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# Structural Analysis of the Prices of Selected Biodiesel Feedstocks

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**ABSTRACT**

**Purpose –** Biodiesel, a plant-based source, is found in oil crops such as. coconut, palm, and soybean. This paper examined the behavior and price relationships of three selected biodiesel feedstocks: coconut oil, palm oil, and soybean oil.
**Design/Methodology/Approach –** This study used monthly data for coconut oil, palm oil, and soybean oil prices from 2006 to 2020. Exploratory data analysis was implemented with time plots constructed and some descriptive statistics computed. The study performed structural analysis, namely, variance decomposition and impulse response analysis using the VAR (vector autoregressive) model to investigate the price relationships among the three biodiesel feedstocks.
**Findings –** It was found that coconut oil, palm oil, and soybean oil prices generally did not affect one another despite being close substitutes. This implies that these commodities do not compete with each other in terms of prices.
**Research Implications –** The findings can help understand price behavior given that these feedstocks are considered to be close substitutes and alternative sources to fossil fuel. Knowing the relationship between prices can contribute to policy development, which is parallel to the sustainable development goal (SDG) 7 that seeks affordable and clean energy sources. Lastly, this study initiates further research involving the bio-fuel industry worldwide since this is only focused on a few biodiesel feedstocks.

***Keywords:*** biodiesel, biofuel, price, structural analysis, vector autoregressive model
***JEL Classifications:*** E30, E64, L11

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## I. Introduction

With the continuous increase in sustainable energy demand and energy security, economic development, and climate change (Demafelis, Badayos, Movillon & Ranola, 2015), finding an appropriate and sustainable replacement for fossil fuels has been considered. This sustainable replacement or substitute for fossil fuel is called biodiesel, and it may come from feedstocks. Biodiesel feedstocks are categorized into edible-vegetable oil and non-edible vegetable oil. Edible vegetable oil consists of soybean, peanut, sunflower, palm oil, and coconut oil, while non-edible vegetable oil consists of rapeseed, jatropha, jojoba, and waste cooking oil. Based on these sources of biodiesel, it can serve as an appropriate alternate solution for diesel due to its renewable, non-toxic, and eco-friendly nature (Singh et al., 2020).

The use of biodiesel has lower exhaust emissions, and thus can help reduce pollution, improve health, and lessen the impacts of global warming. Biodiesel production and use at home also helps reduce the need for foreign oil, providing energy balance and security. Moreover, it is less toxic because biodiesel has a minimal environmental impact. When made from used oils and fats, biodiesel helps ensure proper recycling of former waste products (Biodiesel, 2021).

The benefits of biodiesel fuels drive its production. According to Demafelis et al. (2015), drivers are clustered according to energy security, economic development, and climate change. Energy security has been a universal concern, especially as there has been a continuous increase in sustainable energy demand. The potential risks to energy security are categorized according to: (1) fossil fuel scarcity or disruptions to fossil fuel supplies from international markets; (2) lack of investment in domestic national energy infrastructure; (3) technology and infrastructure failures, and; (4) industrial activism or terrorism. In 2007, the transport sector accounted for 27% of the total delivered energy consumption. About 53% of liquid fuel supplied was consumed by the transport sector, and this is predicted to rise to 61% in 2035. This has been underscored to significantly reduce fuel consumption, which is technically and economically impossible since vehicle engines are designed to utilize liquid fuel. Biofuels have been highlighted as an important potential contributor to address the energy crisis. The Energy Information Administration (EIA) (2017) emphasized that transport biofuels open up diversification possibilities for petroleum and represent a key source for such opportunities.

Moreover, the production of biodiesel fuel is vital as industries that produce fuel by coal mining and oil drilling exacerbate carbon emissions, which then further cause deterioration in the global environment. To avert this issue, renewable sources, such as biofuel, are being sought in order to reduce greenhouse gas (GHG) emissions, and at the same time, address energy security. Biodiesel fuels are considered carbon-neutral when burned since during combustion they release only the carbon dioxide (CO2) absorbed during the plant's growth. At present, there is available technology that will generate significant GHGs emission savings (Zeller & Grass, 2007).

Lastly, the production of biodiesel fuel can spur economic development, especially among developing and emerging nations. This can be achieved by providing incentives for stakeholders, specifically, farmers and processors. This can encourage participation in biofuel production.

## II. Literature Review

With the benefits of and increasing demand for biodiesel fuels, studies were conducted to examine prices as well as delve into how prices were affected by other factors or commodities. In a study by Irwin and Good (2017), the relationship between biodiesel and soybean oil prices were examined and it was observed that outside of the three spikes in 2011, 2013, and 2016, soybean oil and biodiesel prices at the plant appear to be highly correlated. Moreover, a scatterplot showed the correlation between the soybean oil and biodiesel prices outside of the spike years, and it was confirmed that soybean oil and biodiesel prices are indeed highly correlated outside of years when tax credits are set to expire (Irwin & Good, 2017).

Moreover, Taher (2020) investigated the effect of oil prices on food prices using worldwide monthly data covering crude oil prices, wheat, soybeans, and rice prices. The identification of the short-term causal relationship between oil and the selected commodity prices using a Vector-Autoregressive-Model (VAR) as the main model with its post-estimation methods including the impulse response function (IRF) was considered. The results showed that there was no long run relationship between the variables, but a significant causal short-term relationship between oil prices and wheat prices was confirmed. The impulse response results after a simulated shock on oil prices showed a mainly negative response for soybeans prices and a persistent increase in wheat prices. Moreover, for the rice price response, there was a slight increase in rice prices after the shock of oil prices.

In a study by Barbaglia, Croux and Wilms (2020), VAR was used to study volatility spillovers among a large number of energy, agriculture, and biofuel commodities. They found evidence of bidirectional volatility spillovers between energy and agricultural commodities, regardless of whether these were biofuel crops or not.

Wibawa, Syamsun and Arkeman (2012) conducted VAR analysis relative to biodiesel production and palm oil price in Indonesia. The authors found that palm biodiesel feedstock was promising. There was an increase in demand for crude palm oil. Consequently, a Granger causality test showed that the fluctuating production of biodiesel and crude palm oil have no relationship. The biodiesel production was not severely affected by price changes in crude palm oil (CPO) since most of the produced biodiesel was for the export market. Hence, biodiesel prices follow international prices. In addition, the study showed that CPO price movement in Indonesia was unaffected by biodiesel. Rather, it was affected by other economic factors. The study concluded that biodiesel production in Indonesia was relatively sustainable since it did not interrupt the local price and food supply.

Another study, this time by Maghyereh and Sweidan (2020) explored how structural shocks in the crude oil market affected biofuel prices. It was found that crude oil is linked to the gas, diesel, and renewable energy markets. The structural vector autoregressive (SVAR) model was used. The main findings revealed that long run fluctuations in the real prices of biofuels can be attributed to worldwide shocks in demand and shocks in the oil market. Consequently, shocks from oil have a negligible role. The three shocks combined can justify the 68% variation in real prices of biofuel. The aggregate demand shocks were the most significant contributor of about 35%, while 28% came from oil-specific demand shocks. This paper showed that the source of stability in the biofuel market is on the demand side. Henceforth, to stabilize the biofuel market, energy demand management is crucial.

Although several studies were conducted on the price behavior of some biodiesel feedstocks and how such prices were related to some commodities, there do not appear to be any study conducted on the relationship between the major biodiesel feedstocks produced by several countries, namely, the United States of America, the Philippines, Indonesia, and Malaysia. The major biodiesel feedstock produced by the US is soybean oil, while coconut oil is produced by the Philippines and Indonesia, and palm oil is produced by Malaysia (World Bank, 2021). Palm oil, together with its close substitutes of coconut oil and soybean oil, is known as an excellent source of biodiesel raw material due to its similar properties to regular petro-diesel (Zahan & Kano, 2018).

Given these major biodiesel feedstocks, this paper examined their price behavior and investigated their relationships. Specifically, the study aimed: (1) to examine the behavior of the prices of coconut oil, palm oil and soybean oil; (2) to quantify the amount of information each biodiesel feedstock price contributes to the prices of other biodiesel feedstocks; and (3) to examine the interactions between the prices of biodiesel feedstocks in the short run and long run periods.

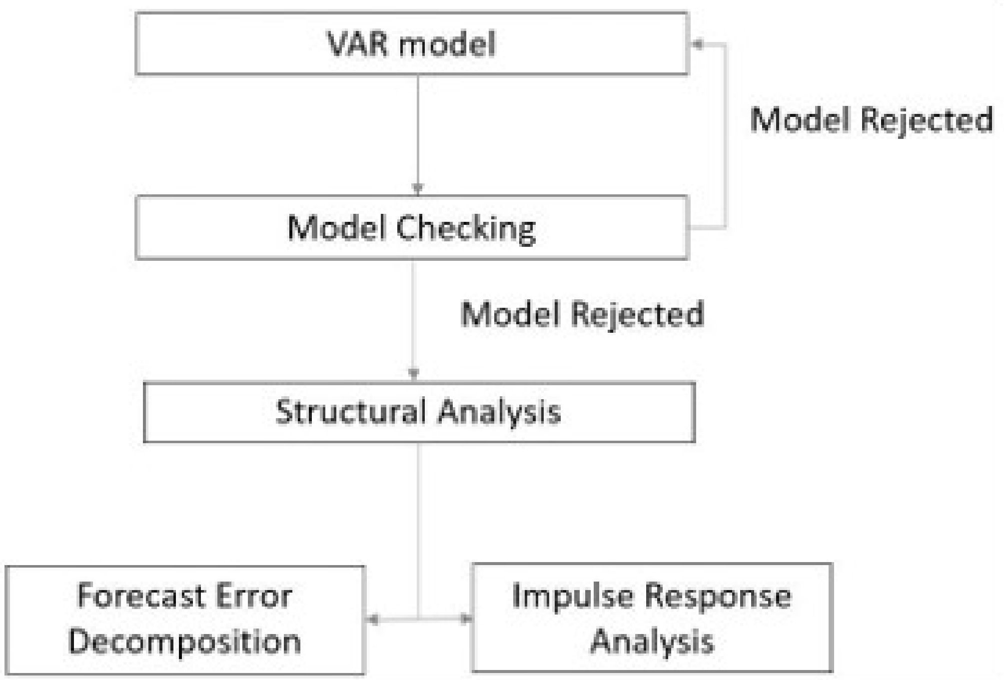
Such objectives were addressed using exploratory data analysis as well as a structural analysis based on a VAR model. Investigating the relationship among these prices of biodiesel feedstocks can help understand the behavior of the prices given that these feedstocks are considered close substitutes. Consequently, these feedstocks serve as alternative sources to fossil fuels, and at the same time, are used as food sources. In addition, knowing the relationship of the prices can contribute to policy development, which is parallel to sustainable development goal (SDG)7 that seeks affordable and clean energy sources.

## III. Methodology

Monthly price data (in US dollars) per metric ton of coconut, palm, and soybean oil from 2006–2020 from the World Bank were used. These variables were considered since these biodiesel feedstock prices were inherently related and are close substitute commodities.

The data sets were analyzed using EXCEL and EViews 11. Exploratory data analysis was implemented with time plots constructed and some descriptive statistics computed. Moreover, an Augmented Dickey Fuller (ADF) test was employed to check the presence of unit root (non-stationarity) in each of the data sets. To investigate relationships among variables, structural analysis was implemented as illustrated in Fig. 1 which shows that structural analysis follows an adequate Vector Autoregressive (VAR) model.

**Fig. 1.** Implementation of Structural Analysis




Source: Luetkepohl (2011).

A VAR expresses each variable as a linear function of its own lagged values, the lagged values of all other variables being considered, and a serially uncorrelated error term. The number of lagged values was determined by Akaike Information Criteria (AIC), Schwarz Bastian Information Criteria (BIC), or Hannan-Quinn Information Criteria (HQ). VAR models were constructed and checked for adequacy with the performance of diagnostic tests. These diagnostic tests were the MARCH VAR for homoscedasticity, LM VAR test for serial correlation, and the Jarque-Bera test for the normality of residuals.

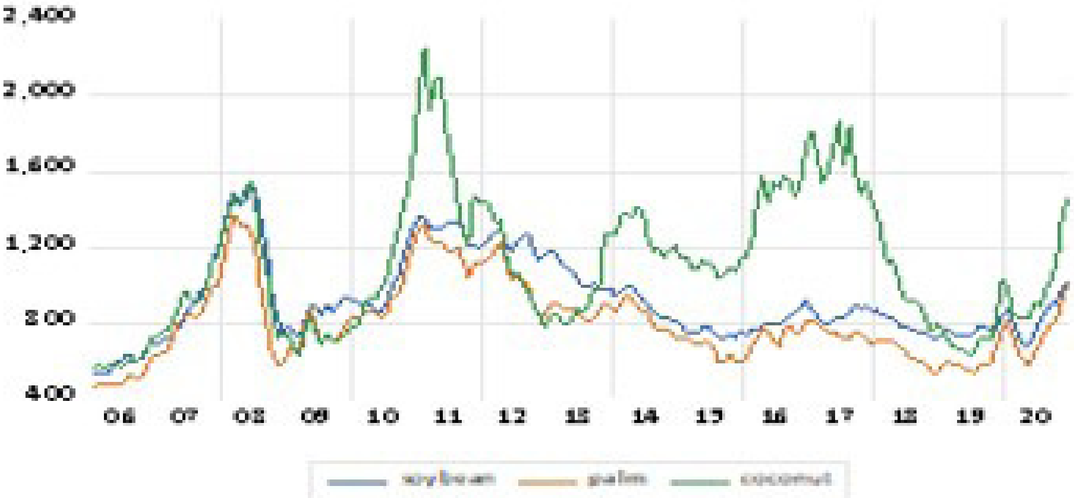
To finally investigate relationships between variables, structural modeling with forecast error variance decomposition and impulse response analysis were conducted. The forecast error variance decomposition was done to investigate the impacts of shocks in VAR models. It indicates how much of the variability in the dependent variable is explained by its own shocks compared with shocks in the independent variables. Thus, it can show which of the independent variables is stronger in explaining the variability in the dependent variable over time. It must be noted that a shock to a dependent variable not only directly affects that dependent variable, but is also transmitted to all independent variables through the dynamic (lag) structure of the VAR. With this, it is of concern to check the effect of a one unit shock in the independent variable on the dependent variable by tracing out the time path (which consists of current and future values) of the variables in the model to a one unit increase in the current value of one of the VAR errors.

## IV. Results and Discussion

### 1. Exploratory Data Analysis

Fig. 2 shows the behavior of the monthly prices of coconut oil, palm oil, and soybean oil as biodiesel commodities from 2006 to 2020. These biodiesel feedstocks are close substitutes of one another and have global importance on food vis-a-vis biofuel use. The behavior of the prices of both soybean and palm oil are generally the same. On the other hand, the price of coconut oil has a more unstable behavior compared to soybean and palm oil, although all prices have a cyclical behavior throughout the years. All oil prices have peaks in 2008, which was the same year when a global crisis gripped the world economy. However, the coconut oil price was highest in 2011, and again in 2017.

**Fig. 2.** Time Plot of the Monthly Prices of Coconut, Palm, and Soybean Oil (in US Dollars)




Source: World Bank (2006-2020).

Table 1 shows the descriptive measures of the three variables. Both palm and soybean oil prices have relatively the same minimum and maximum prices, and are much lower than coconut oil price, which ranges from US $569 to 2,256 per metric ton (MT). Consequently, the mean price of coconut oil is much higher and varies even more than that of palm and soybean oil.

**Table 1.** Descriptive Statistics of the Variables at Raw Time Series Variable (in Philippine Pesos Per Metric Ton)

| Summary Statistics | Coconut Oil | Palm Oil | Soybean Oil |
|---|---|---|---|
| Min | 569.00 | 459.05 | 533.27 |
| Max | 2256.00 | 1377.22 | 1535.16 |
| Mean | 1109.27 | 808.58 | 926.54 |
| Std. Dev. | 365.82 | 210.42 | 221.52 |

Source: Authors' estimation from World Bank (2006-2020).

These raw variables were the natural log transformed (ln) to have a better interpretation of the VAR model.

## 2. Augmented Dickey Fuller (ADF) Test

Table 2 presents the results of unit root with break test using ADF at level. These results show that the prices of coconut (ln_coconut), palm (ln_palm), and soybean (ln_soybean) oil are stationary at level since the corresponding p-values of the ADF test statistic are less than 5%. The results indicate that the order of integration of all variables are I (0). Thus, the VAR approach can be used in modeling these variables.

**Table 2.** Unit Root Result at Level

| Variable | ADF Test Statistic | p-value | Conclusion |
|---|---|---|---|
| Ln_coconut | -3.9174 | 0.0247 | Stationary |
| Ln_palm | -3.7874 | 0.0406 | Stationary |
| Ln_soybean | -2.9433 | 0.0424 | Stationary |

Source: Authors' estimation from World Bank (2006–2020).

## 3. Lag Order

The optimal lag-length of the lagged differences of the tested variable is determined by minimizing the Akaike Information Criteria (AIC), Schwarz Bastian Information Criteria (BIC), and the Hannan-Quinn Information Criteria (HQ). All criteria select a VAR (2) model as shown in Table 3. Thus, the joint optimum lag length of order two was considered (indicated with an asterisk * in the table below).

**Table 3.** VAR Lag Order Selection by Different Selection Criteria

| lag | AIC | BIC | HQ |
|---|---|---|---|
| 1 | -2.4612 | -2.4062 | -2.4388 |
| 2 | -9.6739* | -9.4544* | -9.5849* |
| 3 | -9.9064 | -9.5221 | -9.7505 |

Source: Authors' estimation from World Bank (2006-2020).

## 4. Diagnostic Test

Once a VAR-model is estimated, it is necessary to check whether the residuals satisfy the model's assumptions. Results in Table 4 indicate the non-rejection of the null hypothesis of no serial correlation in the case of the LM test, no heteroscedasticity in the case of the MARCH test, and residuals are multivariate normal at a 5% level of significance.

**Table 4.** Diagnostic Test of VAR (2)

| Test | Test Statistic | p-value | Conclusion |
|---|---|---|---|
| MARCH VAR | 80.28 | 0.2356 | No Heteroscedasticity |
| JB_VAR | 3.97 | 0.6801 | Normality |
| LM_VAR (at lag 1) | 0.62 | 0.7778 | No Serial Correlation |

Source: Authors' estimation from World Bank (2006-2020).

Thus, the results confirm that the model is adequate and has the desired econometric properties, i.e., it has correct functional form, its residuals are serially uncorrelated, homoscedastic, and the multivariate is normal.

## 5. Variance Decomposition

Table 5 shows the results of the variance decomposition analysis on coconut oil price. It is shown that about 99.5% of the variations in coconut prices are explained by shocks to coconut oil prices in the short run. Also, a high percentage is still observed in the long run since about 93.4% of variations are explained by coconut oil prices. On the other hand, around 3.2% and 3.5% of the variations in coconut price are explained by palm oil and soybean oil prices, respectively. This indicates that the impacts of palm and soybean oil on coconut oil are relatively small.

**Table 5.** Variance Decomposition Analysis on Coconut Oil Price

| Period | Standard Error | ln_Coconut | ln_Palm | ln_Soybean |
|---|---|---|---|---|
| 1 | 0.08 | 100.00 | 0.00 | 0.00 |
| 2 | 0.12 | 99.50 | 0.44 | 0.06 |
| 3 | 0.16 | 98.65 | 1.06 | 0.29 |
| 4 | 0.19 | 97.68 | 1.65 | 0.67 |
| 5 | 0.21 | 96.71 | 2.15 | 1.15 |
| 6 | 0.23 | 95.82 | 2.53 | 1.65 |
| 7 | 0.24 | 95.04 | 2.80 | 2.15 |
| 8 | 0.26 | 94.38 | 2.99 | 2.63 |
| 9 | 0.27 | 93.83 | 3.11 | 3.06 |
| 10 | 0.28 | 93.38 | 3.17 | 3.46 |

Moreover, Table 6 shows that almost the same percentages of the variations in palm oil prices are explained by shocks to palm oil prices and coconut oil prices in both the short-run and the long-run. That is, around 49% of the variations in palm oil prices are explained by coconut oil prices in Period 2 and Period 10, and around 51% of the variations in palm oil price are explained by palm oil price in Period 2 and Period 10. A relatively low percentage of the variations of palm oil prices are explained by soybean oil prices in both the short-run and long-run.

**Table 6.** Variance Decomposition Analysis on Palm Oil Price

| Period | Standard Error | ln_Coconut | ln_Palm | ln_Soybean |
|---|---|---|---|---|
| 1 | 0.06 | 43.23 | 56.77 | 0.00 |
| 2 | 0.10 | 49.04 | 50.89 | 0.08 |
| 3 | 0.13 | 51.00 | 48.86 | 0.14 |
| 4 | 0.15 | 51.52 | 48.32 | 0.16 |
| 5 | 0.17 | 51.42 | 48.42 | 0.16 |
| 6 | 0.19 | 51.03 | 48.82 | 0.15 |
| 7 | 0.20 | 50.51 | 49.36 | 0.14 |
| 8 | 0.21 | 49.91 | 49.96 | 0.13 |
| 9 | 0.21 | 49.31 | 50.57 | 0.12 |
| 10 | 0.22 | 48.71 | 51.16 | 0.12 |

Table 7 shows that around 64% (i.e., the sum of 32.23% and 32.13%) of the variations in soybean oil prices in the short-run are explained by both coconut and palm oil prices, while around 49% and 38% of the variations are caused by palm oil and coconut oil prices in the long-run, respectively

**Table 7.** Variance Decomposition Analysis on Soybean Oil Price

| Period | Standard Error | ln_Coconut | ln_Palm | ln_Soybean |
|---|---|---|---|---|
| 1 | 0.04 | 27.66 | 29.57 | 42.77 |
| 2 | 0.07 | 32.23 | 32.13 | 35.64 |
| 3 | 0.09 | 35.23 | 35.33 | 29.44 |
| 4 | 0.11 | 37.21 | 38.39 | 24.40 |
| 5 | 0.13 | 38.41 | 41.04 | 20.55 |
| 6 | 0.14 | 39.03 | 43.29 | 17.69 |
| 7 | 0.16 | 39.23 | 45.18 | 15.59 |
| 8 | 0.17 | 39.14 | 46.79 | 14.06 |
| 9 | 0.17 | 38.87 | 48.20 | 12.94 |
| 10 | 0.18 | 38.47 | 49.43 | 12.11 |

**Fig. 3.** Response of Ln_Palm and Ln_Soybean to Ln_Coconut

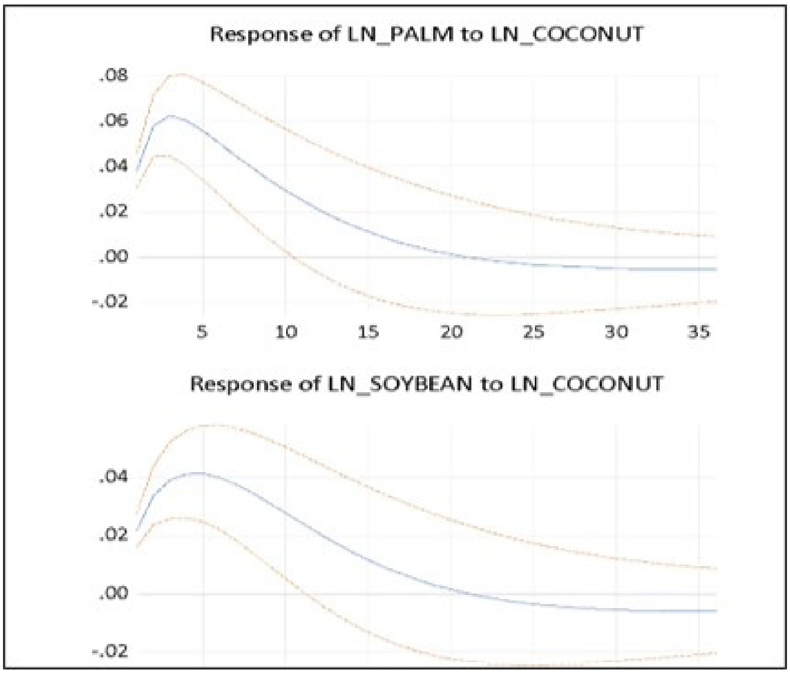
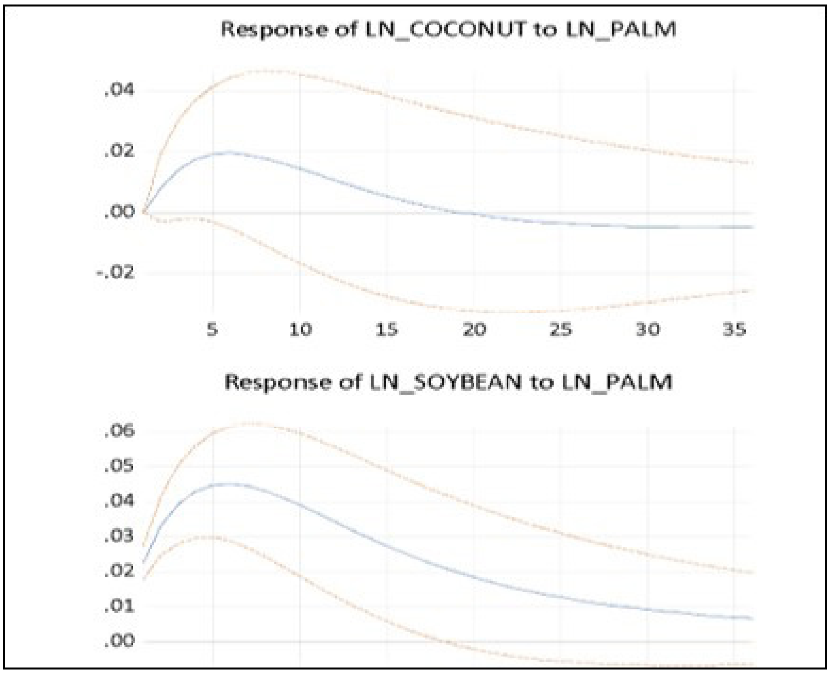



**Fig. 4.** Response of Ln_Coconut and Ln_Soybean to Ln_Palm



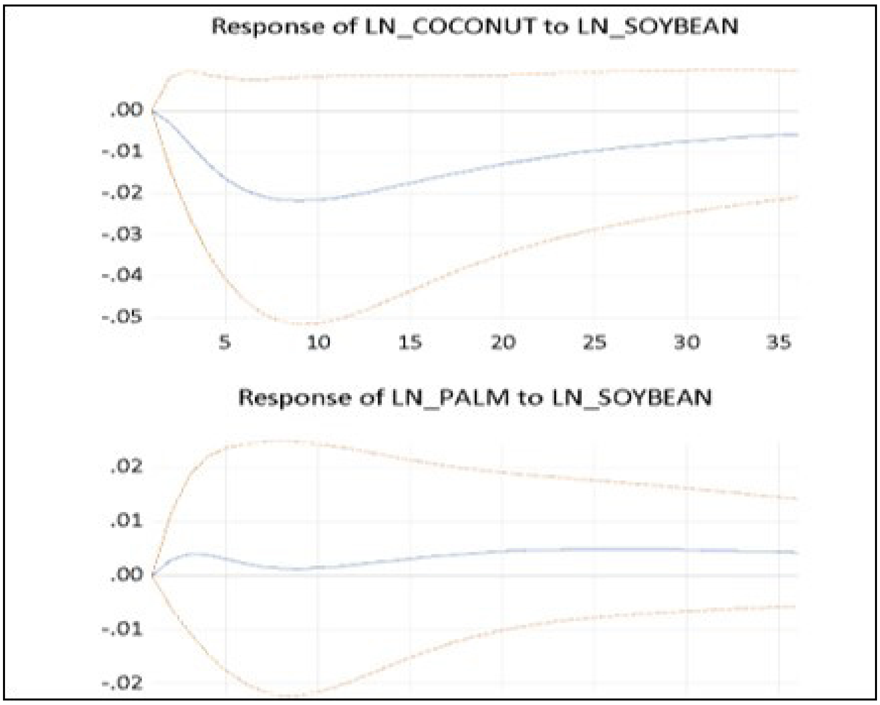
## 6. Impulse Response Analysis

Fig. 3 shows the result of the impulse response analysis with the responses of the natural logarithm of palm (ln_palm) and natural logarithm of soybean oil (ln_soybean) prices in the one standard deviation shock on the natural logarithm coconut oil price (ln_coconut). A one standard deviation shock to ln_coconut initially has an increasing impact on ln_palm and ln_soybean prices in the first three periods or months. The response gradually declines, however, until sometime in Period 24, or the second year, and hits a steady value state from Period 25 onwards. These responses are almost the same as ln_soybean. In general, after an increase in the price of coconut oil, there was an increase in palm and soybean oil price in the short run, but this eventually did not support the increase in the long run. This validates the assumption that coconut oil as biodiesel feedstock is a close substitute to palm oil and soybean oil in the short-run term.

Fig. 4 shows that a one standard deviation shock to ln_palm initially increases ln_coconut and soybean oil price until the seventh month. However, the responses gradually decline until sometime in the 24th month, and becomes stable in the succeeding periods. Thus, shocks to ln_palm did not generally affect coconut and soybean oil prices in the long run.

Fig. 5 shows that a one standard deviation shock to ln_soybean initially decreases ln_coconut until the seventh month and remains negative throughout all periods, although this became stable after 24 months. On the other hand, a one standard deviation shock to ln_soybean generally had a stable impact on ln_palm, indicating that the price of palm oil was not affected by the increase or decrease in the price of soybean oil regardless of whether it is the short-run or long-run period.

**Fig. 5.** Response of Ln_Coconut and Ln_Palm to Ln_Soybean



## V. Conclusion and Recommendation

Structural analysis with a VAR (2) model was performed to examine the behavior and relationships between a few biodiesel feedstock commodities. Coconut oil, palm oil, and soybean oil prices generally did not affect one another, despite being close substitutes. This was confirmed in the results of variance decomposition and impulse response analysis. This implies that these commodities do not compete with each other in terms of prices for food and fuel use. Study results also confirmed that the goal of utilizing biofuel as an additive or complementary product to fuel and as a replacement was validated. Lastly, this study initiates the effort towards further research involving the biofuel industry worldwide since only this study focused on a few biodiesel feedstock.

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# Credit Risk Measurement Study of Commercial Banks Based on the Innovation Discrete Hopfield Neural Network Model*

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## ABSTRACT

**Purpose –** Credit risk is always the major risk in the banking industry, and the main target of regulatory authorities. Based on modern financial theory and new credit instruments, modern risk measurement models have played a great role in the measurement of credit risk. However, most of these models assume normal distribution, which will lead to a deviation between the analysis results and the actual distribution of credit risk, cause the "thick tail" phenomenon, and reduce the accuracy of measurement results. In this context, the development of modern information technology makes it possible to introduce artificial intelligence technology into credit risk measurement, such as an artificial neural network, decision tree, genetic programming, and support vector machine.
**Design/Methodology/Approach –** Firstly, we use the commonly used an expert survey method and the research results and experience of previous scholars for reference to realize the transformation of regulatory indicators from qualitative to quantitative. Then, a credit risk measurement model based on the Hopfield network was constructed in order to evaluate credit risk. Finally, the simulation experiment was carried out using real data from a commercial bank.
**Findings –** The results show that a credit risk measurement model based on Hopfield neural network can accurately reflect the credit risk state of banking institutions. This shows that the credit risk measurement model proposed in this paper not only has the function of supporting decision-making for commercial bank managers, it is also an effective way for financial regulators to grasp the risk change trend in time.
**Research Implications –** A credit risk measurement model of commercial banks based on a discrete Hopfield neural network is proposed. Because an artificial neural network has the advantages of strong "robustness", high prediction accuracy, and is unstructured, this paper uses the associative memory function of DHNN to construct a credit risk measurement model based on a discrete Hopfield neural network. Simulation results show that the model can accurately reflect the credit risk status of banks.

***Keywords:*** commercial bank, credit risk, discrete hopfield neural network
***JEL Classifications:*** G14, G21

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## I. Introducton

Credit risk has always been the most important form of risk in the banking industry, and perhaps even the entire financial industry. It is the main object and core content of prevention and control by financial institutions and regulators (Nickell & Thomas, 1997). Credit risk and control from bank credit businesses have always been the most concerning and thorny problem for commercial banks (Twala, 2010). With the continuous development of the international financial market, especially with the U.S. subprime mortgage crisis in 2008, the asset quality of China's commercial banks deteriorated, the proportion of non-performing loans was high, the credit risk exposure of state-owned commercial banks was not sufficient, and the risks faced by state-owned commercial banks tended to increase (Rosenberg & Schuermann, 2006). In the course of operation, the capital adequacy ratio has decreased, and the anti-risk ability of banks has decreased. The risk of supply interruption under a condition of zero down payment or false down payment occurs frequently. The percentage of individual housing loans is generally high (Hopfield, 1984). After China's accession to the WTO, with the deepening of reform and opening, domestic commercial banks are impacted by more international and domestic factors, and bear more internal and external risks. The prominent credit risk problems of China's commercial banks will increase the operational risk of commercial banks and affect the stable development of China's economy and finance (Kaslik & Sivasundaram, 2011). In addition, there are some defects in the credit risk management system of state-owned commercial banks; the phenomenon of financial repression has been accompanied by the reality of China's economic life for a long time (Wang, Cai, & Yin, 2011). To win in increasingly fierce market competition, strengthening comprehensive credit risk prevention has become an urgent task (Liu, Liu, & Huang, 2014). Therefore, research on credit risk prevention strategies for China's commercial banks has both theoretical value and practical significance. On the basis of discussing relevant theories of credit risk management, this study makes an in-depth study on how to accurately measure credit risk according to the current situation of credit management of commercial banks in China.

In recent years, modern risk measurement models, based on modern financial theory and new credit instruments, have played a great role in the measurement of credit risk (Chen & Aihara, 1995). However, most of these models assume normal distribution, which will cause a deviation between the analysis results and the actual distribution of credit risk, lead to the "thick tail" phenomenon, and reduce the accuracy of measurement results (Hugher, Berg, Coben, & Martin, 1982). In this context, the development of modern information technology makes it possible to introduce artificial intelligence technology into credit risk measurement, such as an artificial neural network, decision tree, genetic programming, and support vector machine The characteristics of high prediction accuracy and being unstructured have become the focus of this research field (Liu & Zhang, 2012). Therefore, considering the complexity of the commercial banking system, this paper attempts to use a discrete Hopfield neural network as an intelligent technology to evaluate the credit risk of commercial banks.

## II. Discrete Hopfield Neural Network Method

A Hopfield Neural Network is a fully connected neural network, and for each memory element, the output signal is fed back by other neurons. A Hopfield Neural Network is also called a feedback neural network.

By using binary neurons in a Discrete Hopfield Neural Network, an output value of 1 or -1 usually indicates the active or inhibitory status of a neuron. DHNN can be regarded as a single layer, binary value, and feedback network.

### 1. Disign Principles of Associative Memory

If certain conditions are met, DHNN will converge to a stable point (attractors). The initial state area is known as the domain of attraction. Considering all stable attractors as a set of memory modes, and the initial state as a guide mode, then the network convergence progress can be seen as a recall progress. Therefore, the problem of how to design a network according to a recall mode can be changed to determine the value of $W$ and $\theta$.

The key to achieve associative memory with DHNN is to make the memory mode sample correspond to the local minimum of the energy function of the network. This article will use the outer product method to design the associative memory.

**Definition 1**.

Let $X^k = [x_1^k, x_2^k, \cdots, x_n^k]^T$ *(k=1,2, ⋯, m)* is $m$ $n$-dimensional vectors, where each value will be $\pm 1$, (i.e. $x_i^k = \pm 1, i = 1,2,\cdots,n$ ), and $I$ is an $n \times n$ unit matrix. Then, the matrix below will be a matrix of the sum of the outer product :

$$\mathbf{W} = \sum_{k=1}^{m} [\mathbf{X^k}(\mathbf{X^k})^T - \mathbf{I}] \tag{1}$$

By expanding the equation above:

$$\mathbf{W} = \sum_{k=1}^{m} \begin{bmatrix} x_1^k \\ x_2^k \\ \vdots \\ x_n^k \end{bmatrix} \begin{bmatrix} x_1^k & x_2^k & \cdots & x_n^k \end{bmatrix} - m\mathbf{I}$$

$$= \begin{bmatrix} \sum_{k=1}^{m}(x_1^k)^2 & \sum_{k=1}^{m}x_1^k x_2^k & \cdots & \sum_{k=1}^{m}x_1^k x_n^k \\ \sum_{k=1}^{m}x_2^k x_1^k & \sum_{k=1}^{m}(x_2^k)^2 & \cdots & \sum_{k=1}^{m}x_2^k x_n^k \\ \vdots & \vdots & & \vdots \\ \sum_{k=1}^{m}x_n^k x_1^k & \sum_{k=1}^{m}x_n^k x_2^k & \cdots & \sum_{k=1}^{m}(x_n^k)^2 \end{bmatrix} - m \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$

Since $\sum_{k=1}^{m}(x_1^k)^2 = \sum_{k=1}^{m}(x_2^k)^2 = \cdots = \sum_{k=1}^{m}(x_n^k)^2 = m$,

$$\boldsymbol{W} = \begin{bmatrix} 0 & \sum_{k=1}^{m}x_1^k x_2^k & \cdots & \sum_{k=1}^{m}x_1^k x_n^k \\ \sum_{k=1}^{m}x_2^k x_1^k & 0 & \cdots & \sum_{k=1}^{m}x_2^k x_n^k \\ \vdots & \vdots & & \vdots \\ \sum_{k=1}^{m}x_n^k x_1^k & \sum_{k=1}^{m}x_n^k x_2^k & \cdots & 0 \end{bmatrix} \tag{2}$$

Obviously, the matrix of the outer product sum defined by equation (1) meets the requirement of $w_j = w_j, w_i = 0(i, j = 1,2,\cdots, = n)$。 Each value of W can be indicated by

$$w_{ij} = \sum_{k=1}^{m} x_i^k x_j^k \tag{3}$$

Therefore, if $X^k (k = 1,2,\cdots,m)$ is an $m$ $n$-dimension memory mode of DHNN, then the connection weights defined by the outer product sum are applicable to Hebb learning rules.

From the above analysis, we can conclude the steps of designing a Discrete Hopfield Model using the outer product method.

Step 1: Given the samples that the model needs to learn, $X^k = [x_1^k, x_2^k, \cdots, x_n^k]^T$ we use equation (1) to build a weight parameters matrix.

Step 2: Let the test sample $p_j (j = 1,2,\cdots,n)$ be the original value of net output $y_j(0) = p_j (j = 1,2,\cdots,n)$ and set the iteration number.

Step 3: Conducting iterative calculation using equation (4).

$$y_j(k+1) = f(\sum_{i=1}^{n} w_{ij} x_i(t)) \tag{4}$$

Step 4: The iterative calculation will end when the iteration number reaches the maximum, or the output of neurons remain unchanged. Otherwise, return to step 3 and repeat the process.

## 2. The Memory Size of Discrete Hopfield Network

The number of stable points of DHNN is a measure of network memory, meaning the total memory size. For outer product design, if the inputs of samples are orthogonal, then the network, which embraces n neurons, will have a maximum memory size of n. In most cases, learning samples are not orthogonal; therefore, memory size will be much smaller than n. For outer product design, this paper chose the estimate formula given by Robert McEliece:

$$K \le \frac{n}{2\lg n} \tag{5}$$

Where n dedicates the number of neurons in the network.

## III. Empirical Analysis of the Credit Risk Measurement of Commercial Banks in China

Credit risk is always the major risk in the banking industry, and the main target of regulatory authorities. Credit risk not only restricts the development of commercial banks themselves, it also has a great impact on financial and economic stability at the same time. How to measure and control the credit risk of commercial banks has always been a concern. Currently, there are many ways to assess the credit risk of commercial banks. However, these methods have a number of drawbacks, such as being tedious, time lags, and subjective factors that have a great impact on the evaluation. The main purpose of this study is to discern how to assess the credit risk of commercial banks faster and more accurately with objective and impartial results.

To solve this problem, we first learn from the expert investigation method, as well as previous research results and experience, to convert regulatory indicators from qualitative into quantitative. Then, we build a DHNN model to measure credit risk. Last, we use real commercial bank data in China to test the accuracy of the model in order to support the decision making of relevant authorities.

### 1. Credit Risk Regulatory Index System

In this paper, the commercial bank credit risk regulatory index system consists of eight metrics, which are based on the principle of prudential indicators of specific financial institutions, as well as a set of comprehensive evaluation index systems and the previous credit risk analysis of influencing factors. The eight metrics are below.

**Table 1.** Supervision Index System of Credit Risk

| Indexes | Formula | Threshold Value |
|---|---|---|
| NPL Ratio (G1) | non-performing loans / total loans×100% | ≤15% |
| Subprime Loan Ratio (G2) | subprime loans/ total loans×100% | ≤8% |
| Doubtful Loan Ratio (G3) | doubtful loans / total loans×100% | ≤5% |
| Loss Loan Ratio (G4) | loss loans/ total loans×100% | ≤2% |
| Loan Interest Owed Ratio (G5) | Current interest receivable / interest income accrued during the period×100% | ≤20% |
| Rate of Loan Extension (G6) | Revolving loan balance / total capital×100% | ≤30% |
| The Same Loan Customer Loans Ratio (G7) | The balance of the loans to the same customer / total capital×100% | ≤10% |
| Largest Ten Customers Ratio (G8) | Largest ten customers loans / total capital×100% | ≤50% |

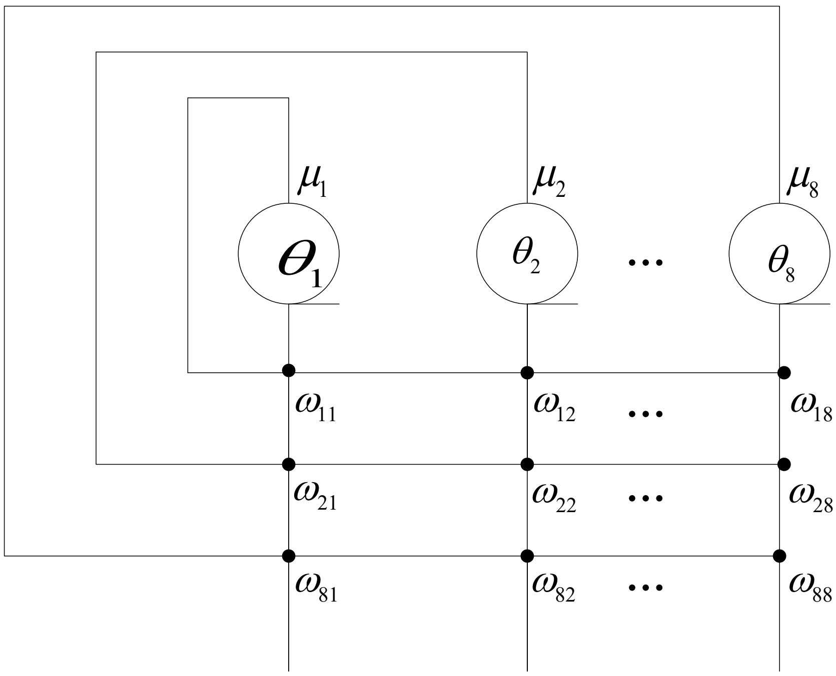
## 2. The Innovation DHNN Measurement Model

### 2.1. Modeling Steps

According to the previous overview of discrete Hopfield network theories, the model is designed with several regulatory index combinations, which correspond to several typical credit risk rating states, designed as stable points in the Hopfield neural network. Then, the DHNN learning process is a gradual approach process from regulatory index combinations to the stable points. After the learning process, typical regulatory index combinations are saved in the stable points of the DHNN. When the unknown regulatory indexes input the model, DHNN will conduct the gradual approach process to reach a stable point. When it is done, the stable point that DHNN reached is the credit risk status that we want to evaluate.

Using DHNN to measure credit risk is actually using its associative memory process. According to the previous introduction of DHNN, we built eight neurons. The network topology is below.

**Fig. 1.** Hopfield Network Structure of Credit Risk Measurement Models



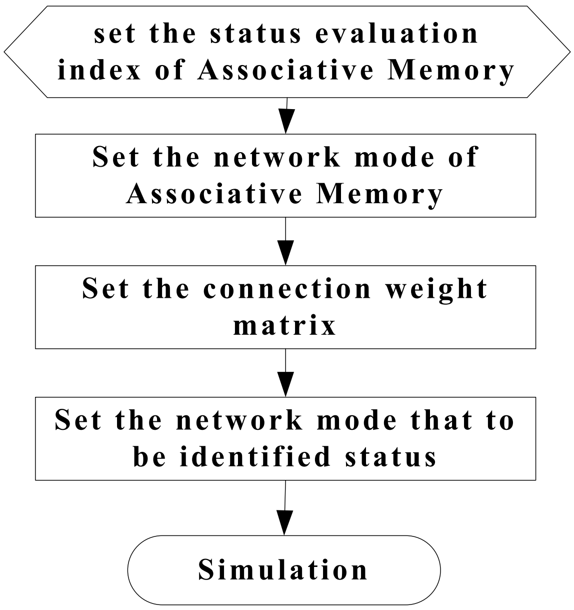

Using equation (5), we can calculate that the memory size is five. According to credit assets risk classification standards, we built five statuses for credit risk.

**Table 2.** Credit Risk State Level Table

| Risk status | Good | Security | General | Danger | Crisis |
|---|---|---|---|---|---|
| Risk level | I | II | III | IV | V |

The values of these 8 neurons are different, so we can indicate the risk levels of credit as different network models. According to different regulatory authorities, we used an expert investigation method for analysis of the 8 indexes that reflect credit risk item by item, and derived 8 different risk levels.

**Fig. 2.** Modeling Steps of Credit Risk Measurement Models




**2.2. Status Level Index of Memory**

According to credit regulatory indicators under the threshold value, as well as the guidance measures published by the central bank regulatory authorities, we divided the evaluation indicators into five levels according to the different threshold ranges.

**Table 3.** Scoring of the Index System of Credit Risk Supervision

| Indexes | Score | Threshold Value Range (%) | Warning Value | Indexes | Score | Threshold Value Range (%) | Warning Value |
|---|---|---|---|---|---|---|---|
| NPL Ratio (G1) | 5 | 0--8 | ≥15% | Loan Interest Owed Ratio (G5) | 5 | 0--10 | ≤20% |
| | 4 | 8--10 | | | 4 | 10--15 | |
| | 3 | 10--15 | | | 3 | 15--20 | |
| | 2 | 15--20 | | | 2 | 20--30 | |
| | 1 | 20--100 | | | 1 | 30--100 | |
| Subprime Loan Ratio (G2) | 5 | 0--5 | ≤8% | Rate of Loan Extension (G6) | 5 | 0--10 | ≤30% |
| | 4 | 5--8 | | | 4 | 10--20 | |
| | 3 | 8--10 | | | 3 | 20--30 | |
| | 2 | 10--15 | | | 2 | 30--40 | |
| | 1 | 15-100 | | | 1 | 40--100 | |
| Doubtful Loan Ratio (G3) | 5 | 0--3 | ≤5% | Same Loan Customer Loans Ratio(G7) | 5 | 0--5 | ≤10% |
| | 4 | 3--5 | | | 4 | 5--10 | |
| | 3 | 5--8 | | | 3 | 10--15 | |
| | 2 | 8--12 | | | 2 | 15--25 | |
| | 1 | 12--100 | | | 1 | 25--100 | |
| Loss Loan Ratio (G4) | 5 | 0--1 | ≤2% | Largest Ten Customers Ratio (G8) | 5 | 0--25 | ≤50% |
| | 4 | 1--2 | | | 4 | 25--40 | |
| | 3 | 2--3 | | | 3 | 40--50 | |
| | 2 | 3--5 | | | 2 | 50--70 | |
| | 1 | 5--100 | | | 1 | 70--100 | |

We took the credit data of ten commercial banks from 2014 as the learning sample. According to Table 3.3 above, and previous literature research, we found the relationship between the credit risk status of 14 commercial banks and 8 regulatory indicators, where the risk levels are given by credit rating agencies.

**Table 4.** Ten Commercial Banks' States of Credit Risk and Corresponding Regulatory

| Index | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | Rank |
|---|---|---|---|---|---|---|---|---|---|
| Bank 1 | 4 | 5 | 5 | 5 | 4 | 5 | 5 | 4 | I |
| Bank 2 | 5 | 5 | 4 | 5 | 5 | 5 | 5 | 5 | I |
| Bank 3 | 3 | 2 | 3 | 3 | 3 | 3 | 2 | 3 | III |
| Bank 4 | 4 | 4 | 4 | 4 | 3 | 4 | 5 | 4 | II |
| Bank 5 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | II |
| Bank 6 | 3 | 3 | 4 | 3 | 3 | 3 | 2 | 3 | III |
| Bank 7 | 2 | 2 | 3 | 2 | 3 | 2 | 2 | 2 | IV |
| Bank 8 | 2 | 2 | 2 | 2 | 2 | 3 | 2 | 2 | IV |
| Bank 9 | 4 | 3 | 4 | 4 | 5 | 4 | 4 | 4 | II |
| Bank 10 | 3 | 3 | 3 | 4 | 3 | 3 | 3 | 3 | III |

We kept the average values of each indicator as memory evaluation indicators, or the stable points of DHNN, as shown in table 3 and 4.

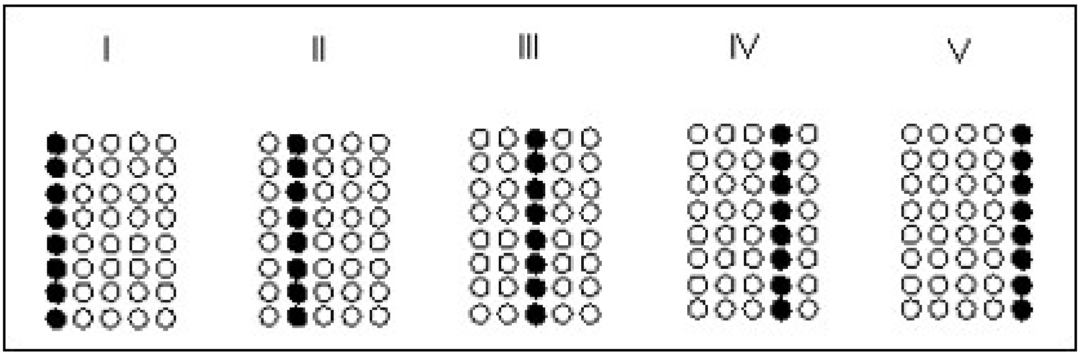
**Table 5.** Associative Memory of the Five States of Credit Risk Evaluation

| Rank | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 |
|---|---|---|---|---|---|---|---|---|
| I | 4.5 | 5 | 4.5 | 5 | 4.5 | 5 | 5 | 4.5 |
| II | 4 | 3.7 | 4 | 4 | 4 | 4 | 4.3 | 4 |
| III | 3 | 2.7 | 3.3 | 3.3 | 3 | 3 | 2.3 | 3 |
| IV | 2 | 2 | 2.5 | 2 | 2.5 | 2.5 | 2 | 2 |
| V | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

### 2.3. The Associative Memory Network Model

Since the neurons in DHNN have only two values, 1 and -1, coding them when mapping any evaluation indicator is necessary. When the value of a neuron is greater than or equal to the value of the indicator of some status, it assigned 1, otherwise -1. Then, using MATLAB, we found the five indicator codes of five memory status below.

**Fig. 3.** Status Indexes Encoding Associative Memory




Where ● indicates that the value of a neuron is 1, greater than or equal to related memory evaluation indicators, it is otherwise indicated by ○. The code is shown below.

**Table 6.** Network Encoded Value of Five Memory Statuses

| Ideal Risk Status | I | | | | | II | | | | | III | | | | | IV | | | | | V | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Network Mode | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |
| | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |
| | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |
| | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |
| | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |
| | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |
| | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |
| | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 |

According to the code above, we found the associative memory models after the training process below.

**Table 7.** Risk Status Associative Memory Network Mode

| Risk Status | | Network Mode | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Good | I | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Security | II | 1 | 1 | -1 | 1 | 1 | -1 | 1 | 1 |
| General | III | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 |
| Danger | IV | -1 | -1 | 1 | -1 | -1 | 1 | -1 | -1 |
| Crisis | V | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |

### 2.4. Connection Weight Matrix

Using equation (2), the connection weight matrix is below.

$$\mathbf{W}=\begin{bmatrix} 0 & \sum_{k=1}^{5} x_1^k x_2^k & \cdots & \sum_{k=1}^{5} x_1^k x_8^k \\ \sum_{k=1}^{5} x_2^k x_1^k & 0 & \cdots & \sum_{k=1}^{5} x_2^k x_8^k \\ \vdots & \vdots & & \vdots \\ \sum_{k=1}^{5} x_8^k x_1^k & \sum_{k=1}^{5} x_8^k x_2^k & \cdots & 0 \end{bmatrix} = \begin{bmatrix} 0 & -1 & 1 & 3 & 1 & -1 & 5 & -1 \\ -1 & 0 & 3 & 1 & 3 & 5 & -1 & 5 \\ 1 & 3 & 0 & -1 & 5 & 3 & 1 & 3 \\ 3 & 1 & -1 & 0 & -1 & 1 & 3 & 1 \\ 1 & 3 & 5 & -1 & 0 & 3 & 1 & 3 \\ -1 & 5 & 3 & 1 & 3 & 0 & -1 & 5 \\ 5 & -1 & 1 & 3 & 1 & -1 & 0 & -1 \\ -1 & 5 & 3 & 1 & 3 & 5 & -1 & 0 \end{bmatrix}$$

Given the original input model $p^{(0)} = (p_1^{(0)}, p_2^{(0)}, \ldots, p_8^{(0)})$, we ran DHNN under equation (4) until it converged to a memory mode.

### 2.5. Network Model to Be Identified

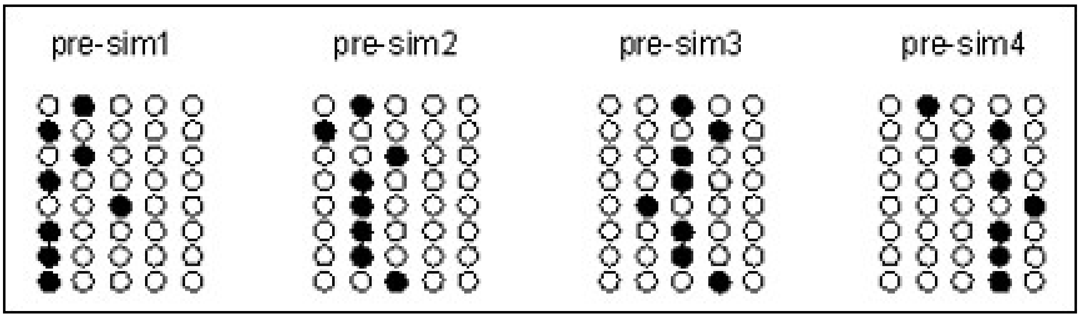
Using observations of credit data from four commercial banks as a test sample, we found the indicator values of credit regulatory as shown in Table 3.8. Meanwhile, according to the rating given by authority credit rating agencies, we compared these with the simulation results to test the accuracy of this model.

**Table 8.** Four Intents to Evaluate the State of Bank Credit Risk and Regulatory Indexes

| Index | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | Rank |
|---|---|---|---|---|---|---|---|---|---|
| Bank 11 | 4 | 5 | 4 | 5 | 3 | 5 | 5 | 5 | I |
| Bank 12 | 4 | 5 | 3 | 4 | 4 | 4 | 4 | 3 | II |
| Bank 13 | 3 | 2 | 3 | 3 | 4 | 3 | 3 | 2 | III |
| Bank 14 | 4 | 2 | 3 | 2 | 1 | 2 | 1 | 2 | IV |

Using MATLAB, we found the indicator codes of the four banks, as shown in Fig. 4.

**Fig. 4.** Input Indexes Encoding of Four Intents to Evaluate Banks




## 3. Simulation and Results

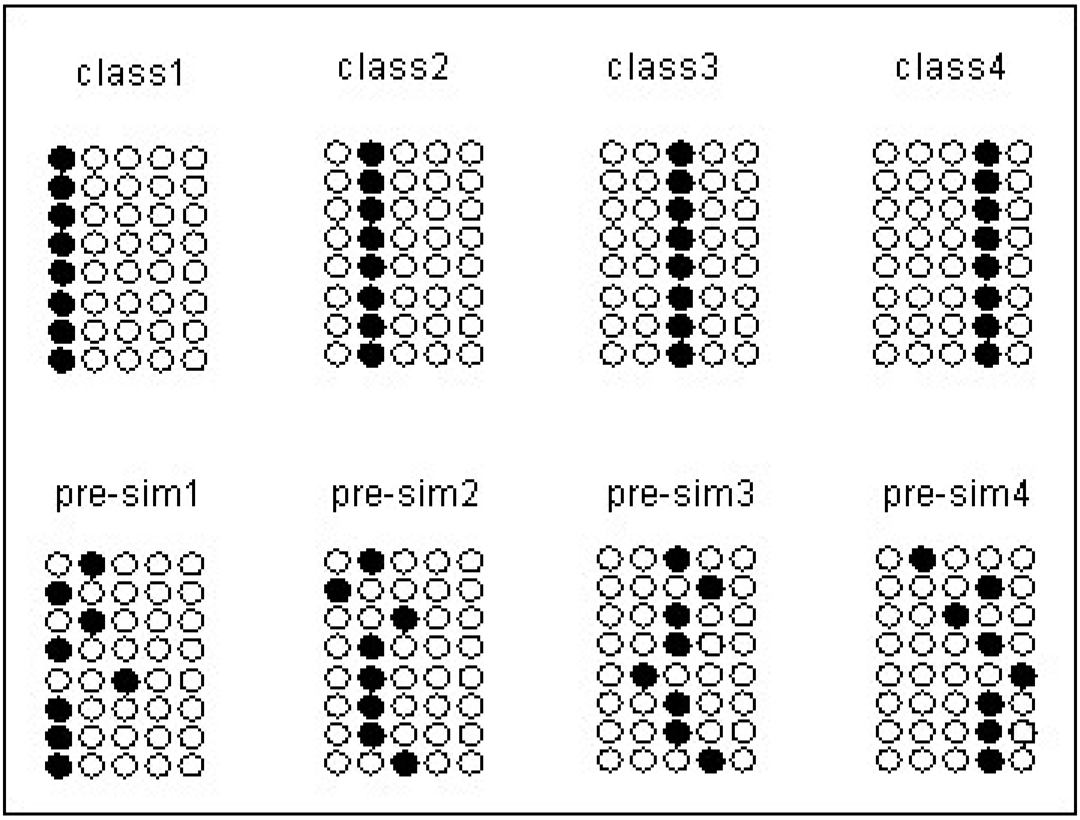
First, we used the indicator codes of credit data from these four banks as the inputs of our DHNN model. By using the associative memory function and the connection weight matrix, we derived the simulation results, which show the credit risk statuses of the four banks.

**Table 9.** Simulation Results of Credit Risk Evaluation (Test Set)

| | | Network Mode | | | | | | | | Risk Status | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bank 11 | Input state | -1 | 1 | -1 | 1 | -1 | 1 | 1 | 1 | Good | I |
| | Test results | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | Good | I |
| Bank 12 | Input state | 1 | 1 | -1 | 1 | 1 | 1 | 1 | -1 | Security | II |
| | Test results | 1 | 1 | -1 | 1 | 1 | -1 | 1 | 1 | Security | II |
| Bank 13 | Input state | 1 | -1 | 1 | 1 | 1 | 1 | 1 | -1 | General | III |
| | Test results | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | General | III |
| Bank 14 | Input state | 1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | Danger | IV |
| | Test results | -1 | -1 | 1 | -1 | -1 | 1 | -1 | -1 | Danger | IV |

At the same time, we also derived the simulation result figures shown in Fig. 3 and 5, wherein the first line indicates the simulation results, and the second line indicates the original indicator codes.

**Fig. 5.** Simulation Results of Credit Risk Evaluation (Test Set)



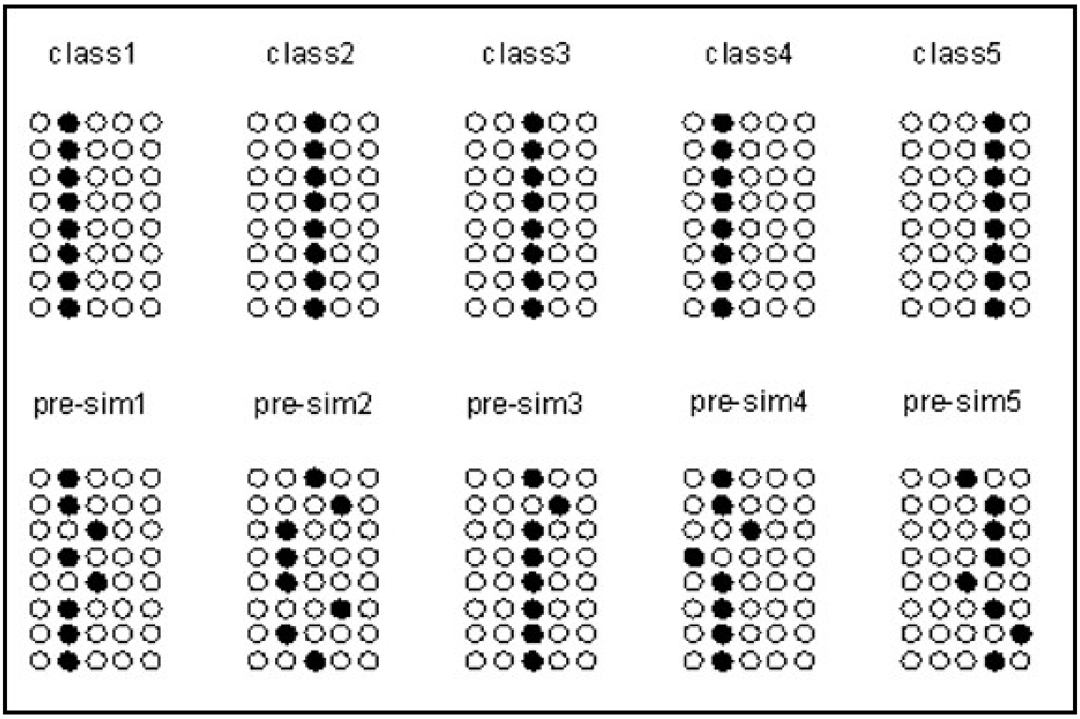

Then, we chose credit data from 2015 Q1 to Q3from five other banks as the forecast sample. This time, we had no ratings for these five banks. We used our DHNN model to evaluate credit risk status. The results of simulation are below.

From the results, we can clearly see that the DHNN model can precisely recall the memory model, and its simulation outputs are just consistent with the actual situation. This evidence has proven that using a DHNN model to evaluate the credit risk of commercial banks is feasible and effective. Based on this, we used the DHNN to forecast these five banks. As the figure shows, the results are stable and reliable, and directly reflect the credit risk status. Therefore, our DHNN model has the ability to not only support decision-making with commercial bank managers, it can also monitor risk changing for financial regulatory authorities.

**Table 10.** Simulation Results of Credit Risk Evaluation (Forecast Set)

| | | Network Mode | | | | | | | | Risk Status | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bank A | Input state | 1 | 1 | -1 | 1 | -1 | 1 | 1 | 1 | Unknown | |
| | Forecast results | 1 | 1 | -1 | 1 | 1 | -1 | 1 | 1 | Good | II |
| Bank B | Input state | 1 | -1 | 1 | 1 | 1 | -1 | 1 | -1 | Unknown | |
| | Forecast results | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | General | III |
| Bank C | Input state | 1 | -1 | 1 | 1 | 1 | 1 | 1 | 1 | Unknown | |
| | Forecast results | 1 | -1 | 1 | -1 | 1 | -1 | 1 | -1 | General | III |
| Bank D | Input state | -1 | 1 | -1 | -1 | 1 | 1 | 1 | 1 | Unknown | |
| | Forecast results | 1 | 1 | -1 | 1 | 1 | -1 | 1 | 1 | Good | II |
| Bank E | Input state | -1 | 1 | 1 | 1 | -1 | 1 | -1 | 1 | Unknown | |
| | Forecast results | -1 | -1 | 1 | -1 | -1 | 1 | -1 | -1 | Danger | IV |

**Fig. 6.** Simulation Results of Credit Risk Evaluation (Forecast Set)



## IV. Conclusions

For a long period, credit risk has been the most important form of risk in the banking industry, and perhaps even the entire financial industry. After the mid-1980s, with the development of financial liberalization and financial globalization, bankruptcy all over the world has increased structurally, and the credit scale and risk degree have increased exponentially. Moreover, the disintermediation effect of financing, the intensification of inter-bank competition, and the decline of collateral value have greatly increased the risk of the traditional banking credit business, which causes credit risk to attract universal attention again and become an important topic faced by the bank's internal risk managers and bank regulators. At the same time, the use of loan sale and loan securitization, the practice of portfolio investment principle in risk management, the significant expansion of derivatives market and the emergence of various credit derivatives also put forward higher requirements for the measurement and control of credit risk.

However, traditional credit risk measurement methods (mainly including the expert method, credit rating method, and credit scoring method) have difficult accurately measuring credit risk because they mainly rely on the appraiser's professional skills, subjective judgment, and simple weighted calculation of key factors that determine the probability of default. Therefore, this paper studies the credit risk measurement of commercial banks based on a discrete Hopfield neural network. Because an artificial neural network has the advantages of strong "robustness", high prediction accuracy, and is unstructured, this paper uses the associative memory function of a DHNN to construct a credit risk measurement model based on a discrete Hopfield neural network. Firstly, this paper uses the commonly used expert survey method and the research results and experience of previous scholars to realize the transformation of regulatory indicators from qualitative to quantitative. Then, a credit risk measurement model based on a Hopfield network was constructed in order to evaluate credit risk. Finally, the simulation experiment was carried out using real commercial bank data. The results show that a credit risk measurement model based on a Hopfield neural network can accurately reflect the credit risk state of banking institutions. This shows that the credit risk measurement model proposed in this paper not only has functionality supporting decision-making for commercial bank managers, it is also an effective way for financial regulators to grasp the risk change trend in real time.

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# Market Efficiency and Volatility Spillover in Bitcoin and Ethereum Prices: Comparisons during the Pre-COVID-19 Period and COVID-19 Pandemic

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**ABSTRACT**

**Purpose –** This study attempts to establish if the markets for the two most popular cryptocurrencies in the world, Bitcoin and Ethereum, follow weak-form market efficiency across various landmarks in time.
**Design/Methodology/Approach –** Traditional testing for establishing weak-form market efficiency rests on whether the price series exhibits a random walk process, which implies that future prices cannot be predicted. However, not all random walk series automatically imply weak-form market efficiency, since some asset price behaviors may exhibit non-constant variance. In such cases, the GARCH model can be used to test for the presence of market efficiency. Since structural breaks in the prices of both cryptocurrencies are common, tests for market efficiency were carried out using sub-temporal price windows. In both price series, the last time window coincided with the 2020 COVID-19 pandemic period.
**Findings –** Results of the GARCH analyses showed that the volatility and persistence parameters ($\alpha$ and $\beta$, respectively) in the Bitcoin and Ethereum models were all statistically significant, implying that prices in their sub-temporal markets were generally weak-form inefficient. The observed market inefficiency in both cryptocurrencies can be attributed to various factors like the price manipulation of crypto whales, security issues, and increased media attention, which led to inflows of information that helped big investors beat and gain from the market by successfully predicting the trend in future prices. During the 2020 COVID-19 pandemic period, both cryptocurrencies' prices were observed to rise significantly, similar to the case of the 2017 Bitcoin price bubble. A cointegrating regression between Bitcoin and Ethereum prices during this period, however, showed a spurious relationship. Despite the absence of a long run relationship between these two price series, the current price bubbles in the cryptocurrency markets are speculated to be tied together.
**Research Implications –** Players in the cryptocurrency market must always be cautious in making investment decisions regarding this type of asset since the markets are generally price inefficient and risky; any idiosyncratic decision that may be triggered by a price bubble burst in one cryptocurrency market may or may not serve as a signal that the other market will do the same. Since the Bitcoin and Ethereum prices were shown to exhibit volatility spillover and persistence, investors can use this information to make informed decisions as to whether to invest in these cryptocurrencies despite the huge risks that are magnified during the COVID-19 pandemic.

***Keywords:*** bitcoin, cryptocurrencies, ethereum, market efficiency, pandemic, volatility spillover
***JEL Classifications:*** G14, O16

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## I. Introduction

Today, there are 4,242 virtual currencies with a total market capitalization of over USD $774 Billion (Investing, 2021). Bitcoin and Ethereum are the top two most popular cryptocurrencies, of which 71% is contributed by Bitcoin, amounting to USD $545.25 Billion, while Ethereum contributed 11%, amounting to USD $85.25 Billion.

In 2008, Satoshi Nakamoto introduced the concept of Bitcoin as a cryptocurrency through a paper entitled "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto, 2008). This paper showed the world the possibility of an electronic cash system that does not need institutional mediation in its financial transactions. It was a response to the global financial crisis of 2008, which brought out the anomalies of banks and financial institutions that led people to lose trust in these institutions (Baghla, 2017).

Ethereum, on the other hand, was first proposed in 2013 by a Russian-Canadian programmer named Vitalik Buterin (Maas, 2017). It introduced smart contracts, or automated business agreements, similar to how multimedia services such as Amazon, Facebook and Grab function, but without the need for trust between application users (Murphy, 2018). Buterin realized that if cryptocurrencies could remove the need for financial intermediaries, Ethereum's smart contracts could eliminate the need for intermediaries that provide trust.

However, long before the emergence of these cryptocurrencies, the idea of a digital currency was already in place. David Chaum, a computer scientist and cryptographer, widely regarded as the "Father of Digital Currency", created the first electronic cash system, aptly named eCash (Heywyre, 2017). It was established in 1983, and was considered innovative cryptographic electronic money, much like Bitcoin and Ethereum today. The arrival of these cryptocurrencies was met with both enthusiasm and doubt (CrushCrypto, n.d.). The idea of having a medium of exchange or payment system without a financial intermediary seemed enticing, but it could be prone to hacking by knowledgeable players at the same time.

The year 2009 marks the start of Bitcoin, as Satoshi Nakamoto mined the first-ever Bitcoin called the "genesis block" (Cochrane, 2018). The cryptocurrency remained relatively unnoticed in its early years, until its dramatic increase in prices in 2017. The rise in Bitcoin prices attracted the attention of different sectors, from private individuals wanting to "mine" Bitcoin by solving complex mathematical problems to countries (like the U.K.) wanting to adopt Bitcoin to track taxpayer money.

Over the years, cryptocurrency has gained traction all over the world. It was not long until various institutions started using them as an alternative money. In 2011, Mt. Gox was launched and became the world's most popular trading site for Bitcoin (Mcmillan, 2014). It was the go-to site for people wanting to buy and sell cryptocurrency at the time. Moreover, the website made a reputation of being an honest player in the cryptocurrency community. Bitcoin prices skyrocketed from a lowly USD $0.10 in July 2010 to USD $29,252.90 by the end of 2020, the highest it has risen to date. The rise in Bitcoin price also benefitted other cryptocurrencies like Ethereum, whose price increased from USD $1.00 in March 2016 to USD $745.95 by the end of the same year. This shows that cryptocurrencies have become more and more popular, especially during the COVID-19 pandemic (2020), with prices soaring.

However, it was not all fun and games for Mt. Gox. By early 2014, it filed for bankruptcy due to an attack that seized USD $460 million, the company's earnings from Bitcoin transactions. To make matters worse, Mark Karpeles, the CEO of Mt. Gox, was arrested in 2015 for allegedly using the site to hoard money amounting to USD $1 million (Soble, 2015). Ethereum also suffered a similar fate, with its system also being compromised. The creation of a decentralized autonomous organization (DAO) for cryptocurrency, which happened during the early years in 2016, raised concerns on the security of the platform since USD $50 million in Ethers were stolen by an anonymous hacker and was nowhere to be found (Francis, 2019). This was a major event in the world of cryptocurrency. It showed that since transactions were mostly computer-based, there are always possibilities that trading sites can be vulnerable to hackers.

This did not stop cryptocurrencies from reaching peak popularity. More than 100,000 merchants accepted Bitcoin as means of exchange for goods (Cuthbertson, 2015). By 2017, countries like Japan and Russia had passed laws that recognized Bitcoin as a legal medium of exchange (Kharpal, 2017). The year also saw the creation of the Enterprise Ethereum Alliance (EEA), with corporate giants like Microsoft and JPMorgan Chase collaborating to create a computing system based on Ethereum (Popper, 2017). These developments boosted the popularity of cryptocurrencies, not only to investors but also to corporate giants and lawmakers.

The rising popularity of cryptocurrencies also made headlines in the academic community. Many financial economists looked into the viability and nature of cryptocurrencies. In a study by Dowd & Hutchinson (2015), Bitcoin mining suffered the problem of monopolies, wherein miners are incentivized to merge and collaborate with each other since it would be faster for them to mine the cryptocurrencies. The problem of negative externalities also exists, particularly in the indirect cost to new miners. Miners are people who compute complex mathematical problems through high powered computers and are rewarded with Bitcoins for every successful mine. With the increase in the number of miners, there was also an increase in the computing power needed to mine, which made entry in the field more costly than before (Dowd & Hutchinson, 2015). Significant events like the Mt. Gox hack of 2013 were also deeply scrutinized to uncover the reason for the compromised security. Gandal, Hamrick, Moore & Oberman et al. (2017) concluded that suspicious trading activity in Mt. Gox made Bitcoin prices rise, which also showed that price manipulation has disastrous effects in Bitcoin trading. There was also evidence that the phenomenal rise of cryptocurrencies made the manipulation of prices much more feasible, regardless of market capitalization (Gandal et al., 2017). Numerous studies concluded that market failures and significant events in the cryptocurrency markets create predictability and inefficiency resulting from prices being easily manipulated by unscrupulous investors.

The predictability of the price behavior of an asset can be analyzed through the financial theory of market efficiency. In 1970, Eugene Fama introduced the Efficient Market Hypothesis (EMH), which states that no one can gain excess benefits for a sustained period of time from financial assets, except through luck, since all information are fully reflected in the prices (Fama, 1970). According to EMH theory, there are three forms of market efficiency, namely (a) weak-form efficiency, which occurs when historical data and past prices are reflected in the current price; (b) semi-strong market efficiency, which is characterized by past prices and all public information being reflected in the current price; and lastly, (c) strong market efficiency, which results when all available information, such as past prices including public, private, and insider information, are reflected in the current price (Fama, 1991).

In general, this study aims to establish if Bitcoin and Ethereum prices exhibit weak-form efficiency in the cryptocurrency market during periods of rising and falling prices. This information is important as if their prices are weak-form efficient, then it implies that they cannot be predicted nor manipulated by Machiavellian traders in the market. Specifically, this study aims to achieve the following objectives: a) characterize the behaviors of Bitcoin and Ethereum prices in the cryptocurrency markets at various price windows defined by drifts in their structural breaks; b) test if volatility clustering occurs in the two cryptocurrency prices across the established sub-temporal market windows; c) compare the size of the volatility spillover and persistence in both prices as to whenever the sub-temporal markets are weak-form inefficient; and d) establish if the prices of Bitcoin and Ethereum have a genuine long run relationship with each other, especially during the 2020 COVID-19 pandemic.

## II. Methodology

Theoretically, weak-form market efficiency states that historical data on past prices cannot be used to predict an asset's current price. This condition is synonymous with the market behaving in a random walk process. Based on econometric literature, the random walk process is a sufficient condition to establish weak-form market efficiency. Specifically, random walk theory states that regardless of what has happened in the past, the chance of the asset price going up in the future is equal to its decline. It was originally described by Maurice Kendall in 1953, in which fluctuations in the market price are independent from one another, and that over time, prices follow an upward trend (Kendall, 1953). In other words, asset prices take a random path and are said to be unpredictable; hence, the asset market is considered weak-form efficient. Note that this phenomenon is true if the fluctuations in the asset price demonstrate constant variances.

However, not all random walk processes exhibit fluctuations with constant variances. This characteristic is fairly common among high frequency data like Bitcoin and Ethereum prices, which often show volatility clustering. In 1982, Engle introduced the autoregressive conditional heteroscedasticity (ARCH) model, which was a new class of stochastic processes that assumes time varying forecast variances to measure volatility clustering and spillover in a time series.

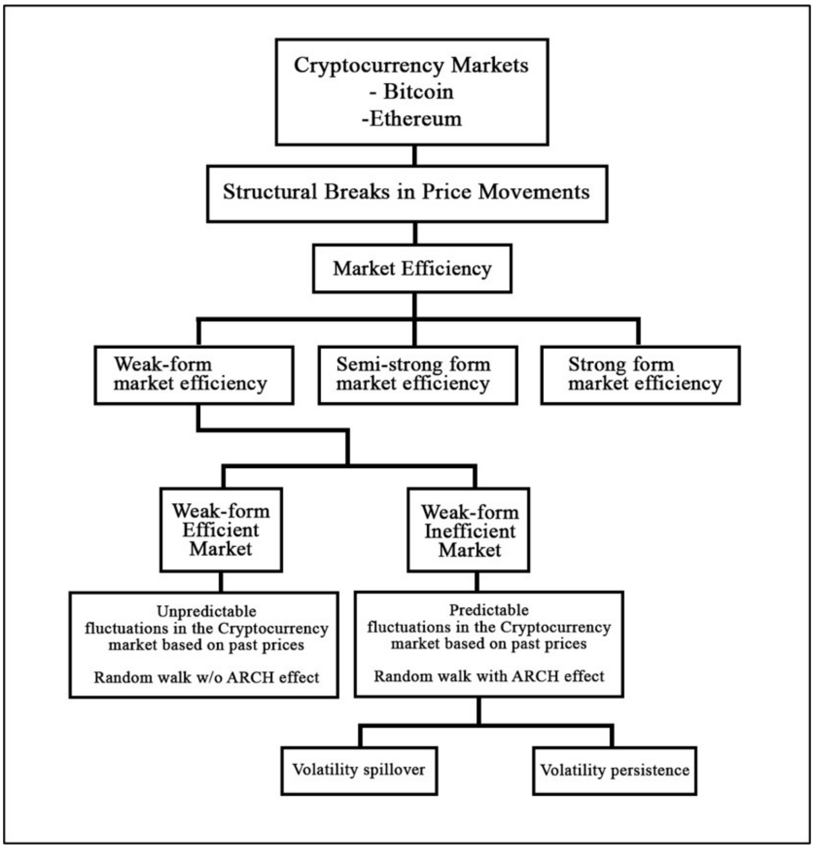
Volatility is a characteristic often found in price series that can provide market signals through its predictability, and are useful in deriving expected future prices (Ezzati, 2013). Traditional econometric models that treat volatility to be constant are found to be inappropriate when the size of fluctuations vary over time. This has led to the development of various econometric models that take into account volatility spillover characterized by fluctuations clustered across time periods: large fluctuations followed by large fluctuations, or small fluctuations followed by small fluctuations. When this phenomenon occurs, the variance of the price series is said to exhibit the ARCH effect (Engel, 1982). In 1986, Bollerslev introduced a more generalized form of the ARCH process, the generalized autoregressive heteroscedasticity process, or GARCH model, to provide a more flexible treatment of the heteroscedastic behavior of a time series (Bollerslev, 1986). In addition to volatility spillover, the GARCH model also allows the measurement of the persistence of volatility clusters. This provides an assessment of how long or short heteroscedastic fluctuations will last. This notion is called volatility persistence.

Therefore, despite the non-predictability characteristic of a random walk series, if the price series can be shown to demonstrate the ARCH effect, then future prices can be still be predicted, and hence, the market can be deemed weak-form inefficient. Given that fluctuations of Bitcoin and Ethereum prices were observed to be highly volatile in recent years, especially during the COVID-19 pandemic, there is a need to establish whether these fluctuations in the two cryptocurrencies are simply random walks or ARCH processes. This information has important implications for their dual roles as investment assets and mediums of exchange. Specifically, volatility patterns can provide market signals to portfolio investors, such as whether future prices can be predicted, and hence, benefits can be abnormally derived from controlling or influencing said markets. The use of the GARCH model can therefore help identify if such bizarre behaviors exist within the Bitcoin and Ethereum markets.

This study focuses on weak-form market efficiency since past prices are readily observable and are conveniently available online. Fig. 1 shows the conceptual framework used study in validating whether the Efficient Market Hypothesis is true in the two cryptocurrency markets. Price analyses were done for all the established time windows defined by drifts in the structural breaks of the two cryptocurrency prices over time. For each price window, weak-form market efficiency is established by testing whether the specific cryptocurrency price behaves in a random walk fashion. If random walk behavior is present, then the price movement of the cryptocurrency in the given sub-temporal market is deemed weak-form efficient. This means that prices in that time period cannot be predicted. Hence, no one can benefit from investing in the asset more than what is normally expected. However, as mentioned earlier, it is still possible to predict the future price movements despite a random walk nature if the variance of the price fluctuations is not constant, thus rendering the market weak-form inefficient. Therefore, for all price windows where random walk behavior was present, the ARCH effect was investigated and a GARCH model was fitted to ultimately conclude whether the market for the cryptocurrency in question was indeed weak-form efficient or not.

This section discusses the different methods used in testing for the presence of weak-form market efficiency in Bitcoin and Ethereum prices. First, structural breaks in the price trends of the two crypto currencies were identified to define the various episodes of price changes into sub-temporal windows. In each price window, the cryptocurrencies were tested for random walk behavior. Traditionally, the respective markets in the relevant time window are considered weak-form efficient if random walk behavior is present. However, the two price series were further tested for the presence of heteroscedastic variances, or whether the ARCH effect was present or not. If the ARCH effect is absent, then the market during the sub-temporal window is deemed weak-form efficient. However, if an ARCH effect was present, a GARCH model was specified to check if future prices could be predicted, which then renders the cryptocurrency in the respective sub-temporal market weak-form inefficient.

**Fig. 1.** Conceptual Framework



The GARCH model can be used to estimate the size and length of the volatility spillover in cryptocurrency prices. There are two components to the GARCH model, the autoregressive (AR) term and the moving average (MA) component, also referred to as the GARCH term. The AR term takes into account the size of the volatility spillover in the model, or how much past fluctuations affect present fluctuations. The GARCH term, on the other hand, takes into account volatility persistence, or the duration of the volatility spillover. It can last for a short or long period of time, depending on the magnitude of the moving average term. If the volatility persistence is long, the cryptocurrency market will remain inefficient for a long time. Moreover, if the volatility spillover is large, price variation in this time period will also be large, implying more risks in the price of the asset. Therefore, if the size and duration of volatility clusters in the cryptocurrency prices can be estimated, future prices can be predicted by the GARCH model, and hence, market stakeholders that possess this information can benefit from the market inefficiency.

This study used published prices of Bitcoin and Ethereum, obtained from Investing.com. Daily data were collected from July 18, 2010 for Bitcoin (Investing, 2020a) and March 10, 2016 for Ethereum (Investing, 2020b), both lasting up to December 20, 2020. The price data were analyzed through initial inspection of the structural breaks that identified the location of the drifts or breakpoints that provided the boundaries for the time windows of the sub-temporal markets used in the study.

Most price series often show changing mean levels over time. Under such conditions, the slope of the price trend is no longer constant, meaning the mean level of the price series varies over time. Sudden changes or shifts in the mean level of the price series are referred to as structural breaks. Identifying these structural break points or drifts and incorporating them into the price model can increase its reliability in producing accurate forecasts. In this study, the structural breaks represent major shifts in the behavior of cryptocurrency prices, important market signals that can help investors manage investment portfolios. Thus, breaking the price trends into episode windows of rising and falling prices will allow market efficiency analysis to be more precise and specific. The dummy variable test was used as a simple tool testing for the presence of structural breaks. It was built on the theory that if the mean levels of the price series vary with respect to time, then such a behavior in the price series must be recognized to make the analysis more accurate. This test specifies the current price as an ANOVA (analysis of variance) function of the time dummies that coincide with the identified break points in the price trends. The dummy variable test for structural breaks in the Bitcoin and Ethereum prices are specified in Equations 1 and 2, respectively:

$$BC_t = \beta_0 + \Sigma\beta_i D_i + \varepsilon_{1t} \quad (1)$$

$$ET_t = \beta_0 + \Sigma\beta_i D_i + \varepsilon_{2t} \quad (2)$$

where $BC_t$ and $ET_t$ are current Bitcoin and Ethereum prices, $\beta_0$ is the intercept term of the model corresponding to the coefficient of the base dummy, and $\beta_i$ are the slope parameters of the time dummies. The dummy variable $D_i$ is equal to 1 if the cryptocurrency's price falls on the ith time window. If the $\beta_i$ are statistically significant in the respective equations, then the identified structural breaks are indeed present in the price series.

## III. Results and Discussion

### 1. Identification of Structural Breaks

Significance of the regression coefficients of the time dummies corresponding to the identified structural break points of each time window for the two cryptocurrency prices are presented in Table 1. All time dummies for both Bitcoin and Ethereum prices showed significant coefficients. This means that each of the identified windows for both prices indeed showed varying behavior, which warrants separate market efficiency analyses.

**Table 1.** Dummy Variable Test for the Presence of Structural Breaks in Bitcoin and Ethereum Prices, 2010-2020

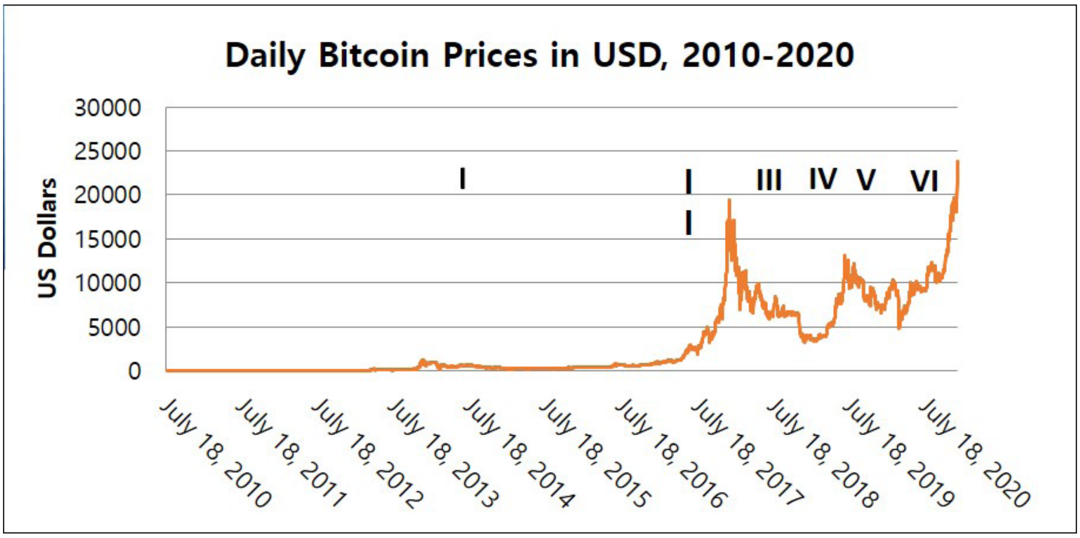
| | Parameter Estimates | |
|---|---|---|
| **Dummy Variables** | **Bitcoin** | **Ethereum** |
| Constant | 256.2279**<br>(36.6949) | 11.50681ns<br>(8.769559) |
| Window 2 | 3637.326**<br>(108.671) | 301.5492**<br>(13.02276) |
| Window 3 | 7297.258**<br>(96.4860) | 454.56**<br>(12.69217) |
| Window 4 | 6625.95**<br>(134.207) | 167.1468**<br>(12.30425) |
| Window 5 | 8164.495**<br>(118.427) | 287.0093**<br>(12.57795) |
| Window 6 | 11598.57**<br>(120.816) | - |

Note: ** significant at α=1%, Window 1 is the dummy base scenario.

Fig. 2 and Fig. 3 show the locations of various structural break points in the Bitcoin and Ethereum prices, respectively. Five structural break dates were identified for Bitcoin prices: a) February 11, 2017; b) December 17, 2017; c) January 27, 2019; d) August 9, 2019; and e) April 20, 2020 (Fig. 1). In the case of Ethereum prices, four (4) structural break dates were identified: a) March 14, 2017; b) January 15, 2018; c) December 19, 2018; and d) Jan 5, 2020 (Fig. 2). These structural break points serve as boundaries for the six and five time windows in the Bitcoin and Ethereum prices, respectively.

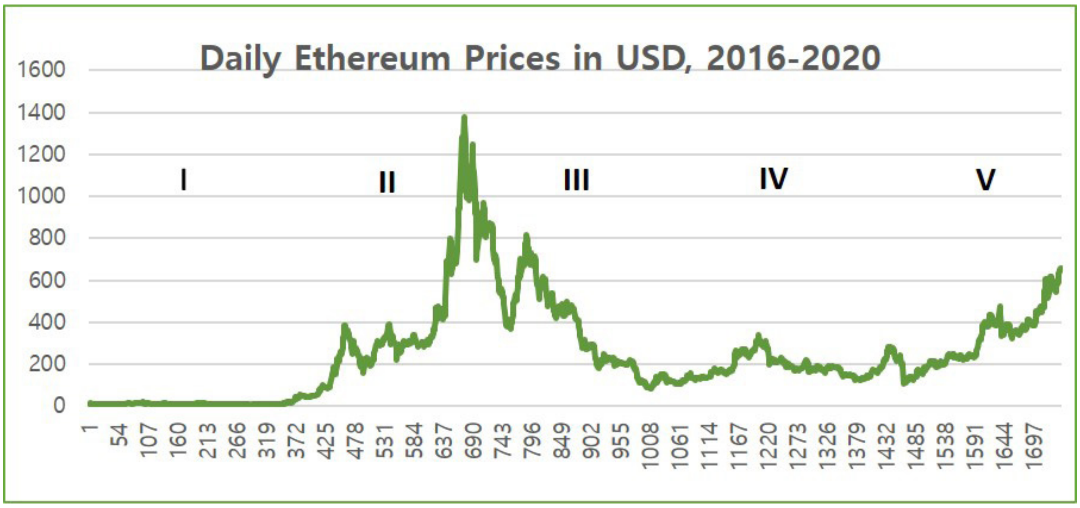
Window 1 of the Bitcoin price shows a period of relatively stable prices, which was attributed to the fact that Bitcoin was just starting to gain recognition as a new form of virtual medium of exchange and asset investment (Fig. 2). It actually took about six and a half years before Bitcoin price increased significantly from its initial offering of USD $0.10 to USD $1,008.30. Window 2 shows the first major increase in the price of Bitcoin, which coincided with when it was being introduced to various financial markets, and enticed a large numbers of users around the world. The sudden increase in price can also be attributed to the opening of public trading sites such as Mt. Gox. In this period, Bitcoin reached USD $17,604.80, which was considered phenomenal at that time. Window 3 shows the first major drop in Bitcoin prices to USD $3,490.20 from the high of USD $17,604.80. Bitcoin was subjected to various security attacks, most notably the Mt. Gox hack of 2013. This made investors skeptical about cryptocurrency, and prices continued to fall for more than a year. Window 4 shows the second major increase in prices, mostly influenced by increased media exposure and countries like China and the USA, which relaxed regulations for cryptocurrencies. During this period, Bitcoin was able to regain some of its lost value, reaching USD $12,191.60. However, it had not recovered the highs it reached in 2017. Window 5 shows the second major drop in prices, where many investors lost not only their money but also their confidence in cryptocurrency. Bitcoin went down to USD $6,833.50, which was attributed to the increased scrutiny of various countries by placing tighter regulations that defeated the basic purpose of cryptocurrency. Finally, Window 6, which coincides with the 2020 COVID-19 pandemic, shows the third major increase in Bitcoin prices. The trend in Bitcoin prices in this period was exceptional and meteoric from April of 2020. To date, the price reached USD $29,000, and is still rising.

**Fig. 2**. Six Time Windows for Bitcoin Prices from 2010-2020




Ethereum followed a similar volatile price pattern. Window 1 shows stable prices from the initial coin offering (ICO) of USD $11.75 to USD $28.66 over one year. It was also during this period that the Ethereum's DAO (Decentralized Autonomous Organization) was hacked. Window 2 exhibits the first major increase, reaching USD $1,380. This was influenced by increased public exposure to cryptocurrency and the opening of trading sites for Ethereum. Window 3 shows the first major decrease in Ethereum prices, reaching a low of USD $127.19. This coincided with the first downfall of Bitcoin with only one month lag. During this period, almost all cryptocurrency values were halved and investors were reminded of the riskiness and uncertainty of the asset class. One cause of the crash was increased regulations set by many countries, which led to the closing of some cryptocurrency exchange sites (McKay, 2018). Another factor was the countless hacks and security breaches, which resulted into millions of dollars being stolen from cryptocurrency investors (Mochizuki & Vigna, 2018). The market recovered in Window 4, but Ethereum remained stable at an average of USD $178.65. This period was characterized by more security breaches and increased regulations, like the banning of advertisements regarding ICO and token sales on exchange sites (Russo, 2018). Lastly, similar to Bitcoin, in Window 5 of Ethereum prices started to show increasing prices, reaching a high of USD $658.17. Despite a sustained increase in price, it has not surpassed the high of 2017, as shown in Window 2.

**Fig. 3**. Five Time Windows in Ethereum Prices, 2016-2020




## 2. Test for Random Walk Process

The test for the presence of random walk process in the Bitcoin and Ethereum prices rests on the stationarity of the price series. Specifically, it requires the level form of the price series to be non-stationary, but its first difference must be stationary. Note that a stationary process has properties where the mean, variance, and autocorrelation structure of the time series do not change over time. Many economic and financial time series are far from stationary in level form and typically exhibits trends, cycles, random-walking, and other non-stationary behaviors. Two types of stationarity exist: strong and weak. For most applications, weak stationarity is sufficient, where the mean and variance of the time series are assumed to be time invariant. This is in contrast to strong stationarity, which assumes that all the moments of the time series are time invariant.

The Dickey-Fuller test is the simplest approach to test for the stationarity of a time series. It tests for the presence of a unit root in a given time series, or whether the coefficient of the autoregressive component ρ in the given equations below is equal to 1 or not.

$$BC_t = \rho BC_{t-1} + \varepsilon_t \tag{3}$$

$$ET_t = \rho ET_{t-1} + \mu_t \tag{4}$$

The null and alternative hypotheses of the Dickey-Fuller test are defined as follows:

$$\text{Ho: } \rho = 1$$
$$\text{Ha: } \rho \neq 1$$

If the value of the $\rho$ coefficient in the random walk model is equal to 1, then Ho is accepted and the time series is deemed non-stationary. Otherwise, when Ha is accepted, the time series does not have a unit root and hence is considered stationary.

Traditionally, to test whether prices in Bitcoin and Ethereum markets are weak-form efficient, they should exhibit a random walk process. As mentioned earlier, a random walk process requires that the level form of the price series ($BC_t$ and $ET_t$) are non-stationary time series, while their first differences ($\Delta BC_t$ and $\Delta ET_t$) are stationary. Note that the first difference is defined by the difference between the current and first lagged value of the price series, or $\Delta BC_t = BC_t - BC_{t-1}$ for the Bitcoin price and $\Delta ET_t = ET_t - ET_{t-1}$ for the Ethereum price.

If Bitcoin and Ethereum prices behave as random walks, it ensures that they follow a volatile path, and thus are unpredictable. Hence, their respective markets can be described as weak-form price efficient. In this study, Bitcoin and Ethereum prices were tested for the presence of random walk behaviors by time windows. Tables 2 and 3 show the results of the Dickey-Fuller tests for the level forms and first differences of Bitcoin and Ethereum prices for all identified windows.

**Table 2.** Test for Random Walk using Dickey-Fuller Test for Bitcoin Prices

| | Level Form | 1st Difference | Random Walk | Market Efficiency |
|---|---|---|---|---|
| Window 1 | -1.161ns | -46.928** | Yes | Efficient |
| Window 2 | 5.172ns | -13.907** | Yes | Efficient |
| Window 3 | -3.884** | - | No | Inefficent |
| Window 4 | -0.346ns | -16.393** | Yes | Efficient |
| Window 5 | -2.377ns | -17.119** | Yes | Efficient |
| Window 6 | 1.855ns | -15.198** | Yes | Efficient |
| All Period | 1.812ns | -60.955** | Yes | Efficient |

Note: **significant at 1%, ns not significant.

**Table 3.** Test for Random Walk using Dickey-Fuller Test for Ethereum Prices

| | Level Form | 1st Difference | Random Walk | Weak Form Efficient |
|---|---|---|---|---|
| Window 1 | 0.996ns | -17.658** | Yes | Efficient |
| Window 2 | 2.575ns | -15.704** | Yes | Efficient |
| Window 3 | -1.637ns | -19.426** | Yes | Efficient |
| Window 4 | -1.750ns | -21.150** | Yes | Efficient |
| Window 5 | 0.308ns | -19.490** | Yes | Efficient |
| All Periods | -1.614ns | -40.405** | Yes | Efficient |

Note: **significant at 1%, ns not significant.

In the case of Bitcoin prices, all price windows showed random walk behavior, except Window 3. This means that prices in time windows 1, 2, 4, 5, and 6 cannot be predicted, which is characteristic of a weak-form efficient market. Interestingly, Bitcoin prices in Window 3 (i.e., between the period of December 18, 2017 to January 27, 2019) appeared to be mean-reverting or stationary, which implies weak-form market inefficiency. On the other hand, Ethereum prices in all five windows exhibited random walk behavior. This implies that for the entire period of 2016-2020, Ethereum prices were always been following a weak-form market efficiency, wherein past prices do not affect present prices, and hence cannot be speculated.

It is important to note that the conclusions of weak-form market efficiency for Bitcoin and Ethereum based on the presence of random walk are correct if the respective price series have homoscedastic variances. In such a case where the variances of the price series are heteroscedastic, then the random walk characteristic does not guarantee that the respective markets are price efficient. This study, therefore, extends the market efficiency test to establish whether the Bitcoin and Ethereum prices are indeed unpredictable across the identified time windows where the two price series were observed to demonstrate random walk processes. On the contrary, can cryptocurrency prices be shown to be predictable using a different analytical model?

## 3. ARCH Effect

When random walk series have time dependent heteroscedastic variances, the Autoregressive Condition on Heteroscedasticity (ARCH) model can be specified to capture its increasing and decreasing volatility. Such a model produces forecasts that are elusive for random walk processes. The ARCH model is defined by two equations. The first equation is specified for the given time series, the Bitcoin or Ethereum prices, as a function of their lagged values (see Equations 5 and 7), while the second equation is defined for their variances as a function of past residual errors of the first equation (see Equations 6 and 8). The ARCH model requires that the relevant time series is stationary; hence, the price series were expressed in their first differences. Similarly, the optimal lag length k of the differenced series need to be established before estimating the first equation to determine how far back the past values of the series can affect present value. The ARCH(p) model for both Bitcoin and Ethereum prices are specified as follows:

$$\Delta BT_t = \beta_0 + \Sigma_1^p \beta_k \Delta BT_{t-p} + \varepsilon_t \tag{5}$$

$$\varepsilon_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + v_{1t} \tag{6}$$

$$\Delta ET_t = \beta_0 + \Sigma_1^p \beta_n \Delta BT_{t-p} + \varepsilon_t \tag{7}$$

$$\mu_t^2 = a_0 + a_1 \mu_{t-1}^2 + v_{2t} \tag{8}$$

where $i$ is the optimal lag length of the respective 1st differenced price series. The coefficient $\beta$'s are the model parameters of the first equation, and $\alpha$'s are the parameters of the variance equation. If $a_1$ is significant in the respective variance equations, then the ARCH effect is present in the price series. This implies that variances are not constant over time, and there is volatility spillover in the past values of the price series. This is the precondition to specifying the GARCH Model that can rebuke the earlier conclusion of weak-form price efficiency in the sub-temporal markets of Bitcoin and Ethereum based on random walk behavior.

## 4. Optimal Lag Length

Before fitting the ARCH model for each time window of the Bitcoin and Ethereum prices, the optimal lag lengths of the price series for both their level form and 1st difference were obtained. This step is crucial since the use of wrong lag lengths for the first equation of the ARCH model can lead to inaccurate results since conclusion on the presence of volatility spillover or ARCH effect is lag-sensitive. In this study, the Akaike Information Criterion (AIC) was used to determine the optimal lag length of the autoregressive (AR) model for the first difference of the price series.

For both the level forms of Bitcoin and Ethereum prices, the optimal lag lengths generally ranged from 1 to 4, except for Window 1 of Bitcoin with an unusually long optimal lag length of 55 (Table 4). This means that in each time window, the current price of the two cryptocurrencies are related to past prices dating back to at most 4 days. The large value of the optimal lag length for Bitcoin in Window 1 can be attributed to the long time (about a quarter of a year) that took for its price to surpass its initial offering of USD $0.10.

**Table 4.** Optimal Lag Lengths for Bitcoin and Ethereum Prices by Windows Based on Akaike Information Criterion (AIC), 2010-2020

| Time Frame | Bitcoin | | Ethereum | |
|---|---|---|---|---|
| | **Level Form** | **1st Difference** | **Level Form** | **1st Difference** |
| Window 1 | 55 | 54 | 1 | 6 |
| Window 2 | 3 | 12 | 3 | 2 |
| Window 3 | 1 | 4 | 4 | 3 |
| Window 4 | 2 | 1 | 2 | 1 |
| Window 5 | 1 | 4 | 1 | 0 |
| Window 6 | 1 | 0 | - | - |
| All Periods | 1 | 0 | 2 | 9 |

For the stationarized (first differenced) series of Bitcoin and Ethereum prices, optimal lag lengths ranged from 0-12 days. Similarly, Window 1 for Bitcoin showed an unusually long optimal lag length of 54 days. The longer lag lengths of the 1st differenced series for both cryptocurrencies imply that daily price increments were affected by past changes that dated much further back in time compared to the level forms.

Table 5 presents the results of the ARCH tests by window for both the Bitcoin and Ethereum. In the case of Ethereum prices, all time windows showed the presence of the ARCH effect, which implies that the variance of the price series in all time windows showed volatility clustering or non-constant variance. On the other hand, for Bitcoin prices, out of the six time windows that were identified, only Windows 3 and 5did not show the presence of the ARCH effect. In the case of Window 3, since it did not demonstrate random walk behavior, it was not tested for the ARCH effect. Window 5 showed a non-significant $\alpha 1$ coefficient, which implies that the ARCH effect is not present. It is interesting to note that the absence of the ARCH effect for both windows occurred during periods of declining prices. This suggests that the likely inefficiency in Bitcoin prices must have occurred during periods of rising prices, where volatility in past prices was passed on to present prices, making the market beatable and predictable.

**Table 5.** Testing for the Presence of the ARCH Effect in Bitcoin and Ethereum Prices by Time Window, 2010-2020

| Time Frame | Bitcoin | | | Ethereum | | |
|---|---|---|---|---|---|---|
| | α1 Coefficient | Standard Error | ARCH Effect | α1 Coefficient | Standard Error | ARCH Effect |
| Window 1 | 0.1247** | 0.0203 | Yes | 0.3386** | 0.0495 | Yes |
| Window 2 | 0.5402** | 0.0484 | Yes | 0.2423** | 0.0561 | Yes |
| Window 3 | - | - | - | 0.3459** | 0.0488 | Yes |
| Window 4 | 0.3099** | 0.0693 | Yes | 0.1271* | 0.0511 | Yes |
| Window 5 | 0.0181ns | 0.0636 | No | 0.1265* | 0.0533 | Yes |
| Window 6 | 0.1928** | 0.0633 | Yes | - | - | - |
| All Periods | 0.2511** | 0.0157 | Yes | 0.3001** | 0.0230 | Yes |

Notes: *significant at 5%; **significant at 1%; ns not significant.

## 5. GARCH Effect

Once an ARCH effect is present, the price series can now be specified as a GARCH model to measure the size of the volatility spillover and length of its persistence. The GARCH (General Autoregressive Condition on Heteroscedasticity) model is a more generalized version of the ARCH model (Bollerslev, 1986). Similar to the ARCH model, there are also two equations to define the model. The first equation is exactly the same as the first equation of the ARCH model. The difference lies in the second equation, where the squared error term of the first equation is specified as an autoregressive function of the past squared residuals and a moving average of the variance of this error term. The GARCH (p, q) model for Bitcoin and Ethereum prices are specified as follows:

$$\Delta BC_t = \beta_0 + \Sigma_k^1 \beta_n \Delta BC_{t-k} + \varepsilon_t \qquad (9)$$

$$\sigma_{\varepsilon t}^2 = \Sigma_1^p a_n \varepsilon_{t-p}^2 + v_t + \Sigma_q^1 \beta_j \sigma_{t-q}^2 \qquad (10)$$

$$\Delta ET_t = \beta_0 + \Sigma_k^1 \beta_n \Delta ET_{t-k} + \mu_t \qquad (11)$$

$$\sigma_{\mu t}^2 = \Sigma_1^p a_n \mu_{t-p}^2 + v_t + \Sigma_q^1 \beta_j \sigma_{t-q}^2 \qquad (12)$$

where $k$ is the optimal lag length of the 1st differenced price series, $p$ is the significant number of lags in the squared error term of the second equation, and $q$ is the significant number of lags in the variance term. Coefficients $\alpha$ and $\beta$ are the ARCH and GARCH terms, respectively. Specifically, the ARCH term represents how price volatility reacts to new information, and measures the volatility spillover in the price series. On the other hand, the GARCH term represents the persistence of price volatility and indicates the time at which the present volatility shock feeds the next period's fluctuations.

In this study, GARCH (1,1) was fitted for both cryptocurrency prices for all time windows to estimate the coefficients $\alpha$ and $\beta$. The sum of α and $\beta$ has important implications since it measures the rate at which the volatility spillover. due to price shocks, dies over time. If the sum of α and β is less than one, it means that the volatility spillover will be long lived. When $\alpha+\beta=1$, then the volatility spillover exhibits an exponential decay, meaning it will take a shorter time to die. On the other hand, if $\alpha+\beta>1$, then the predictions of future volatility are said to be explosive, and volatility persistence will be very short-lived.

Tables 6 and 7 show the estimated α and of the GARCH (1, 1) model for Bitcoin and Ethereum prices, respectively. There are two important points that can be derived from these results. First, the results can reinforce or refute the market efficiency conclusion derived from Table 2, which rendered the sub-temporal market for the two cryptocurrencies efficient whenever they behaved in a random walk process. Second, they can reveal whether the observed volatility spillover will disappear quickly or remain for a long time, allowing speculation by investors to profit from the existing market inefficiency.

Based on previous analyses, two time windows in the case of the Bitcoin prices showed interesting results. The market for Bitcoin in Window 3 was deemed inefficient since it did not exhibit a random walk process in the initial test. On the other hand, the prices in Window 5 were confirmed to be efficient since there was no ARCH effect found, and the GARCH (1, 1) model failed to converge. As mentioned earlier, this is an interesting result since Windows 3 and 5 were both episodes of declining prices for Bitcoin. The difference between these two time windows is that prices were decreasing rapidly (bubble crash) in Window 3, but the price drop in Window 5 was much slower. The rapid deterioration of Bitcoin prices in Window 3 could be attributed to the bursting of the price bubble in 2017, when the price dropped from an all-time high of USD $19,000 to USD $2,700, a more than 600% decline.

Many factors that may have contributed to the dismal performance of Bitcoin in this time window to lead to market inefficiency. One factor could be the over-reaction of investors in response to the idiosyncratic shocks that led to a contagion behavior in investors in the cryptocurrency market. On the other hand, the slow decline in Bitcoin prices in Window 5 can be considered a natural slump in the cryptocurrency market. It can be surmised that minimal speculative activities may have been happening during this period, and thus it is only in this time window that the Bitcoin market was truly running efficiently.

All other time windows, including the overall period, for Bitcoin prices allowed the estimation of the GARCH model, which implies that the sub-temporal markets during these periods were all weak-form inefficient. Notably, three of these time frames, Windows 2, 4, and 6, were all periods of rising prices. This suggests that strong speculative forces may have been at work during these periods that exploited market vulnerability and inefficiency. This has very interesting implications for the Bitcoin market, especially during COVID-19 (Window 6). To date, Bitcoin prices are rising at a dangerously high level, and the price bubble is speculated to burst anytime, which can cause large losses to many investors. This observation is supported by the large ARCH term in Window 6, the largest (0.9971) compared to all other windows, which implies that the present Bitcoin market is relatively jumpy and nervous.

With respect to the sum of $\alpha+\beta$, it was found to be less than unity for all relevant time windows. It was largest in Window 2 (0.8216), and lowest in Window 6 (0.0595). This means that volatility persistence relating to the life of the price bubble was observed to be longest in Window 2, and possibly shortest in Window 6. The COVID-19 pandemic can create a precarious situation for the Bitcoin market as the price bubble is expected to burst in the near future. In fact, the price bubble has already lasted for nearly 244 days (since April 2020 to early January of 2021). During this period, large Bitcoin investors (aka “whales” in the cryptocurrency world) were able to profit from the huge success of the bullish Bitcoin market.

In the case of Ethereum prices, all defined time windows allowed the estimation of the GARCH (1, 1) model, which implies that all time frames indicated weak-form inefficiency in the Ethereum market (Table 7). Therefore, whether prices were stable, increasing, or decreasing, there were always price bubbles in the Ethereum market. This suggests that speculative forces were always present, fueling market’s inefficiency.

**Table 6.** Coefficients of the GARCH (1, 1) Model for Bitcoin Prices by Time Window, 2010-2020

| Time Frame | ARCH Term | GARCH Term | $\alpha+\beta$ | Price Trend | Market Efficiency |
|---|---|---|---|---|---|
| Window 1 | 0.9721** (0.0058) | -0.9071** (0.0098) | 0.0650 | Stable | Inefficient |
| Window 2 | 0.1254** (0.0228) | 0.6962** (0.0243) | 0.8216 | Increasing | Inefficient |
| Window 3 | - | - | - | Decreasing | Inefficient |
| Window 4 | 0.9384** (0.0255) | -0.7330** (0.0424) | 0.2054 | Increasing | Inefficient |
| Window 5 | - | - | - | Decreasing | Efficient |
| Window 6 | 0.9971** (0.0123) | -0.9376** (0.0303) | 0.0595 | Increasing | Inefficient |
| All Periods | 0.9885** (0.0011) | -0.9145** (0.0025) | 0.0740 | - | Inefficient |

Notes: 1. **significant at 1%, ns not significan.
2. Values in parentheses are standard errors.

**Table 7.** Coefficients of GARCH (1, 1) Model for Ethereum Prices by Time Window, 2016-2020

| Time Frame | ARCH Term | GARCH Term | $\alpha+\beta$ | Price Trend | Market Efficiency |
|---|---|---|---|---|---|
| Window 1 | 0.8338** (0.0402) | -0.5621** (0.0514) | 0.2717 | Stable | Inefficient |
| Window 2 | 0.9972** (0.0081) | -0.8976** (0.0255) | 0.0996 | Increasing | Inefficient |
| Window 3 | 0.9971** (0.0011) | -0.8684** (0.0207) | 0.1287 | Decreasing | Inefficient |
| Window 4 | 0.9791** (0.0173) | -0.8926** (0.0328) | 0.0865 | Stable | Inefficient |
| Window 5 | 0.9714** (0.0250) | -0.8681** (0.0442) | 0.1033 | Increasing | Inefficient |
| All Periods | 0.9843** (0.0021) | -0.8794** (0.0047) | 0.1049 | - | Inefficient |

With respect to the size of the volatility spillover, the lowest ARCH term was estimated in Window 1 (0.8338), with the largest found in Windows 2 and 3 (0.9972 and 0.9971, respectively). During the Covid-19 pandemic, the ARCH term for Ethereum prices was found to be similarly large (0.9714), but a bit lower than the earlier periods. These observations imply that the market for Ethereum has always been on its toes and been predictable since its introduction in 2016.

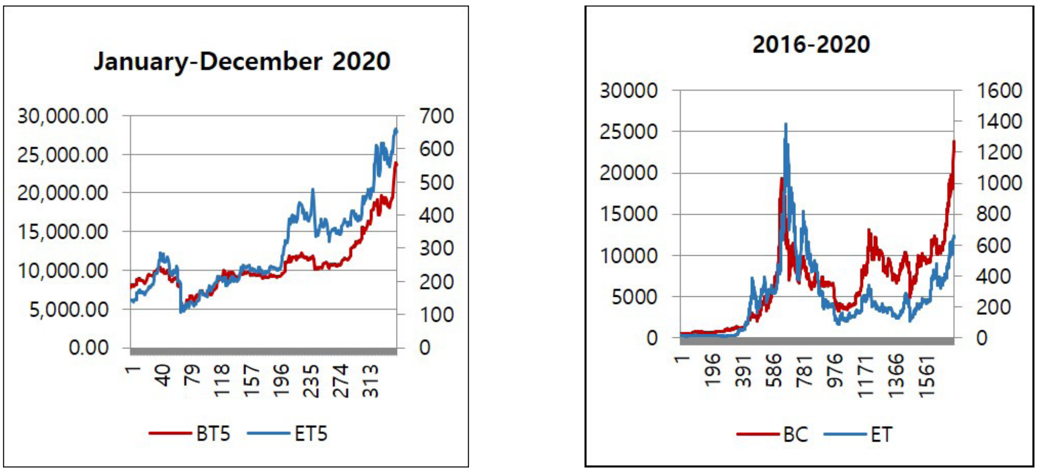
In terms of volatility persistence, the sum of α+ were found to range from 0.09 to 0.27, where the largest value occurred in the inception stage (i.e., Window 1). Generally, it can be said that the span of volatility persistence for Ethereum were generally sustained for a longer period of time before slowly dying down.

Specifically, during the COVID-19 pandemic period, the prices of Ethereum were rising, but not as spectacularly as those of Bitcoin. In fact, it did not surpass the all-time high reached in 2018 of USD $3,050. At present, the highest price so far has reached USD $740. Comparing the duration of the volatility spillover in Bitcoin and Ethereum prices during the pandemic period, it was observed that α+β was larger in Ethereum prices than in Bitcoin prices, at 0.1033 and 0.0595, respectively. These imply that the price bubble for Bitcoin may burst faster than that of Ethereum by about half the time. Hence, for cryptocurrency investors buying for speculative purposes, Bitcoin can be a riskier option since the bullish state of the cryptocurrency market can be enjoyed for a shorter time period than Ethereum. Of course, the huge difference in price is a big issue to contend with when buying these cryptocurrencies as a store of value. At any rate, investors in both assets should always be watchful and must be ready to sell portfolio holdings at any time before the bubble bursts. If investors can play the trading game wisely during COVID-19, they can take advantage of the current inefficiencies of the cryptocurrency markets.

## 6. Cointegration Analysis

Since the behaviors of the two cryptocurrency prices were both increasing in the last time windows, which coincided with the 2020 COVID-19 pandemic (Fig. 4), it is interesting to see if Bitcoin and Ethereum prices show a cointegrated relationship. Through ocular inspection, the two price series tend to move in the same direction and pattern for both the pandemic window and the entire period of 2016-2020. This is a good reason to suspect that a common trend may exist between Bitcoin and Ethereum prices, such that a genuine long run relationship may be present.

**Fig. 4.** Trends in Bitcoin and Ethereum Prices (US$) During the 2020 COVID-19 Pandemic and the Entire Period of 2016-2020



Cointegration between Bitcoin and Ethereum prices implies that the two cryptocurrencies have a genuine long-run relationship, and movements in prices are governed by a common trend they revert to whenever shocks throw them off track. To test for cointegration, the two prices need to reflect the random walk series, and the error term of the regression model should be stationary. The cointegrating regression between Bitcoin and Ethereum prices is specified as follows:

$$BC_t = \beta_0 + \beta_1 ET_t + \mu_t \tag{13}$$

Bitcoin and Ethereum prices are deemed cointegrated if the error term μ of the above model is found to be stationary. Otherwise, if the error term is found to be non-stationary, then their linear relationship is simply spurious and no genuine long run relationship exists. Table 8 shows the results of the cointegration runs for the two prices during the 2020 pandemic period and the total period of 2016 to 2020. In both time periods, the error terms of their regression models were found to be non-stationary; hence, no cointegrating relationship between the two cryptocurrencies can be established. Despite the similarity in price movements in the two periods, there was no genuine long run relationship. This suggests that any regression relationship that defines them is simply spurious. Furthermore, it implies that investors that have both cryptocurrencies in their investment portfolios should treat the two financial assets independently. For example, if the Bitcoin bubble bursts in the near future, investors should not hastily liquidate Ethereum since it is not likely that the Ethereum bubble will burst at the same time. However, since investment decisions for this asset class are highly responsive to external shocks like economic uncertainty brought about by COVID-19, the movements in cryptocurrency prices tend to be tied together, thus giving the semblance of a cointegrated relationship.

**Table 8.** Coefficients of the Cointegrating Regression between Bitcoin and Ethereum Prices During the 2020 COVID-19 Pandemic and the Entire Period of 2016-2020

| **Cointegrating Regression** | **Pandemic Period** | **All Period** |
|---|---|---|
| β0 | 3202.835**<br>(156.2166) | 2843.017**<br>(110.688) |
| β1 | 25.13891**<br>(0.479457) | 13.6936**<br>(0.33003) |
| R square | 0.8876 | 0.4966 |
| Expected Error Term E(μ) | 0.000000437 | 0.0000000542 |
| Dickey-Fuller Test for Stationarity of the Error Term μ | | |
| Z-statistic | -0.770ns | -0.075ns |
| α=5% Critical Value of Z | -2.876 | -2.860 |
| Are Bitcoin and Ethereum prices cointegrated? | No | No |

Notes: 1. **significant at 1%, ns not significant.
2. Values in parentheses are standard errors.

## IV. Summary and Conclusion

Cryptocurrencies have experienced a roller coaster ride of popularity in past years, but they have made a phenomenal comeback during the 2020 COVID-19 pandemic. The main attraction is the use of the blockchain technology to remove the need for a third-party to manage all financial transactions. Bitcoin gave the world its first exposure to cryptocurrencies. It was introduced by Satoshi Nakamoto in 2008, which was his answer to the global financial crisis of 2007-08. Ethereum, on the other hand, was the creation of Vitalik Buterin in 2013. He envisioned it as a means to create smart applications that do not need human intervention and trust to make investment decisions. Prices of these two cryptocurrencies have experienced massive fluctuations over time, but increased phenomenally during the 2020 COVID-19 pandemic. This simply demonstrated the highly volatile and risky nature of this asset class.

In line with this phenomenon, the study aimed to establish if Bitcoin and Ethereum prices follow weak-form market efficiency, and cannot be predicted. This implies that past prices do not affect present prices; therefore, investors cannot beat the market by simply looking at historical prices. Specifically, this study sought to analyze the behaviors of Bitcoin and Ethereum prices across various time windows defined by past structural breaks or changes in the trend of their mean prices. Tests for weak-form market efficiency were then carried out in terms of the presence of random walk behavior in prices by time windows. The initial conclusions regarding market efficiency were subjected to confirmatory tests based on the presence of the ARCH effect or volatility clustering and estimation of the GARCH (1, 1) model to measure volatility spillover and persistence in the two cryptocurrency prices.

Based on the analysis of the study, six time windows were identified for Bitcoin prices from 2010 to 2020, while only five time windows were identified for Ethereum prices from 2016-2020. All of the five time windows of Ethereum prices demonstrated random walk behavior, which implies that the five sub-temporal markets for this cryptocurrency are all price efficient. Similarly, Bitcoin prices demonstrated random walk behavior in five sub-temporal markets, except in Window 3 (December 2017 to January 2019). This implies that it was only during this time period where the Bitcoin market was price inefficient, while for the rest of the time, it was efficient. This tickled some curiosity since the too-good-to-be-true performance of the Bitcoin prior to the bubble burst of 2017 cannot be simply taken as natural market movements. If it was, then the price bubble should not have burst in Window 3.

The market efficiency conclusion based on the presence of random walk behavior can be true if the price series do not possess a heteroscedastic variance. Since there was too much noise in the price movements of both cryptocurrencies, the assumption of homoscedastic variance cannot be left untested. Hence, the study further investigated the presence of the ARCH effect in the price series, which is an indicator for volatility clustering or heteroscedastic variances in the price fluctuations. True enough, the ARCH effect was found to be present in all five time windows of Ethereum prices and four time windows in Bitcoin prices. This new information circumvented the initial conclusion that the Bitcoin and Ethereum markets were weak-form price efficient based on random walk behavior found in the respective sub-temporal windows. The presence of volatility clusters implies that there exist volatility spillovers, which could persist in the price series over time. To uncover this possibility, the GARCH (1, 1) model was fitted for all time windows of the two cryptocurrencies that demonstrated the ARCH effect.

Results of the analysis showed that all $\alpha$ and $\beta$ parameters of the GARCH (1, 1) model in the sub-temporal price windows were statistically significant in Ethereum prices. This means that Ethereum prices can always be predicted for the five time windows, and the respective sub-temporal markets were all deemed price inefficient. This price inefficiency can be attributed to significant market events and imperfections that can be intentional and man-made. For example, the opportunistic behaviors of crypto whales that invest in the asset when the price is low and liquidate when the price is high have debilitating effects on market efficiency.

In the case of the Bitcoin market, aside from Window 3 demonstrating outright weak-form market inefficiency due to the absence of the random walk behavior, all other sub-temporal markets, except Window 5, yielded significant coefficients for the GARCH (1, 1) model. Thus, Bitcoin prices were found to be weak-form market inefficient in Windows 1, 2, 4, and 6. This means that it was only during the period of Window 5 when the market for Bitcoin truly demonstrated weak-form market efficiency. Note that during this time frame, Bitcoin prices were going down. These price declines can be associated with a natural slump in the cryptocurrency market, and not due to any market failure or whale manipulation.

Since the 2020 pandemic started, the cryptocurrency markets are performing unexpectedly well. However, the observed fluctuations in recent prices are indicative of susceptibility to a speculative bubble. This situation is very much evident in the two cryptocurrencies, especially in the case of the Bitcoin.

The study also showed that the movement prices of Bitcoin and Ethereum are not in any way related. This was evidenced by the absence of a cointegrating relationship between their prices. This further implies that any similarity in the movements of their current prices is purely coincidental and spurious.

In general, the study showed that structural breaks are important in determining whether markets are efficient. Specifically, the identification of time windows defined by episodes of rising and falling prices yielded different results for market efficiency for Bitcoin and Ethereum. Based on the results of this study, it is clear that the prices of Bitcoin and Ethereum can be volatile and unpredictable at times, while predictable at other times. This means that both cryptocurrencies are prone to market manipulation by crypto whales whenever prices are predictable. This demonstrates that various events and shocks could turn an efficient market into an inefficient one, and vice versa.

The findings of this study provide useful information to traders and investors that hold cryptocurrencies in their investment portfolios. The issue is whether they can benefit from crypto trading based on price expectations during periods when the market is not efficient. The study is highly relevant during the 2020 COVID-19 pandemic, as the cryptocurrency market is currently experiencing both bullish performance and market inefficiency. Given that the present prices of Bitcoin and Ethereum were shown to exhibit volatility spillover and persistence, investors can now make more informed choices on whether they should invest more in this asset class at any given time or liquidate the investment to minimize losses. Knowing that the cryptocurrency market is now highly susceptible to the control of big time investors and portfolio managers called crypto whales, new and small players to the trading game should weigh decisions carefully and consider whether Bitcoin and Ethereum are worth the money given the large risks, especially during the COVID-19 pandemic.

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# An Empirical Study on the Relationship between Real Estate Price and Real Estate Investment Trusts of Shadow Banking via VAR Model: The Case of China

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## ABSTRACT

**Purpose –** The shadow banking business in China has expanded significantly in the past decade, especially in the real estate industry, which is closely related to the livelihood of many. The purpose of this paper is to investigate the relationship between the realized sale prices of real estates and the real estate investment trusts (REIT) of shadow banking in China.
**Design/Methodology/Approach –** The analysis is performed with a VAR model based on Chinese data collected from Usetrust, CSMAR, the People's Bank of China, and the National Bureau of Statistics of China during 2013 to 2020. It verifies the impact of the realized sale prices of real estate and relative macroeconomic indicators, on the REIT issuance of shadow banking by variance decomposition and impulse response analysis.
**Findings –** The prices of real estate have the greatest impact on REIT, and there is a one-way Granger causality between them. The findings indicate that it would be beneficial to establish a real estate price prediction and warning mechanism for local governments and relevant institutions to avoid the potential risks to consumers, the finance market, and the real estate industry, which might be caused by price declines or shadow banking failures.
**Research Implications –** In previous literature, it was found that the expansion of shadow banking affected the Chinese real estate market significantly, including an increase in real estate prices, risks of real estate bubbles, and a decrease in monetary policy. Most studies related to this topic collected data from official or commercial databases, respectively. Different from previous research to some extent, this paper is based on up-to-date data collected up the end of 2020. Additionally, it collects data from the two data sources from a broader aspect. The purpose of the research is to empirically explore the mutual influence of shadow banking and real estate prices, and facilitate the regulation of shadow banking for regulators and stakeholders.

***Keywords:*** real estates, real estate investment trusts, realized sale prices, VAR model, shadow banking
***JEL Classifications:*** G23, R31, R33

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## I. Introduction

Shadow banking, as a non-bank credit intermediation (Adrian & Ashcraft, 2012) involving financial businesses outside the traditional banking system, has affected the worldwide economy significantly in the past decades. It provides traditional on-balance sheet loans and shadow financing products to business entities when conservative commercial banks could not deliver sufficient financial service in various contexts (Errico et al., 2014). As a financial innovation method under financial restraint contexts, the emergence of shadow banking has reduced the proportion of indirect bank financing in total social financing, promoted the marketization of interest rates through a reversal mechanism, and eased the negative effects of macro-regulations on enterprises to a certain extent.

The growth of the shadow banking industry is particularly significant in China (Allen, Qian, Tu, & Yu, 2019). The size of Chinese shadow banking at the end of 2016 was equivalent to 82% of the country's gross domestic product, according to a survey of the international rating agency Moody's in 2017 (Moody's Investors Service, 2017). It reached its historical peak of 100.4 trillion at the beginning of 2017 (CBIRC, 2020), and decreased to 51.1 trillion at the end of 2017 due to the strict supervision of the central government. However, it was still 7.7 times that of 2008, signifying a surprising annual growth rate of 25.5% and a year-on-year growth rate of over 80%. The stock of Chinese shadow banking at the end of 2018 still remained as high as 48 trillion Chinese yuan, similar to the end of 2017 (Li, 2019). According to the first official shadow banking report of China released by CBIRC in December 2020, the scale of China's broad shadow banking increased to 84.80 trillion Chinese yuan, accounting for 86% of GDP in 2019, equivalent to 29% of total banking assets in the same period. However, there was a reduction of nearly 16 trillion Chinese yuan from the historical peak of 100.4 trillion at the beginning of 2017 (CBIRC, 2020). Moody's stated that although the Chinese government will temporarily decrease the supervision on shadow credit in 2020 due to the epidemic of COVID-19, the regulators will continue to strengthen regulations on shadow banking in the future, and shadow banking assets are expected to be further reduced in 2021.

Compared with other countries, shadow banking in China is generally defined as loans issued beyond the traditional banking sector and used as leverage (Adrian & Jones, 2018). A large portion comes from the purchase of financial products by individual investors, or bundled short-term loans designed by banks and other financial institutions. Dangers exist to some extent since shadow banking is opaque and has almost no formal security guarantees (Lin, Chen, & Huang, 2018). Financing in certain industries may be over-expanded, and interest from investors may suddenly disappear. Today, shadow banking is at a turning point. As government regulation begins to take effect, financing through shadow banking is expected to be accepted as supplementary to mainstream banking services. However, the next phase may also be more shadowy from the perspective of its uncertain derivatives and leverage functions (Jiang, 2015).

The potential risks increase with the growth of the business. Regulatory arbitrage issues arise when shadow banking institutions engage in activities that potentially violate banking regulations (Nersisyan & Wray, 2010). Furthermore, disadvantages such as the high leverage ratio, maturity mismatch, information opacity, and other risks caused by the lack of sufficient supervision have become more prominent. It is believed that the real estate bubble and financial system turbulence will occur if the risk exceeds the controllable range (Jing, Wang, & Fang, 2019). Additionally, the payments method of shadow banking to investors is also regarded by scholars as similar to a Ponzi scheme (Schwarcz, 2017). It is doubtful if shadow banking is necessary for a functioning real estate business.

The top priority of financial supervision in China has always been to avoid systemic financial risks due to its huge economic volume and massive population. The Chinese central government is also concerned about the potential risks of shadow banking since the expansion of real estate investment supported by shadow banks has risen significantly faster than the growth of per capita incomes. The chairman of the Bank of China, Xiao Gang, has also expressed concerns and proposed that shadow banking must be regulated from a variety of aspects (Collier, 2017). According to Xiao, shadow banking starts basically as a funding pool that functions like a Ponzi scheme. He believes that it is a pressing matter to improve the regulation of the shadow banking system, even though it might not amount to a systemic financial risk (Huang, Chang, & Yang, 2012).

Current systemic financial risks related to shadow banking come from three aspects: real estate risks, local debt risks, and shadow banking risks. The three aspects are intricately intertwined, and the downturn in real estate prices may negatively effect bank balance sheets, the revenues of local governments, and economic growth (Zhou, Liu, & Wang, 2020). As a result, China has launched series of strict regulations on housing loans issued by commercial banks in 2013, making it harder for real estate developers to secure sufficient funding from financial institutions, including traditional banks and shadow banks. The latest and more severe regulations on real estate loans both for developers and consumers were launched in December 2020 to avoid possible real estate credit risks (Allen et al., 2019).

It is necessary to observe and evaluate the investment trusts of the shadow banking business for a better understanding of the role of financial regulation and provide appropriate recommendations to stakeholders and policymakers (Adrian & Ashcraft, 2012). However, the purpose of the regulatory is not to eliminate shadow banking as well as traditional banks, but to improve the norms and transparency of performance and avoid disordered expansion. The rise of shadow banking cannot be replaced by traditional banks to some extent. They are still expected to coexist with traditional banks for a long time (Hanson, Shleifer, Stein, & Vishny, 2015).

This research is thus focusing on the issuance of the real estate investment trusts of shadow banks, especially in relation with the realized sale prices of real estate via VAR model based on data from China. The indices related to real estate sales, including currency issuance, real estate consumption, and macroeconomic prosperity index are also adopted in the research and are analyzed to examine how these factors affect the issuance of real estate investment trusts (REIT) from shadow banking institutions. The purpose of the research is to empirically explore the mutual influence of shadow banking and real estate prices, and facilitate the regulation of shadow banking for stakeholders and regulators.

## II. Literature Review

From the perspective of the definition of shadow banking, existing literature defines it as a non-bank financial institution separate from traditional commercial banks from an institutional perspective (McCulley, 2007). From a business perspective, it is defined as the shadow banking business of traditional banks plus non-bank financial institutions (Li, 2019). It is also regarded as non-bank financial activities outside of bank credit that are most likely to cause risks (Engelen, 2017). Shiller (2012) believes that shadow banks could not be defined as commercial banks since they are carefully designed as a specific financial institution, and would not absorb deposits from depositors.

The widely accepted definition of shadow banking is derived from that of the Financial Stability Board 2011-2017. It is defined in broad and narrow aspects (Adrian & Ashcraft, 2016). In a broad sense, it refers to all institutions involved in credit financing activities as a credit intermediary outside the traditional banking system. The common practice in this sense is the focus on asset securitization in developed countries. In a narrow sense, this refers to non-banks that provide banking services such as liquidity or maturity transformation and increased leverage to enterprises, residents, and other financial institutions (Zabala & Josse, 2014). To a certain extent, it can be regarded as a supplement to the commercial banking business (Tucker, 2010).

The concept of China‘s shadow banking remained unclear until 2013, when the People‘s

Bank of China first clarified it in the China Financial Stability Report 2013. According to the report, China does not actually have shadow banking under the international general definition based on its unique financial environment and structure. Although shadow banking emerged and developed relatively late in China, there are indeed some institutions offering similar financing products or services to shadow banks (Hachem, 2018). However, unlike traditional intermediaries, China's shadow banking was not only constructed by financial institutions and businesses, it also has its own uniqueness to a certain extent, such as credit conversion functions (Wang & Liu, 2017). Additionally, unlike the formal banking system, shadow banks are far less secure than the former, which results in negative effects, such as regulatory arbitrage or financial risks (Liu, 2019).

It has been accepted that trusts and financial services are the core business of shadow banking (Fernandez & Wigger, 2016), and the main investment target of trust products is the real estate industry (Adrian & Ashcraft, 2016). However, from the perspective of shadow banking and financial stability, some scholars believe that shadow banking is not conducive to the stability of the financial market or real estate industry.

Pozsar and Singh believed that shadow banks led to the rise of real estate prices and, to some extent, the formation of price bubbles in Europe, the United States, and other countries in 2008 (Pozsar, 2014). Gorton, Metrick, Shleifer, & Tarullo (2010) discussed the transmission mechanism of shadow banking to the currency market. Dell'Ariccia, Igan, and Laeven (2012) found that the release of real estate credit standards were closely related to an increase in bank credit. Gennaioli, Shleifer, and Vishny, (2013) analyzed the types of shadow banking in an empirical model, analyzed the mechanism of systemic financial risk, and summarized the channels and methods of shadow banking risk contagion. Istiak and Serletis (2016) explored the transmission mechanism of shadow banking on monetary policy from the perspective of the relationship between the banking industry and shadow banking services. Hodula (2018) analyzed factors affecting the growth of shadow banking in Europe, and found that the European shadow banking system had a positive relationship with the local economy under strict supervision. It was found in their research that the expansion and development of shadow banking might operate as a supplement to the traditional banking industry to some extent.

Chinese researchers also investigated factors affecting shadow banking credits in China. Xie and Li (2014) discussed the impact of shadow banking on commercial bank credit from both positive and negative aspects, and suggested that the shadow banking industry should be organized and supervised under financing schemes to avoid potential risks since they are closely correlated with livelihoods across the nation. Shen (2016) found that there was a mutual effect between the issuance of shadow bank credits and Chinese monetary regulatory. Zhao and He (2018) believed that shadow banking could affect the interest rate and had a substitution effect on monetary policy, but it was dominated by the interest rate effect, and the prices of real estate and shadow credit had endogenous mechanisms that affect each other.

Chen, Ren, and Zha (2018) discussed the credit creation function of shadow banking and its challenges to monetary policy, and proposed countermeasures to innovate monetary policy tools to meet the challenges of shadow banking. Liu (2019) stated that the demand for real estate credit increases the issuance of real estate investment trusts of shadow banks. Gong, Xiong, and Zhang (2019) found that the expansion of shadow banking has pushed up housing prices, and changes in monetary policy affect the size of shadow credit.

Some scholars conducted research to verity the effect of Chinese shadow banking and real estate prices with a VAR model, based on different data sources and samples. Li and Yan (2018) analyzed the relationship between the scale of shadow banks and real estate prices in Beijing from 2002 to 2015 with a SVAR model using data from CEInet. Lu (2015) explored the effect of shadow banking on real estate prices from 2006 to 2013 with a VAR model using data from CEInet and the People's Bank of China. Sun (2018) examined the effect of interest rate liberalization on shadow banking and the real estate market from 2012 to 2016 with a SVAR model using data from the Bank of China and the China Index Academy. Ren, Xing, and Zhang (2019) analyzed the effect of shadow banking on monetary policy and real estate prices from 2012 to 2017 with a VAR model using data from CIEnet and the People's Bank of China. Zhang (2019) examined the effect of shadow banking on real estate prices and financial stability form 2010 to 2017 with a SVAR model using data from BIS, Wind, the People‘s Bank of China, and the National Statistics of China. It was found in their research that the expansion of shadow banking affects the prices of real estate positively while also increasing the risks of real estate investments.

It was found in previous literature that the expansion of shadow banking affected the Chinese real estate market significantly, including an increase in real estate prices, risks of real estate bubbles, , and a decrease in monetary policy (Hu & Zheng, 2016). A VAR model was thus established in this research to examine the relationship between shadow banking and real estate prices in China, but it collects data from Usetrust and other sources, different from the previous research to some extent. The purpose of the research is to empirically explore the mutual influence of shadow banking and real estate prices, and facilitate the regulation of shadow banking for regulators and stakeholders.

## III. Methodology

### 1. Data Collection

This research focuses on the relationship between the realized sale prices of real estate and the issuance of real estate investment trusts (REIT) of shadow banking in China from 2013 to 2020. The data were collected from Usetrust, CSMAR, the Bank of China, and the National Bureau of Statistics of China. The analysis is focused on the correlation between these and macroeconomic indices related to real estate sales.

Due to the accessibility of the data sources, this research is conducted on data collected from January 2013 to December 2020. There were 96 groups of data collected from the official website of Usetrust on the monthly issuance of REIT. However, since the publication of real estate sales price in China stopped at the end of 2010, we collected another two sets of data, including the monthly growth of total sales and total sale areas of commercial properties, from the official website of the National Bureau of Statistics of China. The average sales price index was derived from the data sets and adopted for further analysis. Other data were collected from the databases of CSMAR and the People's Bank of China.

### 2. Variables

#### 2.1. Explained Variable

The explained variable in the research is the monthly growth of Real Estate Investment Trust (REIT). REIT is different from real estate trust funds, which are the core real estate investment tool in China. A REIT, unlike real estate companies, does not develop real estate properties to resell them. On the contrary, it purchases and develops properties for the purpose of operating them as part of its own investment portfolio. As a result, REIT has been employed as regulated investment vehicles by trust companies that allow investors to invest in a trust with the goal of profiting or receiving income from real estate as beneficiaries. They rely heavily on loans from shadow banking institutions. Therefore, the research adopts REIT to examine the roles of the shadow banking system in real estate financing.

REIT issuance is an indicator of the credit scale of shadow banking in China. Since the People's Bank of China launched strict restrictions on the commercial bank loans on real estate projects by the No. 121 Profile in June 2003, trust companies began to focus on the real estate trust industry as a supplement to traditional financing services and REIT have become a main source of capital for real estate development. Therefore, REIT is introduced in the research to investigate the relationship between real estate prices and shadow banking credits.

**2.2. Explanatory Variable**

*2.2.1. Average Sales Price of Commercial Houses per Month (PRICE)*

The average realized prices of real estate in various areas of a city are the average transaction price of various types of commercial housing (P). The data in this research on monthly sales price and total sales area of real estate are collected from the official website of the National Bureau of Statistics of China. However, the publication of real estate sales prices were stopped at the end of 2010. Therefore, we collected another two sets of data, which include the monthly growth of total sales and total sales area from the same official website. The average sales price index was obtained from this data pool and adopted for further analysis in the research.

Average sales price = monthly growth of sales of commercial houses/monthly growth of sale areas

*2.2.2. Monthly Money Circulation (M1)*

Monthly money circulation (M1) is the total number of currencies issued by a country, including all circulating currencies and non-circulating currencies. The correlation between M1 and asset prices is the strongest among M0, M1, and M2. Therefore, the monthly data of M1 is adopted as a substitute variable for money supply in this research.

*2.2.3. One-Year Fixed Deposit (FD) Interest Rate on Monthly Basis (RATE)*

The fixed deposit interest rate refers to the financial benefits provided by banks to provide investors a higher rate of interest than a regular savings account. The one-year FD interest rate is adopted as the explanatory variable in the research.

*2.2.4. Consumer Price Index per Month (CPI)*

The Consumer Price Index (CPI) is a weighted average of prices in a set of typical consumer products and services in a given period of time. It is used to estimate price inflation linked with the cost of living, and the monthly fluctuations of CPI could influence investor decisions to purchase houses or real estate trusts.

*2.2.5. Main Economic Indicators per Month (MEI)*

The Main Economic Indicators (MEI) present comparative statistics that provide an overview of recent economic developments. It was adopted as the explanatory variable because it reflects the state of macro-economy as a combination of four indexes (Early Warning Index, Coincident Index, Leading Index, and Lagging Index). Among the four indexes, the Leading Index (Composite Index of Leading Economic Indicators) is a composite index composed of 12 financial indicators. The financial indicators of the Leading Index provide indirect indications, whereas non-financial indicators provide more direct evidence for economic changes. The synthesized Leading Index is more comprehensive and could be used to predict economic trends. The Lagging Index is composed of a group of lagging indicators depicting economic events, which confirms recent economic events. The Coincident Index comprehensively indicates events in the national economy and serves as a comparison between the Leading and Lagging Indexes. The hypotheses are proposed below.

**H1:** The price of real estate and REIT issuance are positively correlated.
**H2:** Interest rates and REIT issuance are negative correlated.
**H3:** Money circulation and REIT issuance are positively correlated.
**H4:** The expansion of shadow banking stimulated by arising CPI and the REIT issuance of shadow banking are positively correlated.
**H5:** The fluctuations of the macro-economy and the REIT issuance of shadow banking are positively correlated.

The variables adopted in the research are listed in Table 1.

**Table 1.** Descriptions of Variables

| Variables | | Description | Data Source |
|---|---|---|---|
| Explained Variable | Monthly growth in the issuance of REIT (TRUST) | Monthly growth of REIT issuance | Usetrust |
| Explanatory Variable | Average sales price of commercial houses per month (PRICE) | Average sales price = Monthly growth of sales of commercial houses /Monthly growth of sale areas | National Bureau of Statistics of China |
| | Money circulation per month (M1) | The correlation between M1 and asset prices is the strongest among M0, M1, and M2. Therefore, the monthly data of M1 is adopted as a substitute variable for money supply in the research | the People's Bank of China |
| | One-year fixed deposit (FD) interest rate on monthly basis (RATE) | Changes in interest rates directly affect investor purchase costs and developer financing costs | CSMAR |
| | Monthly Consumer Price Index (CPI) | As a measure that examines price inflation linked with the cost of living, the monthly fluctuations of CPI could influence investor decisions in purchasing houses or real estate trusts | National Bureau of Statistics of China (The announced value is based on the CPI year-on-year index) |
| | Monthly Main Economic Indicators (MEI) | Indexes reflecting the overall changes of China's macro-economy | CSMAR |

## IV. Results and Discussion

### 1. Descriptive Statistics Analysis

Before the empirical analysis, a descriptive statistics analysis was conducted. It included the monthly growth in the issuance of REIT (TRUST), average sales price of commercial houses per month (PRICE), money circulation per month (M1), the one-year deposit interest rate on a monthly basis (RATE), monthly consumer price index (CPI), and Monthly Main Economic Indicators (MEI). The results of descriptive statistics analysis are summarized in Table 2.

According to the results in Table 2, the maximum and minimum value of monthly growth of REIT issuance (TRUST) are 6.37 and 3.89, respectively, with a mean value of 5.0252, an average value of 5.0252, and a standard deviation of 0.5545. The skewness, kurtosis, and JB statistical distributions are 1.2519, 0.3418, and 27.4558, respectively.

The maximum and minimum values of the average sales price of commercial houses per month (PRICE) are 9.0194 and 8.3963, respectively. The mean value is 8.7593, the average value is 8.7587, and the standard deviation is 0.1486. The distribution of skewness, kurtosis, and JB statistics

**Table 2.** Results of Descriptive Statistics Analysis

| | TRUST | PRICE | M1 | RATE (%) | CPI (%) | MEI |
|---|---|---|---|---|---|---|
| Maximum Value | 6.3700 | 9.0194 | 13.2063 | 3.5000 | 6.4500 | 4.6453 |
| Minimum Value | 3.8920 | 8.3963 | 12.3207 | 1.5000 | 0.8000 | 4.5263 |
| Mean | 5.0297 | 8.7593 | 12.6823 | 2.7500 | 2.2250 | 4.5773 |
| Average | 5.0252 | 8.7587 | 12.7177 | 2.4844 | 2.6251 | 4.5775 |
| Standard Deviation | 0.5545 | 0.1486 | 0.2375 | 0.7280 | 1.3506 | 0.0372 |
| Skewness | 1.2519 | 0.3418 | 0.4732 | -0.2118 | 0.2219 | -0.2566 |
| Kurtosis | 3.7710 | 1.8553 | 2.2214 | 2.2798 | 2.7166 | 1.5639 |
| JB Statistics | 27.4558 | 7.1108 | 6.0079 | 2.7926 | 1.1090 | 9.3028 |
| Number of Samples | 96 | 96 | 96 | 96 | 96 | 96 |

are 0.3418, 1.8553, and 7.1108.

The maximum and minimum values of money circulation per month (M1) are 13.2063 and 12.3207, respectively. The mean value is 12.6823, the average value is 12.7177, and the standard deviation is 0.2375. The distribution of skewness, kurtosis, and JB statistics are 0.4732, 2.2214, and 6.0079.

The maximum and minimum values of the one-year deposit interest rate on monthly basis (RATE) are 3.5 and 1.5, respectively. The mean value is 2.75, the average value is 2.4844, and the standard deviation is 0.728. The skewness, kurtosis, and JB statistics distribution are -0.2118, 2.2798, and 2.7926.

The maximum and minimum values of monthly consumer price index (CPI) 6.45 and 0.8, respectively. The median is 2.225, the average is 2.6251, and the standard deviation is 1.3506. The distribution of skewness, kurtosis, and JB statistics are 0.2219, 2.7166, and 1.1090.

The maximum and minimum values of the monthly Main Economic Indicators (MEI) are 4.6453 and 4.5263, respectively. The median value is 4.5773, an average value is 4.5775, and the standard deviation is 0.0372. The skewness, kurtosis, and JB statistics distribution are -0.2566, 1.5639, and 9.3028.

There are 96 groups of samples in the research. If the standard deviation is higher than the mean value, the data may contain extreme outliers that require further analysis. Furthermore, the average value of the variables is greater than relevant standard deviation, indicating that the degree of data dispersion is not high and could be used for further analysis.

## 2. Empirical Analysis

### 2.1. Unit Root Test

The ADF Unit Root Test is conducted respectively in time series, based on the collected data of the monthly growth of issuance of REIT (TRUST), average sales price of commercial houses per month (PRICE), money circulation per month (M1), one-year deposit interest rate on monthly basis (RATE), monthly consumer price index (CPI) and monthly Main Economic Indicators (MEI) .

The results of the ADF Unit Root Test are summarized in Table 3.

**Table 3.** Results of the ADF Unit Root Test

| Variable | Tests (C, T, K) | ADF Value | Critical Value | | | Probability | Results |
|---|---|---|---|---|---|---|---|
| | | | 1% | 5% | 10% | | |
| LNTRUST | (C,0,0) | -4.3742 | -3.5007 | -2.8922 | -2.5832 | 0.0006 | Stable |
| LNPRICE | (C,0,11) | -0.4256 | -3.5103 | -2.8963 | -2.5854 | 0.8990 | Unstable |
| DLNPRICE | (C,0,11) | -3.6010 | -3.5113 | -2.8968 | -2.5856 | 0.0077 | Stable |
| LNM1 | (C,0,1) | -1.5018 | -3.5014 | -2.8925 | -2.5834 | 0.5285 | Unstable |
| DLNM1 | (C,0,0) | -12.3419 | -3.5014 | -2.8925 | -2.5834 | 0.0001 | Stable |
| CPI | (C,0,0) | -1.7132 | -3.5007 | -2.8922 | -2.5832 | 0.4214 | Unstable |
| DCPI | (C,0,0) | -11.8617 | -3.5014 | -2.8925 | -2.5834 | 0.0001 | Stable |
| RATE | (C,0,2) | -1.5582 | -3.5022 | -2.8929 | -2.5836 | 0.4998 | Unstable |
| DRATE | (C,0,1) | -3.8365 | -3.5022 | -2.8929 | -2.5836 | 0.0037 | Stable |
| LNMEI | (C,0,0) | -0.1450 | -3.5007 | -2.8922 | -2.5832 | 0.9405 | Unstable |
| DLNMEI | (C,0,0) | -8.2464 | -3.5014 | -2.8925 | -2.5834 | 0.0000 | Stable |

Note: C, T, K in the Tests (C, T, K) refer to the constant, time trend and lag order in unit root test respectively, and 0 means Not Included.

According to the results in Table 3, LNPRICE, LNM1, CPI, RATE, and LNMEI are non-stationary with unit roots. It could be concluded that the null hypothesis cannot be rejected because the test statistics are all greater than the crucial values at the 1%, 5%, and 10% significance levels.

The sequence of DLNPRICE, DLNM1, DCPI, DTRATE, DLNMEI are obtained by subtracting the first-order differences of LNPRICE, LNM1, CPI, RATE, and LNMEI. After that, the above sequence was evaluated under the unit root test. The results demonstrate that the sequence following the difference is stationary. LNPRICE, LNM1, CPI, RATE, and LNMEI are all first-order single integer sequences, with LNTRUST remaining stationary.

### 2.2. Johansen Cointegration Test

The Johansen cointegration test was adopted for further analysis since the sequences are not always economically significant. The Johansen Cointegration Test, also known as the JJ (Johansen-Juselius) test, is a cointegration test based on the VAR model proposed by Johansen and Juselius to test regression coefficients. It was adopted to test if there is a long-term stable equilibrium connection between the non-stationary initial series, which reflects the economic implications more intensively.

The results of the Johansen Cointegration Test (trace test) and Johansen Cointegration Test (maximum characteristic root rest) are presented in Tables 4 and 5. It can be found in Tables 4 and 5 that there is a co-integration relationship between the four groups of variables, based on the results of the trace test and the maximum characteristic root test, respectively. Further, there are five co-integration variables at the essential level of 5%, indicating that the variables in the long-term equilibrium relationship are in stable connections. The results indicate that the Granger causality test can be conducted in further analysis.

**Table 4.** Results of Johansen Cointegration Test (Trace Test)

| Cointegration Vector | Characteristic Root | Value | 5% Critical Value | Probability (P) |
|---|---|---|---|---|
| None * | 0.4674 | 191.6044 | 95.7537 | 0.0000 |
| At most 1 * | 0.3787 | 133.6471 | 69.8189 | 0.0000 |
| At most 2 * | 0.3322 | 89.8534 | 47.8561 | 0.0000 |
| At most 3 * | 0.2566 | 52.7082 | 29.7971 | 0.0000 |
| At most 4 * | 0.1729 | 25.4311 | 15.4947 | 0.0012 |
| At most 5 * | 0.0829 | 7.9635 | 3.8415 | 0.0048 |

**Table 5.** Johansen Cointegration Test (Maximum Characteristic Root Test)

| Cointegration Vector | Characteristic Root | Value | 5% Critical Value | Probability (P) |
|---|---|---|---|---|
| None * | 0.4674 | 57.9573 | 40.0776 | 0.0002 |
| At most 1 * | 0.3787 | 43.7937 | 33.8769 | 0.0024 |
| At most 2 * | 0.3322 | 37.1453 | 27.5843 | 0.0022 |
| At most 3 * | 0.2566 | 27.2770 | 21.1316 | 0.0060 |
| At most 4 * | 0.1729 | 17.4676 | 14.2646 | 0.0151 |
| At most 5 * | 0.0829 | 7.9635 | 3.8415 | 0.0048 |

### 2.3. Granger Causality Test

The results of the Granger causality test are listed in Table 6. It can be seen that there is a one-way Granger causation between average commercial housing sale prices and the issuance shadow banking REIT. It can be concluded that only the average sales price of commercial housing can affect the issuance of shadow bank REIT, while Granger causality does not exist for the contrary.

In addition, there is also no Granger causation between LNTRUST and any of the variables, indicating that, in the absence of conventional bank financing channels, real estate financing of the shadow banking system has played a supporting role in the real estate business. This suggests that shadow banking credit has become a significant source of real estate finance.

**Table 6.** Results of the Granger Causality Test

| Null Hypothesis | Chi-sq Value | p Value | Results |
|---|---|---|---|
| DLNPRICE is not the Granger for LNTRUST | 5.7362 | 0.0468 | Y |
| LNTRUST is not the Granger for DLNPRICE | 3.7781 | 0.1512 | N |
| DLNM1 is not the Granger for LNTRUST | 1.5921 | 0.4511 | N |
| LNTRUST is not the Granger for DLNM1 | 3.0135 | 0.2216 | N |
| DCPI is not the Granger for LNTRUST | 2.8088 | 0.2455 | N |
| LNTRUST is not the Granger for DCPI | 2.0031 | 0.3673 | N |
| DRATE is not the Granger for LNTRUST | 4.6305 | 0.0987 | N |
| LNTRUST is not the Granger for DRATE | 2.7482 | 0.2531 | N |
| DLNMEI is not the Granger for LNTRUST | 0.6074 | 0.7381 | N |
| LNTRUST is not the Granger for DLNMEI | 1.1955 | 0.5501 | N |

### 2.4. VAR Lag Order Criterion

The VAR model is a form of auto-regressive model. The identification of the lag order, in addition to the selection of relevant variables, is critical to the creation of the model. This research adopts the second-order lag approach based on the AIC criterion. The results of the VAR lag order criterion of the research are present in Table.

**Table 7.** Results of the VAR Lag Order Criterion

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 644.6890 | NA | 0.0000 | -14.0371 | -13.8716* | -13.9703 |
| 1 | 709.4117 | 119.4881 | 1.72E-14 | -14.6684 | -13.5095 | -14.2009* |
| 2 | 748.0868 | 66.3001* | 1.64E-14* | -14.7272* | -12.5750 | -13.8589 |
| 3 | 778.0164 | 47.3612 | 1.92E-14 | -14.5938 | -11.4483 | -13.3248 |
| 4 | 806.4178 | 41.1976 | 2.38E-14 | -14.4268 | -10.2879 | -12.7570 |

### 2.5. Stability of the Research Model and VAR Model Test

The stability of the VAR model in the research has been verified, and the results are confirmed by the previous analyses. In the VAR model, the coefficients of determination R2 for the six regression functions are 0.6309, 0.3650, 0.3755, 0.2897, 0.2116, and 0.2854.

From the perspective of the equation coefficients, the coefficients of the first-order lag and the second-order lag of the coefficients of the equation of LNTRUST regression to DLNPRICE are more significant and positively correlated. It can be found that the average price of commercial houses has a positive impact on the issuance of REIT.

It can be found that the first-order and second-order influence coefficients of the REIT issuance and the average price of commercial houses are 0.9014 and 1.5427. It indicates that every unit change in the average price of commercial housing in the lag phase will result in a 0.9014 unit change in the issuance of REIT, and every change in the Phase 2 Lag will result in a 1.5427 unit change in the issuance of REIT. It can be estimated that changes in the prices of commercial houses may affect the supply of real estate credit provided by trust companies, as both tend to move in the same direction.

However, a negative correlation can be found between the one-year deposit interest rate and the issuing of real estate investment trusts. In addition, M1 has a positive impact on the issuance of REIT in Phase 1 Lag, while it has a negative impact in Phase 2 Lag. It can be concluded that both the CPI and the macroeconomic index have positive impacts on REIT issuance, indicating positive correlations between them.

**Fig. 1.** The VAR Model

$$
\begin{pmatrix} LNTRUST \\ DLNPRICE \\ DRATE \\ DLNM1 \\ DLNMEI \\ DCPI \end{pmatrix}_t = \begin{pmatrix} 1.7226 \\ -0.0749 \\ 0.1671 \\ 0.0277 \\ 0.0078 \\ 0.2916 \end{pmatrix} +
\begin{bmatrix} 0.4418 & 0.9014 & -0.1682 & 2.2066 & 4.6268 & 0.1425 \\ -0.0232 & -0.4374 & 0.0239 & -0.4596 & -1.2350 & -0.0075 \\ -0.0237 & -0.1306 & 0.0253 & -0.2623 & 0.3223 & -0.0156 \\ 0.0018 & 0.0880 & -0.0118 & -0.2123 & 0.3045 & 0.0149 \\ -0.0011 & -0.0024 & 0.0009 & 0.0079 & 0.1782 & 0.0037 \\ -0.1815 & -1.3131 & 0.9385 & 0.1495 & 27.8560 & -0.2273 \end{bmatrix}
\begin{pmatrix} LNTRUST \\ DLNPRICE \\ DRATE \\ DLNM1 \\ DLNMEI \\ DCPI \end{pmatrix}_{t-1} +
$$

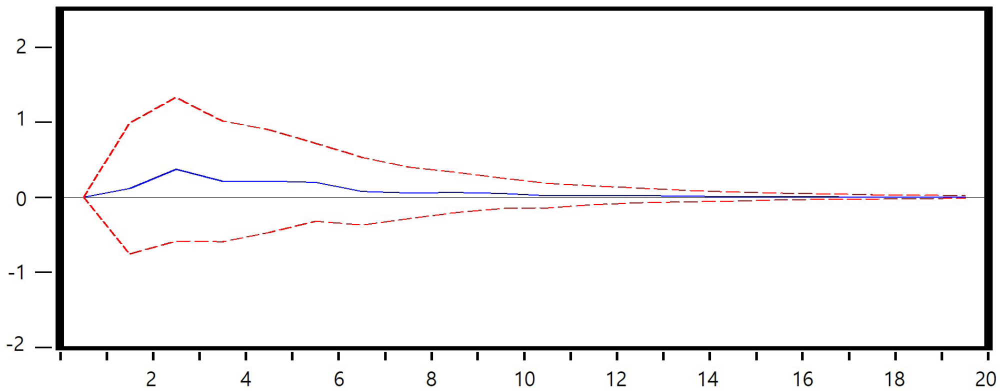
$$
\begin{bmatrix} 0.2135 & 1.5427 & -0.8935 & -1.1426 & 4.4767 & 0.1025 \\ 0.0362 & -0.4389 & 0.0106 & 0.0910 & 0.0265 & 0.0229 \\ -0.0108 & -0.2444 & 0.4018 & -0.5460 & 0.9009 & -0.0059 \\ -0.0091 & 0.0974 & -0.0100 & 0.0361 & -0.7799 & -0.0002 \\ -0.0002 & 0.0082 & 0.0038 & 0.0587 & -0.0836 & -0.0003 \\ 0.1196 & 0.6713 & 0.3640 & 3.2722 & 3.8935 & 0.0349 \end{bmatrix}
\begin{pmatrix} LNTRUST \\ DLNPRICE \\ DRATE \\ DLNM1 \\ DLNMEI \\ DCPI \end{pmatrix}_{t-2} +
\begin{pmatrix} \varepsilon 1t \\ \varepsilon 2t \\ \varepsilon 3t \\ \varepsilon 4t \\ \varepsilon 5t \\ \varepsilon 6t \end{pmatrix}
$$

### 2.6. Impulse Response

#### *2.6.1. Impact of the Average Sales Price of Commercial Houses on REIT Issuance*

The impulse response of REIT issuance to the average sales price of real estate is presented in Fig. 2. In terms of the impulse response of REIT issuance, the average sales price of commercial houses had no immediate impact on REIT issuance. The shock in Phase 1 was zero, but the largest positive shock was formed in Phase 3. Then, the response weakened and approached zero in Phase 4, and a larger positive shock was formed in Phase 6. After that, the fluctuation range of the shock gradually became smaller. It could be found that the average price of commercial real estate had a consistent positive impact on REIT issuance during the investigation period. It can be estimated that when the prices of real estate are stable or on the rise, the rate of bad debts of real estate investment trusts is expected to be unusually low, and the risk is generally low, making REITs the most common type of shadow banking loan. As a result, shadow banks will actively invest in credit funds in the real estate sector, resulting in significant profits. That is, if the price of commercial houses rise, shadow banking's credit investment in real estate enterprises will rise as well.

**Fig. 2.** Impulse Response of REIT Issuance to the Average Sales Price of Real Estate




#### *2.6.2. Impact of the One-Year Interest Rate on REIT Issuance*

It can be seen in Fig. 3 that interest rates have a continual negative impact on REIT issuance during the investigation period. This is because when interest rates rise, so do incomes from savings or bonds, making real estate investment less attractive. When the interest rate rises, the profits of real estate investment are low and real estate investment would not be considered an ideal investment vehicle. When the demand of investors falls, REIT issuance will also decrease. However, when interest rates fall below a certain level, the demand for funds from all parties grows and the economy recovers, and more investment trusts invest in real estate, resulting in an increase in REIT issuance from shadow banks.

**Fig. 3.** Impulse Response of REIT Issuance to Interest Rates

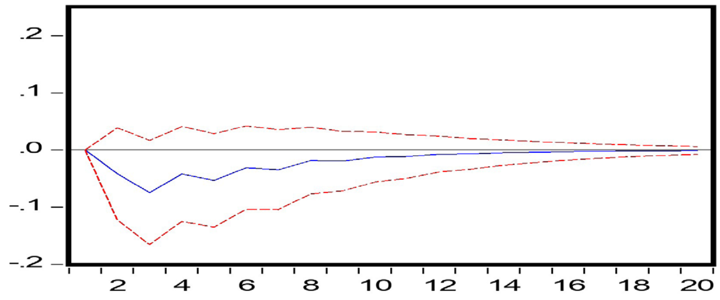



**Fig. 4.** Impulse Response of REIT Issuance to Money Supply

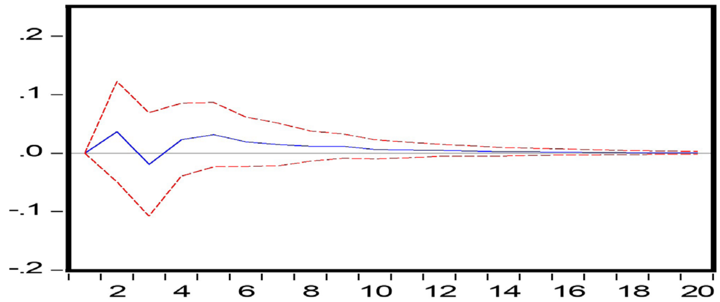



**Fig. 5.** Impulse Response of REIT Issuance to CPI

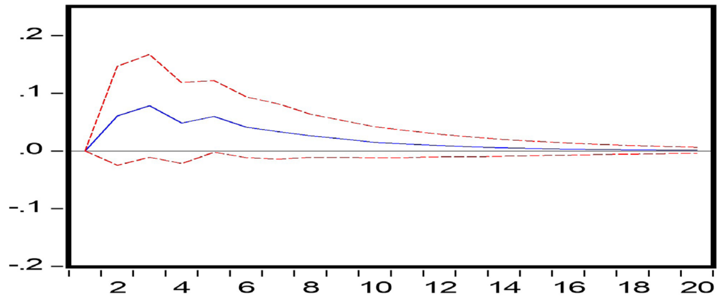
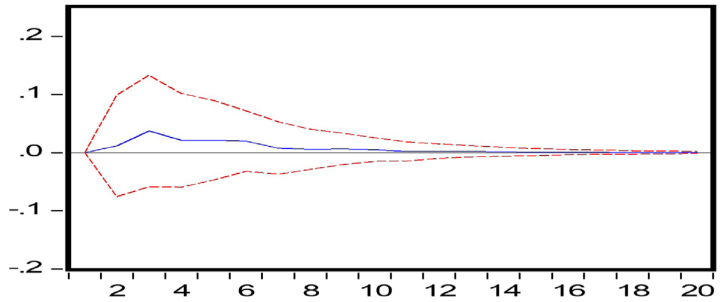



**Fig. 6.** Impulse Response of REIT Issuance to the Macroeconomic Prosperity Index



*2.6.3. Impact of Money Supply on REIT Issuance*

It can be seen in Fig. 4 that the money supply has a positive impact on REIT issuance in the short term during the investigation period. After that, it has a negative impact. It can be seen in Phases 2 and 4 that volatilities are significant. This is because as the money supply expands, consumers are more likely to purchase assets to avoid currency depreciation. The focus on investment shifts to real estate, boosting demand and giving individual investors a psychological anticipation of higher demand for real estate in the near future. As a result, a substantial sum of money is invested in the real estate business, resulting in an increase in REIT issuance.

*2.6.4. Impact of the Consumer Price Index (CPI) on REIT Issuance*

It can be seen in Fig. 5 that CPI has a continuous positive impact on REIT issuance during the investigation period. The reason for this is that when inflation exceeds the nominal interest rate, the realized interest rate received from bank deposits also decreases. In other words, people will not only lose money by saving money, they will also lose money due to the low interest rate for inflation. People will invest elsewhere as a result. However, the mortgage interest rate will also be lower during this period, which encourages consumers to invest savings in real estate, thereby increasing REIT issuance.

*2.6.5. Impact of the Macroeconomic Prosperity Index on REIT Issuance*

According to Fig. 6, the macroeconomic prosperity index has a continuous positive impact on the issuance of REIT during the entire inspection period. The volatility is relatively less significant and the time lag is also relatively short. The reason for this is that the macroeconomic development has boosted not just resident incomes, it has also enhanced the efficiency of socialized production to a certain extent. The growth of the real estate market will attract more investment, which leads to greater REIT issuance.

## V. Conclusion

### 1. Summary

This research analyzes the relationship between the realized sale prices of real estate and the issuance of real estate investment trusts of shadow banking in China from 2013 to 2020. It collected data from Usetrust, CSMAR, the People's Bank of China, and the National Bureau of Statistics of China. It verified the impact of realized sale prices of real estate and relative macroeconomic indicators on the REIT issuance of shadow banking by variance decomposition and impulse response analysis. It found that the prices of real estate had the greatest impact on REIT, and there is a one-way Granger causality between them. The findings indicate that it would be beneficial to establish a real estate price prediction and warning mechanism for local governments and relevant institutions to avoid potential risks to consumers, the finance market, and the real estate industry which might be caused by price declines or shadow banking failures.

### 2. Recommendations

#### 2.1. Establish a Risk Management Scheme to Avoid the Systemic Risks of Shadow Banking

Shadow banking in China is mainly dominated by commercial banks. Shadow banking, on the one hand, participates in higher-risk businesses while avoiding costs associated with conventional banking regulations. At the same time, shadow banks also benefit from the implicit deposit guarantee provided by the government. It naturally obtains higher profits, and it distributes these to segments in the shadow banking chain. However, once a shadow banking crisis occurs, there will be a systemic crisis. It will inevitably force the government to cover the costs, and the burden will fall on all. The fragility of the shadow banking system cannot be selectively ignored or circumvented, nor can it be regarded as destroying factor in financial market. Financial innovation must start with a breach of established financial system agreements, particularly in the area of supervision. It should be recognized for its validity as a member of the financial system, included in the regulatory frame in accordance with the legislation, and be required to establish a competent risk management scheme.

### 2.2. Establish an Early Warning Mechanism for Falling House Prices

The basis for the normal operation of the financial system is the expectation of future benefits from corresponding assets and the promise of future cash flows in financial contracts. When uncertainty increases or financial contract commitments go wrong, expectations for future benefits will change in a short period of time. The most noteworthy impact is large fluctuations in asset prices, especially in housing prices. In particular, positive fluctuations in asset prices will increase credit demands by improving the balance sheets of banks and enterprises, while the negative impact of asset prices will increase credit demands by deteriorating the balance sheets of some enterprises. However, this kind of shock is asymmetrical; that is, the balance sheet effect during the economic downturn is stronger than the effect during the economic upturn. Therefore, the establishment of a comprehensive early-warning mechanism for falling housing prices is of great significance to ensuring the safe operation of the credit market.

### 2.3. Improve Financial Risk Education and the Information Disclosure Mechanism

The supervision scheme for financial tools in China, especially in the private sector, has to be improved. Private finance is the least regulated, but most dangerous, aspect in the shadow banking system due to its concealed and high-risk character. In addition, it is necessary to legislate private finance and regulate private financing. Furthermore, the public institutions should participate in supervision and establish relevant supervising and evaluating schemes for private financing. In particular, investment in illegal private financing, as well as capital fraud or loan sharks, must be resolutely banned or stopped to avoid the spread of financial risks in private financing. It is also critical to inform the public extensively to be aware of the high risks of illegal financial products and financial fraud through risk education or public training projects.

### 2.4. Expand Financing Channels for Real Estate Industry

Due to a lack of sufficient financing products and financing options for the real estate business, it may be difficult for developers to raise necessary funds through traditional channels. To assist real estate developers with appropriate financial support, it is necessary to raise the proportion of direct financing. At the same time, it would be beneficial to establish a price prediction and warning mechanism for real estate to prevent damage to the real estate industry from price declines and shadow banking risks.

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# Revealed Trade Competitiveness between Korea and Japan. Is It Viable to Deepen Economic Integration?

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**ABSTRACT**

**Purpose –** This study examines the trade competitiveness and complementarity of the economic structures of Korea and Japan. We focus on the sectors likely to be directly affected if the export control measures introduced by Japan on its exports of semiconductor machinery and raw materials to Korea in July 2019 are prolonged.
**Design/Methodology/Approach –** The analysis applies Balassa's Revealed Comparative Advantage (RCA), the Normalized Revealed Comparative Advantage (NRCA), the Bilateral Revealed Comparative Advantage (BRCA), the Relative Trade Advantage (RTA), and the Trade Complementarity indices to examine Korea's and Japan's trade competitiveness, bilaterally and globally. The empirical analysis focuses on forty-six major traded sectors and five Electronic integrated circuit-related industries, based on two-digit and six-digit data, respectively. Data applied is from the UNComtrade database.
**Findings –** Expectantly, where Korea has bilateral trade competitiveness, Japan has a disadvantage, and vice versa. A sharp decline in the calculated results for sector HS854232 (Electric, integrated circuit sector) of Korea in 2019 in all indices compared to other periods is identified. Additionally, empirical results indicate that the export control measures by Japan have an immediate impact on Korea's trade competitiveness, especially the Electronic integrated circuits and memory sector.
**Research Implications –** This study provides an impact assessment of the export control measures imposed by Japan on its exports of semiconductor raw materials and machinery to Korea on the trade competitiveness of Korea, focusing on the Electric, integrated circuit sector at six-digit HS product classification. To the best of the authors' knowledge, this is the first study to empirically analyze the impact of the export control measures by Japan on its exports of semiconductor raw materials on the trade competitiveness of Korea at the six-digit HS product code.

***Keywords:*** global value chains, normalized revealed comparative advantage, semiconductor raw materials, trade competitiveness, trade complementarity
***JEL Classifications:*** F13, F14, F15, F17

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## I. Introduction

The dynamic nature of the international trading market calls for the continuous assessment of the trade competitiveness of domestic industries. Globalization and the rapid growth of the information and communication technology (ICT) sector have led to the interdependency and interlinkage of world economies. These phenomena have affected trade transactions and processes that include out-sourcing for raw materials, manufacturing, and investment activities by business enterprises. Furthermore, globalization and the rapid growth of the information and communication technology (ICT) sector have increased the frequency of cross-border trade transactions and the intensity of competition in traded sectors. Most importantly, they have led to the integration of global value chains (GVC) and the globalization of production through multinational corporations, thereby complicating market transactions (Cavusgil, 1993; Dunning & Narula, 1996). Available studies have shown that it is difficult to guarantee the sustainability of existing natural or artificial trade comparative advantages and economic structural complementarity between trading partners (Cavusgil, 1993; Erin, Cassill, & Oxenham, 2014; Saki, Moore, Kandilov, Rothenberg, & Godfrey, 2019).

The theory of comparative advantage by David Ricardo introduces the efficient allocation of resources through production specialization. This theory finds that bilateral trading partners benefit economically if each country specializes in industries in which it is cost-effective. Through trade, world economies are interlinked. Hence, an economic shock in any country will affect other economies. In July 2019, Japan introduced export control measures on critical chemical inputs and machinery used in the semiconductor production industry on its exports to Korea. The targeted semiconductor raw materials include hydrogen fluoride, fluorinated polyimide, and photoresist chemicals. According to Goodman, Kim, and VerWey (2019), the export control measures have an immediate effect on the electronic and integrated circuit industries, and will disrupt the semiconductor global (supply) value chain.

The focus of this study is on quantifying the trade competitiveness and complementarity of bilaterally traded goods and services between Korea and Japan using five economic indices: the Revealed Comparative Advantage (RCA), the Normalized Revealed Comparative Advantage (NRCA), the Bilateral Revealed Comparative Advantage (BRCA), the Relative Trade Advantage (RTA), and the Trade Complimentary (TC) indices. We utilize two distinct data sets, an aggregated set (two-digit) and a disaggregated set (six-digit) of harmonized product classification (HS) trade flow data. The study aims to address three main objectives. The first objective is to evaluate bilateral and global trade competitiveness between Korea and Japan. Here, we apply the RCA, the NRCA, the BRCA, and the RTA indices. The second objective is to analyze the economic structural complementarity using the TC Index. This index helps to identify the extent to which the export supply capacity and import demand between Korea and Japan converge. The third objective is to identify the effect of the export control measures by Japan on Korea's trade competitiveness.

The main contribution of this study is in the findings of the effect of the export control measures imposed by Japan on its exports of semiconductor raw materials and Machinery to Korea through the trade competitiveness of sector HS854232 (Electric, integrated circuit sector). Additional contributions include the provision of comprehensive and comparative analyses of the current competitiveness of Korea's and Japan's electronic and integrated circuit sectors while incorporating the NRCA, the BRCA, and the TC indices at the highest disaggregated HS product classification using the current trade flow data compared to previous studies, which apply at most 4-digit HS trade flow data. Further, a comparative analysis of the empirical findings indicates that using aggregated data to analyze trade competitiveness provides biased results. Hence, unlike the findings of similar studies, the findings of this study do not suffer from aggregation bias.

This study is structured as follows. Following the introduction, Section II describes bilateral trade relations between Korea and Japan. Section III provides a review of the literature on the measurement of trade competitiveness. Section IV outlines the methodology, data, and measurement procedures applied. Section V discusses the empirical findings, and Section VI presents the concluding remarks and limitations of this study.

## II. Bilateral Trade Patterns and the Relations of Korea and Japan

In this section, we illustrate bilateral trade patterns between Korea and Japan. The two countries established economic relations after the normalization of diplomatic ties in 1965. Economic ties have shifted from dependence to interdependence. The concerted efforts by Korea and changes in the global trading environment have contributed to Korea's tremendous economic development during the post-war era. Specifically, Korea's success emanates from the use of intermediate inputs from Japan and the establishment of technical cooperation and joint ventures with Japanese firms. Available literature shows that the dependence of Korean industries on Japanese technical support or technology has sharply declined. In Rhyu and Lee's (2006) analysis of the economic history of Korea, it is argued that the shift in the bilateral relationship between Korea and Japan is due to several factors, which include structural reforms in the Korean domestic market and the economic development of China, including the globalization of Korea's domestic economy.

**Fig. 1.** Share of World Trade for the Period 1998 to 2019

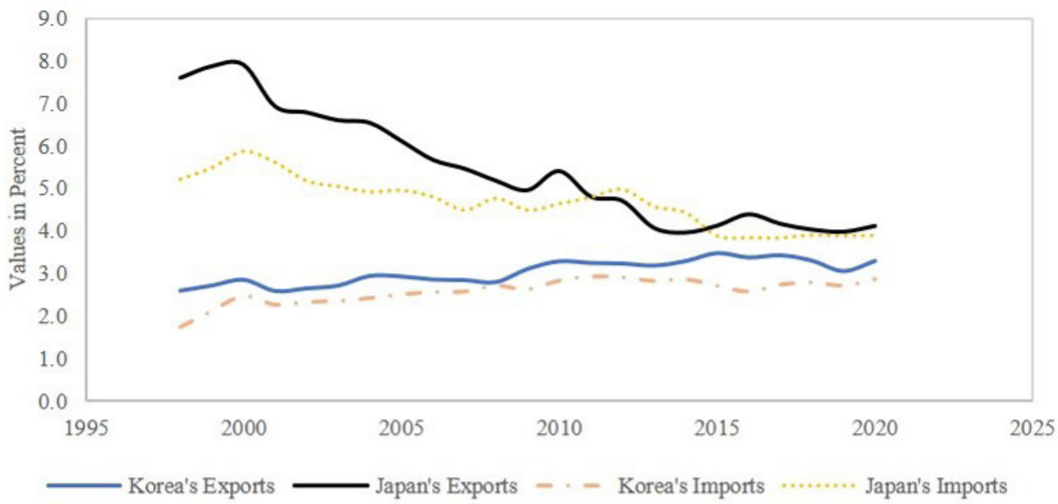
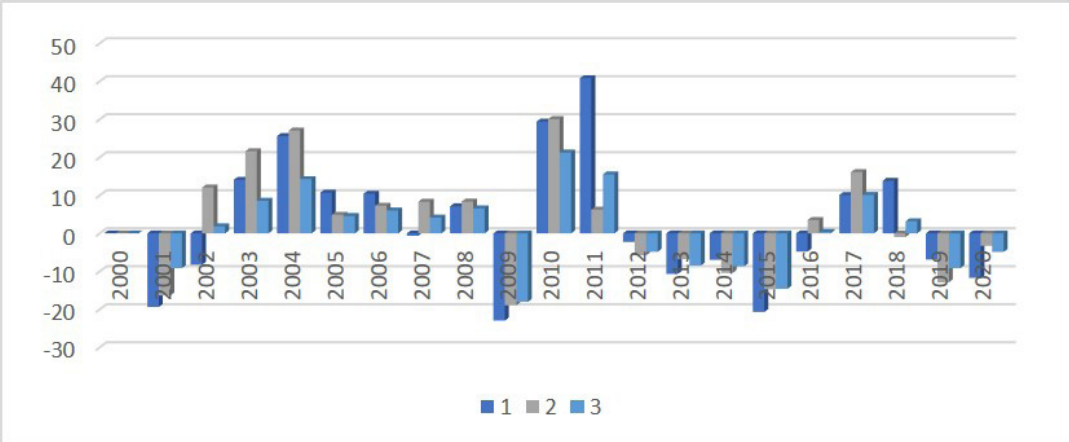


**Fig. 2.** Bilateral Trade Flows between Korea and Japan (US$ Billion and Percent)




Notes: 1. Percentage change in exports of Korea to Japan.
2. Percentage change in imports of Korea from Japan.
3. Percentage change in bilateral trade.
Source: Authors' calculation using United Nations (2021).

The adoption of the export-driven growth policy by Korea in the mid-1980s has contributed to the phenomenal growth of her economy. A review of Korean economic history by Rhyu and Lee (2006) shows that Korea followed the same growth path as Japan. Fig. 1. shows that Korea has a 3% share of the global export trade, while Japan's share of world export trade was about 8% in the year 2000. The Korea's share of world trade has consistently increased from 1998 through 2019, but that of Japan has declined consistently. It is justified to conclude that Korea's exports may be crowding out Japan's global exports in the international market. The share of imports by Japan overtakes exports from 2011 through 2015. Literature indicates that Japan adopted export expansion policies which have been the source of its economic success. Most importantly, Japan experienced the highest export share in the global market from 1985 through 1995, after which it took a consistent decline up to the present (Rhyu and Lee, 2006).

In an unprecedented move, on July 1, 2021, Japan introduced export control measures on its exports of several traded commodities to South Korea, including machinery and chemical raw materials used to manufacture semiconductor parts and products. These export control measures have short-term and long-term effects on Korea's trade competitiveness. Due to the significant contributions of the semiconductor trade to Korea's economy, Korea's economy was likely to be adversely affected. The immediate effect of the export control measures include the disruption of the GVC supply as Korean companies look for alternative sources of raw materials.

Semiconductors and related components accounted for 30% of Korea's total exports (Goodman et al., 2019) in 2018. In the same year, semiconductors accounted for 92% of Korea's export growth and 80% of its current account surplus between 2017 and 2018. According to Goodman et al. (2019), the export control measures introduced by Japan will lead to a decline in Korea's GDP by between 2 and 2.6 percent. Conversely, the study finds that Japan is likely to gain from the export controls.

## III. Literature Review

Classical economic theory applies the concepts of absolute and comparative advantages to describe trade competitiveness. To empirically quantify these theories, economic researchers use trade flow data. The revealed comparative advantage (RCA) index by Balassa (1965) uses export trade flows to compute the ratio of a country's export share of one commodity in the international market to the country's export share of all other sectors. A trade advantage is revealed when the calculated export market share value is above a unit (RCA>1). A relatively low export market share (RCA <1) indicates a trade disadvantage. To evaluate which country or industry has a comparative advantage or disadvantage, we compare their corresponding export shares (Gorton, Davidova, & Ratinger, 2000).

Trade competitiveness emanates from natural factors or government interventions, among other things. Though economic indicators are applied to quantify the intensity of trade competitiveness, they cannot identify the source of the incentive to trade (Hoang, Tran, Tu, Nguyen, & Nguyen, 2017; Hoen and Oosterhaven, 2006; Vollrath, 1991). Notwithstanding, since the main objective is to measure trade competitiveness and not the source of trade competitiveness between Korea and Japan, using economic indicators is appropriate for this study. Several factors that affect the competitiveness of domestic industries include globalization and technological advancement. Saki et al. (2019) applied Balassa's revealed comparative advantage (RCA) index and the normalized revealed comparative advantage (NRCA) index in the short term (2010-2016) and the long-term (1996-2016) using a two-digit harmonized system (HS) product code to provide insight into the current export advantage of the United States of America (USA) textile and Apparel Sectors (TAS). A disaggregated analysis at the four-digit classification identifies several sectors that include cotton fiber (HS5201), artificial filament tow (HS5502), non-woven (HS5603), cotton yarn (HS5205), carpet and other floor coverings (HS5703), and worn clothing to provide export competitiveness within the US textile and apparel sector. The study finds a correlation between the standard RCA and the normalized RCA (NRCA).

Jung (2016) analyzed changes in the export potential and competitiveness of China, Japan, and Korea using the Hidalgo et al. (2007) concept of product space. The first step involves evaluating the comparative advantage of a product using Balassa's (1965) RCA index. The index represents a country's export competitiveness. The study finds that Japan's market share has declined in sectors in which Korea had strong export potential in the early 1990s, implying that Korea's exports crowd out Japan's exports. Conversely, Korea's market share has declined in sectors where China had strong potential in the 2000s. The study suggests that Korea and Japan can enhance core technological capabilities to prevent new entrants from catching up in terms of competitiveness.

The agricultural sector contributes significantly to the economic growth of many developing countries. Hoang et al. (2017) applied RCA and NRCA to quantify the static and dynamic competitiveness of the agricultural industry of Vietnam. The study analyzes the dynamics of the two indices using OLS regression, Markov matrices, trend analysis, and consistency tests on RCA, NRCA, and RTA. The study found that Vietnam embodied strong trade competitiveness in crop and fishery industries, but was weak in livestock and processed food industries. Vietnam's export structure and competitiveness rely on natural resource abundance and agricultural sectors. Finally, the study found that the RCA, NRCA, and RTA indices were appropriate in identifying trade competitiveness.

The World Trade Organization (WTO), the modern form of the General Agreement on Tariffs and Trade (GATT), was established on January 1, 1995, to facilitate the smooth flow of international trade. One of its objectives involves arbitrating trade disputes, such as the Japan and South Korea trade dispute (DS590-WTO) on export control measures on semiconductor raw materials and machinery exported from Japan to South Korea. Due to the integrated nature of the production supply chain between different economic sectors and countries, a trade dispute between partners has a wide-reaching effect on the GVC system. Goodman et al. (2019) provided context and examined the potential implications of the trade dispute between Japan and Korea. This study empirically quantifies Korea's and Japan's competitiveness in industries that utilize semiconductor materials and equipment as inputs in their production processes. In the short term, Japanese chemical providers and Korean semiconductor producers face potential interruptions in production, though the magnitude of disruptions for Korean chipmakers is likely much more than for Japanese chemical suppliers. If these export control measures persist, we expect Korea to look for new sources of specialized chemicals for intermediate inputs in the production of semiconductors and related commodities.

A study by William and Movshuk (2003) applied the (RCA) index to evaluate the feasibility of a free trade agreement between Korea and Japan. The study compared the export trade flow between the two countries and separately with Taiwan, a geographically close trading partner, and an international competitor in the machinery trade. Using 3-digit SITC (Standard International Trade Classification) trade flow data, the study examined trade patterns between Korea-Japan, Korea-Taiwan, and Japan-Taiwan. The study detected convergence between the RCA index of Korea and Taiwan and that of Japan and Taiwan. The empirical findings indicate that the three countries are to be more competitive and less complementary over time. Furthermore, the study detected trade diversion over several traded commodities.

Despite the criticisms and concerns of the inability of economic indicators to identify sources of comparative advantage, scholars hold that the RCA index, when employed judiciously, provides reliable evidence of the trade competitiveness of a sector or country. Balassa's RCA index is one of the most applied indices to evaluate trade competitiveness in many empirical studies, such as Esquivias (2017), Kitetu and Ko (2018), and Nath, Liu and Tochkov (2015). Nevertheless, we have numerous alternative measures to address the shortcomings of Balassa's RCA index. To solve the problem of skewness associated with the RCA index of Balassa (1965), Dalum, Laursen, and Villumsen (1998) proposed the Revealed Symmetric Comparative Advantage (RSCA) index (RCA-1)/(RCA+1). The RSCA values lie between +1 and -1. Hence, unlike the RCA index by Balassa (1965), the RSCA index by Dalum et al. (1998) produces symmetrically distributed index values. Given that the limitations of Balassa's RCA emanate from its multiplicative nature, Hoen and Oosterhaven (2006) addressed this by suggesting the Bilateral Revealed Comparative Advantage (BRCA) index. This index stabilizes the distribution of Balassa's RCA index concerning countries by creating the possibility to compare the competitiveness of different sectors within a country. However, the index has limitations concerning comparability across trading partners (Yu, Cai, & Leung, 2009). Recently, due to the limitations of the RCA index by Balassa (1965), Yu et al. (2009) suggested the Normalized Revealed Comparative Advantage (NRCA) index. The RSCA, BRCA, and NRCA enumerate the efforts by researchers to address the limitations of the RCA index.

To examine the trade competitiveness and complementarity of the agricultural industry between the Central Eastern European (CEE) countries and China, Yu and Qi (2015) employed the RCA and trade complementary (TC) indexes. The study detected significant international trade competitiveness and complementarity. Notwithstanding, the study recommends a readjustment of export structures by both trading partners for long-term mutual benefit.

Kim (2013) applied the trade intensity (TI) and trade complementarity (TC) indices to empirically quantify the international trade competitiveness of the manufacturing sectors of Korea, China, Japan, and the USA. The calculated values for the two indices between Korea and China indicate a decline. Conversely, an increase in the share of the two parameters was detected when Korea traded with the USA. However, when Korea was measured against Japan, trade intensity increased while trade complementarity decreased. The study found that Korea is bound to gain if it integrates its economy with the three countries. Phan and Jeong (2012) employed the RCA, TC, and TI indices to evaluate

Korea's and Vietnam's economic structures. Their study concluded that trade between Korea and Vietnam was predominantly inter-industry. Substantial trade complementarity between trading sectors was detected. That means that there is potential for trade growth between the trading partners.

## IV. Methodology and Data

### 1. Methodology

One of the approaches employed in the analysis of international trade competitiveness and economic structures uses economic indicators. Empirical findings using economic indicators aid in detecting the potential of traded sectors in deepening trade ties. Using Balassa's Revealed Comparative Advantage (RCA), the normalized Revealed comparative advantage (NRCA), the Bilateral Revealed Comparative Advantage (BRCA), the Reveal Trade Advantage (RTA), and the Trade Complementarity (TC) indices, this study reviews Korea's and Japan's trade competitiveness and the complementarity of economic structures. The BRCA index was employed to quantify bilateral trade competitiveness, while the TC index helps quantify the capacity of the exporting sectors to meet import demand between Korea and Japan. The other indices are applied to quantify global trade competitiveness for exporting sectors in the two countries. Available literature confirms the consistency of these indices in measuring a country's export supply capacity relative to its trading partners (Hoang et al., 2017).

#### 1.1. The Revealed Comparative Advantage (RCA)

Theoretically, comparative advantage is the guiding principle upon which international trade thrives. To review the relative production capacity and trade specialization by a specific country, we apply the RCA index. Leissner (1958) was the first to develop the RCA index. Nevertheless, an augmented index by Balassa (1965) is prominent in the analysis of comparative trade advantage.

$$RCA_j^s = \left(\frac{X_j^s}{\sum_{s=1}^{S} X_j^s}\right) / \left(\frac{\sum_{j=1}^{J} X_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s}\right) = \left(\frac{X_j^s}{\sum_{j=1}^{J} X_j^s}\right) / \left(\frac{\sum_{s=1}^{S} X_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s}\right) \quad (1)$$

where $X_j^s$ is the exports of sector $j$ by country $s$, $S$ refers to all other countries, $J$ refers to all sectors, $\sum_{j=1}^{J} X_j^s$ is the total exports by country $s$, $\sum_{s=1}^{S} X_j^s$ is the exports of sector $j$ by all countries $S$, and $\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s$ refers to the total exports by all countries $S$. Balassa's RCA index estimates a country's share of exports of a specific sector relative to total exports in correspondence to the exports of a trading partner or a set of trading partners. If the RCA value is greater than or equal to 1 (RCA≥ 1), it reveals a comparative advantage. A trade disadvantage exists if the RCA value is less than 1. This index applies export trade flow data only. Greenaway and Milner (1993) argued that the omission of the demand side in international trade was likely to produce biased results. This index is applied in this study to evaluate trade competitiveness at a global level.

#### 1.2. The Normalized Revealed Comparative Advantage (NRCA)

The normalized revealed comparative advantage (NRCA) is the brainchild of Dunning (1979). He describes it as the ratio of export RCA to FDI RCA, an indicator of the ownership advantage of an enterprise. Since the RCA index developed by Balassa (1965) cannot provide an RCA index with stable distributions and means across commodities and countries over time, Yu et al. (2009) developed the Normalized Revealed Comparative Advantage (NRCA) index by augmenting Balassa's RCA index. Unlike the study by Dunning (1979), we apply NRCA to estimate relative export advantage rather than enterprise ownership advantage. This approach is consistent with the recent work of Yu et al. (2009).

The NRCA index captures the difference between the expected and actual export trade flow of a country. It measures the magnitude of deviation of a country's actual exports from its comparative-advantage-neutral level regarding its relative scale to the world export market. The index aids in establishing sector and country comparability. NRCA is defined as follows:

$$NRCA_j^s = \left(\frac{X_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s}\right) - \left(\frac{\sum_{s=1}^{S} X_j^s * \sum_{j=1}^{J} X_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s * \sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s}\right) \quad (2)$$

where $X_j^s$ refers to exports of sector $j$ by country $s$, $\sum_{s=1}^{S} X_j^s$ refers to the export of sector $j$ by all countries $S$, $\sum_{j=1}^{J} X_j^s$ is country $s$'s export of all sectors and $\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s$ is the export of all sectors $J$ by all countries $S$. The NRCA index values are symmetrical around zero, whereby a deviation from zero 0 < NRCA > 0 indicates a comparative advantage or disadvantage. An index value of 0 represents the comparative-advantage-neutral point. Although NRCA is relatively new, the initial empirical evaluation indicates the stability of the index across countries and sectors over time (Ahmad, Qayum, & Iqbal, 2017; Yu et al., 2009; Saki et al., 2019).

### 1.3. The Bilateral Revealed Comparative Advantage (NRCA)

We apply the Bilateral Revealed Comparative Advantage (BRCA) index to calculate bilateral trade competitiveness between Korea and Japan. The index employs export trade flow data only. Hence, the index does not capture the supply side of the economy. Even though available literature acknowledges this limitation, the additive capacity of the index in quantifying the trade competitiveness of trading partners is acknowledged (Kitetu and Ko, 2018; O'Callaghan, 2009).

$$BRCA_j^s = \left(\frac{X_j^s}{\sum_{j=1}^{J} X_j^s}\right) / \left(\frac{X_j^{Ref}}{\sum_{j=1}^{J} X_j^{Ref}}\right) \quad (3)$$

where $s$ is the export source country, $j$ is the trade sector, Ref is the reference country (a bilateral trading partner), $X_j^s$ refers to the exports of sector $j$ by country $s$, $\sum_{j=1}^{J} X_j^s$ refers to the total exports by country $s$, $X_j^{Ref}$ refers to the exports of sector $j$ of the reference country, and $\sum_{j=1}^{J} X_j^{Ref}$ refers to the total exports of the reference country. $BRCA_j^s$ values range between –1 and +1. A positive value indicates that a sector or a country has a comparative advantage, while a negative value reveals a disadvantage. Greenaway and Milner (1993) argued that there was ambiguity in the value of zero. However, researchers agree that a BRCA value of zero denotes the comparative advantage-neutral point (Hoang et al., 2017).

### 1.4. Relative Trade Advantage (RTA) Index

The Relative Trade Advantage (RTA) developed by Vollrath (1991) is employed to quantify a country's relative trade advantage. This index accounts for the supply and demand side of the international trading market, where the Relative Import Advantage (RIA) index or the Relative Comparative Import Performance (RCIPI) index is subtracted from the Relative Export Advantage (RXA) index or Relative Comparative Export Performance (RCEP) index. The advantage of this index is the inclusion of demand and supply effects. Index values calculated are not significantly affected by the double-counting drawback.

$$RTA_j^s = RXA_j^s - RIA_j^s \quad (4)$$

where $RXA_j^s = RCEPI_j^s = \left(\frac{X_j^s}{\sum_{s=1}^{S} X_j^s}\right) / \left(\frac{\sum_{j=1}^{J} X_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s}\right) \quad (5)$

$$RIA_j^s = RCIPI = \left(\frac{M_j^s}{\sum_{s=1}^{S} M_j^s}\right) / \left(\frac{\sum_{j=1}^{J} M_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} M_j^s}\right) \quad (6)$$

Hence,

$$RTA_j^s = \left(\frac{X_j^s}{\sum_{s=1}^{S} X_j^s}\right) / \left(\frac{\sum_{j=1}^{J} X_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s}\right) - \left(\frac{M_j^s}{\sum_{s=1}^{S} M_j^s}\right) / \left(\frac{\sum_{j=1}^{J} M_j^s}{\sum_{s=1}^{S}\sum_{j=1}^{J} M_j^s}\right) \quad (7)$$

where $X_j^s$ refers to the exports of sector $j$ by country $s$, $\sum_{j=1}^{J} X_j^s$ refers to the total exports by country $s$, $\sum_{s=1}^{S} X_j^s$ refers to the exports of sector $j$ by all countries $S$, and $\sum_{s=1}^{S}\sum_{j=1}^{J} X_j^s$ refers to the total exports by all countries $S$, $M_j^s$ refers to the imports of sector $j$ by country $s$, $\sum_{j=1}^{J} X_j^s$ refers to the total imports by country $s$, $\sum_{s=1}^{S} M_j^s$ refers to the imports of sector $j$ by all countries $S$, and $\sum_{s=1}^{S}\sum_{j=1}^{J} M_j^s$ refers to the total imports by all countries $S$.

### 1.5. Trade Complementarity (TC) Index

The trade complementarity index shows how well the exporting industries of a country can meet the import demand of a bilateral trading partner. The existence of significant homogeneity between the exporting and importing sectors of trade to expand bilateral partners indicates there is potential for trade between the two. In this study, we apply the TC index to empirically quantify how well the exporting structures of Korea and Japan can meet bilateral import demand. This study implements the TC index design by Vaillant and Ons (2002) (see also Kitetu and Ko, 2018). The index based on Balassa (1965) revealed comparative advantage. We execute the TC index as below:

$$TC_j^s = \left(\frac{X_j^s}{t_j^{ws}}\right) * \left(\frac{m_j^d}{t_j^{ws}}\right) * t_j^{ws} \tag{8}$$

where, $x_j^s$ represents the share of sector $j$ in country $s$'s exports, $m_j^d$ represents the share of sector $j$ in country $d$'s imports, $t_j^{ws}$ represents the share of sector $j$ in all imports by countries $S$ (world imports) from the point of view of country $s$'s exports.

where $x_j^s = \frac{X_j^s}{\sum_{j=1}^{J} X_j^s}$ represent8s the share of sector $j$ in country $s$'s exports, $m_j^d = \frac{M_j^d}{\sum_{j=1}^{J} M_j^d}$ represents the share of sector j in country d's imports. Further, $t_j^{ws} = \frac{\sum_{k\neq s}^{K} M_j^k}{\sum_{j=1}^{J}\sum_{k\neq s}^{K} M_j^k}$ represents the share of sector $j$ in all imports by countries $K$ (world imports), $X_j^s$ refers to the exports of sector $j$ by country $s$, $\sum_{j=1}^{J} X_j^s$ refers to the total exports by country $s$, $M_j^d$ refers to the imports of sector $j$ by country $d$, $\sum_{j=1}^{J} M_j^d$ refers to the total imports by country $d$, $\sum_{k\neq s}^{K} M_j^k$ refers to imports of sector $j$ by all countries $K$, and $\sum_{j=1}^{J}\sum_{k\neq s}^{K} M_j^k$ refers to the total imports by all countries $K$. Therefore, TC is a by-product of the export specialization index of country $s$ and the import efficiency index of bilateral trading partners. A TC value equal to or greater than 1 indicates the existence of a strong complementarity between the export specialization of a country and the import demand of its trading partner (Michaely, 1996). A TCI<1 indicates weak complementarity. When the TC value is 0, there is no trade complementarity.

## 2. Data

This study applies two and six-digit product-level trade-flow data based on the 1996 and 2007 revisions of the HS (harmonized system), respectively. The two-digit product-level trade data involves 43 bilaterally traded sectors between Korea and Japan. These sectors account for 95.54% and 98.34% of bilateral trade between Korea and Japan, respectively. The disaggregated six-digit sector analysis follows the study by Goodman et al. (2019). The study highlights sectors likely to suffer if the new export regulations introduced by Japan in 2019 on its export of semiconductor raw materials and machinery to South Korea are maintained. Analysis using a disaggregated data set focuses on the electrical sectors that consume semiconductor products as intermediate inputs. All data is from the United Nations Commodity Trade Database (UNComtrade). The description of major traded sectors (at two-digit HS product code) and the electronic, integrated circuit sectors (at six-digit HS product code) are in Tables A and B in the appendices.

# V. Empirical Results

This section presents calculated empirical results based on aggregated two-digit and disaggregated six-digit HS product-level trade flow data. We describe the empirical results on trade competitiveness and complementarity between Korea and Japan on bilateral and global frameworks. To calculate trade competitiveness, we utilize product-level trade flow data between Korea and Japan and between the two countries and their trading partners. The findings from the BRCA (bilateral revealed comparative advantage) index display a complementary nature since the sectors that reveal a comparative advantage for Korea display a disadvantage for Japan, and vice versa. For presentation purposes, we multiply NRCA results by ten to the power of three (10^3) since the values are extremely small.

## 1. Empirical Results for the Six-Digit Data Set

The calculated results for all indices (Balassa's RCA, NRCA, BRCA, RTA, and TC) are in Tables 1, 2, 3, 4, and 5. All indices for Korea display a revealed comparative advantage for over three years consecutively for most evaluated sectors. According to the empirical results from the six-digit trade flow data set, the Electronic integrated circuits, processors & controllers (HS854231) and Electronic integrated circuits, memories (HS854232) sectors have maintained trade competitiveness throughout the 13 years under study. However, the comparative advantage for the sector of Electronic integrated circuits, processors & controllers (HS854231) seems to decline from 2016 through 2019. The empirical results indicate that the comparative advantage of the Electronic, integrated circuit, and memories sector for Korea is highest comparative advantage. On the contrary, the BRCA and TC empirical results show a downward trajectory for trade competitiveness and trade complementarity for the same sector.

**Table 1.** Calculated Balassa's Revealed Comparative Advantage (RCA) Index Results

| HS Codes | Description | Korea | | | | Japan | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 |
| 854231 | EIC, processors & controllers | 4.98 | 4.96 | 4.48 | 3.41 | 1.70 | 1.13 | 0.77 | 0.44 |
| 854232 | EICs, memories | 12.60 | 12.87 | 14.88 | 15.83 | 3.22 | 3.49 | 2.96 | 1.71 |
| 854233 | EIC, amplifiers | 0.40 | 0.12 | 0.18 | 0.15 | 6.69 | 4.45 | 1.25 | 1.02 |
| 854239 | Other EIC | 0.54 | 0.54 | 0.76 | 0.61 | 2.42 | 1.92 | 1.65 | 1.28 |
| 854290 | Parts of EIC | 0.41 | 0.43 | 0.52 | 0.69 | 5.26 | 4.45 | 4.27 | 4.21 |
| 85 | EICPC 2-digit | 2.09 | 2.04 | 2.18 | 2.11 | 1.62 | 1.50 | 1.34 | 1.10 |

Notes: 1. EIC refers to electronic integrated circuits.
2. EICPC refers to electronic integrated circuits processors and controllers two-digit sector HS85.
Source: Authors' estimation using United Nations (2021).

The empirical results calculated using the RCA by Balassa (1965) and the NRCA index indicate a positive correlation as sectors with a comparative advantage using the RCA by Balassa (1965) have a comparative trade advantage when calculated using the NRCA index, and vice versa. This finding is similar to that of Saki et al. (2019). Calculated results show that certain sectors for Japan, Electronic, integrated circuit memories (HS854232), Other Electronic, integrated circuits (HS85439), and Parts of electronic, integrated circuits (HS854290), have maintained competitiveness throughout the period under study. However, competitiveness has been declining over the period. All sectors for Japan indicate trade competitiveness at the base year, except for sector HS854233 (Electronic integrated circuits, amplifiers). Conversely, two sectors, Electronic, Integrated circuit processors and controllers (HS854231) and HS854233 (Electronic, integrated circuit amplifiers), lose competitiveness towards the end of the study period. See Tables 1 and 2.

**Table 2.** Calculated Normalized RCA Index (NRCA) Results

| HS Codes | Description | Korea | | | | Japan | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 |
| 854231 | EIC, processors & controllers | 7.96 | 9.24 | 9.51 | 8.71 | 2.82 | 0.56 | -0.90 | -2.87 |
| 854232 | EICs, memories | 10.80 | 11.74 | 15.45 | 32.00 | 4.52 | 4.67 | 3.57 | 2.39 |
| 854233 | EIC, amplifiers | -0.06 | -0.11 | -0.19 | -0.19 | 0.76 | 0.48 | 0.02 | -0.01 |
| 854239 | Other EIC | -1.18 | -1.33 | -0.77 | -1.62 | 5.93 | 3.76 | 2.37 | 1.38 |
| 854290 | Parts of EIC | -0.25 | -0.20 | -0.13 | -0.07 | 2.53 | 1.52 | 0.92 | 0.81 |
| 85 | EICPC 2-digit | 3.70 | 3.72 | 4.53 | 5.05 | 3.77 | 2.74 | 1.56 | 0.59 |

Notes: 1. EIC refers to electronic integrated circuits.
2. EICPC refers to electronic integrated circuits processors and controllers two-digit sector HS85.
Source: Authors' estimation using United Nations (2021).

**Table 3**. Calculated Results of the Revealed Trade Advantage (RTA)

| HS Codes | Description | Korea | | | | Japan | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 |
| 854231 | EIC, processors & controllers | 1.48 | 2.57 | 1.80 | 1.15 | 1.06 | 0.70 | 0.31 | -0.09 |
| 854232 | EICs, memories | 9.83 | 10.39 | 12.53 | 13.32 | 0.94 | 2.10 | 2.30 | 1.27 |
| 854233 | EIC, amplifiers | 0.30 | 0.12 | 0.17 | 0.15 | 6.09 | 3.94 | 0.84 | 0.54 |
| 854239 | Other EIC | -1.00 | -0.56 | -0.38 | -0.10 | 1.19 | 0.90 | 0.63 | 0.29 |
| 854290 | Parts of EIC | 0.24 | 0.36 | 0.41 | 0.62 | 5.05 | 4.33 | 4.19 | 4.12 |
| 85 | EICPC 2-digit | 0.86 | 0.98 | 1.04 | 0.97 | 0.75 | 0.61 | 0.39 | 0.18 |

Notes: 1. EIC refers to electronic integrated circuits.
2. EICPC refers to electronic integrated circuits processors and controllers two-digit sector HS85.
Source: Authors' estimation using United Nations (2021).

Table 3. presents the calculated results of the Bilateral Revealed Comparative Advantage (BRCA) index. We applied this index to analyze the revealed comparative advantage between Korea and Japan as bilateral trading partners. Expectantly, in sectors where Korea has a comparative advantage, Japan has a disadvantage, and vice versa. Sectors in which Korea has a comparative advantage include Electronic, integrated circuit processors and controllers (HS854231), Electronic, integrated circuit memories (HS854232), and Electronic, integrated circuit amplifiers (HS854233); however, Japan has competitiveness in the Other Electronic integrated circuits sector, other than Amplifiers/ Memories/ Processors & controllers (HS854239). The empirical findings of this study indicate that neither Korea nor Japan has bilateral competitiveness in the Parts of the electronic, integrated circuit sector (HS854290).

**Table 4.** Calculated Results of the Revealed Trade Advantage (RTA)

| HS Codes | Description | Korea | | | | Japan | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 |
| 854231 | EIC, processors & controllers | 1.48 | 2.57 | 1.80 | 1.15 | 1.06 | 0.70 | 0.31 | -0.09 |
| 854232 | EICs, memories | 9.83 | 10.39 | 12.53 | 13.32 | 0.94 | 2.10 | 2.30 | 1.27 |
| 854233 | EIC, amplifiers | 0.30 | 0.12 | 0.17 | 0.15 | 6.09 | 3.94 | 0.84 | 0.54 |
| 854239 | Other EIC | -1.00 | -0.56 | -0.38 | -0.10 | 1.19 | 0.90 | 0.63 | 0.29 |
| 854290 | Parts of EIC | 0.24 | 0.36 | 0.41 | 0.62 | 5.05 | 4.33 | 4.19 | 4.12 |
| 85 | EICPC 2-digit | 0.86 | 0.98 | 1.04 | 0.97 | 0.75 | 0.61 | 0.39 | 0.18 |

Notes: 1. EIC refers to electronic integrated circuits.
2. EICPC refers to electronic integrated circuits processors and controllers two-digit sector HS85.
Source: Authors' estimation using United Nations (2021).

**Table 5**. Calculated Trade Complementarity Index Results Between Korea and Japan

| HS Codes | Description | Korea | | | | Japan | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 | 2007 2009 | 2010 2012 | 2013 2015 | 2016 2019 |
| 854231 | EIC, processors & controllers | 0.021 | 0.016 | 0.018 | 0.021 | 0.036 | 0.020 | 0.017 | 0.011 |
| 854232 | EICs, memories | 0.034 | 0.024 | 0.015 | 0.034 | 0.012 | 0.012 | 0.013 | 0.021 |
| 854233 | EIC, amplifiers | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 854239 | Other EIC | 0.004 | 0.004 | 0.006 | 0.006 | 0.022 | 0.014 | 0.014 | 0.009 |
| 854290 | Parts of EIC | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 85 | EICPC 2-digit | 0.22 | 0.20 | 0.26 | 0.28 | 0.24 | 0.18 | 0.18 | 0.17 |

Notes: 1. EIC refers to electronic integrated circuits.
2. EICPC refers to electronic integrated circuits processors and controllers two-digit sector HS85.
Source: Authors' estimation using United Nations (2021).

The forces of demand and supply play a fundamental role in explaining the efficient allocation of scarce resources through trade, both domestically and internationally. In a free market, the forces of demand and supply determine the equilibrium point where all goods and services supplied and demanded balance. Furthermore, the theory of comparative advantage explains how international trade benefits trading partners through specialization, even when one partner has an absolute trade advantage in all traded commodities.

A review of the calculated results indicate that Korea has slightly strong trade competitiveness in the Electronic, integrated circuit memories (HS854232) sector in view of Japan. However, in 2019, Korea's global trade competitiveness in the Electronic, integrated circuit memories (HS854232) sector declined sharply. Korea's trade competitiveness in the Electronic, integrated circuit memories sector declined from 44.7% to 151.7% in 2019. At the same time, trade competitiveness for other sectors declined by less than 26.5%. Hence, this sharp decline in trade competitiveness for the Electronic, integrated circuit memories sector is likely due to export control measures introduced by Japan in July 2019, though it may not be entirely due to these export control measures. Though Japan has competitiveness in the supply of semiconductor machinery and raw materials, it has significantly lost trade competitiveness in all sectors during the period under study, especially in the six-digit trade flow data analysis.

## 2. Empirical Results for Two Digit Data Set

This section describes the empirical results of the two-digit data analysis. A review of the calculated results of the two-digit data analysis shows that both Korea and Japan possess significant trade competitiveness in the global market. Bilaterally, sectors in which Korea has a comparative advantage, Japan has a disadvantage, and vice versa. Empirical results also indicate that a significant number of sectors are complementary. Sectors with a comparative advantage for Korea include HS38, HS48, HS54, HS84, HS85, HS88, and HS94, while for Japan, sectors with a comparative advantage include HS35, HS71, HS82, HS85, HS94, and HS96. Sector HS48 for Korea reveals a strong trade advantage. Calculated RTA results indicate that sectors HS35, HS71, HS85, and HS96 for Japan have strong and increasing RTA throughout the period under study. The highest RTA values are for sector HS48 (Paper and paperboard) for Korea, with an average RTA index value of 7.82 from 1996 to 2000. For Japan, it is sector 35, with RTA index values of 7.38. Sector 96 for Japan also indicates a strong RTA with index values ranging from 2.78 – 6.71. The Relative Trade Advantage for both Korea and Japan seem to emanate from resource abundance and/or technological advancement.

Marginal trade complementarity between both trading partners was detected in several trade sectors. Korea has strong trade complementarity in 14 sectors considering the two-digit trade flow data empirical analysis, with respect to Japan. Likewise, in view of Korea, Japan has a strong trade complementarity in 16 sectors. Based on the six-digit empirical analysis findings, Korea has consistently shown strong trade competitiveness and structural complementarity regarding Japan relative to the world in 2 sectors: Electronic integrated circuits processors and controllers (HS 854231) and Electronic integrated circuits, memories (HS854232).

Expectantly, marginal trade complementarity between Korea and Japan as bilateral trading partners was detected in three sectors considering the six-digit trade flow data analysis. Sectors with marginal trade complementarity include Electronic integrated circuits processors and controllers (HS854231) and Electronic integrated circuits, memories (HS854232), and Electronic integrated circuits processors and controllers (HS 854239). Specifically, in view of Japan, Korea has trade complementarity in 14 sectors considering the two-digit trade flow data empirical analysis. On the other hand, in view of Korea, Japan has strong trade complementarity in 16 traded sectors. Korea has consistently held strong trade competitiveness and structural complementarity regarding Japan relative to the world in 2 sectors, the Electronic integrated circuits processors and controllers

(HS854231) and Electronic integrated circuits, memories (HS854232) sectors.

## VI. Concluding Remarks

This study's focus is to examine (1) the impact of the export control measures introduced by Japan on its exports of semiconductor raw materials and machinery on Korea's trade competitiveness; (2)) bilateral and global trade competitiveness between Korea and Japan on major bilaterally traded sectors; and (3) the economic structural complementarity between Japan and Korea. Additionally, we compare the calculated results using two different data sets to evaluate convergence or divergence.

The empirical results from the analysis of global trade competitiveness at the disaggregated (six-digit) HS product code indicate that Japan has strong competitiveness in 3 sectors: HS854233, HS854239, and HS854290. On the other hand, Korea has strong competitiveness in HS854231 and HS854232, but a trade disadvantage in HS854239. In terms of bilateral trade competitiveness, empirical results indicate that Korea has competitiveness in three sectors, while Japan is competitive in one. A comparative review of empirical results from the two data sets (aggregated two-digit and disaggregated six-digit trade flow data) shows a wide variance in the calculated values. Since estimations using the aggregated data take the average value, the empirical results suffer from aggregation bias. Furthermore, since trading in the international market relies on disaggregated sectors, we find that this study provides unbiased and readily actionable findings.

The empirical results from the BRCA index calculation using the six-digit data set a subset of sector HS85 (Electrical machinery equipment parts thereof; sound recorder etc.) indicate that where Korea has bilateral trade competitiveness, Japan has a disadvantage, and vice versa. Korea has bilateral trade competitiveness in 3 sectors, while Japan has a comparative advantage in only one. However, Korea's bilateral comparative advantage shows a consistent decline in all three sectors. For Japan, the bilateral trade advantage increases over time. Nevertheless, empirical results from the two-digit analysis show that Korea has an absolute advantage in sector HS85. Korea's comparative advantage in Electrical machinery equipment and parts thereof, sound recorders, etc.) has been declining, while Japan's disadvantage in the same sector shows a consistent decline during the period. Calculated results from the disaggregated data set identify some effect from the export control measures; however, results from the aggregated two-digit data set do not. Our empirical results support the use of disaggregated data in estimating bilateral comparative advantage.

Empirical findings show that it is difficult to maintain trade competitiveness, whether natural or resulting from government interventions. In this context, though Japan supplies the largest share of critical raw materials (hydrogen fluoride 43%, photoresist, and Fluorinated Polyimide) used in the manufacture of semiconductor parts globally, empirical results indicate that its trade competitiveness has a downward trajectory. Likewise, despite Korea's technological advancement, this analysis shows that trade competitiveness for all sectors, except for the Electronic, integrated circuit memories (HS854232) sector, has declined over time. New producers or suppliers (such as Taiwan) in the semiconductor global supply chain may be crowding out exports from Korea in the semiconductor market. It may call for both Japan and Korea to be innovative and invest in research and technology to counter emerging new competitors in the semiconductor GCV.

This study has demonstrated that the Korean economy will be adversely affected if the export control measures imposed by Japan on its exports of the semiconductor raw materials to the Republic of Korea are sustained. The Electronic, integrated circuit memories (HS854232) sector contributes to over 50 percent of Korea's monthly exports in the Electronic integrated circuit sub-sector. However, it is negatively affected by these export control measures. A 30% to 40% export decline in the Electronic, integrated circuit memories (HS854232) sector will reduce total foreign exchange receipts by between US$19,890 to US$26,520 million annually, negatively affecting Korea's trade balance and the economy in general. The two countries should open a diplomatic dialogue to resolve political and trade disputes to minimize negative economic impacts.

Like many other studies, this study suffers from three main limitations: method, scope, and data. First, the approaches applied to analyze trade competitiveness provide very insightful information. However, the statical distributions of the calculated values for some indices suffer from an asymmetric problem. Therefore, some of the calculated index values violate the normality of distribution. Additionally, the applied analysis tools employed do not provide tangible information regarding the sources of trade comparative advantage or disadvantage.

Secondly, this study focuses on Korea and Japan. However, the interlinked nature of the global value chain of the semiconductor industry means that the export control measures have an economy-wide impact beyond Korea and Japan. Thirdly, the two-digit data set was available from 1996 to 2019, while the six-digit data set was available from 2007 to 2019. Therefore, it is impossible to carry out a comprehensive dynamic comparative analysis of the results from the two data sets.

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# Appendices

**Table A.** Bilaterally Traded Sectors -Two-Digit HS Product Classification[1)]

| HS Code | Sector Description |
|---|---|
| 03 | Fish & crustacean, mollusk & other aquatic invertebrate |
| 07 | Edible vegetables and certain roots and tubers |
| 12 | Oil seed, oleagi fruits; misc. grain, seed, fruit etc. |
| 16 | Prep of meat, fish or crustaceans, mollusks etc. |
| 17 | Sugars and sugar confectionery |
| 21 | Miscellaneous edible preparations. |
| 22 | Beverages, spirits and vinegar |
| 24 | Tobacco and manufactured tobacco substitutes |
| 27 | Mineral fuels, oils & product of their distillation, etc. |
| 28 | Inorganic chemicals; compounds of prec mtl, radioactive elements etc. |
| 29 | Organic chemicals |
| 30 | Pharmaceutical products |
| 32 | Tanning/dyeing extract; tannins & derives; pigments etc. |
| 33 | Essential oils & resinoids; perf, cosmetic/toilet prep |
| 34 | Soap, organic surface-active agents, washing prep, etc. |
| 35 | Albuminoidal subs; modified starches; glues; enzymes |
| 37 | Photographic or cinematographic goods |
| 38 | Miscellaneous chemical products |
| 39 | Plastics and articles thereof |
| 40 | Rubber and articles thereof |
| 48 | Paper & paperboard; art of paper pulp, paper/paperboard |
| 54 | Man-made filaments |
| 61 | Art of apparel & clothing access, knitted or crocheted |
| 62 | Art of apparel & clothing access, not knitted/crocheted |
| 68 | Art of stone, plaster, cement, asbestos, mica/sim mat |
| 69 | Ceramic products |
| 70 | Glass and glassware |
| 71 | Natural/cultured pearls, precious stones & metals, coin etc. |
| 72 | Iron and steel |
| 73 | Articles of iron or steel |
| 74 | Copper and articles thereof |
| 75 | Nickel and articles thereof |
| 76 | Aluminum and articles thereof |
| 81 | Other base metals; cermets; articles thereof |
| 82 | Tool, implement, cutlery, spoon & fork, of base metal etc. |
| 84 | Nuclear reactors, boilers, mchy & mech appliance; parts |
| 85 | Electrical mchy equip parts thereof; sound recorder etc. |
| 87 | Vehicle's o/t railw/tramw roll-stock, pts & accessories |
| 88 | Aircraft, spacecraft, and parts thereof |
| 90 | Optical, photo, cine, meas, checking, precision, etc. |
| 94 | Furniture; bedding, mattress, matt support, cushion etc. |
| 96 | Miscellaneous manufactured articles |
| 99 | UN Special Code |

1) For detail chapter-by-chapter listing of the Harmonized Tariff Schedule refer to, https://hts.usitc.gov/current or http://wits.worldbank.org/WITS/WITS/AdvanceQuery/RawTradeData/QueryDefinition.aspx?Page=RawTradeData

**Table B.** Sectors Affected by Japan's Export Control Measures at Six-Digit HS Product Classification

| HS Code | Sector Description |
|---|---|
| 854231 | Electronic integrated circuits, processors & controllers, |
| 854232 | Electronic integrated circuits, memories |
| 854233 | Electronic integrated circuits, amplifiers |
| 854239 | Other Electronic integrated circuits, other than Amplifiers/ Memories/ Processors & controllers |
| 854290 | Parts of electronic integrated circuits |