Journal of Management and Sustainability; Vol. 6, No. 1; 2016
ISSN 1925-4725 E-ISSN 1925-4733
Published by Canadian Center of Science and Education

Cointegration between Equity- and Agricultural Markets: Implications for Portfolio Diversification

Marcio Genovevo da Costa[1] & Nils Donner[1]

[1] Lucerne University of Applied Sciences and Arts, Switzerland

Correspondence: Nils Donner, Lucerne University of Applied Sciences and Arts, Switzerland. E-mail: nils.donner@stud.hslu.ch

Received: December 9, 2015 Accepted: December 28, 2015 Online Published: February 25, 2016

doi:10.5539/jms.v6n1p24 URL: http://dx.doi.org/10.5539/jms.v6n1p24

Abstract

Commodities are well known to act anti-cyclical to stocks and are therefore used for portfolio diversification. However, various banks, asset managers and hedge funds were inculpated to speculate with agricultural commodities, especially after the food price bubble in 2007/08. This paper aims to investigate whether there is a diversification effect between equity- and commodity markets in the period from 1990 until 2014. We found evidence for a significant relationship between these two asset classes after the financial crisis using a cointegration framework.

Keywords: cointegration, portfolio diversification, agricultural markets, commodity, equity, speculation, food price bubble

1. Introduction

Over the last decade, commodity futures have become a popular asset class for investors, just like stocks and bonds. This process is sometimes also called the financialization of commodity markets. Concurrently, a large number of commodities across the energy, metal, and agricultural sectors experienced a synchronized boom and bust cycle in 2007 and 2008. During this turbulent period, the price volatility of many commodities spiked and food prices have been on the rise due to bad weather conditions and potentially other external factors (Institute for Agriculture and Trade Policy [IATP], 2011, p. 5).

However, traders have always speculated on the agricultural commodity future market, just as they do in other commodities like copper or oil. As a matter of fact, commodity markets have always been volatile. Prices are particularly vulnerable to being moved by big speculative investors when a commodities supply and demand relationship is tight due to production failures, high demand or lack of supply management mechanisms (The Economist, online). This is also the reason why financial speculation in basic food commodities played a key role in the food crisis, which pushed millions of people deep into hunger (World Food Programme, online).

Furthermore, the IATP states that agricultural supply and demand are by no means the only factors that caused the 2007/2008 food crisis: "Agricultural supply and demand factors could not explain, by themselves, the extreme price volatility and price hikes that were damaging both U.S. farm cash-flow management and food security globally" (IATP, 2011, p. 5). Hence, there may also be more sophisticated reasons for investment banks and private financial actors to trade on commodities.

Through financial diversification, for example, an investor is able to effectively reduce his overall portfolio risk. The general idea behind diversification is that (agricultural-) commodities do theoretically correlate negatively with other assets in a well-diversified financial portfolio. Consequently, this could significantly lower the risk of the portfolio and thus lead to better risk/return-ratios for the holder of the portfolio (Gilbert, 2010, pp. 27-29). In this study, we do therefore attempt to investigate if there is a significant opportunity for diversification purposes a traditional equity investor may achieve through investing in agricultural commodities. According to this pivotal question, we deliver answers along the following three key aspects:

(1) Is there empirical evidence for a long-run relationship between different agricultural commodities and major equity markets?

(2) What are the characteristics and dynamics of these relationships?

(3) How robust are the relationships regarding different geographical areas, pre- and post-crisis time periods and different underlying along the two asset classes?

In order to answer the above mentioned questions properly, we will first show an overview about the current state of research regarding existing cointegration relationships for commodity and equity markets followed by the key characteristics of commodity investments and their diversification aspects. Next, we will introduce the applied statistical methodology implying the Johansen cointegration test and the Error Correction Model. Furthermore, sample data beginning from February 1990 until March 2015 of international stock and commodity markets is used. In the key section of this paper, we show our results with the help of in-depth descriptive statistics, correlation matrices, Johansen cointegration test and estimating Error Correction Model. Consistent to our results, we further analyse the characteristics and dynamics of the observed cointegration relationships. In conclusion, we derive the economic reasoning and benefits regarding the diversification aspect for potential investors.

2. Review of the Literature

Most recent academic studies test for correlation among different stock markets or between crude oil and other asset classes. For example, Hassan and Malik (2007) applied a multivariate GARCH model concluding that oil price shocks in periods of world turmoil and political events have an important impact on the relationship between oil and stock market prices. Kumar, Managi, and Matsuda (2012) showed that oil prices and technology stock prices each individually Granger cause the stock prices of clean energy firms. Sadorsky (2012) analysed correlation and volatility spill-overs between oil and stock prices of clean energy and technology firms concluding the same results as Hassan and Malik (2007).

The purpose of this paper, however, is to determine whether there is a long-run relationship between agricultural commodity prices and four major stock market indices. In contrast to the above-mentioned studies, we apply the methodology of cointegration developed by Engle and Granger (1987). So far, Alexander (1999) used the Johansen cointegration test to find out if asset spreads are mean reverting. Büyükşahin, Haigh, and Robe (2010) analysed cointegration for American markets and found that the relation between the returns on investable commodity and equity indices has not changed significantly in the last fifteen years. Further, they observed no evidence of an increase in co-movement during periods of extreme returns. Nevertheless, Bansal, Kumar, and Verma (2014) examined that there is no long-term cointegration between commodity future prices and equity prices.

Agricultural goods were also analysed in several other papers. Kristoufek, Janda and Zilberman (2012) used different agricultural commodity sorts like corn, wheat, sugar and soybean to determine the correlation among themselves and fuel/biofuel prices. In a deductive reasoning, they found out that correlation is considerably higher in the post-crisis period compared to the pre-crisis period. Nazlioglu and Soytas (2012) examined the relationship between oil prices and 24 agricultural commodity prices resulting from changes in the strength of the US Dollar. They applied cointegration and the Granger causality method for a period from 1980 to 2010 and figured out that there is strong evidence for an impact of oil prices on prices of several agricultural commodities.

In addition to that, the following Table 1 provides an overview about the current state of research of various authors in the field of cointegration of equity and commodity markets. As an added value to this current state of research, our study aims to explain the long-term relationship between equity and agricultural commodity markets in Europe, the United States and Japan and also across borders. Furthermore, this paper analyses the impact of the financial crisis (pre- and post-crisis) whereby the potential long-term equilibrium between equity and agricultural commodity asset classes is accurately discussed.

Table 1. Review of the literature

Authorship	Sample Period	Equity Underlying	Commodity Underlying	Cointegration	Methodology
Bansal, Kumar & Verma (2014)	June 2005 - December 2011 (daily data)	S&P CNX Nifty (India)	MCX COMDEX	Not confirmed, unidirectional relationship	Johansen, VAR
Nazlioglu & Soytas (2012)	January 1980 - February 2010 (monthly data)	US Dollar	FAO Food price index, 24 agricultural commodities, worldwide oil prices	Confirmed	Panel cointegration by Pedroni (1999), VECM
Ciaian & Kancs (2011)	January 1994 - December 2008 (weekly data)	./.	FAO Food agricultural commodities, world crude oil prices	1994-1998: no cointegration, 1999-2003: only corn and soybeans are cointegrated with oil prices, 2004-2008: all nine agri-commodities cointegrated	Johansen, VAR
Gupta & Guidi (2010)	January 1999 - January 2009 (daily data)	DAX 30 (Germany)	PX50 (Czech Republic), Bux (Hungary), Wig (Poland)	Not confirmed	Johansen, VAR
Büyükşahi, Haigh & Robe (2010)	January 1991 - May 2008 (daily, weekly, monthly data)	S&P 500, DJIA (U.S.)	./.	Confirmed	Johansen, VECM
Apergis & Miller (2009)	1981-2007 (monthly)	Stock market worldwide	Oil price worldwide	Not confirmed	Johansen, VAR

3. Characteristics of Commodity Investments

Commodity investing offers a broad range of different underlying. As shown in Figure 1, commodities are divisible into four different groups. One of these groups represents livestock where investors have the possibility to invest in agricultural goods like pork, sheep, beef and chicken. On the contrary, there are energy commodities of which the most important ones are coal, natural gas and crude oil. Furthermore, metals are subdivided in base and precious metals. Industry metals are mainly used as raw material in manufacture processes. Precious metals, however, were historically used as a functional currency and are nowadays requested by investors in times of rising inflation expectations and financial crises (Stoll & Whaley, 2009, pp. 54-57).

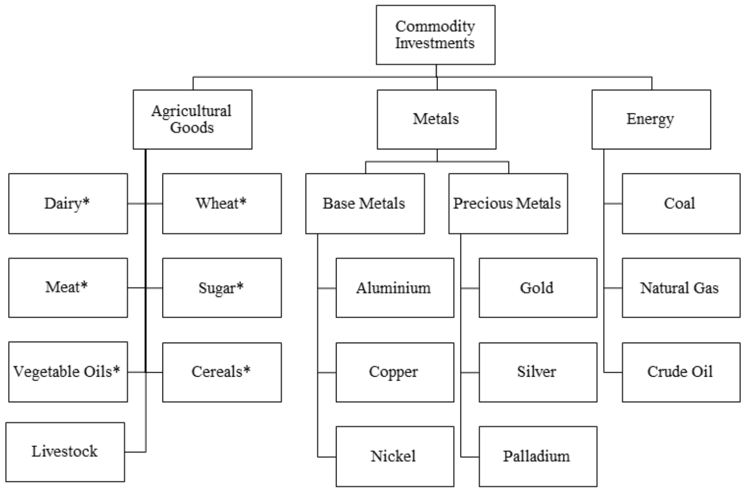

Figure 1. Commodity investments at a glance (Stoll & Whaley, 2009, pp. 54-57)

Note. All commodities are covered by the sub-index S&P GSCI. The S&P GSCI Agriculture covers mentioned agricultural goods. Asterisks (*) indicates commodities that are individually covered in the analysis.

An investment in the commodity market is practicable using different investment instruments. The most common way to invest in commodities is through the future market. A future contract is an agreement to buy or sell a specific asset or in this case a commodity at a specific price in the future. The daily trading volume on April 15, 2015 in agricultural futures amounts up to 1 415 614 USD compared to 1 387 708 USD in equity futures, which clearly demonstrates the importance and the scale of this market segment (Chicago Mercantile Group, online).

Besides the indirect investment in future contracts, another possibility to access the commodity market is the actual physical purchase. In particular, this method of investing is mainly used when dealing with precious and base metals. Principally, private investors purchase gold or silver physically in form of bullions or even coins. The manufacturing industry uses physical commodities as raw materials in their production processes in order to achieve an added value. Some ordinary examples are aluminium, copper and nickel. The use of futures instead of a direct purchase of the commodity avoids the trouble and costs of managing the physical position. Moreover, the purchase of future contracts does not require any initial payment and only implies the deposition of an initial margin. Therefore, future contracts allow much higher leverage than physical investments in commodities and thus are the more interesting alternative for speculators (Gilbert, 2010, pp. 26-27).

Stocks serve as an alternative instrument when investing in the commodity market. Investors of stock commodities do not directly invest in commodities as the basis underlying, more precisely, they invest in companies that do either produce or trade with commodities. An example is British Petrol, who produces both oil and gas, and Barrick Gold, representing the mining industry in gold production. However, mutual funds as well as index funds became a popular investment especially for private investors. This makes sense since asset managers offer their knowledge in terms of portfolio management and asset allocation. Furthermore, commodity investments are historically appreciated for their diversification effect (Gilbert, 2010, pp. 26-27). Therefore, the following paragraph has the goal to explain why investing in commodities could have a beneficial impact on total portfolio risk.

4. Commodity Investments for Diversification Purposes

As part of a long-term diversification strategy, many fund managers have started advising their customers to devote a share of their portfolio to commodity-related products. Most of the time, this behaviour is motivated by the belief that, over the long-run, commodities may display a low or negative correlation with other asset classes (Gorton & Rouwenhorst, 2006). The common theory behind diversification is held by Markowitz (1959), who suggests choosing the optimal risk/performance portfolio on the efficient frontier. By choosing assets that do not exactly move in the same direction (low correlation coefficients), his model shows how investors are able to reduce risk through diversification. Apparently, there are weaknesses in Markowitz' model. First of all, he only considers two independent variables (risk & performance) as the only allocation parameters to determine the efficient frontier. This, however, leads to portfolio compositions, which are difficult to imply in reality as portfolios only consist of a few underlying. Furthermore, the recommended output is highly dependent on input factors, which can cause the recommendation of short selling of some assets. In addition, for Markowitz' model to work properly, one does need historical correlation data between assets. This, indeed, is the main weakness of his theory as its diversification success for the future is strongly dependent on correlation data, which may be insufficient (Fama & French, 1996).

However, the success of diversification is generally measured by the correlation coefficient. The correlation coefficient determines the grade of a linear relationship between two variables (Hartung, 1999, p. 545). A correlation of minus one suggests a totally negative linear relationship and therefore the strongest possible diversification effect, as the downside potential of asset A is perfectly counterbalanced through the upside potential of asset B. In contrary, a correlation of plus one leads to a linear movement of both assets towards the same direction. Correlation coefficients can also be equivalent to a value of zero, where assets do deviate independently leading to an orthogonal portfolio (Hartung, 1999, p. 74). Since correlation assumes a linear relationship between two variables, it is only applicable to potential dependencies in the very short run. The correlation reflects co-movement in returns that are not stable over time. After a shock to the system there is nothing that guarantees the mean reversion. For instance, there are biases in economic time series due to volatility clustering (Simon, 2012, p. 467). Furthermore, data has to be normally distributed and the correlation coefficients have to be statistically significant. If these assumptions are violated, results are subject to spurious correlation (Renkl, 1993, pp. 118-119). To have the edge over correlation approaches, cointegration measures the co-movement in prices and takes the issue of non-stationarity in times series into account (Alexander, 1999, p. 2041).

One theory to explain a negative correlation between equity and commodity investments can be deducted from expressing equity prices as the discounted value of future corporate dividends. If commodity prices increase, for example, companies will have less profit at the end of the year and will therefore have fewer dividends to distribute to their shareholders. More precisely, this theory suggests that commodity prices are driven exogenously (Lombardi & Ravazzolo, 2013, p. 5). However, it is nowadays widely known that this theory does not empirically hold. Increasing commodity prices are mainly the result of an increasing demand on the buy-side due to booming economic activity. As a result, the actual sign of the correlation becomes much less obvious as both equity and commodity prices could potentially increase on positive news about the global outlook. Following the seminal work by Kilian (2009), this fact is pretty well established and could therefore explain the increase in correlations (pp. 1053-1055).

5. Research Methodology

In the following section we introduce important implications for economic time series analysis and the related statistical test.

5.1 Common Characteristics of Economic Data

With regard to building models for economic data, it is essential to take the following unique characteristics into account. First of all, economic data is affected by feedback. More precisely, this means that outputs affect inputs in a closed-loop system. Second, the data has a non-linear structure and change through time (Chatfield, 2004, pp. 242-243). However, a sample of data consists of a number of observations of consecutive points in time and the value of each variable depends on their value of several previous periods. Furthermore, economic time series can be viewed as a result of shocks occurring at different times and different time frequencies. Therefore, it is important to distinguish between short-run and long-run relationships (Banerjee, Dolado, Galbraith, & Hendry, 1993, p. 1-3). For the following analysis, we focus on long-run relationship, because these will often hold on average over time. For testing the existence of an equilibrium relationship, it is further necessary to establish the order of integration of individual time series in case of non-stationarity (Banerjee et al., 1993, p. 8).

5.2 Presence of Non-Stationarity and Unit Root Test

As already mentioned, the most common observed trends for economic time series are stochastic ones. This means that shocks have a persistent effect and cumulative shocks lead to a trend. The random walk with β_1 equal to one, for instance, is a simple example for a non-stationary process. The Variance $Var(y_t)$ is dependent from the index t and therefore not stationary in variance (Drobetz, 2003, p. 8).

$$y_t = y_{t-1} + \varepsilon_t, \text{ with } E(y_t) = y_0 \text{ and } Var(y_t) = t * \sigma^2 \quad (1)$$

The fact of non-stationarity imposes two threats in contrast to conventional regressions. First, the integration of order one of truly related non-stationary variables results in a misspecified model (Murray, 1994, p. 38). Second, the regression of two unrelated non-stationary variables results in a small regression coefficient with a comparatively high standard error. Therefore, the use of standard distributions will lead to spurious regression in this specific case. To prevent the above-mentioned problem, Granger and Newbold (1974) recommend using the first difference Δy_t of the variables which are involved in the equation (p. 117).

$$\Delta y_t = y_t - y_{t-1} = \varepsilon_t \tag{2}$$

The difference Δy_t is equal to the series of the residuals ε_t with a constant expected value of zero and a constant variance without autocorrelation. The first difference leads to weak stationary time series. If non-stationary series become stationary when differenced d times they are called integrated of order d, or $I(d)$ (Drobetz, 2003, p. 9). To determine the order of integration $I(d)$ of the economic time series, we apply the so-called Augmented Dickey-Fuller-Test (ADF). In contrast to the ADF test, heteroscedasticity is not a problem anymore. The idea of this test is that a process is stationary if the roots of the equation lie outside of the unit circle. Generally, the test implies the null hypothesis that there is a unit root and the order of integration is $I(1)$. This is based under the general assumption, that many economic series are known to be close to a random walk or ARIMA (0,1,0) process (Chatfield, 2004, pp. 262-263). Regarding the simulation results of the ADF test we use the critical values of MacKinnon (1996) due to the fact that the calculated response surfaces are suitable for any sample sizes.

5.3 Cointegration and Johansen Test

This section provides a short introduction in the methodology of cointegration for economic data and their empirical analysis. The concept of cointegration was developed by Engle and Granger (1987). They faced the problem that the integration of time series leads to a loss of information. In particular, a regression of differenced time series implies that the level of the regressor and regressand differ in any way, because of the non-stationary residuals, although there is an economic equilibrium. Therefore, they define that a set of series is to be called cointegrated, if each number of the set is being integrated of the same order d and if some linear combination r of the series is integrated of order k less than d. In other words, the amount of linear combinations has to be smaller than the amount of underlying variables (Drobetz, 2003, p. 15; Murray, 1994, p. 38).

Regarding these aspects, Chatfield (2004) recommends applying cointegration when attempting to model economic data. This method allows us to describe the existence of equilibrium among two or more time-series provided that each of the variables can be non-stationary (Chatfield, 2004, p. 253). To examine a cointegrated relationship, we use the Johansen cointegration test (maximum-likelihood estimation). In contrast to the Engle-Granger test (ordinary least squares estimation), this test allows us to apply a multivariate model with more than one cointegration vectors. In particular, this test determines the most stationary cointegrated relationship (Johansen, 1991, p. 1551; Drobetz, 2003, p. 19).

5.4 Vector Autoregressive Model

The Vector Autoregressive Model (VAR) is one of the most successful and flexible models for the analysis of multivariate time series. In the case of multiple variables, there is a vector of error-correction terms, of length equal to the number of cointegrating relationships, or cointegrating vectors, among the series. If there is some evidence of cointegration among two or more series, we apply the restricted vector autoregressive model (VAR), which is also called Vector Error Correction Model (VECM). If we do not find cointegrated variables, we run the unrestricted VAR. The model is fitted to the first differences of the non-stationary variables. The main feature of the ECM is the correction of any disequilibrium that may shock the system from time to time. Thus, the error correction-term observes such disequilibrium and guides the variables of the system back to their equilibrium (Engle & Granger, 1987, pp. 253-254).

We use the equation 3 to explain the single components of the ECM. First, α describes the intercept. The ECM uses automatically the first difference estimator. In combination with the fact that our sample consists of logarithmic data we have continuous returns. Therefore, the intercept can be set as zero in case of zero mean data. Furthermore, the short-term relationship is indicated by β and shows the effect of an increase in x on y. The sign of this coefficient also delivers an indication about the direction of the impact. Further, λ is the explanatory coefficient describing the speed of return to the equilibrium per time period after a deviation. λ should normally reach a value between $-1 < \lambda < 0$ since a positive coefficient does suggest a movement away from equilibrium and the model can be considered as not stable. Finally, λu_{t-1} is the magnitude by which y was above or below its long-run equilibrium in the previous period. This one is also known as error correction term and can be interpreted as long run elasticity (Parker, 2012, p. 95).

$$\Delta yt = \alpha + \beta \Delta xt + \lambda ut\text{-}1 + \varepsilon t \tag{3}$$

Note. Δ first difference operator, α intercept, β cointegrating vector, λ adjustment coefficient, λu_{t-1} error correction term, ε_t residual.

6. Data and Empirical Analysis

We obtain a data set of international stock and commodity indices from Bloomberg. In order to increase the number and thus the frequency of sample observations we use end-of-month data instead of annual or quarterly data (Hakkio, 1991, p. 571). With regard to the data availability of different indices, we chose the period from February 1990 to March 2015 to deliver a broad range of statistical evidence. To capture the non-trading days of different countries, however, we use the last-observation-carried-forward method (Siddiqui & Ali, 1998, p. 545).

Further, we consider the important fact, that many economic time series follow structural breaks in their behaviour (Hamilton, 2014, p. 1). In particular, huge positive growth rates can be observed due to the food price crisis starting in the first quarter of 2007 until prices reach their peak in June 2008. Driven by the consequences of the financial crisis, commodity and equity indices reached very low prices in the first quarter of 2009. However, to analyse the impact of these shocks to the (co-) movements of the commodity and equity time series, we define two major sub-periods. The first period, referred to as pre-crisis, replicates the time from January 1990 until December 2006. In contrast, the second period, which is referred to as post-crisis, contains the above-mentioned shocks and thus captures the period from January 2007 until March 2015. Consequently, we run the following analysis for the whole sample period and the two sub-periods. The ambition behind this methodology is to identify significant distinctions between the two sub-periods, which allows us to make more customized suggestions for diversification. The above-mentioned method to define sub-periods in order to be aware of the influence of economic shocks is also applied by Chen and Saghaian (2015) and Büyükşahin et al. (2010).

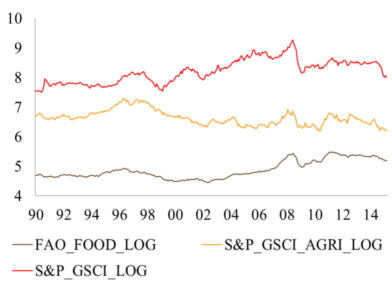

Figure 2. Determining sub-periods commodities

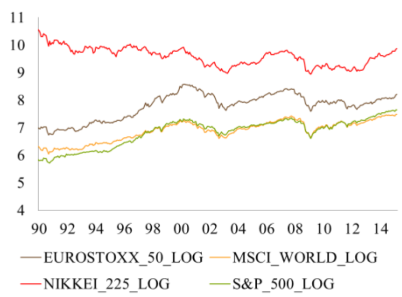

Figure 3. Determining sub-periods stocks

We focus on equity, as a proxy for traditional investment markets, and commodity markets. Specifically, the equity indices in our sample include the S&P 500, the Nikkei 225, the EuroStoxx 50 and the MSCI World. As commodity indices we chose the S&P GSCI, the S&P GSCI Agriculture and the Food Price Index calculated by the Food and Agriculture Organization of the United Nations (FAO) including the different sub-indices. Detailed information about the stocks is shown in Table 2. To be able to take into account the dividend effect of equity and the rollover effect of commodity futures, we only use total return indices. This approach emulates the methodology of the studies from Büyükşahin et al. (2010) and Georgiev (2001).

Table 2. Description of stock indices

Index	Description	Start date
EuroStoxx 50	The EuroStoxx 50 Index, Europe's leading blue-chip index for the Eurozone, provides a blue-chip representation of super sector leaders in the Eurozone. The index covers 50 stocks from 12 Eurozone countries. The index is licensed to financial institutions.	Feb 1998
MSCI World	The MSCI World is a stock market index of 1 612 world stocks. It is maintained by MSCI Inc., formerly Morgan Stanley Capital International, and is used as a common benchmark for world or global stock funds. The index includes a collection of stocks of all the developed markets in the world, as defined by MSCI. The index includes securities from 23 countries.	Jan 1969
Nikkei 225	The Nikkei 225 Stock Average is a price-weighted average of 225 top-rated Japanese companies listed in the First Section of the Tokyo Stock Exchange.	May 1949
S&P 500	S&P 500 Index is a capitalization-weighted index of 500 stocks. The index is designed to measure performance of the broad domestic US economy through changes in the aggregate market value of 500 stocks representing all major industries.	Jan 1941

Note. Index description according to Bloomberg database.

Primarily, we choose the above mentioned equity indices to cover a broad geographical area of the global stock market: the United States (S&P 500), Europe (EuroStoxx 50), Japan (Nikkei 225) and worldwide (MSCI World). We do not include the Dow Jones Industrial Average as it only covers the 30 largest publicly owned companies based in the United States. In contrast, the S&P 500 is designed to measure the performance of the entire economy in the United Sates through changes in the equity market value of 500 different stocks representing all major industries. As those indices do reflect a wide range of different international companies in various business models and are known to be those with the highest volume traded in international stock markets, they are perfectly suited for our analysis (Standard & Poor's, 2012).

Similar to worldwide equity markets, we use indices to describe commodity markets. To capture the dynamics of food prices, we use the FAO Food Price Index. The index measures the monthly change in international prices of cereals, vegetable oils, dairy, meat and sugar on average. All prices are weighted with the average export share of each group for 2002 until 2004. For instance, the FAO Meat is computed from average prices of four types of meat calculated using 27 price quotations in total. The index includes poultry products, three bovine meat products, three pig meat products and one ovine meat product. Table 3 reveals underlying for every commodity group.

Table 3. Description of commodity indices

Index	Description	Start date
FAO Food	The FAO Food Price Index is a measure of the monthly change in international prices of a basket of food commodities. It consists of the average of five commodities group price indices mentioned below, weighted with the average export shares of each of the groups for 2002-2004. In total 73 price quotations are included in the overall index.	Jan 1990
FAO Cereals	The FAO Cereals Index includes an average of 10 different wheat price quotations. Price quotations are combined into three groups consisting of India, Japonica and Aromatic varieties. The index is compiled by weighting each commodity with its average export trade share for 2002-2004.	Jan 1990
FAO Dairy	FAO Dairy Price Index consists of butter, skim milk powder, whole milk powder and cheese price quotations. The average is weighted by world average export trade share for 2002-2004.	Jan 1990
FAO Meat	The FAO Meat Price Index is computed from average prices of four types of meat calculated using 27 price quotations in total. The FAO Meat price index includes poultry products, three bovine meat products, three pig meat products and on ovine meat product weighted with the average export trade shares of each product for 2002-2004.	Jan 1990
FAO Oils	The FAO Vegetable Oil Price Index consists of 10 different oils (palm oil, soybean oil, olive oil, sunflower oil) weighted with the average export trade shares of each oil product for 2002-2004.	Jan 1990
FAO Sugar	The Sugar Price Index forms the international sugar agreement prices with 2002-2004 as base. The index includes different sugar types such as white sugar, brown sugar and liquid sugars.	Jan 1990
S&P GSCI	The S&P GSCI serves as a benchmark for investments in commodity markets and as a measure of commodity performance over time. The index currently comprises 24 commodities from all commodity sectors - energy products, industrial metals, agricultural products, livestock products and precious metals.	Jan 1970
S&P GSCI Agriculture	The S&P GSCI Agriculture Index is a sub-index of the S&P GSCI and serves as a benchmark for investment performance in the agricultural commodity markets. The index includes wheat, corn, soybeans, cotton, sugar, coffee and cocoa as agricultural goods.	Jan 1970

Note. Index description according to FAO (2015) and Standard & Poor's (2012).

Further, we include the S&P GSCI Agriculture as the (agricultural-) index with the longest history since January 1970 in our sample. The S&P GSCI Agriculture is a future based index, which comprises wheat, corn, soybeans, cotton, sugar, coffee and cocoa. The agriculture index, as one of the sub-indices, represents 14.7% of the S&P GSCI. The S&P GSCI is also considered in the following analysis for robustness purposes. The dynamics of the

S&P GSCI are mainly driven by the energy sector, since it is a world production weighted index (Gunzberg, 2014, pp. 1-7). Figure 4 reports the current dollar weights of both indices.

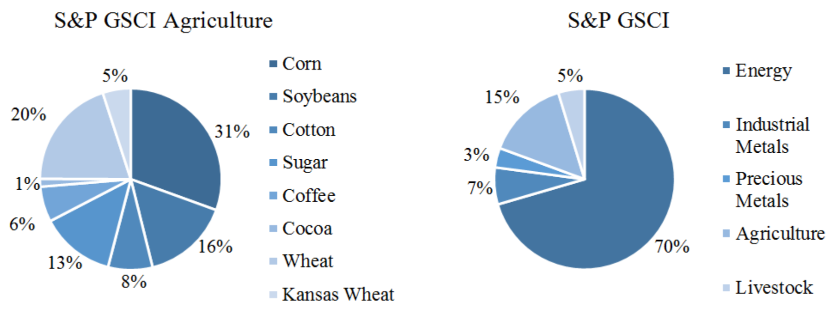

Figure 4. Current asset-weights of S&P GSCI and S&P GSCI Agriculture (Standard & Poor's, 2012)

6.1 Summary Statistics

First of all, we report in Figure 5 and 6 the dynamics of the monthly commodity and equity prices on level data from February 1990 until March 2015. The FAO commodity indices reveal similar shapes and it seems to be the case that meat prices had the highest volatility during the whole sample period. In addition, the equity indices follow a stochastic trend as well.

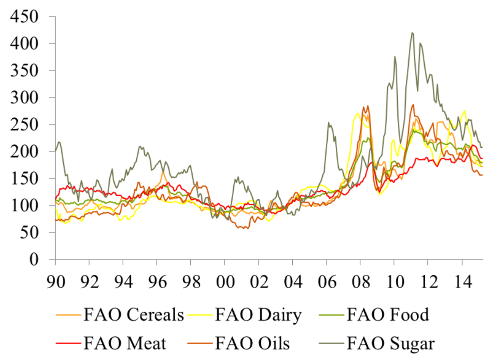

Figure 5. Dynamics of agricultural commodities

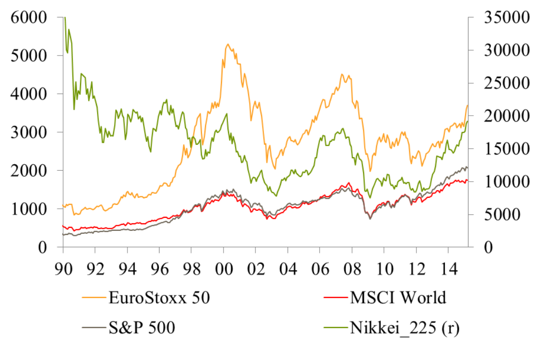

Figure 6. Dynamics of stocks

Moreover, Table 4 shows the summary statistics of monthly continuous returns also known as the first difference of log data. To annualize the monthly return, it is only necessary to multiply the means of the data by twelve. Further, the summary statistics represents the whole sample with a total of 302 observations in the first column followed by the pre-crisis with 203 respectively the post-crisis with 99 observations. All equity indices, except the Nikkei 225, reveal on average positive monthly returns during the whole period. Most of the commodity indices also show positive monthly returns on average during this period. As an outlier, only the S&P GSCI Agriculture reports negative returns over all periods. The maximum monthly drawdown happened in the Nikkei 225 with negative 27.22% in the post-crisis period. Meanwhile, when looking at the commodity indices, the S&P GSCI showing a monthly loss of 33.13% dominates the maximum drawdown. As already expected, we observe higher volatilities for all indices in the post-crisis period. The Nikkei 225, the FAO Sugar Price Index and the S&P GSCI Index reveal the highest volatilities that are above 6.2% over the whole period.

Table 4. Summary statistics of monthly rates of return

	D_EuroStoxx 50_LOG			D_Nikkei 225_LOG			D_S&P 500_LOG			D_MSCI World_LOG			D_FAO Cereals_LOG			D_FAO Dairy_LOG		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Mean	0.41%	0.66%	-0.11%	-0.22%	-0.38%	0.11%	0.61%	0.72%	0.39%	0.39%	0.50%	0.17%	0.16%	0.14%	0.20%	0.22%	0.21%	0.23%
Median	1.20%	1.33%	0.61%	0.18%	-0.26%	0.34%	1.10%	1.04%	1.21%	1.04%	1.06%	1.02%	0.03%	0.09%	-0.43%	0.09%	0.09%	0.07%
Maximum	13.70%	13.34%	13.70%	18.29%	18.29%	12.09%	10.58%	10.58%	10.23%	10.35%	9.83%	10.35%	15.33%	9.57%	15.33%	25.81%	14.70%	25.81%
Minimum	-20.62%	-20.62%	-15.89%	-27.22%	-21.35%	-27.22%	-18.56%	-15.76%	-18.56%	-21.13%	-14.45%	-21.13%	-16.72%	-13.46%	-16.72%	-22.27%	-22.27%	-13.90%
S.D.	5.38%	5.32%	5.48%	6.35%	6.44%	6.19%	4.24%	4.00%	4.69%	4.42%	4.05%	5.10%	3.96%	3.34%	5.01%	4.60%	3.88%	5.83%
Jarque-Bera	46.345***	42.603***	8.396***	24.439***	3.005	49.623***	72.470***	28.156***	31.517***	89.366***	20.429***	41.242***	74.925***	13.427***	15.576***	501.18***	735.94***	53.538***
Probability	0.00	0.00	0.02	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Skewness	-0.73	-0.77	-0.65	-0.49	-0.25	-1.02	-0.81	-0.64	-0.98	-0.87	-0.64	-1.03	0.27	-0.09	0.46	-0.01	-1.25	0.74
Kurtosis	4.25	4.63	3.58	4.00	3.32	5.81	4.76	4.29	4.95	5.02	3.87	5.40	5.38	4.25	4.71	9.31	11.99	6.29
Observations	302	203	99	302	203	99	302	203	99	302	203	99	302	203	99	302	203	99

	D_FAO_Meat_LOG			D_FAO_Oils_LOG			D_FAO_Sugar_LOG			D_FAO_Food_LOG			D_S&P_GSCI_Agri_LOG			D_S&P_GSCI_LOG		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Mean	0.17%	0.04%	0.44%	0.25%	0.30%	0.16%	0.01%	-0.10%	0.23%	0.17%	0.11%	0.28%	-0.16%	-0.11%	-0.27%	0.16%	0.54%	-0.63%
Median	0.11%	-0.09%	0.77%	0.12%	0.11%	0.13%	-0.08%	0.41%	-0.49%	0.11%	0.13%	0.00%	-0.43%	-0.34%	-0.61%	0.44%	0.58%	0.23%
Maximum	9.15%	9.15%	5.98%	20.52%	20.52%	13.76%	21.56%	21.56%	19.69%	7.05%	5.70%	7.05%	16.28%	10.96%	16.28%	20.65%	20.65%	17.95%
Minimum	-9.08%	-7.64%	-9.08%	-27.45%	-12.23%	-27.45%	-30.93%	-17.66%	-30.93%	-12.90%	-4.47%	-12.90%	-21.03%	-11.17%	-21.03%	-33.13%	-15.56%	-33.13%
S.D.	2.77%	2.75%	2.82%	5.21%	4.65%	6.24%	7.37%	7.31%	7.54%	2.40%	1.81%	3.30%	5.49%	4.15%	7.56%	6.20%	5.63%	7.20%
Jarque-Bera	6.431***	4.865***	24.151***	140.490***	27.468***	60.844***	10.064***	1.761	21.357***	132.100***	3.759	19.395***	25.538***	0.744	0.281	110.500***	6.258***	64.351***
Probability	0.04	0.09	0.00	0.00	0.00	0.00	0.01	0.41	0.00	0.00	0.67	0.00	0.00	0.69	0.87	0.00	0.04	0.00
Skewness	-0.14	0.28	-0.98	-0.42	0.28	-0.96	0.09	0.22	-0.16	-0.39	0.05	-0.55	-0.12	-0.15	-0.06	-0.52	0.20	-1.10
Kurtosis	3.65	3.50	4.42	6.24	4.71	6.32	3.88	3.15	5.25	6.14	2.71	4.86	4.40	2.99	3.23	5.77	3.76	6.28
Observations	302	203	99	302	203	99	302	203	99	302	203	99	302	203	99	302	203	99

Note. (1) Whole sample, (2) pre-crisis, (3) post-crisis. Asterisks (***) indicates that normality of the return distribution is rejected at the 10% level.

Next, we examine the statistical distribution of the indices and apply the Jarque-Bera test for normality. Since the requirement for a normal distributed times series is a kurtosis of three and a skewness value equal to zero, the outcome of the Jarque-Bera test should equal to zero. Our sample shows, that some returns have negative skewness implying that the distribution has a long right tail. Furthermore, the kurtosis values are relatively high in all cases implying that the distributions are peaked in comparison to a normal distribution. Consistent with this fact, the Jarque-Bera test statistic is significant on a 10% confidence level for all indices. As a result, this indicates that the return distribution is not normally distributed. In comparison to the level data, the log-differentiated time series are approximately normally distributed as it can be graphically observed in Figure 7. In order to take this fact into account and in order to stabilize the variance of the series, we use log-differentiated data (Hamilton, 1989, p. 357; Lütkepohl & Xu, 2010, p. 620).

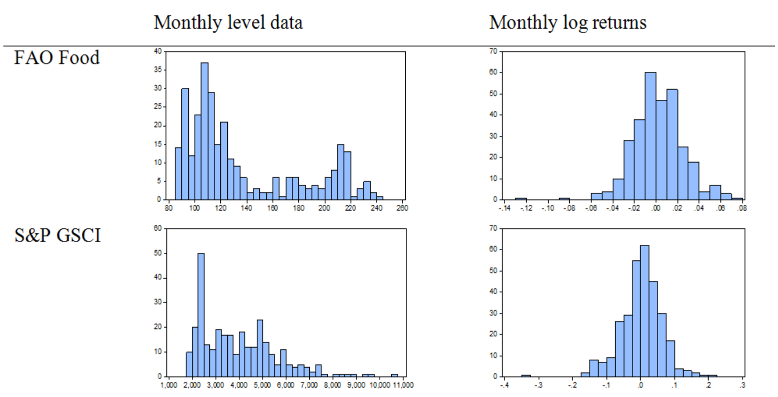

Figure 7. Distribution of commodity prices (level data vs. log returns)

However, Figure 5 and 6 provides statistical evidence that the time series are in fact non-stationary. Thus, we apply the ADF test to identify the order of integration *I(d)*. Consistent with this assumption Table 5 indicates non-stationarity among the whole level data and the prevalence of a unit root. As already expected, the first difference of the data is clearly stationary. Therefore, we follow the approach first carried out by Engle and Granger (1987) and adjust the data by first difference for the following analysis (p. 252).

Table 5. Result of ADF test

	Level data		First difference	
Index	t-Statistic	Prob.	t-Statistic	Prob.
Equity				
EuroStoxx 50_LOG	-1.529	0.818	-15.475	0.000
Nikkei 225_LOG	-2.034	0.580	-16.583	0.000
S&P 500_LOG	-1.666	0.764	-16.434	0.000
MSCI World_LOG	-2.162	0.509	-15.813	0.000
Commodity				
FAO Cereals_LOG	-2.401	0.378	-10.923	0.000
FAO Dairy_LOG	-2.968	0.143	-11.501	0.000
FAO Meat_LOG	-1.968	0.616	-4.542	0.002
FAO Oils_LOG	-2.865	0.176	-6.348	0.000
FAO Sugar_LOG	-2.785	0.204	-11.195	0.000
FAO Food_LOG	-2.069	0.561	-7.664	0.000
S&P GSCI Agri_LOG	-2.227	0.472	-16.913	0.000
S&P GSCI LOG	-2.006	0.595	-5.369	0.000

Note. P-values (one sided) according to MacKinnon (1996): 1%: -3.452, 5%: -2.871, 10% -2.572.

In the following section we observe the dependencies among the variables in the short run. The correlation matrix between equity and commodity prices based on first difference of log data (Table 6). In this short run analysis, we also distinguish between the whole sample and the two sub-periods. We only focus on the correlation relationships of FAO Food instead of all other sub-indices, as this would not generate any additional statistical benefit. When looking at the correlation coefficients, we first document only positive significant correlations among all variables. Additionally, the correlation coefficients of the equity indices are highly significant and above 0.4 in all investigated periods. The highest correlation occurred between MSCI World and S&P 500 due to the high weighted share of U.S. stocks (56.79% in December 2014) in the MSCI World (MSCI Inc., 2014, p. 2). Further, we found greater prevalence that the S&P GSCI is highly significant positively correlated with all other mentioned equity markets in the post-crisis period. Consistent with this fact, the S&P GSCI Agriculture is also positively correlated (greater than 0.3) with the S&P 500 in the post-crisis period and with the MSCI World during the post-crisis period and therefore also in the whole sample period. Similar results can be observed for the FAO Food.

Table 6. Sample correlation matrix

	(1)			(2)			(3)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
(1) D_EuroStoxx 50_LOG	1	1	1						
(2) D_Nikkei 225_LOG	0.515***	0.439***	0.688***	1	1	1			
(3) D_S&P 500_LOG	0.777***	0.740***	0.843***	0.515***	0.414***	0.712***	1	1	1
(4) D_MSCI World_LOG	0.804***	0.762***	0.881***	0.690***	0.667***	0.753***	0.91***	0.867***	0.971***
(5) D_FAO Food_LOG	0.047	-0.113	0.232**	0.075	-0.031	0.205**	0.127**	-0.097	0.352***
(6) D_S&P GSCI Agri_LOG	0.170***	0.108	0.251**	0.147***	0.131***	0.184*	0.281***	0.183***	0.388***
(7) D_S&P GSCI_LOG	0.100*	-0.114	0.421***	0.202***	0.073	0.436***	0.205***	-0.077	0.586***

	(4)			(5)			(6)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
(1) D_EuroStoxx 50_LOG									
(2) D_Nikkei 225_LOG									
(3) D_S&P 500_LOG									
(4) D_MSCI World_LOG	1	1	1						
(5) D_FAO Food_LOG	0.171***	-0.079	0.403***	1	1	1			
(6) D_S&P GSCI Agri_LOG	0.308***	0.162**	0.449***	0.51***	0.397***	0.583***	1	1	1
(7) D_S&P GSCI_LOG	0.264***	-0.039	0.647***	0.335***	0.028	0.626***	0.347***	0.134*	0.546***

Note. Second row (1) whole sample, (2) pre-crisis, (3) post-crisis. Asterisks (*), (**) and (***) indicates significant at 10%, 5% and 1% level.

Our results suggest, however, that commodity price speculation has indeed taken place in the end of the pre-crisis period. As a result of uncertainty in the market, panic sale has led to downward sloping prices over all reviewed asset classes. As a matter of fact, positive correlation coefficients can be observed in the post-crisis period. Since we did not observe any diversification potential in the short-run we are greatly interested in the investigation of the long-run relationship.

6.2 Results from Johansen Cointegration Test

To examine the long-run relationship between equity and commodity markets, we use the Johansen cointegration test. Due to the sensitivity of this test regarding the chosen lag length, we estimate pairwise length (Ahking, 2002, p. 52). To identify the optimal lag length, which is shown in Table 7 we observe the Akaike information criterion (AIC) based on a VECM, which automatically assumes first difference of monthly log data. In our analysis, we chose pairwise the lowest AIC until a lag-length of 12. Following the results of Ahking (2002, p. 60) and Emerson (2007, p. 883), this criterion is the most robust one to determine the actual lag.

Table 7. Optimal lag length according to AIC

	EuroStoxx 50_LOG			Nikkei 225_LOG			S&P 500_LOG			MSCI World_LOG		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
FAO Cereals_LOG	1	1	2	2	1	2	1	1	1	2	1	2
FAO Dairy_LOG	5	4	2	5	5	1	5	5	5	5	4	1
FAO Meat_LOG	3	1	5	4	1	4	5	3	5	5	4	1
FAO Oils_LOG	4	4	4	4	5	3	3	4	4	5	4	3
FAO Sugar_LOG	1	1	1	1	1	1	1	1	1	1	1	1
FAO Food_LOG	4	3	2	4	4	1	4	4	4	4	4	1
S&P GSCI Agri_LOG	1	1	3	1	1	1	1	1	1	1	1	3
S&P GSCI_LOG	1	1	2	2	1	2	3	4	3	3	3	3

Note. Number indicates optimal lag length regarding AIC. (1) whole period, (2) pre-crisis, (3) post-crisis.

To determine cointegrating vectors among the data, we test for cointegration between the four equity markets and the agricultural commodity indices using the trace and maximum eigenvalue statistics. Both tests determine the cointegration rank r, which is reported in Table 8. Considering the monthly log level of input data, we run the test with intercept, without trend and each with individual lag length. However, cointegration appears when the null hypothesis $r = 0$ can be rejected, more specifically, when the trace statistic is significant and consequently higher than the critical value at a 10% level of significance. In addition to that, $r = 1$ must fail to be rejected. For robustness purposes, we only consider a relationship as statistically cointegrated when the maximum eigenvalue statistic confirms our result which is primarily based on trace statistic.

With regard to our findings, we observe nine cointegration relationships across all equity indices that occurred mainly in the post-crisis. However, we found evidence of cointegration relationships in the pre-crisis as well. In contrast, there is no evidence for cointegrating relationships in the whole period. To find significant cointegration equations in a sub-period with relatively smaller sample size indicates more robustness along the results (Johansen & Juselius, 2002, p. 8). In particular, FAO Oils are cointegrated with the S&P 500 and the MSCI World in the pre-crisis period, whereas we observe a cointegration relationship with the Nikkei 225 in the post-crisis period. Even though most cointegration relationships can be found in the period up to January 2007, we found evidence, that the S&P GSCI is, in fact, cointegrated with all four stock indices. Additionally, the S&P GSCI Agriculture shows a long-term relationship to the European stock market.

In general, the results reported in Table 8 are somehow consistent with our assumptions regarding the potential diversification aspect of commodities. Nevertheless, the observed cointegrating equations between FAO Oils and FAO Dairy on the one side and equity markets on the other side seems to be not economically explainable. To evaluate the estimated cointegration relationships, we next apply an Error Correction Model.

Table 8. Result of Johansen cointegration test

	Whole Sample: 1990M2-2015M3				Pre-Crisis: 1990M2-2006M12				Post-Crisis: 2007M1-2015M3			
	Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic	
EuroStoxx 50	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1
FAO Cereals	5.58*	2.34	3.24*	2.34	8.03*	0.65	7.38*	0.65	17.86	4.65	13.21	4.65
	(0.744)	(0.126)	(0.929)	(0.126)	(0.462)	(0.420)	(0.445)	(0.420)	(0.022)	(0.031)	(0.073)	(0.031)
FAO Dairy	7.39*	2.14	5.25*	2.14	6.64*	1.00	5.65*	1.00	14.94	5.23	9.70*	5.23
	(0.532)	(0.144)	(0.709)	(0.144)	(0.619)	(0.318)	(0.658)	(0.318)	(0.060)	(0.022)	(0.232)	(0.022)
FAO Meat	3.68*	0.73	2.96*	0.73	8.46*	1.27	7.19*	1.27	6.91*	0.25	6.66*	0.25
	(0.927)	(0.394)	(0.949)	(0.394)	(0.417)	(0.259)	(0.466)	(0.259)	(0.588)	(0.616)	(0.530)	(0.616)
FAO Oils	7.15*	2.33	4.83*	2.33	10.3*	1.17	9.18*	1.17	28.25	4.45	23.80	4.45
	(0.559)	(0.127)	(0.763)	(0.127)	(0.254)	(0.279)	(0.271)	(0.279)	(0.000)	(0.035)	(0.001)	(0.035)
FAO Sugar	7.54*	2.65	4.89*	2.65	8.37*	0.70	7.67*	0.70	13.50	2.79	10.7*	2.79
	(0.516)	(0.103)	(0.756)	(0.103)	(0.426)	(0.402)	(0.413)	(0.402)	(0.098)	(0.095)	(0.170)	(0.095)
FAO Food	4.12*	1.38	2.74*	1.38	4.62*	0.01	4.61*	0.01	18.28	5.40	12.88	5.40
	(0.894)	(0.240)	(0.962)	(0.240)	(0.847)	(0.912)	(0.790)	(0.912)	(0.019)	(0.020)	(0.082)	(0.020)
S&P GSCI Agri.	9.09*	2.70	6.40*	2.70	8.53*	2.37	6.16*	2.37	15.98	2.41*	13.57	2.41*
	(0.356)	(0.101)	(0.562)	(0.101)	(0.411)	(0.124)	(0.592)	(0.124)	(0.042)	(0.121)	(0.064)	(0.121)
S&P GSCI	8.28*	2.06	6.22*	2.06	3.70*	0.41	3.29*	0.41	25.24	0.82*	24.41	0.82*
	(0.436)	(0.151)	(0.585)	(0.151)	(0.926)	(0.524)	(0.925)	(0.524)	(0.001)	(0.363)	(0.001)	(0.363)

	Whole Sample: 1990M2-2015M3				Pre-Crisis: 1990M2-2006M12				Post-Crisis: 2007M1-2015M3			
	Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic	
Nikkei 225	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1
FAO Cereals	8.89*	2.66	6.23*	2.66	13.69	4.38	9.31*	4.38	10.1*	1.93	8.22*	1.93
	(0.375)	(0.103)	(0.583)	(0.103)	(0.092)	(0.036)	(0.261)	(0.036)	(0.269)	(0.164)	(0.357)	(0.164)
FAO Dairy	14.76	6.21	8.55*	6.21	11.1*	1.75	9.38*	1.75	12.2*	2.03	10.1*	2.03
	(0.064)	(0.013)	(0.325)	(0.013)	(0.203)	(0.185)	(0.256)	(0.185)	(0.147)	(0.154)	(0.200)	(0.154)
FAO Meat	9.53*	1.56	7.97*	1.56	12.2*	1.51	10.7*	1.51	7.35*	0.25	7.10*	0.25
	(0.318)	(0.212)	(0.381)	(0.212)	(0.147)	(0.220)	(0.170)	(0.220)	(0.537)	(0.617)	(0.477)	(0.617)
FAO Oils	13.3*	5.26	8.11*	5.26	13.63	2.64*	10.9*	2.64	14.93	2.24*	12.68	2.24*
	(0.102)	(0.022)	(0.367)	(0.022)	(0.094)	(0.104)	(0.155)	(0.104)	(0.061)	(0.134)	(0.088)	(0.134)
FAO Sugar	13.72	4.73	8.99*	4.73	15.41	6.54	8.87*	6.54	12.9*	1.64	11.2*	1.64
	(0.091)	(0.030)	(0.287)	(0.030)	(0.052)	(0.011)	(0.297)	(0.011)	(0.118)	(0.201)	(0.141)	(0.201)
FAO Food	9.81*	2.20	7.61*	2.20	12.2*	1.51	10.7*	1.51	10.9*	1.69	9.23*	1.69
	(0.295)	(0.138)	(0.420)	(0.138)	(0.147)	(0.220)	(0.170)	(0.220)	(0.216)	(0.193)	(0.267)	(0.193)
S&P GSCI Agri.	12.0*	3.55	8.53*	3.55	11.3*	1.65	9.69*	1.65	6.23*	0.63	5.59*	0.63
	(0.153)	(0.060)	(0.327)	(0.060)	(0.191)	(0.199)	(0.233)	(0.199)	(0.668)	(0.427)	(0.665)	(0.427)
S&P GSCI	15.17	4.88	10.2*	4.88	8.91*	1.52	7.39*	1.52	15.57	0.04*	15.53	0.04*
	(0.056)	(0.027)	(0.194)	(0.027)	(0.373)	(0.218)	(0.443)	(0.218)	(0.049)	(0.834)	(0.031)	(0.834)

	Whole Sample: 1990M2-2015M3				Pre-Crisis: 1990M2-2006M12				Post-Crisis: 2007M1-2015M3			
	Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic	
S&P 500	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1
FAO Cereals	4.94*	1.63	3.30*	1.63	10.5*	0.84	9.72*	0.84	6.86*	0.17	6.70*	0.17
	(0.815)	(0.201)	(0.924)	(0.201)	(0.240)	(0.361)	(0.231)	(0.361)	(0.593)	(0.684)	(0.525)	(0.684)
FAO Dairy	7.34*	1.65	5.68*	1.65	7.65*	1.44	6.21*	1.44	16.66	0.10*	16.56	0.10*
	(0.538)	(0.199)	(0.653)	(0.199)	(0.503)	(0.230)	(0.586)	(0.230)	(0.033)	(0.748)	(0.021)	(0.748)
FAO Meat	4.23*	0.00	4.22*	0.00	8.74*	0.84	7.91*	0.84	8.33*	0.21	8.12*	0.21
	(0.884)	(0.946)	(0.835)	(0.946)	(0.389)	(0.360)	(0.388)	(0.360)	(0.430)	(0.646)	(0.366)	(0.646)
FAO Oils	6.58*	2.60	3.98*	2.60	21.52	1.68*	19.84	1.68*	11.3*	0.35	10.9*	0.35
	(0.626)	(0.107)	(0.861)	(0.107)	(0.006)	(0.194)	(0.006)	(0.194)	(0.191)	(0.552)	(0.155)	(0.552)
FAO Sugar	8.87*	1.12	7.75*	1.12	9.98*	0.99	8.99*	0.99	9.26*	1.01	8.25*	1.01
	(0.378)	(0.290)	(0.405)	(0.290)	(0.282)	(0.319)	(0.287)	(0.319)	(0.341)	(0.315)	(0.353)	(0.315)
FAO Food	3.65*	1.11	2.54*	1.11	10.9*	0.09	10.8*	0.09	9.46*	0.59	8.86*	0.59
	(0.930)	(0.293)	(0.972)	(0.293)	(0.213)	(0.764)	(0.160)	(0.764)	(0.324)	(0.441)	(0.297)	(0.441)
S&P GSCI Agri.	10.0*	2.60	7.47*	2.60	10.0*	3.70	6.33*	3.70	4.66*	0.01	4.65*	0.01
	(0.275)	(0.107)	(0.435)	(0.107)	(0.279)	(0.055)	(0.571)	(0.055)	(0.843)	(0.911)	(0.784)	(0.911)
S&P GSCI	7.34*	0.29	7.06*	0.29	3.52*	0.91	2.61*	0.91	40.02	0.63*	39.38	0.63*
	(0.537)	(0.592)	(0.482)	(0.592)	(0.938)	(0.341)	(0.969)	(0.341)	(0.000)	(0.424)	(0.000)	(0.424)

	Whole Sample: 1990M2-2015M3				Pre-Crisis: 1990M2-2006M12				Post-Crisis: 2007M1-2015M3			
	Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic		Trace Statistic		Max-Eigen Statistic	
MSCI World	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1	H_0: r=0	H_0: r=1
FAO Cereals	6.10*	2.11	3.98*	2.11	7.97*	0.16	7.81*	0.16	11.2*	2.17	9.11*	2.17
	(0.684)	(0.146)	(0.861)	(0.146)	(0.468)	(0.686)	(0.398)	(0.686)	(0.195)	(0.141)	(0.277)	(0.141)
FAO Dairy	7.76*	1.70	6.07*	1.70	7.17*	0.38	6.79*	0.38	12.9*	1.97	10.9*	1.97
	(0.490)	(0.193)	(0.604)	(0.193)	(0.557)	(0.538)	(0.513)	(0.538)	(0.117)	(0.161)	(0.155)	(0.161)
FAO Meat	3.88*	0.01	3.87*	0.01	8.60*	0.25	8.35*	0.25	9.41*	2.39	7.02*	2.39
	(0.913)	(0.917)	(0.872)	(0.917)	(0.403)	(0.615)	(0.344)	(0.615)	(0.329)	(0.122)	(0.486)	(0.122)
FAO Oils	6.74*	1.99	4.75*	1.99	17.29	0.91*	16.38	0.91*	12.5*	1.60	10.9*	1.60
	(0.607)	(0.158)	(0.773)	(0.158)	(0.027)	(0.340)	(0.023)	(0.340)	(0.133)	(0.207)	(0.158)	(0.207)
FAO Sugar	7.60*	1.24	6.36*	1.24	7.84*	0.26	7.58*	0.26	9.82*	2.01	7.81*	2.01
	(0.509)	(0.266)	(0.567)	(0.266)	(0.482)	(0.611)	(0.423)	(0.611)	(0.294)	(0.156)	(0.398)	(0.156)
FAO Food	3.68*	1.34	2.34*	1.34	6.94*	0.01	6.93*	0.01	10.3*	1.82	8.52*	1.82
	(0.927)	(0.247)	(0.980)	(0.247)	(0.584)	(0.929)	(0.497)	(0.929)	(0.255)	(0.177)	(0.328)	(0.177)
S&P GSCI Agri.	7.01*	0.83	6.18*	0.83	4.61*	0.76	3.85*	0.76	9.85*	0.56	9.29*	0.56
	(0.576)	(0.362)	(0.590)	(0.362)	(0.849)	(0.383)	(0.875)	(0.383)	(0.292)	(0.453)	(0.263)	(0.453)
S&P GSCI	5.92*	0.35	5.57*	0.35	3.46*	0.10	3.36*	0.10	36.47	0.10*	36.37	0.10*
	(0.705)	(0.556)	(0.668)	(0.556)	(0.942)	(0.746)	(0.920)	(0.746)	(0.000)	(0.745)	(0.000)	(0.745)

Note. Johansen (1991) trace and maximum eigenvalue statistics. *r=0* indicates no cointegration relationship; $r = 1$ indicates at most one cointegration relationship. Critical values at 10% level are 13.43 ($r = 0$) and 2.71 ($r = 1$) for the trace test and 12.30 ($r = 0$) and 2.71 ($r = 1$) for the maximum eigenvalue statistic. Asymptotic significance level (p-values) according to MacKinnon-Haug-Michelis (1999) in parenthesis. Asterisk (*) denotes rejection of the hypothesis at the 10% level.

6.3 Robustness and Validity

Beforehand, we want to introduce our findings along the robustness of the test. We also considered the impact of different lag structures and confidence intervals to examine the robustness of our results. The sensitivity on different lag structures was actually pretty low. A variation of lag length in the interval of plus/minus two lags had no impact on the cointegrated relationships. A change in the confidence level from 10% to 5% led to a slightly different result. The cointegration relationship between Nikkei 225 and FAO Oils in the post-crisis period can not be accepted anymore. Furthermore, the relationship between the S&P GSCI Agriculture and the EuroStoxx 50 does only appear when taking the trace statistic into consideration. As a validation, the maximum eigenvalue statistic can not confirm this result since $r = 0$ cannot be rejected. To cut a long story short, all values that are subject to the following constraints are being presumed to be cointegrated additionally, if we lower the confidence level from 10% to 5%. In the following equations the parenthesis indicates the p-value:

$$r = 0 < (0.05) \text{ and } (0.05) < r = 1 < (0.10) \tag{4}$$

In contrast, all cointegration relationships that are subject to the following values are being presumed to disappear when lowering the confidence level from 10% to 5%:

$$(0.1) > r = 0 > (0.05) \tag{5}$$

Generally speaking, we found robust cointegration relationships since none of them disappeared either by changing the lag structure, or by applying a 5% confidence level. However, we found cointegration relationships in the whole sample period. Therefore, we suppose that the structural break observed prior to the global food crisis has changed the long-term relationship between the two asset classes. To determine whether there is a potential diversification effect, the direction of cointegration and the time of adjustment to the equilibrium are required. Consequently, we apply an Error Correction Model to identify these, so far, unknown coefficients. For further analysis, we run our estimation on a 10% confidence level. From a statistical point of view, the reason for this decision is that cointegration is more likely to be rejected than on a 5% level of significance, thus the results of the Error Correction Model are more solid.

6.4 Cointegration Vectors

In this section, we apply ECM to observe the direction of response to impulse which is indicated by the sign of the cointegrating coefficient β. Furthermore, λ is the speed-to-adjustment parameter and reveals how much time does it take to bring the variable back to towards equilibrium. A positive λ does imply a move away from equilibrium. In this specific case, the model can not be considered as stable. The following Table 9 reports the observed cointegration equations. The relationship between FAO Oils and S&P 500 respectively MSCI World as well as the cointegration between S&P 500 and FAO Dairy can not be considered as stable since λ has a positive sign. In the short run, the S&P GSCI is positively related to the EuroStoxx 50, the Nikkei 225, the S&P 5000 and the MSCI World. From a diversification perspective, investors can only benefit from this perception taking a short position in one of the two assets. However, we only consider negative cointegration as diversification potential, since many investors are restricted to short selling positions. In contrast, diversification potential is found between the S&P GSCI Agriculture and the EuroStoxx 50 as well as between the Nikkei 225 and FAO Oils. The cointegration coefficient as well as λ is negatively related in both cases. This observation is especially of interest since the S&P GSCI Agriculture does drive the EuroStoxx 50. The λ coefficient of -0.1001 suggests a 10.01% movement per month back towards equilibrium following a shock to the model. FAO Oils reveals a more moderate progress with a movement towards equilibrium of 3% per month.

Table 9. Result of error correction model

Impulse Δy_t	β	Response Δx_t	λ*
(1) Whole Sample: 1990M2-2015M3			
No cointegration equations			
(2) Pre-crisis: 1990M2-2006M12			
FAO Oils	positive	S&P 500	5.90%
FAO Oils	positive	MSCI World	5.25%
(3) Post-crisis: 2007M1-2015M3			
S&P GSCI Agri	negative	EuroStoxx 50	-10.01%
S&P GSCI	positive	EuroStoxx 50	-13.51%
Nikkei 225	negative	FAO Oils	-3.00%
S&P GSCI	positive	Nikkei 225	-11.10%
S&P 500	positive	FAO Dairy	2.03%
S&P GSCI	positive	S&P 500	-15.51%
S&P GSCI	positive	MSCI World	-16.50%

Note. λ indicates adjustment per month. Asterisks (*) indicates significant at 10% level.

6.5 Impulse Response Analysis

In the following section, we examine how many time periods it takes until a long-run equilibrium relationship between the variables occurs. Thus, we derive the impulse response function (IRF) from the VAR. The function measures the effect of a one-time one standard deviation shock to an endogenous variable on itself or on another endogenous variable (Chatfield, 2004, p. 171). Figure 8 shows the response of EuroStoxx 50 after a one-time shock to S&P GSCI Agriculture. The IRF confirms the results according to the impact of λ because the response of EuroStoxx 50 is higher than the response of S&P GSCI Agriculture. Further, the shape indicates that it takes roughly six months until the EuroStoxx 50 reaches zero. Nevertheless, we observe similar results for the response of FAO Oils.

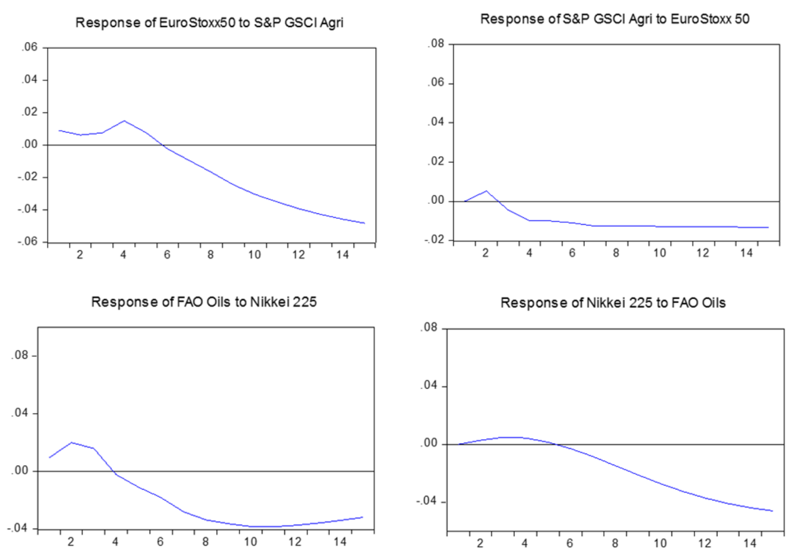

Figure 8. Impulse response function

7. Economic Reasoning and Implications

In the following section we want to discuss the economic reasoning for all cointegration equations. Our results suggest a diversification effect between the S&P GSCI Agriculture and the EuroStoxx 50 as well as between the Nikkei 225 and FAO Oils. Regarding the S&P GSCI Agriculture, we found positive cointegration to all the applied stock indices. Since this outcome can be used as an investment strategy we aim to identify the economic reasoning for this observation.

7.1 Impulse of S&P GSCI to Stock Markets

The latter observation can be explained by high weights of WTI (24.47%) and Brent Crude Oil (24.70%) in the S&P GSCI Index (Standard & Poor's, 2012). Industries, especially manufacturing and mining industries, are highly exposed to oil as an indispensable resource. Accordingly, a negative movement in oil price can lead to a cost saving effect or a decreasing margin, depending on which industry the company belongs to.

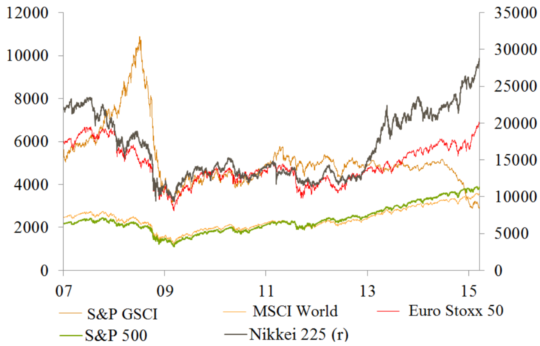

Figure 9. Dynamics of S&P GSCI and stock indices

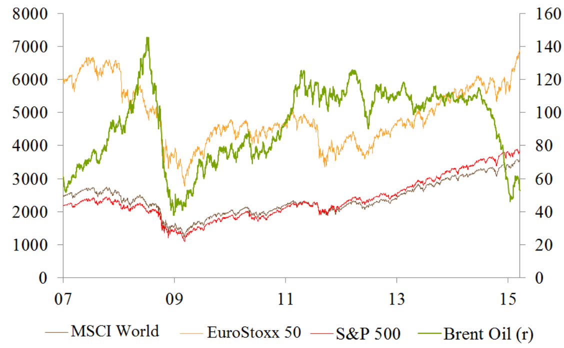

Figure 10. Dynamics of Brent Oil and stock indices

Figure 10 shows Brent Oil prices in comparison to the applied stock indices. In 2007 oil prices began to rise and reached their all-time high in the beginning of 2008, initiating a downward trend. This crash was triggered by concerns about an upcoming recession as a result of the financial crisis, which was now overlapping to the European and Asian economy. High oil prices, in addition to the financial crisis, started slowing worldwide economy down. As motioned above, mining industries do benefit from higher margins when oil prices rise, however, most companies are oil consumers (Gilbert, 2010, pp. 35-36). Therefore a high oil price does rather harm than stimulate the economy. In the mid of 2008, oil prices started to rise again, since the Chinese and Indian economy started to recover. As a result of expansionary monetary policy, decreasing interest rates and low oil prices, stock markets started their bullish trend as well. In addition, as oil is quoted in US Dollar, Japan also benefited from the stronger Yen. However, due to the earthquake affecting the nuclear reactor in Fukushima the Nikkei 225 only recovered in the very short-run. The European market did not fully benefit from falling oil prices due to a weakening Euro. Taking into account that the oil price does impact on almost all goods, since it is influences transportation costs, we suppose that the oil price is the main reason for the observed relationship between the S&P GSCI and all applied stock indices.

7.2 Impulse of S&P GSCI Agriculture to EuroStoxx 50

As mentioned in the beginning of this paper we test different commodity indices to avoid biased outcomes caused by high weights for individual assets. Since the S&P GSCI Agriculture, considering its individual asset weights, only shows a convergence in wheat (24.9%) and corn (30.5%), we have to look at them in more detail but also take other agricultural goods into consideration (Standard & Poor's, 2012). In general, cereals can be considered as an important driver of the S&P GSCI Agriculture since these are an indispensable resource in the production process of eggs, meat and dairy derived products (Brandt, 2014, p. 41).

The FAO Cereals chart and the S&P GSCI Agriculture chart paint an upward trend in 2007-2008 as well as in 2011-2012. We suppose that the world food crisis in 2008 played a substantial role as a major reason according to our findings. The world food crisis came up in 2007-2008 and caused a huge rise in food prices. This development was mainly caused by subsidized biofuel production, population growth and rising energy prices. For instance, this provoked a food price bubble, which was further fuelled by capital diverting from collapsing stock markets (Braun, 2008, p. 3). This can be observed in Figure 11 where the S&P GSCI Agriculture increases even though the EuroStoxx 50 initiated his downward trend. The second trend is observable in 2011-2012. In this time period economic healthiness was turning bad in Europe related to excessive indebtedness of southern

European countries. This led to poor liquidity in many asset classes, rising risk premiums for corporates, governments and the banking sector due to the distrust in the markets (Aizenman, Hutchison, & Jinjarak, 2013, pp. 37-38). In the very short run, a stock market collapse could lead to lose the conditional link between equity and commodity price returns. In particular, the higher market risk can lead to a flight to quality and consideration of agriculture commodity investments as refuge instruments (Silvennoinen & Thorp, 2013, p. 64; Chong & Miffre, 2010, p. 61). Taking these arguments into consideration we suppose that the observed long-term relationship is a result of an ongoing and dynamic shift in asset allocation in the post-crisis period.

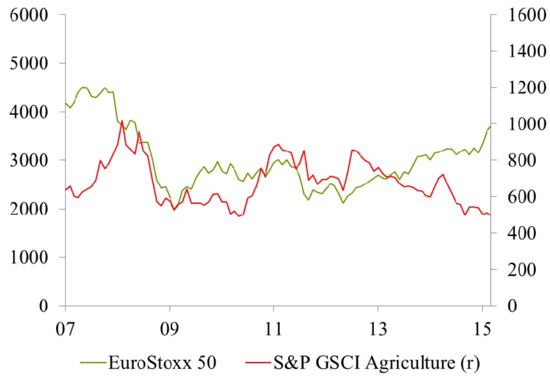

Figure 11. S&P GSCI Agri and EuroStoxx 50

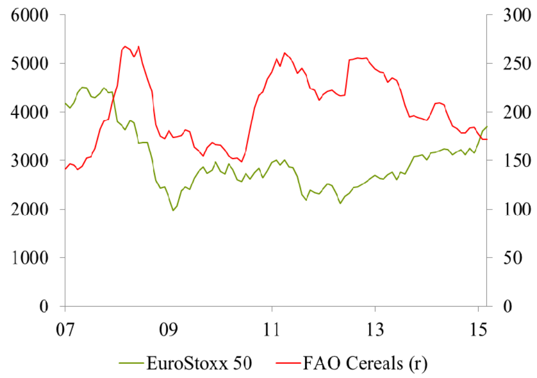

Figure 12. FAO Cereals and EuroStoxx 50

7.3 Impulse of Nikkei 225 to FAO Oils

Figure 13 shows the development of FAO Oils and the Nikkei 225. Japanese stocks suffered as well from uncertainty and panic springing up from the U.S. housing crisis (Braun, 2008, p.1). On the March 10, 2009, as a result, the Nikkei 225 fell to its greatest absolute low since 1982. Ever since then Japanese stocks started rising due to the interventions of the European Central Bank, the Federal Reserve and the Bank of Japan announcing their quantitative easing programs. However, uncertainty resulting from exceeding public indebtedness and the earthquake in March 2011 kept stock prices low in a sideward tendency until 2013. Japanese stocks since then recovered up to its 2008 high whereas FAO Oils follow a more dynamic development. According to the commodities mentioned so far, oil prices also decreased as a result of the bursting food price bubble reaching its post-crisis low in 2009. Since then FAO Oils increased due to high WTI and Brent Oil prices, which led to increasing demand of biofuels. Since 2011 a drop in FAO Oil prices is observable. This is a result of increasing palm oil supply, the key commodity in the index, due to higher supply from Indonesia and Malaysia, as well as weaker global import demand (Hiraga, 2015, p. 179; FAO, 2015).

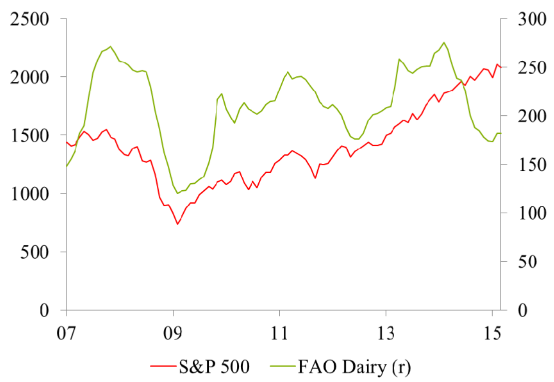

Figure 13. Dynamics of Nikkei 225 and FAO Oils

8. Concluding Remarks

This study is one of the former examining the dynamic relationship between worldwide stock prices and agriculture prices under portfolio diversification aspects. The data spanning from February 1990 to March 2015 is divided into two sub-periods consisting of the period from February 1990 to December 2006 (pre-crisis) and January 2007 to March 2015 (post-crisis). In the descriptive analysis we observe, as expected, higher volatility among all variables in the post-crisis period caused by falling asset prices due to the financial crisis and dropping commodity prices resulting from the bursting food price bubble. We indicate that all assets are non-stationary at level but stationary at first difference. This allows us to apply cointegration analysis. To observe the long-run relationship we pairwise applied Johansen cointegration test and investigate cointegration equations based on monthly log returns. We further estimate the Error Correction Model with individual lag lengths for all asset combinations.

Our results suggest statistically high significant cointegration relationships in the post-crisis period. A diversification effect can be observed between the S&P GSCI Agriculture and the EuroStoxx 50 as well as between the Nikkei 225 and FAO Oils. Regarding the S & P GSCI we found positive cointegration to all the applied stock indices. Again, we would like to emphasize that a positive cointegration can be used for diversification if an investor is short positioned in one of the assets.

Overall, our results deliver only evidence for cointegration in the post-crisis period. This suggests that the financial crisis as well as the food price crisis led to a structural change in asset relations. Our results therefore imply that investors should still take the diversification potential of agricultural commodities into account. However, investors should also monitor the development of both asset classes. Fundamental changes in monetary policy, agricultural supply and demand, as well as macroeconomic shocks can lead to structural changes. In this scenario the diversification potential of agricultural commodities has to be determined again. Nevertheless, future studies can extend the analysis in different ways. First, there are various types of commodity investments with diversification potential for instance base and precious metals or energy commodities. Second, instead of equity markets bond markets could be observed to determine diversification potential between commodity and credit markets. Finally, our results are exposed to the used methodology - Johansen cointegration framework. We advise other researchers to overcome this issue using alternative approaches.

References

Ahking, F. (2002). Model mis-specification and Johansen's cointegration analysis: An application to the US money demand. *Journal of Macroeconomics, 24,* 51-66. http://dx.doi.org/10.1016/s0164-0704(02)00017-4

Aizenman, J., Hutchison, M., & Jinjarak, Y. (2013). What is the risk of European sovereign debt defaults? Fiscal space, CDS spreads and market pricing of risk. *Journal of International Money and Finance, 34,* 37-59. http://dx.doi.org/10.1016/j.jimonfin.2012.11.011

Alexander, C. (1999). Optimal hedging using cointegration. *Philosophical Transactions of the Royal Society, 357,* 2039-2058. http://dx.doi.org/10.1098/rsta.1999.0416

Apergis, N., & Miller, S. (2009). Do oil market shocks affect stock prices. *Energy Economics, 31,* 569-575. http://dx.doi.org/10.1016/j.eneco.2009.03.001

Banerjee, A., Dolado, J., Galbraith, J., & Hendry, D. (1993). *Cointegration, error correction, and the econometric analysis of non-stationary data.* New York: Oxford University. http://dx.doi.org/10.1093/0198288107.001.0001

Bansal Y., Kumar S., & Verma, P. (2014). Cointegration and causality between equity and commodity futures: Implications for portfolio diversification. *Global Journal of Management and Business Research: C Finance, 14,* 35-44. Retrieved from https://globaljournals.org/GJMBR_Volume14/4-Co-Integration-and-Causality-between.pdf

Brandt, M. (2012). Starter cultures for cereal based foods. *Food Microbiology, 37, 41-43*. http://dx.doi.org/10.1016/j.fm.2013.06.007

Braun, J. (2008). Food and financial crises: Implications for agriculture and the poor. Retrieved from http://dx.doi.org/10.2499/0896295346

Büyükşahin, B., Haigh, M., & Robe, M. (2010). Commodities & equities: A market of one. *Journal of Alternative Investments, 12,* 76-95. http://dx.doi.org/10.3905/jai.2010.12.3.076

Chatfield, C. (2004). *The analysis of time series: An introduction* (6th ed.). London: Chapman & Hall.

Chen, B., & Saghaian, S. (2015). The relationship among ethanol, sugar and oil prices in Brazil: Cointegration analysis with structural breaks. Retrieved from http://ageconsearch.umn.edu//handle/196788

Chicago Mercantile Group (Ed.). (2015, May 5). Trading quotes. Retrieved from http://www.cmegroup.com/trading/products/

Chong, J., & Miffre, J. (2010). Conditional correlation and volatility in commodity futures and traditional asset markets. *Journal of Alternative Investments, 12,* 61-75. http://dx.doi.org/10.3905/jai.2010.12.3.061

Ciaian, P., & Kancs, A. (2011). Interdependencies in the energy–bioenergy–food price systems: A cointegration analysis. *Resource and Energy Economics, 33,* 326-248. http://dx.doi.org/10.1016/j.reseneeco.2010.07.004

Drobetz, W. (2003). Nichtstationarität und Kointegration: Eine Einführung. Retrieved from https://www.researchgate.net/publication/228472962_Nichtstationaritat_und_Kointegration_Eine_Einfuhrung

Emerson, J. (2007). Cointegration analysis and the choice of lag length. *Applied Economics Letters, 14,* 881-885. http://dx.doi.org/10.1080/13504850600689956

Engle, R., & Granger, C. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica, 55,* 251-276. http://dx.doi.org/10.2307/1913236

Fama, E., & French, K. (1996). The CAPM is wanted, dead or alive. *Journal of Finance, 51,* 1947-1958. http://dx.doi.org/10.2307/2329545

Food and Agriculture Organization of the United Nations (Ed.). (2015). World food situation: FAO food price index. Retrieved from http://www.fao.org/worldfoodsituation/foodpricesindex/en/

Georgiev, G. (2001). Benefits of commodity investment. *Journal of Alternative Investments, 4,* 40-48. http://dx.doi.org/10.3905/jai.2001.318997

Gilbert, L. (2010). Commodity speculation and commodity investment. In FAO (Ed.), *Commodity Market Review* (pp. 25-46). Rome: FAO.

Gorton, G., & Rouwenhorst, K. (2006). Facts and fantasies about commodity futures. *Financial Analyst Journal, 62,* 47-67. http://dx.doi.org/10.2469/faj.v62.n2.4083

Granger, C., & Newbold, P. (1974). Spurious regression in econometrics. *Journal of Econometrics, 2,* 111-120. http://dx.doi.org/10.1016/0304-4076(74)90034-7

Gunzberg, J. (2014). Weighing in on the Dow Jones Commodity Index and the S&P GSCI. Retrieved from http://us.spindices.com/documents/education/weighing-in-on-the-djci-and-the-spgsci.pdf

Gupta, R., & Guidi, F. (2010). Cointegrating relationship and time varying co-movements among Indian and Asian developed stock markets. *International Review of Financial Analysis, 21,* 10-22. http://dx.doi.org/10.1016/j.irfa.2011.09.001

Hakkio, C. (1991). Cointegration: How short is the long run?. *Journal of International Money and Finance, 10,* 571-581. http://dx.doi.org/10.1016/0261-5606(91)90008-8

Hamilton, J. (1989). A new approach to the economic analysis of nonstationary time series and business cycle. *Econometrica, 57,* 357-384. http://dx.doi.org/10.2307/1912559

Hamilton, J. (2014). Macroeconomic regimes and regimes shifts. Retrieved from http://econweb.ucsd.edu/~jhamilto/handbook_regimes.pdf

Hartung, J (1999). *Statistik.* München: R. Oldenbourg.

Hassan, S., & Malik, F. (2007). Multivariate GARCH modeling of sector volatility transmission. *Quarterly Review of Economics and Finance, 47,* 470-480. http://dx.doi.org/10.1016/j.qref.2006.05.006

Hiraga, M. (2015). Sucked into the global vegetable oil complex: Structural changes in vegetable oil supply chains in China and India, compared with the precedents in Japan. In S. Hongladarom (Ed.), *Food security and food safety for the twenty-first century* (pp. 179-194). Singapore: Springer. http://dx.doi.org/10.1007/978-981-287-417-7_16

Institute for Agriculture and Trade Policy. (2008). Commodities market speculation: The risk to food security and agriculture. Retrieved from http://www.iatp.org/files/451_2_104414.pdf

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica, 59,* 1551-1580. http://dx.doi.org/10.2307/2938278

Johansen, S., & Juselius, K. (2002). Identification of the long-run and the short-run structure an: Application to the ISLM model. *Journal of Econometrics, 63,* 7-36. http://dx.doi.org/10.1016/0304-4076(93)01559-5

Kilian, L. (2009). Not all oil price shocks are alike: Distangling demand and supply shocks in the crude oil market. *American Economic Review, 3,* 1053-1069. http://dx.doi.org/10.1257/aer.99.3.1053

Kristoufek, L., Janda, K., & Zilberman, D. (2012). Correlations between biofuels and related commodities before and during the food crisis: A taxonomy perspective. *Energy Economics, 34,* 1380-1391. http://dx.doi.org/10.1016/j.eneco.2012.06.016

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics, 34,* 215-226. http://dx.doi.org/10.1016/j.eneco.2011.03.002

Lombardi, M., & Ravazzolo, F. (2013). On the correlation between commodity and equity returns: Implications for portfolio allocation. *Bank for International Settlements Working Papers, 420,* 1-32. http://www.bis.org/publ/work420.pdf

Lütkepohl, H., & Xu, F. (2012). The role of the log transformation in forecasting economic variables. *Empirical Economics, 42,* 619-638. http://dx.doi.org/10.1007/s00181-010-0440-1

MacKinnon, J. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics, 11,* 601-618. http://dx.doi.org/10.1002/(sici)1099-1255(199611)11:6<601::aid-jae417>3.0.co;2-t

Markowitz, H. (1959). *Portfolio selection: Efficient diversification of investments*. New York: John Wiley and Sons.

MSCI Inc. (Ed.). (2014). MSCI World Index factsheet. Retrieved from https://www.msci.com/resources/factsheets/index_fact_sheet/msci-world-index.pdf

Murray, M. (1994). A drunk and her dog: An illustration of cointegration and error correction. *The American Statistician, 48,* 37-39. http://dx.doi.org/10.2307/2685084

Nazlioglu, S., & Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics, 34,* 1098-1104. http://dx.doi.org/10.1016/j.eneco.2011.09.008

Parker, J. (2012). Learning time-series econometrics: Vector autoregression and vector error-correction models. Retrieved from http://academic.reed.edu/economics/parker/s14/312/tschapters/S13_Ch_5.pdf

Renkl, A. (1993). Korrelation und Kausalität: Ein ausreichend durchdachtes Problem in der pädagogisch-psychologischen Forschung? In C. Tarnai (Ed.), *Beiträge zur empirischen Forschung* (pp. 115-123). Münster: Waxmann.

Sadorsky, P. (2012). Modeling renewable energy company risk. *Energy Policy, 40,* 39-48. http://dx.doi.org/10.1016/j.enpol.2010.06.064

Siddiqui, O., & Ali, M. (1998). A comparison of the random-effects pattern mixture model with last-observation-carried-forward analysis in longitudinal clinical trials with dropouts. *Journal of Biopharmaceutical Statistics, 8,* 545-563. http://dx.doi.org/10.1080/10543409808835259

Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money, 24,* 42-65. http://dx.doi.org/10.1016/j.intfin.2012.11.007

Simon, H. (2012). Spurious correlation: A causal interpretation. *Journal of the American Statistical Association, 49,* 467-479. http://dx.doi.org/10.2307/2281124

Standard & Poor's (Ed.). (2012). S&P GSCI Agriculture Index: Commodity indices. Retrieved from https://us.spindices.com/indices/commodities/sp-gsci-agriculture

Stoll, H., & Whaley, R. (2011). Commodity index investing: Speculation or diversification. *Journal of Alternative Investments, 14,* 50-60. http://dx.doi.org/10.3905/jai.2011.14.1.050

The Economist (Ed.). (2010, November 11). Commodity Speculators: Dr Evil, or drivel? Retrieved from http://www.economist.com/node/17465323

World Food Programme (Ed.). (2009, February 6). Financial speculation and the food crisis. Retrieved from https://www.wfp.org/stories/dr-timmer