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MODELING LONG-TERM RELATIONSHIPS IN PHILIPPINE STOCK MARKET (PSE) INDICES: A COINTEGRATION ANALYSIS

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ABSTRACT

Over previous decades, market participants have been unsure about how to forecast the movement of the stock market. Coming up with a good forecasting model could lead stock market participants towards a less risky investment portfolio. This study attempts to explore the haphazard nature of Philippine Stock indices and the long-term relationship between Philippine Stock Exchange (PSE) sectoral indices and the PSE index. The data series used are the daily closing values of the PSE index and six sectoral indices between July 2010 to December 2019. This study employs an Augmented Dickey-Fuller (ADF) unit root test and a Johansen cointegration test. The results revealed that all indices are non-stationary at index level, but stationary at first difference. The results showed that all indices followed a random walk; however, no long-term relationships between the PSE index and five sectoral indices were found. Therefore, long-term investors are able to diversify their portfolio to reduce investment risk.

Contribution/ Originality: This study contributes to the existing literature on employing a cointegration analysis on the Philippine stock indices. It provides investors with additional perspectives on forecasting the stock market movement at a macro level. The results offer long-term investors vital information they can use when managing their portfolio.

1. INTRODUCTION

Wealth maximization is the primary goal of every investor (Shaffie, Moradi, & Rahmani, 2014), which is why investors must make the right investment decisions in order to maximize the profit of their investments. With the objective of capital appreciation, investors must also consider the significant risk involved in every investment decision. This practice helps them to develop an effective financial strategy and achieve investment growth (Sanjabi & Jamshidinavid, 2017). It is for this reason that investors prefer to lower the investment risk. Investors use any information they can obtain, with the intent of reducing investment risk. The absence of the right information would result in uncertainty, which would lead to investment frustration (Khana & Palepu, 2010).

Investment in stocks is considered high-risk due to its associated price volatility (Bahri, 2015). Since the movement of stocks is highly indeterministic, experts have developed models and indicators to reduce investment risk. The most common approaches used to analyze stock behavior are: (1) fundamental analysis and (2) technical analysis. A fundamental analysis explains the reasons behind stock movements, whereas a technical analysis guides investors towards the direction of stock prices (Ivanovski, Ivanovska, & Narasanov, 2017).

However, stable forecasting patterns, such as technical analyses, are unlikely to become effective in the long-term. As a lot of investors are already using this analysis, it is unlikely to work anymore. This is why market forecasters must continually develop models that predict stock prices (Timmermann & Granger, 2004). However, Palamalai and Kalaivani (2015) have argued that stock prices do not move in predictable patterns, due to their random fluctuations. Both Palamalai and Kalaivani noted that the concept of stock price unpredictability can be traced back to the work of Regnault in 1863 and Bachelier in 1900. Fama (1970) shared his work on unpredictability when he investigated the daily price changes of the Dow Jones Industrial Average in the US during the period 1957–1962.

Over the past few decades, several academic scholars and financial market experts have been focusing their attention on modelling stock movements, particularly through stock indices. Generally, studies link stock indices with macroeconomic variables (Basci & Karaca, 2013; Pyeman & Ahamad, 2017). Forecasting the movement of stock prices is deemed to be one of the main problems of every investor and fund manager. Traditional forecasting information, such as fundamental indicators and technical indicators, may not be useful in the long-term. The analysis of these indicators depends on the skills and experience of every investor.

This study is an attempt to present an additional forecasting model to predict the stock market, which differs from traditional fundamental and technical analyses. Researchers were motivated by the lack of investigations conducted on the long-term relationship between sectoral indices and the Philippine Stock Exchange (PSE) index. The information obtained in this study has been deemed useful, especially in terms of deciding the combination of stocks to be included in one's investment portfolio and whether sectoral diversification could benefit both prospective and existing investors.

2. LITERATURE REVIEW

2.1. Finance Theories

In 1952, Markowitz introduced a mean-variance analysis that focused on reducing investment risk through diversification. This model is now known as the Modern Portfolio Theory (MPT) (Dos Santos & Brandi, 2017), and it explains how investors can structure their investment portfolios to minimize investment risk. The diversification of investments limits the risk (Brigham & Houston, 2019), as balancing a portfolio is a significant issue faced by several investors. One strategy to reduce portfolio risk is sectoral diversification, as the indices that have no long-term relationships can be diversified (Ahmed, Ali, Ejaz, & Ahmad, 2018).

In 1960, Eugene Fama introduced a financial market concept that explored the efficiency of information in the market. This idea became known as the Efficient Market Hypothesis (EMH), which is considered to be foundational, as it played the central role in neo-classical financial theory (Raines & Leathers, 1996). Fama's hypothesis asserted that current stock prices have already considered all internal and external information about the stocks (Jordan, 1983). Therefore, it is impossible to determine whether the asset is undervalued or overvalued. The only way investors could beat the market would be if they had access to information before the firm published it, or before an event happened. As a result, price patterns and returns are unlikely to be forecastable (Timmermann & Granger, 2004).

On the other hand, Fama (1995) posited that consecutive market stock prices are seen as being independent from each other, as they move haphazardly because of stock information. This market theory is known as the Random Walk Hypothesis (RWH). The RWH emphasizes the fact that past stock prices do not affect current or future prices. Instead, the movement depends on how market participants respond to new information and current events. As a result, the movement of stock prices cannot be determined. According to Rufino (2013), investors, educators, and other financial market players commonly ask whether stock price trends are deterministic or stochastic. Most investors and market speculators believe that market stock prices are predictable, as they follow a deterministic trend. This deviates from what most economists and academics believe, which is that the market follows an unpredictable random walk. Nalin and Güler (2015) asserted that RWH is sometimes associated with a weak-form of EMH. However, for Fama (1965), this theory challenges chartists and believers of technical and fundamental analyses.

Stephen Ross developed the Arbitrage Pricing Theory (APT), which is also called the risk factor model, in 1977. Whereas the EMH believes that asset returns and prices are unpredictable, APT asserts that the expected return of a particular asset, such as stocks assets, are affected by other factors, such as macroeconomic indices or other assets (Bahri, 2015). This theory assumes that the return of securities was related to an unknown number of unidentified factors and was sensitive to the movement of various factors or indices (Sharpe, Alexander, & Bailey, 1999). According to Jones (2016), evidence from different markets revealed that a lot of factors or drivers can explain the correlation between risks and returns. The APT model suggests that investors could not sell assets with the same attributes at different prices.

2.2. Empirical Studies

Cooray and Wickremasinghe (2007) analyzed the efficiency of stock indices in India, Sri Lanka, Pakistan, Bangladesh using the Augmented Dickey-Fuller (ADF) test. This study revealed the fact that stock prices have a unit root that confirms the series is non-stationary and follows a random walk. In Africa, Chitenderu, Maredza, and Sibanda (2014) tested the existence of RWH in the All Shares index of the Johannesburg Stock Exchange. The period covered in the study was the year 2000 to 2011, and the outcome of the unit root test revealed that the data series was non-stationary and, therefore, followed a random walk.

Meanwhile, Babu and Hariharan (2014) analyzed the stationarity of five selected sectoral indices of the National Stock Exchange in India using the ADF test. The result revealed that the chosen indices did not have a unit root during the period covered and did not follow a random walk. Lastly, Roy (2018) examined the unpredictability of the log-returns of the Nihon Keizai Shimbun (NIKKI), EuroStoxx 50, Bombay Stock Exchange (BSE), London Stock Exchange (LSE), and the Shanghai Composite Stock Exchange. The ADF test revealed that all series were stationary and, therefore, did not follow a random walk.

Conversely, in Sri Lanka, Ahmed et al. (2018) explored cointegration in certain sectoral indices of the Colombo Stock Exchange (CSE), intending to develop a portfolio diversification strategy. The study employed Pairwise cointegration tests to test the long-term relationship, finding that the 20 sectoral indices analyzed were not cointegrated. In Romania, Kralik, Acatrinei, and Sava (2013) explored the correlation between thirteen Romanian sectoral indices and the Bucharest Stock Exchange Trading (BET) index and the primary indices in Germany (DAX), UK (FTSE), Czech Republic (PX), and Austria (ATX). The Johansen cointegration test provided evidence of cointegration between three sectoral indices (banking, pharmaceutical, and financial services) and BET after the 2008 financial crisis. Finally, Sahabuddin, Muhammad, Dato, Shah, and Rahman (2018) tested the long-term comovement between two leading indices of the Malaysian Stock Market and ten sectoral indices. The result revealed that a long-term relationship exists among the variables.

The study validated the following null hypotheses:

$H0_1$: PSE sectoral indices and the PSE index are, significantly, a non-stationary series.

$H0_2$: There is no sectoral index that could significantly cointegrate with the PSE index.

3. METHODS

3.1. Operational Framework

Figure 1 outlines the process carried out in this study in the form of an operational framework. The PSE index and six sectoral indices were used as input variables. The endogenous (dependent) variables were the PSE index and the six sectoral indices. These variables were processed using a different statistical method, in order to provide information on long-term relationships between the PSE index and sectoral indices.

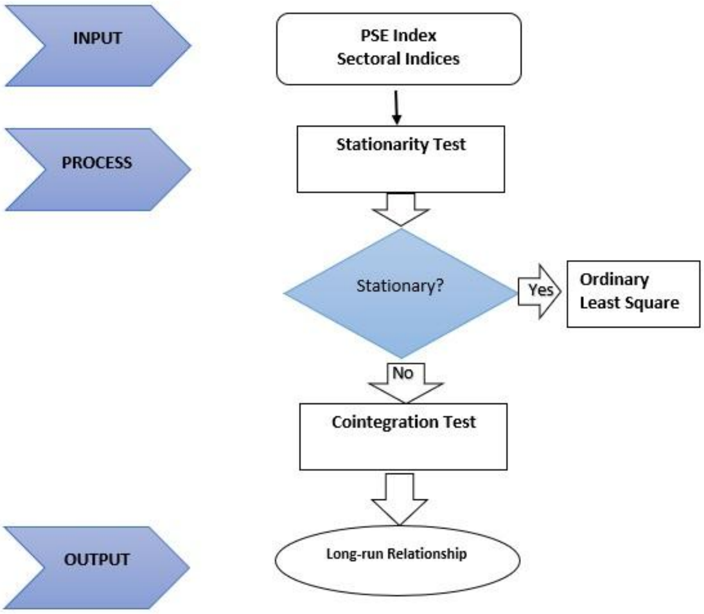

Figure 1. Operational Framework

3.2. Data

This study used secondary data to test the unpredictability of Philippine stock market indices. The researcher used the daily closing prices of the PSE index and six sectoral indices: Financial, holding firms, industrial, services, mining and oil, and property. The period of time covered in the study was July 2010 to December 2019.

3.3. Unit Root Test

The following steps were conducted to determine whether the indices are cointegrated. First, the integration of every index in the data series was tested. In this test, the researcher performed a stationary analysis on the seven indices. The possible outcomes of this test were the following:

1. All data series are non-stationary, or the data follows a random walk.
2. All data series are integrated of order 0 or I(0), meaning that the series is stationary at level.
3. All data series are integrated of order one or I(1), meaning that the data is stationary at first difference.
4. The data series are integrated into different orders, meaning that the series are integrated of order 0 as well as of order 1.

A unit root test was employed to determine the extent of stationarity in the data series (Al-Jafari, 2013). This study used the ADF test to examine whether or not the data series has a unit root. According to Nalin and Güler (2015), an ADF test is the most common method to examine the existence of a unit root in a series. The null hypothesis of the ADF unit root test is the data series' non-stationarity, or the series following a random walk. Al-Jafari pointed out that "the ADF tests assume that y series follows an AR(p) process and add p lagged difference terms of the dependent variable y to the right side of the test regression" (p. 175). An ADF test, without a drift or trend, uses the Equation 1:

$$\Delta y_t = \delta y_{t-1} + \beta \sum_{i=1}^{p} \Delta y_{t-i} + u_t \qquad (1)$$

Where Δy_t is the difference between the current index and the previous index, y_{t-1} is the previous index or lag 1, μ is the error or the white noise, and p is the lag order (Al-Jafari, 2013).

The null hypothesis of the ADF is $\mathbf{\delta = 0}$, which means that the series is considered to have a unit root or non-stationary. Sahabuddin et al. (2018) asserted that the objective of the unit root test is to assess whether the series is an I(0) process with a deterministic trend or an I(1) process with a stochastic trend. It is crucial that this information is uncovered before the cointegration test is conducted. The lag length should be selected using the Akaike's Information Criterion (AIC), Hannan–Quinn Information Criterion (HQIC), or Schwarz's Bayesian Information Criterion (SBIC). In this study, the researchers selected the lag length of the method that has the lowest information criterion value. According to Brooks (2008), the purpose of the lag length criterion test is to select the number of parameters that will minimize the value of the information criteria.

3.4. Cointegration Test

Kirchgässner and Wolters (2007) have argued that investigating two or more stationary stochastic series using traditional statistical procedures may lead to serious problems, citing previous work that regressed to an independent non-stationary series. They expected that the r-square would reach zero; however, the results gave a high coefficient of determination. This process is an example of spurious regression. In order to solve this problem, Johansen, Engle, and Granger (1991) developed statistical procedures to capture the relationship between non-stationary variables. These procedures are known as the theory of cointegrated relations, which was formed in the 1980s.

If two or more series are stationary at first difference or I(1), the next step is to perform a cointegration test to establish the long-term relationship of the variables. In this study, the Johansen cointegration test was used to test whether or not the data series are cointegrated. According to Vardar, Tunc, and Aydogan (2012), the Johansen cointegration test is a vector autoregressive (VAR) based method. This method employs maximum likelihood estimates that could test and estimate more than one cointegrating vector in the multivariate system. Equation 2 shows the model representation of the Johansen, which is a VECM representation, where Y_t is the vector of the endogenous variables.

$$\Delta Y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Pi_i \, \Delta Y_{t-i} + u_t \qquad (2)$$

Dwyer (2015) emphasized that the matrix Π is equal to the product of the vector of adjustment parameters α and the vector of cointegrating vectors β or Π = αβ. If the rank of vector Π is equal to zero, the data series are not cointegrated. Therefore, if the rank of Π is not equal to zero, two or more data series are cointegrated. This study used AIC, HQIC, or SBIC to determine the optimal lag length for cointegration analysis.

This study employed a Pairwise cointegration to identify the long-term relationship between a specific sector and the PSE index. This method is similar to what Claver, Dinga, Louis, Felix, and Gabriel (2019) used in their analysis on the African Stock Market and what Ahmed et al. (2018) used in their study on sectoral indices analysis of the Colombo Stock Exchange. According to Claver et al. (2019), "although Johansen test is best known to test for cointegration in a multivariate situation, it could equally be used for a bivariate approach to test for cointegration between pairs of stock indices."

The MPT emphasizes that investors should not maintain two correlated financial assets in their portfolio. The cointegration test provides information on the long-term relationships of the indices, which is useful for investors and fund managers when managing their investment portfolios to reduce investment risk.

4. EMPIRICAL RESULTS

4.1. Descriptive Results

Table 1 presents the descriptive statistics of the sectoral indices from July 1st, 2010, to December 27th, 2019. The mining and oil sector yielded the highest mean score (14,238.02) of all sectors, meaning that the mining and oil industry is the most valued sector by investors, especially between 2011 and 2012. The standard deviation (4,937.45) and coefficient of variation (35%) results show that the mining and oil sector was the fastest moving (upward or downward) index, compared to other industry indices. Meanwhile, the industrial sector made its own run during the nine-and-a-half-year period. The industrial index performed second to the mining and oil index, based on how the investors valued the sector ($\bar{x} = 9,951.98$). The industrial index climbed from its lowest closing point (5,116.99) during July 2010 to its all-time closing high of 13,068.24 in February 2015. This means that long-term investors earned as much as 155 percent during this uptrend, gaining 1.55 million for every 1 million worth of investment. After reaching its all-time high, the index moved within a range, which benefited range traders. The standard deviation (1,853.63) and coefficient of variation (19%) results revealed that investing in that industry was not that risky compared to other industries.

Table 1. Descriptive Statistics

Indices	Mean ($\bar{x}$)	Max	Min	Std Dev	Coefficient of Variation
PSE Index	6,600.75	9,058.62	3,290.98	1408.21	21%
Industrial	9,951.98	13,068.24	5,116.99	1,853□63	19%
Financial	1,567.56	2,325.65	741.26	352.58	22%
Holding Firm	6,135.89	9,362.95	2,228.92	1,688.23	28%
Property	2,837.84	4,507.29	1,176.82	869.54	31%
Services	1,706.55	2,263.47	1,257.79	234.81	14%
Mining	14,238.02	27,194.44	7,100.34	4,937.45	35%

Moreover, the holding firms index during this period was notable. Although the mining and industrial sectors were valued more by investors, the holding firms sector index climbed higher than those two indices in terms of growth percentage. In July 2010, the index was as low as 2,228.92; after eight years, it went up to 9,362.95. If long-term investors had invested Php1 million in this sector in July 2010, the value of their investment in February 2018 would be Php3.2 million, or a 320 percent return. Nine years after reaching its lowest closing value (1,176.82), the property index climbed to its all-time highest closing value (4,507.29), which is the equivalent of a 283 percent increase. Furthermore, the financial sector also had an impressive development during this period; from a three-digit index value, the industry made climbed to a four-digit value.

In summary, all sector indices performed very well over the last nine and a half years. The mining and oil sector experienced both its best and worst performance. The mining and oil index moved upwards (bullish) in the first two years; however, it had a downward move (bearish) for the next seven years. Since the first day of this time period, the holding firms, such as the mining and oil sector, slowly climbed to their peak and did not return to where they started. In July 2010, the lowest value index was 3,290.98, which slowly climbed the ladder until it reached its all-time high of 9,058.62 in February 2018. Long-term investors who held their investment position for ten years earned a 175 percent return, or 17.5 percent per annum. In the year 2012, growth was 33 percent, which was the best performance for the last ten years.

4.2. Unit Root Test Results

Table 2 presents the results of the stationarity test using the ADF test of index levels. The t-stat result was compared to the critical value of five percent, as a critical value approach was applied to test the hypothesis. If the t-stat absolute value is greater than the absolute critical value, the series is stationary. The results show that the indices' t-stats (PSE: -2.173; Financial: -2.180; Industrial: -2.652; Holding Firm: -2.159; Property: -1.337; Service: -2.026; Mining and Oil: -1.180) are lower than the five percent critical value (-2.860). Therefore, the results indicate that the indices data series contains a unit root, meaning that all series are non-stationary. The results failed to reject the hypothesis that the data series is non-stationary.

Table 2. ADF test results at index level

Indices	t-stat	Critical (5%)	Decision	Stationarity
PSE Index	-2.173	-2.86	Do not Reject	Non-stationary
Financial	-2.18	-2.86	Do not Reject	Non-stationary
Industrial	-2.652	-2.86	Do not Reject	Non-stationary
Holding Firms	-2.159	-2.86	Do not Reject	Non-stationary
Property	-1.337	-2.86	Do not Reject	Non-stationary
Services	-2.026	-2.86	Do not Reject	Non-stationary
Mining	-1.18	-2.86	Do not Reject	Non-stationary

On the other hand, since all indices were non-stationary at the index level, the data need to be evaluated in order to assess whether the series are stationary at the first difference before proceeding to the cointegration test. Table 3 presents the results of the stationarity test using the ADF test first difference. The result showed that the indices t-stats (PSE: -25.873; Financial: -25.783; Industrial: -24.404; Holding Firms: -35.307; Property: -25.569; Services: -24.502; Mining and Oil: -28.084) are greater than the five percent critical value (-2.860). This indicates that the indices data series does not contain a unit root, and therefore, all series are stationary. Thus, the hypothesis that the data series are non-stationary was rejected. All data series were integrated in the order of one (1), which was required for the cointegration test. These results are similar to those in the study on the Indian stock market, in which Minimol and Makesh (2017) found that the main indices, BSE Sensex and CNX Nifty, were stationary at first difference. Moreover, other sectoral indices in the NSE (India) market were also stationary at the first difference (Pyeman & Ahamad, 2017).

Table 3. ADF test results at first difference

Indices	t-stat	Critical (5%)	Decision	Stationarity
PSE Index	-25.873	-2.86	Reject	Stationary
Financial	-25.783	-2.86	Reject	Stationary
Industrial	-24.404	-2.86	Reject	Stationary
Holding Firm	-35.307	-2.86	Reject	Stationary
Property	-25.569	-2.86	Reject	Stationary
Services	-24.502	-2.86	Reject	Stationary
Mining	-28.084	-2.86	Reject	Stationary

4.3. Cointegration Test Results

Table 4 exhibits the results of the Johansen cointegration test between the PSEi and the six sectoral indices. The maximum column represents the number of cointegrating equations; the maximum number of cointegrating equations must be *k-1*, where *k* is the number of variables in the equation. As there are two variables, the maximum number of cointegrations is only one (1). The eigenvalues shown in the second and third row were used to determine the trace statistics. These trace statistics were compared to the five percent critical value, in order to test the null hypothesis. The first step was to check the null hypothesis of zero cointegration, which is displayed in the first row; if the null hypothesis is rejected, the researchers were able to proceed to the next row.

Table 4. Johansen cointegration test results

Indices	Rank	Trace	5% Critical	$H0_2$ Decision	Result
PSE Index and Financial	0	8.65	15.41	Do not reject	Not Cointegrated
	1	1.41	3.76		
PSE Index and Industrial	0	11.6	15.41	Do not reject	Not Cointegrated
	1	4.63	3.76		
PSE Index and Holding Firms	0	11.28	15.41	Do not reject	Not Cointegrated
	1	4.5	3.76		
PSE Index and Property	0	7.58	15.41	Do not reject	Not Cointegrated
	1	0.43	3.76		
PSE Index and Services	0	8.07	15.41	Do not reject	Not Cointegrated
	1	1.47	3.76		
PSE Index and Mining	0	24.75	15.41	Reject	Cointegrated

The results show that, among the six indices, only the mining and oil index is significantly cointegrated with the PSE index. This outcome differs to the index movement of the Malaysian stock market, where sectoral indices are cointegrated with the main index (Sahabuddin et al., 2018). These movements in the Philippine stock market have provided an opportunity for investors to diversify their investment portfolio. In their portfolio, investors could combine PSE index-related investments in any sector, apart from the mining and oil sector.

5. CONCLUSION

The results of this study confirm the RWH's notion that the previous market values of stocks do not affect its future value. Likewise, the unpredictability of the movement of indices in the results support the EMH. Finally, the unit root tests reject the overreaction hypothesis in terms of forecastability. According to Mynhardt and Plastun (2013), a market overreaction would result in market inefficiency.

The results of the stationarity test provide valuable information for market participants, whether they are seasoned or new to the market, which states that index movements cannot be predicted based on the past values. Most stock traders today use technical analyses, such as moving averages (MA) and candlestick analyses. Even though this practice does not really forecast movements, it is hoped that history will repeat itself if the prices are equal or near to the traders' chosen MA. This traditional practice is based on the behavior of market participants, as opposed to statistical concepts like the unit root test. Day traders could use the first difference to predict the movement of the index, as indices are stationary at this level. Since the data series is stationary, short-term investors such as day traders can buy PSE index-related stocks if the index is negative, or they can sell if the index becomes positive, as they would know the index would be positive the next day.

On the contrary, the Johansen cointegration test results can be used to apply the MPT with regard to investment portfolio diversification. Based on MPT, investors can diversify sectors that are not cointegrated. Based on the results of the study, long-term investors can diversify their portfolio by creating a portfolio across all sectors, apart from the mining and oil sector. These result provide long-term investors with vital information that they can use when managing their portfolio. An investment portfolio that contains stocks of the same nature, characteristics, and fluctuations, would expose the fund to considerable amounts of risk. One of the methods to reduce this risk is to distibute it by buying stocks that have different movements. This strategy is called stock diversification. Based on these results, long-term investors could manage their stock portfolio by employing sectoral diversification. The results show that most of the indices are not cointegrated and their movements have no relationship in the long-term. This means that there is no comovement between indices, which implies that the risk can be shared between different stocks in different sectors, instead of investing in stocks from one sector.

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