)}$$

RSS_R = Residual sum of square from conditional regression
RSS_{UR} = Residual sum of square from unconditional regression
p = Amount of Lag
n = Amount of Observation
b = Amount of parameters estimated on the model

3.5.6 Impulse Response Function

The structure of the Impulse Response Function is used to describe how the shock variables receive both from the variable itself and other variables. The IRF test also aims to see how long the shock a variable receives (Batubara & Nyoman Saskara, 2015). The IRF gives the interaction and the response between variables (Leshoro, 2020). The Impulse response functions show the effects of shocks on the adjustment path of the variables. The forecast error variance decompositions measure the contribution of each type of shock to the forecast error variance. Both the computations are useful in assessing how the shocks to economic variables reverberate through a system[9].

[8] https://faculty.washington.edu/ezivot/econ584/notes/varModels.pdf
[9] http://www.learneconometrics.com/class/5263/notes/gretl/Impulse responses and variance decompositions_gretl.pdf

3.5.7 Variance Decomposition (VD)

Variance decomposition is a classical statistical method in multivariate analysis for uncovering simplifying structures in a large set of variables (Lütkepohl, 2010). Variance Decomposition is one of the methods to see the dynamics of the system. Variance Decomposition decomposes the endogenous variables into the components of the shock for the endogenous variables in VAR. Variance Decomposition provides the IRF-based approach. Variance Decomposition separates the existing variants in endogenous variables into the shock components in the existing endogenous variables in VAR, which means the Variance Decomposition provides info about the significance of each variable shocks contained in VAR[10].

[10] http://lib.ui.ac.id/file?file=digital/119807-T 25359-Dampak fluktuasi-metodologi.pdf