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The Correlation and Hedging Effects between Commodity and Stock Markets

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Abstract

This study uses the Rogers International Commodity Index (RICI) for composite commodities and RICI-Agriculture (RICA), RICI-Energy (RICIE), and RICI-Metals (RICIM) indices to examine the relationship between various commodity and stock markets. The empirical results indicated that stable long-term relationships exist between some commodity and stock markets, and that commodity indices generally lead stock market indices. Thus, in a number of countries/regions, investors can predict fluctuations in stock prices using variations in commodity indices. However, the RICI composite commodities index, RICIA agricultural commodity index, and RICIM metals index are subject to the influence of the U.S. stock market. Furthermore, when serious crises or high volatility occurs in stock markets, investors can use the RICIM metals index as a safe haven asset, incorporating it into investment portfolios to reduce risk. Under normal stock market circumstances, no hedging effects exist between commodity market indices and stock markets. Consequently, investors cannot use commodity indices as hedging instruments.

JEL classification numbers: G10, G11, G14, G15
Keywords: cointegration test, commodity index, hedging effect, safe haven effect

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1 Introduction

In recent years, a financial crisis has caused worldwide economic turmoil, leading to crashes and sharp declines in the stock markets of advanced countries in North America and Europe, and indirectly causing declines in the stock markets of emerging countries. By contrast, international raw material prices have posted strong gains and exhibited bullish characteristics, particularly the gold market. In an environment characterized by global economic uncertainty resulting from systematic risk, investors of market capital have sought out risk aversion and hedging strategies, causing the prices in the gold market to skyrocket. In addition, the U.S. government has engaged in repeated monetary easing policies to create capital flows and stimulate economic activity, leading to constant devaluation of the U.S. dollar (USD). Consequently, the prices of commodities denominated or valued in USD have risen consistently.

Commodities are a necessity of human life. Regardless of economic trends, necessities including food, clothing, shelter, and transport, as well as basic industries such as construction, transportation, mining, and agriculture, require commodity supply. Commodities are the basic upstream raw materials of all economic development. Thus, the supply and demand of commodities and associated price trends affect economic development throughout the world. The relationship between oil prices and economic development was first highlighted by Hamilton (1983), who noted that oil prices influence the macroeconomic performance of the United States and have a significant negative influence on production growth rates.

Since 2002, commodity prices have risen continually. Global raw material markets have exhibited bullishness, leading and driving various price indices, such as the Rogers International Commodity Index (RICI), Reuters/Jefferies Commodity Research Bureau Index, Goldman Sachs Commodity Index, and Dow Jones AIG Commodity Index. Specifically, the RICI includes 38 commodities that facilitate economic activity and operation and, thus, reflects global raw material price trends. This index has risen by 278.83% since its creation, and in July 2008, the index rose to 5,832.91, setting a record high price in conjunction with Brent crude. Baur and Lucey (2010) also demonstrated that whether the market is operating normally or experiencing shocks from extreme incidents, gold can serve as a hedge or safe haven . Hence, investors can incorporate raw material commodities or financial instruments derived from these commodities into their investment portfolios as a hedging strategy, thereby reducing investment portfolio risk.

Commodity markets are highly diverse with significantly different economic characteristics. For example, energy and agriculture are quite dissimilar in their economic influence. Consequently, this study contends that commodities must be separated into categories for examination. Previous studies have primarily focused on the correlation between the overall economy and oil or gold prices, or the correlation between the price of a single commodity (oil, gold, or copper) and stock markets, currency exchange markets, bond markets, or the overall economy. Few studies have divided commodities into categories to examine the relationships between different product characteristics and the overall economy. Therefore, this study examines the relationship between the characteristics of different commodities and stock markets, and also further analyzes whether the characteristics of different categories of commodities have hedging or safe haven effects for investment portfolio strategies in the stock market. The results can provide a reference for investors to make appropriate and accurate investment portfolio decisions.

2 Literature Review

The primary purpose of this study was to examine the correlation between commodity markets and stock markets. Based on the RICI, the commodity market indices were categorized into the four categories of RICI composite commodities, RICI-Agriculture (RICIA) for agricultural commodities, RICI-Energy (RICIE) for energy, and RICI-Metals (RICIM) for metals. This study observes the roles played by composite, energy, metal, and agricultural commodities in stock-market investment portfolio strategies, as well as whether these commodities exhibit cointegration or spillover effects. This study also examines whether the four types of commodities exert hedging or safe haven effects for investment portfolio strategies in stock markets.

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Related literature (Gorton & Rouwenhorst, 2006; Hunjra, Azam, Niazi, Butt, Rehman, & Azam, 2011; Jalil, Ghani, Daud, & Ibrahim, 2009; Park & Ratti, 2008; Summer, Johnson, & Soenen, 2010; Wang, Wang, & Huan, 2010) indicates that the returns on commodity futures are inversely related to returns in the stock and bond markets. However, the relationship between returns in commodity futures markets and stock markets changes according to economic or business cycles. By contrast, no consensus has been reached on whether cointegration relationships exist between crude oil prices, gold prices, and stock market prices. Consequently, long-term stable relationships between crude oil prices, gold prices, and stock market prices have yet to be verified.

Hamilton (1983) examined the post-WWII relationship between crude oil prices and the overall economy of the United States. The results showed that after WWII, volatility in the gross national product (GNP) of the United States was significantly and negatively correlated with volatility in oil prices, and the U.S. economy entered a recession period following dramatic increases in crude oil prices. Therefore, it can be inferred that shocks in oil prices may be one of the primary causes of economic downturns. Consequently, increases in the international prices of foodstuffs or crude oil are observed to negatively influence overall national economies. At the microeconomic level, price hikes increase production costs for enterprises, affecting industry. Thus, raw material prices are inseparably linked to and influence the performance of national economies.

Edwards and Caglayan (2001) found that commodity funds provide superior downside protection compared to hedge funds. In bearish stock markets, commodity funds provide higher returns compared to hedge funds and also exhibit inverse relationships with stock market returns. By contrast, hedge fund returns and stock market returns show a positive or direct relationship, and this phenomenon is particularly pronounced in bearish stock markets.

Summarizing other literature, the results of most studies (Baur & Lucey, 2010; Ciner, Gurdgiey, & Lucey, 2010; Coudert & Raymond, 2010; Hillier, Draper, & Faff, 2006) have shown that returns in the metals and stock markets are negatively associated, indicating that precious metals exhibit a safe haven effect. Consequently, incorporating precious metals into stock-market investment portfolios can effectively reduce investment portfolio risk. Furthermore, among the precious metals, gold has the most obvious safe haven effect. However, this effect is only short term. Gold also demonstrates a better hedging effect in bearish markets compared to bullish markets.

3 Research Methodology

The primary purpose of this study was to examine the correlation between the commodity and stock markets. Based on the categories adopted in the RICI, the commodity market indices were divided into the four categories of composite commodities, agricultural commodities, energy, and metals. This study analyzes the role that the characteristics of these four commodity indices play in stock-market investment portfolio strategies. First, this study examined whether cointegration or spillover effects existed between the commodity and stock markets. Second, the researchers assessed whether hedging or safe haven effects existed for any of the four categories of commodities regarding stock-market investment portfolio strategies. Then, the researchers proposed the following two hypotheses, which are explained below :

Hypothesis 1: Commodity markets act as hedging assets in stock-market investment portfolio strategies; in other words, commodity index prices and stock market prices are not linked under normal stock market conditions.

Hypothesis 2: Commodity markets act as safe haven assets in stock-market investment portfolio strategies; in other words, during periods of poor returns for stock prices (low returns) or abnormal volatility (high volatility) in stock markets, or during severe financial crises, commodity index prices and stock market prices are not linked.

3.1 Market Testing Model 1

To verify Hypotheses 1 and 2, and assess whether the four category indices, that is, composite commodities, agricultural commodities, energy, and metals, exhibited hedging and safe haven effects in stock-market investment portfolio strategies, this study established Equations (1) and (2) below. First, data from the research period, which ranged from January 31, 2005, to February 17, 2012, were divided into two portions: (a) data from before the 2008 financial crisis, and (b) data from after the 2008 financial crisis. The declaration of bankruptcy by Lehman Brothers Holdings Inc. in the United States on September 15, 2008, was set as the dividing point for segmentation.

Based on the market model developed by Hillier, Draper, and Faff (2006), if stock market volatility values exceeded two standard deviations for one period, the period was considered a high volatility period. Similarly, a period in which stock market return performance was lower than two standard deviations was considered a low returns period. Both of these conditions are represented by dummy variables acting as proxy variables; the conditional variance of the model fit THE autoregressive conditional heteroskedasticity (ARCH) with a lag of one period. The market testing model for the composite commodities, agricultural commodities, energy, and metals commodity indices are shown below.

$$R_{j,t} = \beta_{j,0} + \beta_{j,1} R_{Stock,t} + \beta_{j,2} D(Vol2\sigma) R_{Stock,t} + \beta_{j,3} D(R_{Stock}2\sigma) R_{Stock,t} + u_{j,t} \tag{1}$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u_{j,t-1}^2 \tag{2}$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

In Equations (1) and (2), $R_{j,t}$ represents the daily returns for the four commodity indices of composite commodities $R_{RICI,t}$, energy $R_{Energy,t}$, metals $R_{Metals,t}$, and agricultural commodities $R_{Agriculture,t}$ in period *t*. $R_{Stock,t}$ is the daily returns of the stock market index in period *t*. $D(Vol2\sigma)$ is a dummy variable that indicates that stock market returns are in a period of high volatility, and is set to 1 when the stock market return volatility exceeds two standard deviations of the mean market volatility value; otherwise, it is set to 0. $D(R_{Stock}2\sigma)$ is a dummy variable that indicates that the stock market returns are in a period of low returns, and is set to 1 when the stock market returns are at least two standard deviations lower than the mean market returns value; otherwise, it is set to 0.

This model can be used to test Hypothesis 1, that is, whether commodity indices act as hedging assets in stock-market investment portfolio strategies. If coefficient $\beta_{j,1}$ is positive and approaches 1, then a high and positive correlation and, therefore, linkage exists between commodity indices and stock markets. Conversely, if $\beta_{j,1}$ is negative and approaches -1, then commodity indices and stock markets exhibit a high and negative correlation, which indicates that commodity indices have a hedging effect in stock markets. This model can also be used to test Hypothesis 2, that is, whether commodity indices are safe haven assets in stock-market investment portfolio strategies. If coefficient $\beta_{j,2}$ in Equation (1) is significant and 0, then the composite commodities, agricultural commodities, energy, and metals indices have a weak safe haven effect during periods of high volatility in the stock market. If coefficient $\beta_{j,2}$ is significantly negative, then the four categories of commodity indices exhibit strong safe haven effects. In addition, if coefficient $\beta_{j,3}$ is significant and 0, then the four commodity indices have a weak hedging effect during periods of extremely low returns in stock markets; if $\beta_{j,3}$ is significantly negative, then the four categories of commodity indices exhibit strong hedging effects.

3.2 3.2 Market Testing Model 2

To enhance the tests described above, this study adopted the model established by Baur and Lucey (2010) to test for correlations between the gold, stock, and bond markets to determine whether composite commodity, energy, metals, and agricultural commodity indices have hedging or safe haven effects in stock-market investment portfolio strategies. The above model was divided into three short-term shocks to examine whether the four commodity indices exhibited safe haven effects (for stock-market investment portfolio strategies) during the three stock market stages.

3.2.1 Low returns period

When stock markets experience extremely low returns, investors pursue other investment instruments as safe havens. Thus, the following model uses the distribution of stock market returns to establish threshold values of 10%, 5%, and 1% and examine changes in the returns of the stock and commodity markets. The model is shown below.

$$R_{j,t} = \beta_{j,0} + \beta_{j,t} R_{Stock,t} + u_{j,t} \tag{3}$$

$$\beta_{j,t} = \lambda_{j,1} + \lambda_{j,2} D(R_{Stock}\, q_{10}) + \lambda_{j,3} D(R_{Stock}\, q_5) + \lambda_{j,4} D(R_{Stock}\, q_1) \tag{4}$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u_{j,t-1}^2 \tag{5}$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

In Equation (3), $R_{j,t}$ separately represents the daily returns of the four commodity indices of composite commodities $R_{RICI,t}$, energy $R_{Energy,t}$, metals $R_{Metals,t}$, and agricultural commodities $R_{Agriculture,t}$ in period *t*. $R_{Stock,t}$ represents the daily returns of the stock market index during period *t*. In Equation (4), $D(R_{Stock}\, q_{10})$, $D(R_{Stock}\, q_5)$, and $D(R_{Stock}\, q_1)$ serve as the dummy variables for extremely poor stock market returns and were designed to capture the condition of stock market returns. When the returns distribution in stock markets is lower than the set thresholds of 10%, 5%, or 1%, the dummy variables are set to 1; otherwise, they are set to 0. The conditional heteroskedasticity of each model fits the ARCH with a one-period lag, and the simultaneous equations among the models were solved using the maximum likelihood estimation (MLE) method.

Under circumstances of extremely low returns in stock markets, if coefficient $\lambda_{j,1}$ in Equation (4) was significant and 0, the four types of commodity indices exhibited weak hedging effects. If coefficient $\lambda_{j,1}$ was significantly negative and $\lambda_{j,2} + \lambda_{j,3} + \lambda_{j,4} < \lambda_{j,1}$, then the four commodity indices exhibited strong hedging effects. In addition, if the coefficients $\lambda_{j,2}$, $\lambda_{j,3}$, or $\lambda_{j,4}$ were significantly 0, the four commodity indices showed t weak safe haven effects. Finally, if the coefficients $\lambda_{j,2}$, $\lambda_{j,3}$, or $\lambda_{j,4}$ were significantly negative, the four commodity indices demonstrated strong safe haven effects.

3.2.2 3.2.2 Periods of high market volatility

Under conditions of abnormal volatility (high volatility) in stock markets, investors pursue other investment instruments as safe havens to avoid uncertainty in the market. This study uses a conditional volatility ARCH (1) model with a delay of one period as a proxy variable for abnormal market volatility to examine changes in the returns of the stock and commodity markets. The model was as follows:

$$R_{j,t} = \beta_{j,0} + \beta_{j,t} R_{Stock,t} + u_{j,t} \tag{6}$$

$$\beta_{j,t} = \lambda_{j,1} + \lambda_{j,2} D(h_{Stock}\, q_{90,t-1}) + \lambda_{j,3}(h_{Stock}\, q_{95,t-1}) + \lambda_{j,4}(h_{Stock}\, q_{99,t-1}) \tag{7}$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u_{j,t-1}^2 \tag{8}$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

The dummy variables $D(h_{Stock}\, q_{90,t-1})$, $D(h_{Stock}\, q_{95,t-1})$, and $D(h_{Stock}\, q_{99,t-1})$ were set to capture different levels of return volatility in stock markets. When the stock market return volatility exceeded the predefined thresholds of 90%, 95%, and 99%, the dummy variables were set to 1; otherwise, they were set to 0. The conditional heteroskedasticity of each model fit the ARCH with a one-period lag, and the simultaneous equations among the models were solved using the MLE method.

Under conditions of abnormal volatility (high volatility) in stock markets, if coefficient $\lambda_{j,1}$ of Equation (7) was significant and 0, the composite commodities, agricultural commodities, energy, and metals commodity indices were regarded as having weak hedging effects; if coefficient $\lambda_{j,1}$ was significantly negative and $\lambda_{j,2} + \lambda_{j,3} + \lambda_{j,4} < \lambda_{j,1}$, the four commodity indices had strong hedging effects. Similarly, if the coefficients $\lambda_{j,2}, \lambda_{j,3}$, or $\lambda_{j,4}$ were significant and 0, the composite commodities, agricultural commodities, energy, and metals commodity indices had weak safe haven effects; if coefficients $\lambda_{j,2}, \lambda_{j,3}$, or $\lambda_{j,4}$ were significantly negative, the four commodity indices showed strong safe haven effects.

3.2.3 3.2.3 Market crisis period

During severe financial crises in stock markets, investors pursue other or alternate investment instruments as safe havens to avoid the crisis. This study set September 15, 2008, the day Lehman Brothers Holdings Inc. (in the United States) declared bankruptcy, as the date when the financial crisis began and observed the changes in returns between the stock and commodity markets within the six months after the beginning of the 2008 subprime mortgage crisis. The dummy variable $D(subprime, 2008)$ denoted the subprime mortgage event that occurred in 2008 and lasted for a period of six months. The conditional heteroskedasticity of each model fit the ARCH with a one-period lag, and the simultaneous equations among the models were solved using the MLE method. The model was as follows:

$$R_{j,t} = \beta_{j,0} + \beta_{j,t} R_{Stock,t} + u_{j,t} \tag{9}$$

$$\beta_{j,t} = \lambda_{j,1} + \lambda_{j,2} D(subprime, 2008) \tag{10}$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u_{j,t-1}^2 \tag{11}$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

If coefficient $\lambda_{j,2}$ was 0 or negative in Equation (10), the composite commodities, agricultural commodities, energy, and metals commodity indices exhibited safe haven effects during the crisis period. If coefficient $\lambda_{j,2}$ was positive, the four commodity indices exhibited a connection during crisis periods and, thus, did not demonstrate a safe haven effect.

4 Empirical Results and Analysis

This study adopted four commodity indices and stock market indices from 12 countries or regions to examine the correlation and hedging effects between commodity and stock market prices. The data employed were extracted from daily data collected between January 31, 2005, and February 17, 2012, comprising a total of 1,767 pieces of data. The commodity indices used were the RICI composite commodities index, RICIA agricultural commodities index, RICIE energy index, and RICIM metals index. The stock market indices employed were the Morgan Stanley Capital International (MSCI) indices for Europe, the United States, Japan, Canada, Australia, China, India, Russia, Brazil, South Korea, Taiwan, and Africa. These 12 countries or regions comprised developed markets, emerging markets, and undeveloped countries/regions, and included exporters and importers of agricultural commodities, energy, and metals. Therefore, the stock market indices of the 12 countries or regions were used to represent stock markets to clearly observe the correlation between commodity indices and the stock markets of countries/regions that demanded or supplied raw material commodities. The indices employed in this study were all valued in USD, eliminating the need to consider foreign exchange rate issues.

We compiled the time series data for the various variables and found that all variable distributions were not consistent with a normal distribution. This study subsequently conducted model testing of the hedging and safe haven effects, and considering the market structure, divided the data into pre- and post-2008 financial crisis sections to analyze the differences in results for the two periods.

During the research period, the metals index yielded the highest daily average returns among the RICI indices. However, the energy index exhibited the highest standard deviation, which indicated that it possessed the greatest risk. Generally, the standard deviations of the RICI indices were less than those of the MSCI indices for most countries or regions, with the notable exception of the energy index. Regarding the MSCI indices, the average daily returns were higher for the emerging markets, such as China, India, Russia, Brazil, and South Korea, compared to other markets. Nevertheless, these markets also exhibited higher standard deviations, indicating that higher returns were accompanied by higher risk.

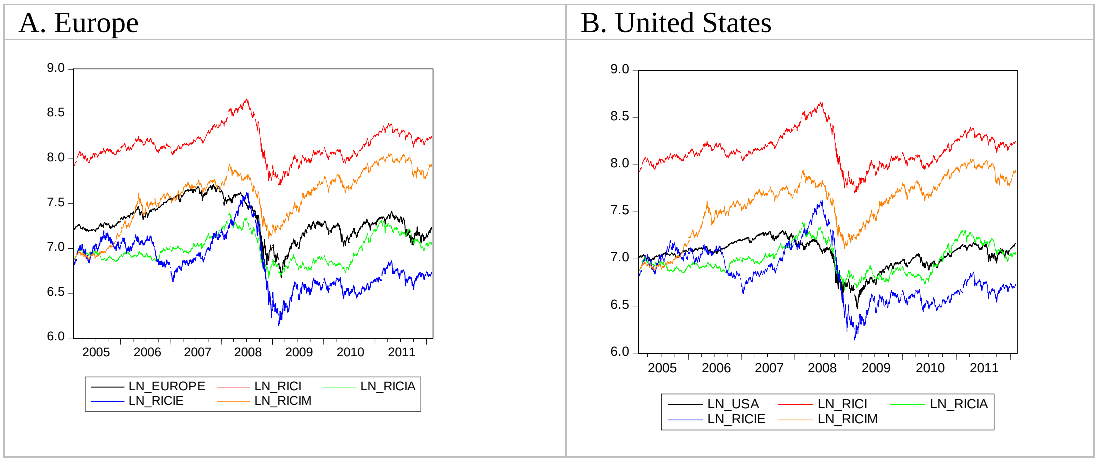

Figure 1: Trend chart of MSCI indices for various countries or regions and RICI commodity indices

Further analysis of the direction and strength of the linear relationships between variables showed that among the RICI indices, only the RICI composite commodities index was negatively correlated with the metals and energy indices; the other indices were positively related to each another. Finally, to identify the relationship between the MSCI indices for various countries and regions and the commodity indices, this study produced trend charts for the MSCI indices and the RICI commodity indices after deriving the logarithms for original variable data, as shown in Fig. 1. The results indicate that the trend lines for the MSCI indices and the RICI commodity indices are extremely similar, preliminarily suggesting a high correlation.

Typical economic and financial data exhibit random walk characteristics. This study conducted first-order difference equations for the data. The results showed that the null hypotheses for all variables were rejected under the 1% significance level, which indicates that the data were consistent with steady state characteristics. The integrated order was of the first order, as expressed by the term .

This study adopted the Johansen cointegration test model to observe whether cointegration existed between the variables. We found that in the short term, the MSCI index for India led the RICI composite commodities index, and that when the two deviated from long-term equilibrium, the MSCI index for India exhibited adjustment functions. By contrast, the RICI composite commodities index led the MSCI index for Russia. When the two deviated from long-term equilibrium, the adjustment function was represented by the MSCI index for Russia.

Regarding the vector error correction model for the RICI commodity indices and the MSCI indices for Europe, the United States, Canada, Australia, South Korea, and Taiwan, only a single adjustment coefficient was significant. In the short term, the RICI composite commodities index led the MSCI indices for Europe, Australia, China, South Korea, and Taiwan. By contrast, the MSCI indices for the United States and Canada led the RICI composite commodities index.

This study further tested for causal relationships to determine unidirectional or bidirectional and leading or lagging relationships in the commodity and stock markets. As shown in Tables 1 to 4, bidirectional causal relationships existed between the RICI composite commodities index and the MSCI indices for Europe, Canada, China, and

Brazil, highlighting the mutual influence between the MSCI indices and RICI composite commodities index of these countries or regions. Furthermore, the RICI composite commodities index maintained a leading relationship with the stock markets in most countries/regions. Therefore, changes in the RICI composite commodities index can be used to predict stock market price changes in these countries/regions. Only the U.S. stock market led the RICI composite commodities index. In other words, the RICI composite commodities index is influenced by the U.S. stock market, which indicates that a unidirectional causal relationship exists. However, the Indian stock market and the RICI composite commodities index were mutually independent, indicating that the price changes in one index could not be used to predict price changes in the other.

Of the causal relationships between the MSCI indices for various countries or regions and the RICIA agricultural commodities index, bidirectional causal relationships existed for Europe, Canada, Australia, and Russia, indicating that mutual influences existed between the MSCI indices and the RICIA agricultural commodities index for these countries and regions. The RICIA agricultural commodities index led the stock markets of most countries/regions.

Furthermore, of the causal relationships between the MSCI indices for various countries or regions and the RICIE energy index, bidirectional causal relationships were observed for Europe, the United States, China, India, and South Korea, indicating that a mutual influence existed between the MSCI indices and the RICIE energy index of these countries/regions. The RICIE energy index led the MSCI indices of most countries/regions, which suggests that changes in the RICIE energy index can be used to predict stock market price changes in these areas. Only the stock markets of Canada and Brazil led the RICIE energy index, which implies that for these two countries, the RICIE energy index is influenced by the stock market, exhibiting a unidirectional causal relationship.

Table 1: Granger causal relationship testing – MSCI indices for various countries/regions and RICI (composite commodities) index

Country/Region	Excluded variable	Dependent variable	Chi-sq	df	Prob.	Granger causal relationship
Europe	$\Delta\, ln\left(RICI\right)$	$\Delta\, ln\left(EUROPE\right)$	12.954 9	7	**0.07***	RICI $\leftrightarrow$ EUROPE
	$\Delta \ln\left(EUROPE\right)$	$\Delta\, ln\left(RICI\right)$	14.307 3		**0.05****	
United States	$\Delta\, ln\left(RICI\right)$	$\Delta\, ln\left(USA\right)$	3.8351	3	0.28	USA $\rightarrow$ RICI
	$\Delta\, ln\left(USA\right)$	$\Delta\, ln\left(RICI\right)$	49.529 0		**0.00*****	

Note: *, **, and *** respectively represent that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.

Table 2: Granger causal relationship testing—MSCI indices for various countries/regions and RICIA (agricultural commodities) index

Country/Region	Excluded variable	Dependent variable	Chi-sq	df	Prob.	Granger causal relationship
Europe	$ln(RICIA)$	$ln(EUROPE)$	12.2911	6	**0.06***	RICIA $\leftrightarrow$ EUROPE
	$\ln(EUROPE)$	$ln(RICIA)$	26.7654		**0.00*****	
United States	$ln(RICIA)$	$ln(USA)$	1.2310	3	0.75	USA $\rightarrow$ RICIA
	$ln(USA)$	$ln(RICIA)$	33.5645		**0.00*****	

Note: *, **, and *** respectively represent that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.

Finally, an examination of the causal relationships between the RICIM metals index and the MSCI indices for various countries/regions indicated that bidirectional causal relationships existed for Japan, Canada, Australia, and Brazil. Furthermore, the RICIM metals index led the stock markets of most countries/regions. Consequently, changes in the RICIM metals index can be used to predict changes in stock market prices for these areas. Only the U.S. stock market led the RICIM metals index in a unidirectional causal relationship. However, the European stock market and the RICIM metals index were mutually independent; indicating that price changes for one index could not be used to predict price changes in the other.

Table 3: Granger causal relationship testing—MSCI indices for various countries/regions and RICIE (energy) index

Country/Region	Excluded variable	Dependent variable	Chi-sq	df	Prob.	Granger causal relationship
Europe	$ln(RICIE)$	$ln(EUROPE)$	13.9227	6	**0.03****	RICIE $\leftrightarrow$ EUROPE
	$\ln(EUROPE)$	$ln(RICIE)$	17.7031		**0.01*****	
United States	$ln(RICIE)$	$ln(USA)$	6.2759	3	**0.10***	RICIE $\leftrightarrow$ USA
	$ln(USA)$	$ln(RICIE)$	37.8654		**0.00*****	

Note: *, **, and *** respectively represent that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.

Table 4: Granger causal relationship testing—MSCI indices for various countries/regions and RICIM (metals) index

Country/Region	Excluded variable	Dependent variable	Chi-sq	df	Prob.	Granger causal relationship
Europe	$\Delta \ln(RICIM)$	$\Delta \ln(EUROPE)$	0.4609	1	0.50	Mutually independent
	$\Delta \ln(EUROPE)$	$\Delta \ln(RICIM)$	0.8332		0.36	
United States	$\ln(RICIM)$	$\ln(USA)$	2.8553	3	0.41	USA $\rightarrow$ RICIM
	$\ln(USA)$	$\ln(RICIM)$	67.6787		**0.00*** **	

Note: *, **, and *** respectively represent that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.

The above tests were conducted to determine whether cointegration and leading/lagging relationships existed between commodity and stock markets. This study then further examined whether hedging or safe haven effects existed for the four commodity indices in stock-market investment portfolio strategies.

4.1 Market Testing Model 1

When examining the model for safe haven effects, if stock market volatility values exceeded the mean market volatility value by two standard deviations in one period, that period was defined as a high volatility period. In addition, if the returns performance of a stock market was lower than the mean market returns value by two standard deviations in one period, that period was defined as a low returns period. Dummy variables are used as proxy variables in the model to represent these conditions, and the conditional heteroskedasticity of the model fits the ARCH with a one-period lag.

Table 5 shows that when testing the returns coefficient ($\beta_{j,1}$) for Hypothesis 1 regarding hedging effects over the entire research period, the coefficient for the RICI composite commodities index was negative in relation to the MSCI indices of Japan, Australia, and India. In addition, the coefficients of the RICI composite commodities index, RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were all negative for the MSCI index for Africa; however, the results were not statistically significant. Conversely, the returns coefficients for the hedging effect were significant and positive for the RICI composite index, RICIA agricultural products index, RICIE energy index, and RICIM metals index in relation to the MSCI indices for the United States and Canada. The coefficients for the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were positive and significant in relation to the MSCI indices for Europe, Australia, China, India, Russia, Brazil, and South Korea. These results show that during the research period, none of the commodity indices exhibited a significant hedging effect for the MSCI stock indices of the 12 countries/regions; instead, the four commodity indices exhibited a significant link with the MSCI stock indices for most of the countries/regions.

During periods of high volatility in stock markets, the results for the returns coefficients

($\beta_{j,2}$) for Hypothesis 2 regarding safe haven effects showed that the RICI composite commodities index was significantly negative for Russia's MSCI index, and that the coefficient for the RICIE energy index was significantly negative for Canada's MSCI index. In addition, the coefficient for the RICIM metals index was significantly negative in relation to the MSCI indices for Europe, the United States, Canada, China, India, Russia, and South Korea. The results indicated that the RICI composite commodities index had a safe haven effect for Russia's stock market index, and that the RICIM metals index also had a safe haven effect for Europe, the United States, Canada, China, India, Russia, and South Korea.

Finally, during periods of low returns in stock markets, an examination of the returns coefficient ($\beta_{j,3}$) for Hypothesis 2 regarding safe haven effects showed that the coefficient of the RICI composite commodities index was significantly negative for the MSCI indices of China and South Korea, and that the coefficient of the RICIM metals index was also significantly negative in relation to the MSCI index for Canada. Conversely, the safe-haven-effect returns coefficients for the RICIA agricultural commodities index were significantly positive for the MSCI indices of most countries/regions, excluding Canada and Africa. These results show that the RICI composite commodities index had a safe haven effect for the stock indices of China and South Korea; the RICIM metals index also had a safe haven effect for the stock market index of Canada. However, the RICIA agricultural commodities index was linked to the MSCI indices of most countries/regions.

Summarizing the above results, we determined that the four commodity indices were linked to the MSCI indices for most countries/regions during the research period. Therefore, the hedging effects were poor. Regarding safe haven effects, the safe haven effects of the commodity indices were stronger during periods of high volatility compared to periods of low returns. Specifically, the RICIM metals index had safe haven effects for the stock indices of most countries/regions, whereas the RICIA agricultural commodities index did not have safe haven effects.

Table 6 shows that before the 2008 financial crisis, the test results of the returns coefficient ($\beta_{j,1}$) for Hypothesis 1 regarding hedging effects indicate that no commodity indices had significant hedging effects for MSCI stock indices before 2008. Instead, these four commodity indices were significantly linked to the MSCI stock indices of most countries/regions. This trend was identical to results for the entire research period.

During periods of high volatility in stock markets, the results for the returns coefficient ($\beta_{j,2}$) for Hypothesis 2 regarding the safe haven effect showed that the RICI composite commodities index had safe haven effects for the stock index of South Korea, and that the RICIM metals index had a safe haven effect for the stock index of India. However, the RICIA agricultural commodities index was significantly linked with the MSCI stock indices for Europe and Canada. The same was true of the RICIM metals index in relation to the MSCI stock indices of Canada, Russia, and Brazil.

During periods of low returns in stock markets, the results of the returns coefficient for safe haven effects ($\beta_{j,3}$) indicated that the coefficient of the RICI composite commodities index was significantly negative for the MSCI index of China. Conversely, the returns coefficient for the safe haven effect of the RICIA agricultural commodities index was significantly positive for the MSCI indices of five countries/regions: Europe, Australia, China, India, and South Korea. However, the RICIE energy index was only significantly positive for Taiwan’s MSCI index. The RICIM metals index was significantly positive for the MSCI indices of Europe, China, India, Brazil, and Taiwan. The results showed that the RICI composite commodities index exhibited a safe haven effect for the stock market index of China. Nevertheless, the RICIA agricultural commodities index and RICIM metals index were linked to the MSCI stock indices of most countries/regions.

In summation, these results indicate that the four commodity indices were linked to the MSCI indices of most countries/regions before the 2008 financial crisis and, therefore, had poor hedging effects. These results were identical for the entire research period. Regarding safe haven effects, only a few safe haven effects existed among the commodity indices. Additionally, the RICIA agricultural commodities index did not exhibit a safe haven effect.

Table 7 shows that after the 2008 financial crisis, the test results of the returns coefficients ($\beta_{j,1}$) for Hypothesis 1 regarding hedging effects indicated that the coefficients of the RICI composite commodities index for the MSCI indices of Europe, Japan, Australia, and South Korea were all negative. Furthermore, the RICI composite commodities index, RICIA agricultural commodities index, RICIE energy index, and RICIM metals index all had negative coefficients in relation to the MSCI index for Africa; however, these relationships were not statistically significantly. By contrast, regarding the returns coefficients for hedging effects, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index had significantly positive coefficients in relation to the MSCI indices for Europe, the United States, Canada, Australia, China, India, Russia, and South Korea. These four commodity indices also exhibited a significant link with the MSCI index of Brazil. The results indicate that after the 2008 financial crisis, no commodities index showed significant hedging effects in relation to the MSCI stock indices. Instead, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were all significantly linked to the MSCI indices for most countries/regions. These results are similar to those published in extant studies.

Table 5: Market Testing Model 1 – Entire period

Country/Region	RICI (Composite commodities)			RICIA (Agricultural commodities)			RICIE (Energy)			RICIM (Metals)		
	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.
Europe	$\beta_{rici,0}$	0.0007	**(0.02)****	$\beta_{ricia,0}$	0.0002	(0.32)	$\beta_{ricie,0}$	0.0007	**(0.08)***	$\beta_{ricim,0}$	0.0007	**(0.01)*****
	$\beta_{rici,1}$	0.0028	(0.93)	$\beta_{ricia,1}$	0.2596	**(0.00)*****	$\beta_{ricie,1}$	0.4727	**(0.00)*****	$\beta_{ricim,1}$	0.6191	**(0.00)*****
	$\beta_{rici,2}$	-0.0070	(0.87)	$\beta_{ricia,2}$	0.0067	(0.82)	$\beta_{ricie,2}$	0.0253	(0.63)	$\beta_{ricim,2}$	-0.1478	**(0.00)*****
	$\beta_{rici,3}$	-0.0066	(0.91)	$\beta_{ricia,3}$	0.1065	**(0.00)*****	$\beta_{ricie,3}$	0.1619	**(0.00)*****	$\beta_{ricim,3}$	0.0484	(0.19)
	(1) 0.0064	$(1)^2$ 0.8322		(1) 0.1933	$(1)^2$ 0.3579		(1) 2.3661	$(1)^2$ 1.3046		(1) 0.0248	$(1)^2$ 0.1958	
	(2) 0.3249	$(2)^2$ 2.2462		(2) 3.5288	$(2)^2$ 0.6123		(2) 2.5499	$(2)^2$ 3.8362		(2) 0.2177	$(2)^2$ 0.7090	
	LM test	0.8299(0.36)		LM test	0.3568(0.55)		LM test	1.3011(0.25) 0.1105		LM test	0.1952(0.66)	
United States	$\beta_{rici,0}$	0.0006	**(0.03)****	$\beta_{ricia,0}$	0.0003	(0.30)	$\beta_{ricie,0}$	0.0006	(0.12)	$\beta_{ricim,0}$	0.0009	**(0.00)*****
	$\beta_{rici,1}$	0.1298	**(0.00)*****	$\beta_{ricia,1}$	0.2161	**(0.00)*****	$\beta_{ricie,1}$	0.4613	**(0.00)*****	$\beta_{ricim,1}$	0.4213	**(0.00)*****
	$\beta_{rici,2}$	-0.0150	(0.77)	$\beta_{ricia,2}$	-0.0051	(0.89)	$\beta_{ricie,2}$	0.0285	(0.66)	$\beta_{ricim,2}$	-0.1670	**(0.00)*****
	$\beta_{rici,3}$	0.0417	(0.50)	$\beta_{ricia,3}$	0.1396	**(0.00)*****	$\beta_{ricie,3}$	0.1995	**(0.00)*****	$\beta_{ricim,3}$	0.0791	(0.18)
	(1) 3.3154	$(1)^2$ 0.7409		(1) 0.1490	$(1)^2$ 0.1959		(1) 3.4533	$(1)^2$ 2.8953		(1) 5.4824	$(1)^2$ 0.2419	
	(2) 3.9100	$(2)^2$ 3.7813		(2) 0.8181	$(2)^2$ 0.5549		(2) 3.5183	$(2)^2$ 3.5698		(2) 5.6336	$(2)^2$ 1.8287	
	LM test	0.7389(0.39)		LM test	0.1953(0.66)		LM test	2.8907(0.09)		LM test	0.2411(0.62)	

Note: *, **, and *** respectively indicate that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.
(1) and (2) respectively indicate the Ljung-Box Q statistic for the standardized residuals with a one- and two-period lag.
$(1)^2$ and $(2)^2$ respectively indicate the Ljung-Box Q statistic for the squared standardized residuals quadratic with a one- and two-period lag.

$$R_{j,t} = \beta_{j,0} + \beta_{j,1} R_{Stock,t} + \beta_{j,2} D(Vol2\sigma) R_{Stock,t} + \beta_{j,3} D(R_{Stock} 2\sigma) R_{Stock,t} + u_{j,t}$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u_{j,t-1}^2$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

$D(Vol2\sigma)$ is the dummy variable indicating high volatility in stock market returns. When the volatility of stock market returns exceeds two standard deviations from the mean volatility value, the variable is set to 1; otherwise, it is set to 0. $D(R_{Stock}2\sigma)$ is the dummy variable indicating a low stock market return period. When the stock market returns are less than two standard deviations from the mean returns value, the variable is set to 1; otherwise, it is set to 0.

Table 6: Market Testing Model 1 – Pre-2008 financial crisis

Country/Region	RICI (Composite commodities)			RICIA (Agricultural commodities)			RICIE (Energy)			RICIM (Metals)		
	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.
Europe	$\beta_{rici,0}$	0.0007	**(0.05)****	$\beta_{ricia,0}$	0.0002	(0.59)	$\beta_{ricie,0}$	0.0008	(0.16)	$\beta_{ricim,0}$	0.0008	**(0.04)****
	$\beta_{rici,1}$	0.0349	(0.42)	$\beta_{ricia,1}$	0.1657	**(0.00)*****	$\beta_{ricie,1}$	0.2392	**(0.00)*****	$\beta_{ricim,1}$	0.5276	**(0.00)*****
	$\beta_{rici,2}$	-0.0860	(0.26)	$\beta_{ricia,2}$	0.1362	**(0.03)****	$\beta_{ricie,2}$	0.1232	(0.37)	$\beta_{ricim,2}$	0.0378	(0.63)
	$\beta_{rici,3}$	-0.1406	(0.20)	$\beta_{ricia,3}$	0.2222	**(0.01)*****	$\beta_{ricie,3}$	0.2255	(0.36)	$\beta_{ricim,3}$	0.3390	**(0.00)*****
	(1) 0.7793	$(1)^2$ 0.1256		(1) 0.0486	$(1)^2$ 1.7034		(1) 0.6741	$(1)^2$ 0.0171		(1) 0.1665	$(1)^2$ 0.0572	
	(2) 0.9418	$(2)^2$ 1.7590		(2) 1.9607	$(2)^2$ 2.4627		(2) 0.8271	$(2)^2$ 5.5275		(2) 0.1679	$(2)^2$ 0.2215	
	LM test	0.1250(0.72)		LM test	1.6957(0.19)		LM test	0.0170(0.90)		LM test	0.0569 (0.81)	
United States	$\beta_{rici,0}$	0.0007	**(0.05)****	$\beta_{ricia,0}$	0.0002	(0.58)	$\beta_{ricie,0}$	0.0008	(0.17)	$\beta_{ricim,0}$	0.0010	**(0.01)*****
	$\beta_{rici,1}$	0.1926	**(0.00)*** *****	$\beta_{ricia,1}$	0.0775	**(0.02)****	$\beta_{ricie,1}$	-0.0693	(0.34)	$\beta_{ricim,1}$	0.1167	**(0.02)****
	$\beta_{rici,2}$	-0.0859	(0.32)	$\beta_{ricia,2}$	0.0804	(0.56)	$\beta_{ricie,2}$	0.2553	(0.21)	$\beta_{ricim,2}$	0.1824	(0.16)
	$\beta_{rici,3}$	-0.0051	(0.99)	$\beta_{ricia,3}$	0.1227	(0.39)	$\beta_{ricie,3}$	0.0451	(0.80)	$\beta_{ricim,3}$	0.1018	(0.66)
	(1) 1.3955	$(1)^2$ 0.0026		(1) 0.0051	$(1)^2$ 0.2639		(1) 0.7385	$(1)^2$ 0.0000		(1) 0.2421	$(1)^2$ 1.3108	
	(2) 2.1761	$(2)^2$ 0.6142		(2) 1.8704	$(2)^2$ 0.9964		(2) 1.1942	$(2)^2$ 4.6652		(2) 0.4118	$(2)^2$ 2.2648	
	LM test	0.0026(0.96)		LM test	0.2623(0.61)		LM test	0.0000(1.00)		LM test	1.3058(0.25)	

Note: *, **, and *** respectively indicate that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.
(1) and (2) respectively indicate the Ljung-Box Q statistic for the standardized residuals with a one- and two-period lag.
$(1)^2$ and $(2)^2$ respectively indicate the Ljung-Box Q statistic for the squared standardized residuals with a one- and two-period lag.

$$R_{j,t} = \beta_{j,0} + \beta_{j,1} R_{Stock,t} + \beta_{j,2} D(Vol2\sigma) R_{Stock,t} + \beta_{j,3} D(R_{Stock} 2\sigma) R_{Stock,t} + u_{j,t}$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u_{j,t-1}^2$$

$$j = RICI,\ RICI\text{ - }Agriculture, RICI\text{ - }Energy,\ RICI\text{ - }Metals$$

$D(Vol2\sigma)$ is the dummy variable indicating high volatility in stock market returns. When the volatility of stock market returns exceeds two standard deviations from the mean volatility value, the variable is set to 1; otherwise, it is set to 0. $D(R_{Stock}2\sigma)$ is the dummy variable indicating a low stock market return period. When the stock market returns are less than two standard deviations from the mean returns value, the variable is set to 1; otherwise, it is set to 0.

During periods of high volatility in stock markets, the test results of the returns coefficients ($\beta_{j,2}$) for Hypothesis 2 regarding safe haven effects indicated that the coefficients of the RICI composite commodities index were significantly negative in relation to the MSCI indices for Russia and Brazil. In addition, the coefficients of the RICIA agricultural commodities index were significantly negative for the MSCI indices of Europe, the United States, Canada, Australia, and Russia; the coefficients of the RICIE energy index were significantly negative for the MSCI indices of Europe, the United States, Canada, Russia, and South Korea; and the RICIM metals index exhibited significantly negative coefficients in relation to the MSCI indices of Europe, the United States, Canada, China, India, Russia, Brazil, and South Korea. These results suggest that the RICI composite commodities index had a safe haven effect in relation to the stock indices of Russia and Brazil. Moreover, the RICIA agricultural commodities index, the RICIE energy index, and the RICIM metals index had safe haven effects in relation to the MSCI stock indices of most countries/regions, including Europe, the United States, Canada, and Russia.

During periods of low returns in stock markets, the test results of the returns coefficients ($\beta_{j,3}$) for Hypothesis 2 regarding safe haven effects show that the RICIM metals index had a significantly negative coefficient in relation to the MSCI index of Canada. By contrast, the RICIA agricultural commodities index had significantly positive coefficients for the MSCI indices of most countries/regions, including Europe, the United States, Canada, China, India, and Taiwan. The coefficients of the RICIE energy index were also significantly positive in relation to the MSCI indices of Europe, the United States, and South Korea. In addition, the RICIM metals index had significantly positive coefficients in relation to the MSCI indices of Canada, China, India, and South Korea. These results show that only the RICIM metals index exhibited a safe haven effect in relation to the stock market index for Canada. By contrast, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were linked to the MSCI indices of most countries/regions; this trend was particularly pronounced for the RICIA agricultural commodities index.

Table 7: Market Testing Model 1 – After the 2008 financial crisis

Country/Region	RICI (Composite commodities)			RICIA (Agricultural commodities)			RICIE (Energy)			RICIM (Metals)		
	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.
Europe	$\beta_{rici,0}$	0.0005	(0.33)	$\beta_{ricia,0}$	0.0002	(0.54)	$\beta_{ricie,0}$	0.0004	(0.42)	$\beta_{ricim,0}$	0.0007	**(0.07)***
	$\beta_{rici,1}$	-0.0179	(0.72)	$\beta_{ricia,1}$	0.3730	**(0.00)*****	$\beta_{ricie,1}$	0.6200	**(0.00)*****	$\beta_{ricim,1}$	0.6791	**(0.00)*****
	$\beta_{rici,2}$	-0.0039	(0.95)	$\beta_{ricia,2}$	-0.1057	**(0.01)*****	$\beta_{ricie,2}$	-0.0989	**(0.10)***	$\beta_{ricim,2}$	-0.2100	**(0.00)*****
	$\beta_{rici,3}$	0.0102	(0.87)	$\beta_{ricia,3}$	0.0845	**(0.07)***	$\beta_{ricie,3}$	0.1127	**(0.04)****	$\beta_{ricim,3}$	-0.0102	(0.80)
	(1) 0.7638	$(1)^2$ 0.9126		(1) 0.4485	$(1)^2$ 0.4439		(1) 1.6407	$(1)^2$ 2.4829		(1) 0.6618	$(1)^2$ 0.4676	
	(2) 0.8038	$(2)^2$ 15.1840		(2) 2.5273	$(2)^2$ 4.1064		(2) 3.7549	$(2)^2$ 23.8250		(2) 0.8915	$(2)^2$ 0.5582	
	LM test	0.9076(0.34)		LM test	0.4413(0.51)		LM test	2.4730(0.12)		LM test	0.4647 (0.50)	
United States	$\beta_{rici,0}$	0.0004	(0.36)	$\beta_{ricia,0}$	0.0002	(0.64)	$\beta_{ricie,0}$	0.0001	(0.83)	$\beta_{ricim,0}$	0.0007	(0.13)
	$\beta_{rici,1}$	0.0662	(0.25)	$\beta_{ricia,1}$	0.4433	**(0.00)*****	$\beta_{ricie,1}$	0.8676	**(0.00)*****	$\beta_{ricim,1}$	0.7247	**(0.00)*****
	$\beta_{rici,2}$	0.0080	(0.91)	$\beta_{ricia,2}$	-0.2167	**(0.00)*****	$\beta_{ricie,2}$	-0.3371	**(0.00)*****	$\beta_{ricim,2}$	-0.4432	**(0.00)*****
	$\beta_{rici,3}$	0.0296	(0.68)	$\beta_{ricia,3}$	0.1122	**(0.10)***	$\beta_{ricie,3}$	0.1890	**(0.02)****	$\beta_{ricim,3}$	0.0401	(0.55)
	(1) 0.7314	$(1)^2$ 1.1624		(1) 0.0546	$(1)^2$ 0.4668		(1) 3.8348	$(1)^2$ 10.055		(1) 6.0410	$(1)^2$ 2.3528	
	(2) 0.8198	$(2)^2$ 16.3480		(2) 0.0553	$(2)^2$ 6.0782		(2) 4.1515	$(2)^2$ 10.534		(2) 6.0472	$(2)^2$ 2.8914	
	LM test	1.1564(0.28)		LM test	0.4641(0.50)		LM test	**10.1071(0.00)**		LM test	2.3473 (0.13)	

Note: *, **, and *** respectively indicate that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.
(1) and (2) respectively indicate the Ljung-Box Q statistic for the standardized residuals with a one- and two-period lag.
$(1)^2$ and $(2)^2$ respectively indicate the Ljung-Box Q statistic for the squared standardized residuals with a one- and two-period lag.

$$R_{j,t} = \beta_{j,0} + \beta_{j,1} R_{Stock,t} + \beta_{j,2} D(Vol2\sigma) R_{Stock,t} + \beta_{j,3} D(R_{Stock} 2\sigma) R_{Stock,t} + u_{j,t}, h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u_{j,t-1}^2$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

$D(Vol2\sigma)$ is the dummy variable indicating high volatility in stock market returns. When the volatility of stock market returns exceeds two standard deviations from the mean volatility value, the variable is set to 1; otherwise, it is set to 0. $D(R_{Stock} 2\sigma)$ is the dummy variable indicating a low stock market return period. When the stock market returns are less than two standard deviations from the mean returns value, the variable is set to 1; otherwise, it is set to 0. it is set to 0.

Overall, the results indicate that after the 2008 financial crisis, the four commodity indices were linked to the MSCI indices of most countries/regions and, thus, exhibited poor hedging performances. These results were identical for the entire research period. Regarding safe haven effects, the commodity indices performed better during periods of high volatility compared to periods of low returns. This trend was particularly true for the RICIA agricultural products index, the RICIE energy index, and the RICIM metals index, which exhibited safe haven effects for the stock indices of most countries/regions. However, the safe haven effect for the RICI composite commodities index existed for only a few countries/regions.

4.2 4.2 Market Testing Model 2

To enhance the hypothesis testing described above, this study further examined three short-term shocks. First, we assessed whether the four commodity indices provided hedging or safe haven effects in stock-market investment portfolio strategies during periods of low returns in the stock market. Second, we examined periods of high stock market volatility before finally investigating periods of crisis in financial markets.

Table 8 shows that concerning the returns coefficient for Hypothesis 1 regarding hedging effects ($\lambda_{j,1}$) during periods of low stock market returns, only the coefficient for the RICI composite commodities index was significantly negative in relation to the MSCI indices for Australia and China. By contrast, regarding the returns coefficients for hedging effects, the RICI composite commodities index, RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were all significantly positive in relation to the MSCI indices for the United States and Brazil. In addition, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index exhibited significantly positive coefficients in relation to the MSCI indices for Europe, Japan, Canada, Australia, China, India, Russia, South Korea, and Taiwan. These results indicate that, during periods of low stock market returns, only the RICI composite commodities index had significant hedging effects for the MSCI indices of Australia and China. By contrast, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were significantly linked with the stock markets of most countries/regions. These results show that the commodity indices generally have poor hedging effects, and are identical to those produced using Testing Model 1.

When the returns distribution for stock markets was lower than the predefined 10% threshold, the results of the returns coefficient ($\lambda_{j,2}$) for Hypothesis 2 regarding safe haven effects showed that the RICI composite commodities index, RICIE energy index, and RICIM metals index all had safe haven effects in relation to the stock index for Brazil, and that the RICIM metals index had safe haven effects for Europe, the United States, and Canada.

When the returns distribution for stock markets was lower than the predefined 5% threshold, the results of the returns coefficient ($\lambda_{j,3}$) for Hypothesis 2 regarding safe haven effects showed that the RICI composite commodities index had safe haven effects in relation to the stock indices of Australia and South Korea; the RICIE energy index had safe haven effects for the stock indices of the United States and Russia; and the RICIM metals index had a safe haven effect for the stock indices of Canada and Russia.

Finally, when the returns distribution for stock markets was lower than the predefined 1%

threshold, the results of the returns coefficient ($\lambda_{j,4}$) for Hypothesis 2 regarding safe haven effects showed that only the RICIE energy index had a safe haven effect for the stock indices of the United States; however, the RICI composite commodities index, RICIA agricultural commodities index, and RICIM metals index were linked with the MSCI stock indices of a number of countries/regions.

The results indicate that the four indices were linked to the MSCI indices of most countries/regions during periods of low market returns; only the RICI composite commodities index had a hedging effect in relation to the stock index of Australia. Overall, the commodity indices performed poorly regarding hedging effects; these results are identical to those provided using Testing Model 1. The safe haven effects of the commodity indices were more pronounced and optimal when the stock market returns distribution was lower than the thresholds of 10% and 5%, particularly for the RICIM metals index. However, the RICIA agricultural commodities index did not exhibit safe haven effects. When the stock market returns distribution was lower than the 1% threshold, only the RICIE energy index exhibited a safe haven effect for the United States stock index.

Table 9 shows that during periods of high stock market volatility, the test results of the returns coefficients for Hypothesis 1 regarding hedging effects ($\lambda_{j,1}$) showed that only the RICI composite commodities index had a significantly negative coefficient in relation to the MSCI index of Africa. By contrast, the RICI composite commodities index, RICIA agricultural commodities index, RICIE energy index, and RICIM metals index had significantly positive coefficients in relation to the MSCI indices of the United States, Canada, and Brazil. Furthermore, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index also had significantly positive coefficients in relation to the MSCI indices of Europe, Japan, Australia, China, India, Russia, South Korea, and Taiwan. These results suggest that during periods of high market volatility, only the RICI composite commodities index exhibited a significant hedging effect for the MSCI index of Africa. By contrast, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were significantly linked to the stock markets of most countries/regions. These results indicate that these commodity indices had poor hedging effects, which is consistent with the results provided using Testing Model 1.

Table 8: Market Testing Model 2 – Periods of low market returns

Country/Region	RICI (Composite commodities)			RICIA (Agricultural commodities)			RICIE (Energy)			RICIM (Metals)		
	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.
Europe	$\beta_{rici,0}$	0.0007	**(0.03)****	$\beta_{ricia,0}$	0.0004	(0.17)	$\beta_{ricie,0}$	0.0012	**(0.01)*****	$\beta_{ricim,0}$	0.0010	**(0.00)*****
	$\lambda_{rici,1}$	0.0061	(0.83)	$\lambda_{ricia,1}$	0.2456	**(0.00)*****	$\lambda_{ricie,1}$	0.4262	**(0.00)*****	$\lambda_{ricim,1}$	0.5194	**(0.00)*****
	$\lambda_{rici,2}$	-0.0081	(0.94)	$\lambda_{ricia,2}$	0.1037	**(0.05)****	$\lambda_{ricie,2}$	0.0494	(0.53)	$\lambda_{ricim,2}$	-0.1516	**(0.01)*****
	$\lambda_{rici,3}$	-0.0006	(0.99)	$\lambda_{ricia,3}$	-0.0087	(0.89)	$\lambda_{ricie,3}$	-0.0396	(0.62)	$\lambda_{ricim,3}$	-0.0324	(0.58)
	$\lambda_{rici,4}$	-0.0193	(0.79)	$\lambda_{ricia,4}$	0.0824	(0.14)	$\lambda_{ricie,4}$	0.2555	**(0.00)*****	$\lambda_{ricim,4}$	0.1591	**(0.01)*****
	(1) 0.0005	$(1)^2$ 0.7959		(1) 0.2017	$(1)^2$ 0.3656		(1) 1.9329	$(1)^2$ 1.7445		(1) 0.1113	$(1)^2$ 0.3015	
	(2) 0.3909	$(2)^2$ 2.1884		(2) 4.0218	$(2)^2$ 0.5159		(2) 2.2086	$(2)^2$ 6.1995		(2) 0.4059	$(2)^2$ 0.8437	
	LM test	0.7937 (0.37)		LM test	0.3646 (0.55)		LM test	1.7409 (0.19)		LM test	0.3006 (0.58)	
United States	$\beta_{rici,0}$	0.0006	**(0.03)****	$\beta_{ricia,0}$	0.0003	(0.34)	$\beta_{ricie,0}$	0.0004	(0.40)	$\beta_{ricim,0}$	0.0011	**(0.00)*****
	$\lambda_{rici,1}$	0.1234	**(0.00)******	$\lambda_{ricia,1}$	0.2086	**(0.00)*****	$\lambda_{ricie,1}$	0.5010	**(0.00)*****	$\lambda_{ricim,1}$	0.3242	**(0.00)*****
	$\lambda_{rici,2}$	0.0968	(0.30)	$\lambda_{ricia,2}$	0.0292	(0.73)	$\lambda_{ricie,2}$	0.1454	(0.16)	$\lambda_{ricim,2}$	-0.1644	**(0.09)***
	$\lambda_{rici,3}$	-0.0272	(0.74)	$\lambda_{ricia,3}$	0.2283	**(0.00)*****	$\lambda_{ricie,3}$	0.3042	**(0.00)*****	$\lambda_{ricim,3}$	0.1222	(0.17)
	$\lambda_{rici,4}$	0.0184	(0.81)	$\lambda_{ricia,4}$	-0.0935	(0.15)	$\lambda_{ricie,4}$	-0.2109	**(0.03)****	$\lambda_{ricim,4}$	0.0455	(0.59)
	(1) 3.2711	$(1)^2$ 0.5185		(1) 0.0405	$(1)^2$ 0.3633		(1) 3.5967	$(1)^2$ 3.3579		(1) 4.3510	$(1)^2$ 0.0841	
	(2) 3.7875	$(2)^2$ 3.7553		(2) 0.7264	$(2)^2$ 0.8180		(2) 3.7117	$(2)^2$ 3.8766		(2) 4.3917	$(2)^2$ 1.9510	
	LM test	0.5170 (0.47)		LM test	0.3622 (0.55)		LM test	3.3538 (0.07)		LM test	0.0838 (0.77)	

Note: *, **, and *** respectively indicate that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.
(1) and (2) respectively indicate the Ljung-Box Q statistic for the standardized residuals with a one- and two-period lag.
$(1)^2$ and $(2)^2$ respectively indicate the Ljung-Box Q statistic for the squared standardized residuals with a one- and two-period lag.

When the volatility of stock market returns exceeded the predefined 90% threshold, the test results of the returns coefficient ($\lambda_{j,2}$) for Hypothesis 2 regarding safe haven effects showed that the RICI composite commodities index had a significantly negative coefficient in relation to the MSCI index of South Korea, and that the RICIA agricultural commodities index had a significantly negative coefficient in relation to the MSCI index of Japan. Furthermore, the RICIM metals index also had significantly negative coefficients for the MSCI indices of the United States, Japan, Canada, and Australia. These results indicate that the RICI composite commodities index exhibited a safe haven effect for the stock index of South Korea, and that the RICIA agricultural commodities index had a safe haven effect for the stock index of Japan. Finally, the RICIM metals index also exhibited safe haven effects in relation to the stock indices of the United States, Japan, Canada, and Australia.

When the volatility of stock market returns exceeded the predefined 95% threshold, the results of the returns coefficient ($\lambda_{j,3}$) for Hypothesis 2 regarding safe haven effects showed that the RICIE energy index had a significantly negative coefficient in relation to the MSCI index of Canada, and that the RICIM metals index had a significantly negative coefficient in relation to the MSCI index of Russia. These results demonstrate that the RICIE energy index exhibited a safe haven effect for the stock index of Canada and the RICIM metals index exhibited a safe haven effect for the stock index of Russia.

Finally, when the volatility of stock market returns exceeded the predefined 99% threshold, the results of the returns coefficient ($\lambda_{j,4}$) for safe haven effects showed that the RICI composite commodities index, RICIA agricultural commodities index, RICIE energy index, and RICIM metals index had significantly negative coefficients in relation to the MSCI index of Russia, and that the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index also had significantly negative coefficients in relation to the MSCI index for South Korea. In addition, the RICIE energy index exhibited a significantly negative coefficient in relation to the MSCI index of the United States, and the coefficient of the RICIA agricultural commodity index regarding the MSCI index for Brazil was also significantly negative. These results suggest that the four commodity indices all had safe haven effects for the stock indices of Russia, whereas the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index also had safe haven effects for the stock index of South Korea.

In summary, we found that the four commodity indices were linked to the MSCI indices of most countries/regions during periods of high market volatility. Only the RICI composite commodities index exhibited a hedging effect in relation to the stock market index for Africa. Overall, the commodity indices performed poorly regarding hedging effects. These results are identical to those produced using Testing Model 1. The commodity indices generally showed superior performance regarding safe haven effects compared to hedging effects when the volatility of stock market returns exceeded the 90% and 99% thresholds; the RICIM metals index performed particularly well. However, the RICI composite commodities index performed relatively poorly regarding safe haven effects. When the volatility of stock market returns exceeded the 95% threshold, only the RICIE energy index and RICIM metals index exhibited safe haven effects for the stock market indices of Canada and Russia, respectively.

Table 10 shows that during crisis periods in stock markets, the test results of the returns coefficient ($\lambda_{j,1}$) for Hypothesis 1 regarding hedging effects indicate that only the RICI composite commodities index had a significant hedging effect for the MSCI index of Africa. By contrast, the RICIA agricultural commodities index, RICIE energy index, and RICIM metals index were significantly linked to the stock markets of most countries/regions. These results indicate poor hedging effects, which is consistent with the findings of Testing Model 1.

During crisis periods in stock markets, the results of the returns coefficient ($\lambda_{j,2}$) for Hypothesis 2 regarding safe haven effects showed that the RICIM metals index had significantly negative coefficients for the MSCI indices of Europe, the United States, Canada, Australia, Russia, Brazil, and South Korea; the RICIE energy index also showed significantly negative coefficients in relation to Canada and Russia. In addition, the RICI composite commodities index exhibited a significantly negative coefficient in relation to the MSCI index of Russia, which indicates that the RICI composite commodities index provides a safe haven effect for the stock index of Russia. The RICIE energy index also exhibited a safe haven effect for the stock indices of Canada and Russia. Finally, the RICIM metals index showed safe haven effects for the stock indices of Europe, the United States, Canada, Australia, Russia, Brazil, and South Korea.

Table 9: Market Testing Model 2 – Periods of high market volatility

Country /Region	RICI (Composite commodities)			RICIA (Agricultural commodities)			RICIE (Energy)			RICIM (Metals)		
	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.
Europe	$\beta_{rici,0}$	0.0007	**(0.02)****	$\beta_{ricia,0}$	0.0001	(0.56)	$\beta_{ricie,0}$	0.0005	(0.18)	$\beta_{ricim,0}$	0.0007	**(0.01)*****
	$\lambda_{rici,1}$	0.0038	(0.88)	$\lambda_{ricia,1}$	0.2683	**(0.00)*****	$\lambda_{ricie,1}$	0.4833	**(0.00)*****	$\lambda_{ricim,1}$	0.5794	**(0.00)*****
	$\lambda_{rici,2}$	-0.0292	(0.66)	$\lambda_{ricia,2}$	0.0263	(0.53)	$\lambda_{ricie,2}$	0.1515	**(0.07)***	$\lambda_{ricim,2}$	-0.0796	(0.11)
	$\lambda_{rici,3}$	-0.0477	(0.62)	$\lambda_{ricia,3}$	0.0937	(0.16)	$\lambda_{ricie,3}$	0.0592	(0.62)	$\lambda_{ricim,3}$	-0.0430	(0.60)
	$\lambda_{rici,4}$	0.2359	(0.20)	$\lambda_{ricia,4}$	-0.0831	(0.44)	$\lambda_{ricie,4}$	-0.0848	(0.67)	$\lambda_{ricim,4}$	-0.0394	(0.69)
	(1) 0.0007	$(1)^2$ 0.8625		(1) 0.4216	$(1)^2$ 0.2573		(1) 1.5439	$(1)^2$ 0.8575		(1) 0.0235	$(1)^2$ 0.2180	
	(2) 0.2761	$(2)^2$ 2.2344		(2) 3.4515	$(2)^2$ 0.3627		(2) 1.7101	$(2)^2$ 4.4741		(2) 0.2305	$(2)^2$ 0.7350	
	LM test	0.8601 (0.35)		LM test	0.2565 (0.61)		LM test	0.8552 (0.36)		LM test	0.2174 (0.64)	
United States	$\beta_{rici,0}$	0.0006	**(0.03)****	$\beta_{ricia,0}$	0.0002	(0.53)	$\beta_{ricie,0}$	0.0005	(0.24)	$\beta_{ricim,0}$	0.0009	**(0.00)*****
	$\lambda_{rici,1}$	0.1250	**(0.00)*****	$\lambda_{ricia,1}$	0.2423	**(0.00)*****	$\lambda_{ricie,1}$	0.5155	**(0.00)*****	$\lambda_{ricim,1}$	0.4371	**(0.00)*****
	$\lambda_{rici,2}$	0.0239	(0.77)	$\lambda_{ricia,2}$	-0.0007	(0.99)	$\lambda_{ricie,2}$	-0.1086	(0.22)	$\lambda_{ricim,2}$	-0.2625	**(0.00)*****
	$\lambda_{rici,3}$	-0.0490	(0.61)	$\lambda_{ricia,3}$	0.0371	(0.65)	$\lambda_{ricie,3}$	0.2894	**(0.02)****	$\lambda_{ricim,3}$	0.0572	(0.59)
	$\lambda_{rici,4}$	0.2085	(0.16)	$\lambda_{ricia,4}$	-0.0729	(0.42)	$\lambda_{ricie,4}$	-0.3219	**(0.03)****	$\lambda_{ricim,4}$	-0.0728	(0.52)
	(1) 3.0601	$(1)^2$ 0.7686		(1) 0.0419	0.4328		(1) 1.9721	$(1)^2$ 1.6763		(1) 4.9267	$(1)^2$ 0.3838	
	(2) 3.6951	$(2)^2$ 3.9082		(2) 0.8660	$(2)^2$ 0.7578		(2) 2.0021	$(2)^2$ 2.0110		(2) 4.9955	$(2)^2$ 1.4222	
	LM test	0.7665 (0.38)		LM test	0.4315 (0.51)		LM test	1.6725 (0.20)		LM test	0.3826 (0.54)	

Note: *, **, and *** respectively indicate that the null hypothesis was rejected under a 10%, 5%, and 1% significance level. (1) and (2) respectively indicate the Ljung-Box Q statistic for the standardized residuals with a one- and two-period lag. (1)2 and (2)2 respectively indicate the Ljung-Box Q statistic for the squared standardized residuals with a one- and two-period lag. Dummy variables $D(h_{Stock}\, q_{90,t-1})$, $D(h_{Stock}\, q_{95,t-1})$, and $D(h_{Stock}\, q_{99,t-1})$ were designed to capture different levels of returns volatility in the stock market; these variables were set to 1 if the volatility of stock market returns exceeded the predefined thresholds of 90%, 95%, and 99%; otherwise, they were set to 0.

$$R_{j,t} = \beta_{j,0} + \beta_{j,t} R_{Stock,t} + u_{j,t}$$

$$\beta_{j,t} = \lambda_{j,1} + \lambda_{j,2} D(h_{Stock}\, q_{90,t-1}) + \lambda_{j,3}(h_{Stock}\, q_{95,t-1}) + \lambda_{j,4}(h_{Stock}\, q_{99,t-1})$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u^2_{j,t-1}$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

Table 10: Market Testing Model 2 – Market crisis periods

Country/Region	RICI (Composite commodities)			RICIA (Agricultural commodities)			RICIE (Energy)			RICIM (Metals)		
	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.	Variable	Coefficient	Prob.
Europe	$\beta_{rici,0}$	0.0007	**(0.01)***	$\beta_{ricia,0}$	0.0001	(0.55)	$\beta_{ricie,0}$	0.0005	(0.21)	$\beta_{ricim,0}$	0.0007	**(0.01)***
	$\lambda_{rici,1}$	0.0065	(0.78)	$\lambda_{ricia,1}$	0.2609	**(0.00)***	$\lambda_{ricie,1}$	0.5018	**(0.00)***	$\lambda_{ricim,1}$	0.5889	**(0.00)***
	$\lambda_{rici,2}$	-0.0780	(0.19)	$\lambda_{ricia,2}$	0.1179	**(0.00)***	$\lambda_{ricie,2}$	0.1663	**(0.02)**	$\lambda_{ricim,2}$	-0.1818	**(0.00)***
	(1) 0.0009	$(1)^2$ 0.9676		(1) 0.3492	$(1)^2$ 0.1666		(1) 1.6625	$(1)^2$ 1.1208		(1) 0.0555	$(1)^2$ 0.0611	
	(2) 0.3259	$(2)^2$ 2.3189		(2) 3.6031	$(2)^2$ 0.3234		(2) 1.8288	$(2)^2$ 5.3190		(2) 0.1967	$(2)^2$ 0.4723	
	LM test	0.9650 (0.33)		LM test	0.1661 (0.68)		LM test	1.1181 (0.29)		LM test	0.0609 (0.81)	
United States	$\beta_{rici,0}$	0.0006	**(0.02)**	$\beta_{ricia,0}$	0.0002	(0.53)	$\beta_{ricie,0}$	0.0004	(0.29)	$\beta_{ricim,0}$	0.0009	**(0.01)***
	$\lambda_{rici,1}$	0.1191	**(0.00)***	$\lambda_{ricia,1}$	0.2347	**(0.00)***	$\lambda_{ricie,1}$	0.5166	**(0.00)***	$\lambda_{ricim,1}$	0.4053	**(0.00)***
	$\lambda_{rici,2}$	0.0745	(0.17)	$\lambda_{ricia,2}$	0.0463	(0.28)	$\lambda_{ricie,2}$	0.0286	(0.68)	$\lambda_{ricim,2}$	-0.1855	**(0.00)***
	(1) 3.0911	$(1)^2$ 0.4635		(1) 0.0714	$(1)^2$ 0.3358		(1) 2.5517	$(1)^2$ 2.4902		(1) 4.3846	$(1)^2$ 0.3177	
	(2) 3.7444	$(2)^2$ 3.8225		(2) 0.7835	$(2)^2$ 0.6851		(2) 2.5810	$(2)^2$ 2.772		(2) 4.4268	$(2)^2$ 2.2842	
	LM test	0.4622 (0.50)		LM test	0.3348 (0.56)		LM test	2.4860 (0.12)		LM test	0.3167 (0.57)	

Note: *, **, and *** respectively indicate that the null hypothesis was rejected under a 10%, 5%, and 1% significance level.
(1) and (2) respectively indicate the Ljung-Box Q statistic for the standardized residuals with a one- and two-period lag.
$(1)^2$ and $(2)^2$ respectively indicate the Ljung-Box Q statistic for the squared standardized residuals with a one- and two-period lag.

$$R_{j,t} = \beta_{j,0} + \beta_{j,t} R_{Stock,t} + u_{j,t}$$

$$\beta_{j,t} = \lambda_{j,1} + \lambda_{j,2} D(subprime, 2008)$$

$$h_{j,t} = \alpha_{j,0} + \alpha_{j,1} u^2_{j,t-1}$$

$$j = RICI, RICI\text{ - }Agriculture, RICI\text{ - }Energy, RICI\text{ - }Metals$$

The dummy variable $D(subprime, 2008)$ represents the subprime mortgage event that occurred in 2008

In summary, this study determined that during periods of market crisis, the four commodity indices were linked to the MSCI indices of most countries/regions. Only the RICI composite commodities index had hedging effects for the stock index of Africa. Therefore, the commodity indices generally exhibited poor hedging effects. These results are identical to those obtained using Testing Model 1. Regarding safe haven effects, during market crises, the RICIM metals index exhibited a safe haven effect for the stock indices of most countries/regions. However, the RICIA agricultural commodities index did not exhibit safe haven effects. Consequently, during serious stock market crises, investors should include the RICIM metals index in their investment portfolios to reduce investment portfolio risk.

5 Conclusion

This study examined the relationship between commodity and stock markets. Numerous types of commodity markets that have economic characteristics exhibiting substantial differences exist. For example, the metals and agricultural commodity markets have differing influences on economic activity. Consequently, a holistic commodities index cannot be used to identify the correlation between stock markets and different types of commodity characteristics, thereby preventing the development of clear hedging strategies for investors. Therefore, this study examined commodities divided into individual categories, using the RICI composite commodities, agricultural commodities, energy, and metals commodity indices to examine the relationships between commodity and stock markets. We first performed cointegration testing to observe the long-term relationships between the two markets, and then conducted causal relationship testing to examine whether spillover effects existed between the returns in the markets. Based on the models developed by Hillier, Draper, and Faff (2006) and Baur and Lucey (2010), this study also further tested whether hedging and safe haven effects existed in stock-market investment portfolio strategies for the four commodity categories, or whether only safe haven effects existed.

The empirical results of cointegration testing showed that the RICI composite commodities index exhibited cointegration relationships with the MSCI indices of the following nine countries/regions: Europe, the United States, Canada, Australia, China, India, Russia, South Korea, and Taiwan. The RICA agricultural commodities index exhibited cointegration relationships with the MSCI indices of four countries, namely, Australia, India, South Korea, and Taiwan. The RICIE energy index exhibited cointegration relationships with the MSCI indices of the six countries of Canada, Australia, China, Brazil, South Korea, and Taiwan. Finally, the RICIM metals index exhibited cointegration relationships with the MSCI indices of the following nine countries/regions: Europe, Japan, Canada, India, Russia, Brazil, South Korea, Taiwan, and Africa. These results indicate that long-term stable relationships exist between the stock markets and commodity indices of these countries/regions.

Moreover, the empirical results of the causal relationship tests indicated that the commodity markets generally led stock markets. For example, the RICI composite commodities index led the stock market indices of Japan, Australia, Russia, South Korea, Taiwan, and Africa; the RICIA agricultural commodities index led the stock market indices of Japan, China, India, Brazil, South Korea, Taiwan, and Africa; the RICIE energy index led the stock market indices of Japan, Australia, Russia, Taiwan, and Africa;

and finally, the RICIM metals index led the stock market indices of China, India, Russia, South Korea, Taiwan, and Africa. Therefore, investors can predict stock market price fluctuations in these countries/regions using changes in the four commodity indices. By contrast, the stock market index for the United States led the RICI composite commodities index, RICIA agricultural commodities index, and the RICIM metals index, indicating that these three indices are influenced by the stock market of the United States.

Finally, the empirical results for the testing models concerning hedging and safe haven effects demonstrate that for Hypothesis 1 regarding hedging effects for the commodity market, the RICI composite commodities, RICIA agricultural commodities, RICIE energy, and RICIM metals indices were linked to the MSCI indices of most countries/regions regardless of whether the period examined was the entire research period or the period before/after the 2008 financial crisis. These results indicate that the four commodity indices exhibited poor hedging performances.

Concerning Hypothesis 2 regarding safe haven effects in the commodity market, the RICIA agricultural commodities, RICIE energy, and RICIM metals indices exhibited safe haven effects for the stock indices of most countries/regions following the 2008 financial crisis. However, the commodity indices only showed safe haven effects in a few countries/regions prior to the 2008 crisis.

Furthermore, the safe haven relationship results differed between the two periods, which suggested that commodity markets exhibit safe haven effects when stock markets experience crises. Of these indices, the RICIM metals index exhibited the best hedging performance. In addition, the safe haven effects of the commodity indices were superior during periods of high stock market volatility compared to periods of low returns. This trend was particularly true for the RICIM metals index, which showed safe haven effects in relation to the stock indices of most countries/regions. By comparison, the RICIA agricultural commodities index exhibited significantly poorer hedging effects. The findings discussed above suggest that the hedging effects exhibited by the RICI composite commodities index were comparatively less apparent; this was possibly because the RICI composite commodities index is a general or holistic commodities index with many categories of commodities, hindering its display of specific commodity characteristics. Moreover, the RICIA agricultural commodities, RICIE energy, and RICIM metals indices exhibited differing safe haven effects. Among these indices, the RICIM metals index exhibited the strongest hedging effects, unlike the hedging effects of the RICIA agricultural commodities index, which were relatively less evident. As a result, this study contends that commodities should be divided into categories to facilitate individual examination of their relationships with stock markets.

In summation, long-term relationships were observed between several commodity and stock markets, and the commodity indices generally led the stock market indices. Thus, investors can predict price changes in the stock markets of various countries/regions using variations in commodity indices. However, the U.S. stock market influences the RICI composite commodities, RICIA agricultural commodities, and RICIM metals commodity indices. In addition, when severe crises or high volatility occurs in stock markets, investors can include the RICIM metals index in investment portfolios as a safe haven asset, thereby reducing risk. Nevertheless, the results of this study showed that hedging effects do not exist between commodity market indices and stock markets under normal circumstances, which means that commodity indices typically cannot be employed in hedging strategies.

This study adopted the RICI composite commodities, agricultural commodities, energy, and metals commodity indices and the MSCI stock indices for 12 countries/regions to examine the correlation and hedging effects that exist between commodity markets and stock markets. The results showed that commodity markets exhibit a poor hedging performance in relation to stock markets. Therefore, this study suggests that bond markets be included in future research to examine the correlation and hedging effects between commodity markets, bond markets, and stock markets, and thereby provide investors with a reference for hedging strategies.

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