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Cycles and Dynamic Correlations Between Agricultural and Stock Markets

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CYCLES AND DYNAMIC CORRELATIONS BETWEEN AGRICULTURAL AND STOCK MARKETS

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Table of Contents

List of Tables

List of Figures

Abstract

This study conducts two interrelated econometric analyses; it first analyzes the cyclical relationship between stock and commodity markets and second, it studies the dynamic conditional correlation between them. The cyclical analysis uses the bandpass filter proposed by Christiano-Fitzgerald (2003) to isolate the trend component in the long-run relationship of stocks relative to commodity markets. The results show that stock and commodities have alternated in return leadership nine times during the last 151 years, three full cycles (from peak to peak) can be clearly identified, each one with an average duration of 31 years. While the COVID-19 pandemic had little impact on the long-term pattern, the 2008 financial crisis marked a turning point for this countercyclical behavior. Individuals and other investors may benefit from commodities by defining investment horizons according to these cycles. The conditional volatility/GARCH model results confirm that the relationship between stocks and commodity markets is interdependent and can lead to improved risk and financial management once the dynamic correlation is quantified. After the 2008 financial crisis, there was a significant increase in the correlation between the two asset classes, commodity, and traditional equity markets, where equity markets were measured by the S&P 500 index. The findings support a peak in the commodity market leadership in the years ahead.

Chapter 1. Introduction

The estimation of risk and return characteristics of agricultural assets has been of recurrent interest to academicians and the investment community over the several past decades. Farming is a risky business and prosperity in farming comes and goes in waves that are connected to the up-and-down swings in the general economy. Agricultural assets and their pricing are unique relative to the pricing of nonfarm financial assets. Returns to farming, for example, are driven by the biological nature of agriculture and the myriad of factors that impact yields. When the inherent biological aspect of agriculture is combined with the need for substantial capital investments to enhance agricultural production and productivity, a fluctuating pattern arises in the returns obtained from land, labor, and capital used in farming. These returns are frequently complemented by government policies. Agriculture is also unique in that the demand for food keeps increasing with increases in population, and given the inelastic demand for food, farming certainly will continue as a business. Like other financial assets, the value of farm assets is affected by economic factors, and in times of economic uncertainty, investing in agriculture has often been considered a hedge against factors such as inflation. While unique in some ways, returns to farming are subject to other macroeconomic fluctuations and policies. For instance, when interest rates increase, the value of farmland land tends to decline and so do the returns to farming, making investing in farming less attractive. When commodity prices increase, however, returns to farmland increase and so does the wealth in farming. It seems plausible to hypothesize that, given the uniqueness and similarity between farm and nonfarm investments, returns and risks in farm and nonfarm asset investments will tend to move together but not necessarily in the same direction, and/or magnitude, and dynamically over time. If this hypothesis is correct, and agricultural assets as investments offer diversification potential, then

investors can benefit from research that measures the risk/return characteristics of both asset classes by explicitly modeling, not only the dynamic conditional correlation between the two but also volatility and risk in both asset classes. In periods of economic uncertainty and increasing volatility, like during the 2008-2009 financial crisis, and the COVID-19 pandemic, investors will be able to find efficient portfolios, that is, portfolios that maximize returns for a given level of risk or that minimize risk to achieve a given level of return. When tied to any possible cyclical co-movement between the farm and nonfarm sectors, these measures of risk/returns can guide the selection of long-term efficient portfolios. In the history of U.S. financial markets, events such as the ones mentioned above have been recurring, and perhaps the dominant example is the stock market crash of 1929 and the high levels of inflation and interest rates experienced in the 1970s and early 1980s. As a result, frequent estimates of potential returns and volatility are required to update portfolios, and moreover, if the two asset classes, farm and nonfarm, are impacted by the same economic and business factors, it seems natural to investigate the extent to which returns, and volatility fluctuates within each asset class and across the two asset classes. If the aforementioned swings in the agricultural economy are long-lasting, what specific questions of research interest may long-term investors benefit from? First, are returns and risks the same or significantly different between the two asset classes? Is the risk-return relationship stable over time? How do the levels of volatility compare within each asset class and between the two asset classes? Is there volatility spillover between the two sectors, and if it exists, how can this information contribute to finding an efficient farm-based portfolio? These are some of the specific questions that in the context of financial investing in agriculture, compared to the broad market, are awaiting to be investigated. For long-run portfolio management, accuracy in risk estimation and how risk and returns correlate over time, and between assets, is required in order

to design risk-efficient portfolios. Conditional correlations and dynamic volatility have been the subject of extensive research in finance, but a direct econometric analysis of the relationship between the broad financial markets and agriculture is missing in the context of the questions raised above. The economic contraction and expansion of the business cycle, and the implied behavior in risk and returns, are investigated in this thesis research.

Academic research evaluating the risk-return characteristics of agriculture dates back several decades. One seminal article (Barry, 1980), using a capital asset pricing model, examined the risk-return characteristics of farmland returns. Subsequent expanded Barry's research, including Sherrick & Barry (2003), Sherrick et al., (2013), and Hennings et al., (2005). A different line of research has focused on the pricing performance of agriculture relative to the broad financial market, using the S&P 500 market index. One study examining this relationship (Zapata et al., 2012) found that boom-bust phases in the relative pricing performance of commodity markets relative to the broad market last over a decade each and that for long-term investors this repeating pattern, and how it has changed over time, may offer opportunities for improved risk management. The observation that in the history of US stock markets, commodities prices and stocks alternate in pricing performance was first documented in Bannister and Forward, 2002. Naturally, the question of whether agricultural asset prices maintain such a relationship to the broad market and whether the length of the cycle is the same as that of a decade ago, is another inquiry of interest to this thesis research.

In summary, this thesis fills this gap in the literature by re-examining and updating the cyclical relationship in stock versus commodity markets found in Zapata et al., (2012). Furthermore, given that the changing nature of markets can impact the risk-return characteristics of a portfolio composed of agricultural and non-farm financial assets (e.g., stocks), this research

measures the dynamic correlation between agricultural assets and the broader stock market. Farm and nonfarm assets are correlated and dynamic, and estimators of the dynamic conditional correlation between farm assets and a general market portfolio can lead to improved portfolio diversification. For long-term investors, measures of the cyclical relationship in pricing performance between the two markets and of the dynamic conditional correlations in the context of the DCC Multivariate Generalized Autoregressive Conditional Heteroskedasticity (DCC-MGARCH) model (Engle, 2002) can be used to improve risk estimation. Studies on the DCC-MGARCH model have shown to be more accurate in measuring the conditional covariances and conditional correlations among financial time series.

1.1. Problem Statement

The return-risk characteristics of agricultural assets change continuously and follow the financial health of the general economy as reflected in the boom-bust periods experienced over the past century (e.g., Melichar, 1984; Zapata et al., 2012). The dynamics implied by the wave-like (cyclical) behavior in the pricing performance of farm assets relative to the overall market can last for several decades. Long-term investment planning in agriculture and the attractiveness of farm assets to non-farm investors can benefit from quantifiable knowledge of the current cyclical behavior in the pricing performance of farm assets and what such behavior implies for long-term portfolio management in agriculture and outside. Moreover, quantifying the dynamic correlation between farm assets and the overall market, in the context of market volatility, provides more accurate estimates of the risk involved in farm investing.

1.2. Objectives

The general goal of this thesis is to analyze the cyclical and dynamic risk-return characteristic of agricultural assets, this goal will be achieved through the following two specific objectives:

1. To re-examine the cyclical pricing performance leadership between commodity and stock markets in the US.
2. To econometrically measure the temporal behavior of the risk-return relationship between farm-related investments and the stock market.

1.3. Procedures

For objective one, Zapata et al., (2012) found that commodity markets alternate in price leadership relative to stocks in a cyclical manner using a relative strength (RS) measure obtained by dividing the Standard and Poor's 500 (S&P 500) over the Producer Price Index (PPI) for the period of 1871 to 2010. This thesis re-examines this finding and provides outlook information for commodity and stock markets. By understanding cycles in agricultural investing, farm and non-farm investors would be able to improve financial risk management using investment horizons defined by these cycles. Given the major economic downturns experienced over the past two decades, namely the financial crisis of 2008-2009 and the COVID-19 pandemic, this research addresses the extent to which cyclical patterns can be affected by such events.

The second objective will be achieved using the DCC-MGARCH model (Engle, 2002) for a range of commodity and agribusiness indices that represent various agricultural asset classes. The DCC-MGARCH uses a combination of univariate GARCH models to yield a correlation value for each point in time.

1.4. Thesis Outline

The rest of this proposal is outlined as follows. Chapter 2 addresses the literature review including previous and contemporary research related to cycles in stock-commodity markets, the function of agricultural assets in investment portfolios, and the dynamic correlation between agricultural investment and the stock market. Chapter 3 consists of the econometric models used for the cyclical analysis, including the bandpass filter (Christiano-Fitzgerald, 2003) methodology, and the DCC-MGARCH model to measure correlations. Chapter 4 includes the results and conclusions are presented in Chapter 5.

Chapter 2. Review of Literature

The literature review is organized into two sections that correspond to the two objectives of this research. First, cycles in agricultural investing relative to the broad market will be reviewed. The second section reviews the econometric models used to model the dynamic conditional correlation of returns and volatility in agricultural asset returns.

2.1. Cyclicality in Agricultural Investing

Cycles in commodity markets

A cycle is a series of recurrent events, it is made up of four typical phases: expansion, peak, contraction, and through. Cycles in commodity prices can have a tremendous impact on the social and economic aspects of countries, particularly for developing countries for which agriculture constitutes the main economic activity. For instance, while a rise in the price of commodities increase revenue for producers, it may negatively impact consumers' purchasing power, which would likely lead to a reduction in consumption of, for instance, food and energy. On the contrary, a low price of commodities means low income for farmers, thus discouraging production.

According to Hallberg and Herendeen (1996), agricultural cycles in the U.S. are influenced by changes in agricultural exports, farm policy, and interest rates, while Johnson & Soenen (2002) state that commodities are related to inflation and even to fluctuations in stock market prices. Consequently, much of the literature devoted to commodity cycles has focused on the length, causes, and consequences of the expansion(booms) or contraction (busts) of commodity cycles as well as the interaction between commodity markets and equity markets.

In the search of literature related to cycles in commodity markets, the Web of Science (WoS) database was employed to obtain an objective review of the literature relevant to this

thesis research. From WoS, publication and citation data were collected. The search began by first searching for “commodity cycles and agriculture”. The option “All Fields” was specified and the search period ranged from January of 2002 to November 2022, as the research was carried out in early December of 2022. The results yielded a diverse variety of scientific publications from many fields (e.g., environmental sciences, engineering environmental, economics, agricultural economics policy, agronomy, energy fuels, agriculture multidisciplinary, etc.). To illustrate, the number of publications per year increased from 4 in 2002 to 34 in late 2022, which means a 750 % increase in annual publications. Similarly, citations increased from 4 also in 2002 to more than 1,100 in late 2022. The exponential growth in the literature dedicated to the subject is shown in Figure 1 and it emphasizes the importance that cyclical investing has received during the last two decades.

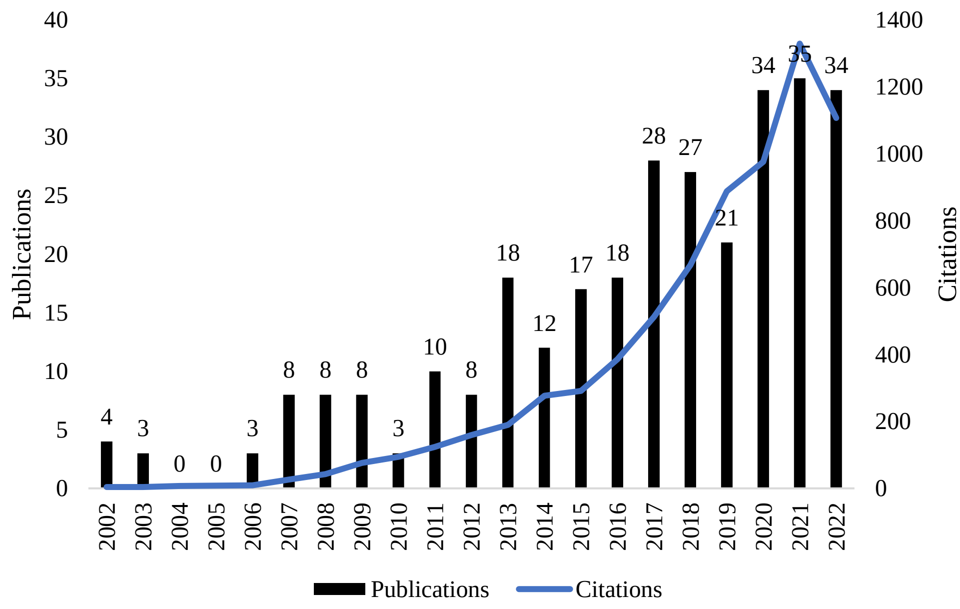

Figure 1. Trend in the number of articles cited/published on “commodity cycles in agriculture.”
Source: Web of Science, 2002-2022

Several authors have suggested the existence of cycles in commodity prices and that these commodity cycles also move contrary to stock market cycles (e. g., Radetzki, 2006).

Radetzki described and contrasted the causes of the most notorious rise in commodity markets after World War II. By analyzing indices of annual prices for three commodity groups (e.g., all non-fuel commodities, metals and minerals, and oil) from 1948 to 2005, he found strong evidence of "three commodity booms" that occurred in 1950-1951, 1973-1974, and the third one that began approximately in 2003. For example, the first "boom" was caused by the accumulation of commodity inventories in fear of the Korean War[1] spreading to other countries, thus increasing the demand for commodities, and raising prices. The second rise in commodity prices was attributed to the oil crisis of 1973 and two previous years of crop failures. Lastly, the third boom started approximately thirty years after the oil crisis of 1973 and was triggered by the growth in the demand for raw materials by China and India. In their analysis related to the causes and consequences of global food price shocks, Abbott & Borot (2011) noted that not all agricultural commodity prices increased at the same rate during the last commodity boom. For example, they found that cocoa, coffee, and cotton prices increased at a much smaller rate than prices for grains and oilseeds.

Along with Radetzki (2006), Carter et al. (2011) empirically described the economic events that caused the two commodity "booms and busts" that occurred after the Korean War. The first boom was in 1974, and the second occurred when commodity prices peaked 34 years later, in 2008. Instead of a singular explanation for the rise in commodities, Carter et al., concluded that commodity booms were caused by a series of supply and demand shocks (e.g. macroeconomic events, cross-commodity linkages, and macroeconomic policies) that reduced commodity inventories.

[1] The Korean war was a major conflict fought between North Korea and South Korea from 1950 to 1953.

Concerned with the study and identification of cycles in commodity prices and their importance for a variety of production and governance decisions, Erten and Ocampo (2013) utilized the bandpass filter (Christiano and Fitzgerald, 2003) to decompose oil and non-oil commodity real prices from 1865 to 2009. Non-oil commodities were sub-grouped into five categories: total non-oil commodities, metals, total agriculture, tropical agriculture, and non-tropical agriculture. Data for non-oil commodities were obtained from Ocampo and Parra (2010), while oil prices were based on West Texas International data available from the World Economic Outlook and the Global Financial Data in the Erten and Ocampo (2013) study. The results of the bandpass filter offered strong evidence of the presence of "four super-cycles" in commodity prices lasting about 30 to 40 years. Non-oil commodity cycles closely followed world GDP and were influenced by agricultural prices. On the other hand, oil prices move opposite to world GDP. Using the same methodology, Büyükşahin et al., (2016) analyzed data of the Bank of Canada commodity index spanning from 1899 to 2015 and found strong evidence of cycles in commodity prices averaging 32 years in length.

Another important contribution to the analysis of cycles in commodity markets was done by Zapata et al. (2012), who studied the historical relationship between stock and agricultural commodity markets. Zapata et al. used the CF bandpass filter to perform a cyclical analysis for the relative price strength of stocks and commodity markets. Using yearly values of the stock market measured by the S&P 500 and the Producer Price Index from 1871-2010, Zapata et al., found that stocks and commodity markets move over time in a countercyclical pattern. They called this cycle, the RS cycle. The RS cycle was estimated to last slightly over 30 years, which is consistent with the findings of Bannister and Forward (2002) who estimated that the RS cycle lasts approximately 36 years. The turning points of the RS points and thus, the length of the RS

is determined by major economic events. For example, the last boom (expansion) for commodity markets began when the dot com bubble burst and ended when the stock market started to recover from the 2007-2009 financial crisis. Booms in commodity markets are characterized by a sustained period of expansion, usually driven by strong growth in demand for raw materials, such as metals, energy, and agricultural products in a way that exceeds what commodity producers can supply. Zapata et al., (2012) also found that the RS cycle was impacted by numerous economic and non-economic events, including wars, high inflation rates, oil crises, and congressional acts. This long-lived cyclical repeating pattern indicates that the relative performance of stocks versus commodity markets alternated in trends over the long period of study.

The countercyclical behavior between stock and commodity markets found by Zapata et al., is consistent with the results of Bodie & Rosansky (1980) who analyzed the risk-return characteristics of a benchmark portfolio[2] of commodities traded in American futures markets from 1950 to 1976. Summary statistics show that commodities' annual rate of return was 13.83 % and a standard deviation equal to 22.43 %, while common stock yielded a yearly return of 13.05 % with a standard deviation of 18.95 %. Thus, the results clearly indicate that the mean returns on both, commodity futures and common stocks were almost the same even though there was a higher risk associated with commodity returns over the study period. Another important finding was how well commodity futures performed during contractions in the stock market and inflationary periods and vice versa. For example, in 1974 the inflation rate was 12.2 %, and the annual returns were -26.48 % and 31.96 % for stocks and commodities, respectively. The inverse relationship of stock versus commodity markets was supported by a correlation coefficient of

[2] A benchmark portfolio of commodities is a portfolio consisting of equal dollar amounts invested in each commodity.

-0.24, suggesting that, there are periods when both assets run in opposite direction. The results of Bodie & Rosansky (1980) provided valuable information to understand the interaction of stocks and commodities over time, however, they did not specifically address any type of cyclicality in the performance of commodities over time.

More recently Vasileios (2019) employed the Hamilton filter to determine the presence of cycles and trends in the extended Grilli-Yang[3] dataset for a total of 112 observations from 1900 to 2011. The original Grilli-Yang data series includes 24 globally traded non-fuel commodities divided into three categories: food, nonfood, and metals. The results suggest that the transition from peak to trough (contraction) is around 10 years, and the transition from through to peak (expansion) is approximately 20 years, implying a cycle length of 30 years approximately. Similar results were found by Awaworyi-Churchill et al., (2022) who used the CF filter to analyze eight sub-index commodity price series: beverages, soft foods, grains, livestock, oils and meal, non-food agricultural, base metals, and precious metals. They used historical commodity prices data over the period from 1300 to 2019 and estimated that cycles in commodities ranged between 30 and 35 years as well.

An understanding of cycles in commodity markets can lead farm and non-farm investors to improve long-term portfolio allocations. The counter-cyclical behavior of commodities versus stock markets suggests that including commodities in a diversified portfolio is an issue worth investigating.

2.1.1. Modern Portfolio Theory and the Role of Agricultural Assets in Portfolios

Given that commodity markets can outperform securities during declines in the broad financial markets and vice versa, and that the empirical literature provides strong evidence of this

[3] Source: https://www.humanprogress.org/dataset/world-agricultural-price-grilli-yang-index/

repetitive pattern, investors would seek to diversify stock portfolios by including agricultural-related assets.

The above statement fits within the theory and intuition behind portfolio diversification, which is first discussed below, then the literature on agricultural commodities and publicly traded agribusiness is reviewed.

Modern Portfolio Theory

Harry Markowitz (1952) published his well-known “Portfolio Selection”, work that established the foundation of modern portfolio theory (MPT) and offered a mathematical framework for examining the risk-return trade-off of a combination of assets (portfolio). MPT, often referred to as mean-variance analysis, proposes that an investor can achieve higher returns only by assuming higher risk. To illustrate the trade-off between risk and expected returns on a portfolio, MPT employs the historical mean of returns as a measure of expected returns and the variance of returns as a measure of risk.

Investment risk can be divided into two types of risk: systematic and unsystematic risk. Systematic risk refers to the risk inherent to the entire market portfolio. Unsystematic risks may apply only to a single firm due to factors such as management, financial commitments, or geographic location. Contrary to systematic risk, MPT suggests that --unsystematic-- risk can be diversified away by constructing a portfolio with low correlated or uncorrelated assets so that an investor can expect higher returns without incurring more risk or what is the same, an investor can keep the expected returns constant but minimize the risk through diversification.

The popular Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) provides a way to measure the systematic risk that cannot be mitigated through

diversification, and this model is often used to study the risk/return characteristics of farm assets relative to other financial assets.

2.1.2 Agricultural Assets in Portfolios

Agricultural Investing

Barry (1980) used the capital asset pricing model (CAPM), a linear regression estimated by least squares, using farm real estate for various regions of the U.S. relative to market indexes such as stock and bonds for the period 1950-1977. Descriptive statistics (e.g., mean, standard deviation, coefficient of variation) and estimates of beta from the CAPM model were reported. One of the first observations from the study was that the excess rate of return for farm real estate at the national level was 6.60 % with a standard deviation of about the same magnitude (6.31). Significant variation in excess mean returns and risk were found across different regions of the U.S. The CAPM theory suggests that the constant term in the linear regression is zero, but Barry found values significantly different from zero with much variation in the size alpha across regions. The same result is observed for estimates of risk (beta). Very little systematic risk in farm real estate at the national or regional levels were reported, implying that farm real estate adds to portfolio diversification. Furthermore, the remaining nonsystematic risk was attributed to unique supply and demand conditions of agriculture which may be eliminated by effective diversification. Barry also points out that the low beta in farm real estate may be due to higher unanticipated inflation, especially during the latter years of the sample period, which the CAPM did not account for.

Two decades after Barry published his article on farm real estate, the new millennium began with a surge in the popularity in commodity investing. Several factors that affected the economy, including the growth in commodity demand caused by countries such as China and

India (Kat, 2006; Radetzki, 2006), together with the poor performance of the stock market during the tech bubble and the increase in the price of commodities reignited the debate on whether or not commodities offered risk diversification benefits. Bodie and Rosansky (1980) used mean-variance analysis and provided the mean return (expected return) and standard deviation (risk) of a set of portfolios consisting of different combinations of common stocks and commodity futures using data from 1950-1976. Two of the portfolios analyzed were made up of either 100 % stocks (μ=13.05 σ=18.95) or 100 % commodities (μ=13.83 σ=22.43). The remaining portfolios were obtained by combining different portions of both assets. The results showed that the most ideal portfolio is that composed of 40 % commodities and 60 % stocks, which has a mean of 13.36 % but the standard deviation is much lower (σ=12.68), thus indicating that the diversified portfolio provides the same expected return than an undiversified portfolio, but at a much lower risk.

Using Markowitz' mean-variance model, Jensen et al., (2000) investigated the efficiency in using commodity futures in portfolios comprised of stocks, bonds, T-bills, and real estate over the period 1973-1997. They concluded that portfolio returns are increased by including commodities, regardless of the level of risk. Jensen et al., also find that the weight of commodities in efficient portfolios is higher during restrictive economic policy. Recent research conducted by Hernandez et al., (2021) used differential evolution optimization to analyze individual risk contribution of a series of nine major traded agricultural commodities to the total risk of agricultural commodities portfolio. They used daily prices of wheat, corn, soybeans, coffee, sugar cane and sugar beets, cocoa, cotton, and lumber for the period 2009-2019. The results suggest that sugar cane, wheat and corn add the most risk to the portfolio, therefore, they should have lower allocation of the total financial resources available. Contrarily, cocoa, cotton,

and lumber contributed with the lowest risk to the total risk in the agricultural commodities portfolio.

Saiti et al., (2018) compared the diversification benefits of a set of commodities (e.g. metal, energy, and agricultural commodities) for Islamic stock investors. A DCC-MGARCH model was employed to analyze diversifications benefits and the conditional correlation between commodities and the MSCI[4] World Islamic Index over the period 2007 to 2017. According to the findings, agricultural commodities offer more diversification benefits than metal and energy commodities for Islamic equity investors. Using wavelet-based diversified and undiversified portfolios, Boako (2020) examine the portfolio performance of the African stock markets with other commodities including agricultural commodities. The findings support the notion that combining a portfolio of commodities and stocks can improve its performance over a range of time horizons.

Publicly Traded Agribusiness Firms

The nonfarm interest in adding agricultural commodities and publicly traded agricultural companies (or agribusinesses) to portfolios has increased. By investing in agribusiness and food companies, farmers may obtain benefits compared to simple market diversification (Duval & Featherstone, 2002). For example, Katchova & Enlow (2013) performed a Dupont analysis to evaluate the return on equity for agribusiness and all the other firms in the market. They also employed several indicators of firm success, including financial ratios and balance sheet/income statement to evaluate the “financial performance of publicly traded agribusiness” firms in comparison to all the other firms in the market from 1961-2011. The results related to profitability, liquidity, and market ratios showed that agribusiness outperformed at the median

[4] MSCI stands for Morgan Stanley Capital International.

the sample of all firms. The outcome from the Dupont analysis indicated that agribusiness firms have higher returns on equity due to higher asset turnover ratios, thus suggesting that agribusiness firms are more efficient in generating revenue by comparison to other firms.

The interest of investors in publicly traded agricultural firms can be seen as well in the development of composite indices of publicly traded agribusiness. Clark et al., (2012) created an agribusiness stock index (AGB index) using the market capitalization of publicly traded companies classified as “agribusiness” by the USDA Economic Research Service and then compared the AGB index to indices of the broader stock market. The market capitalization of the AGB index grew from $24.675 billion in 1970 to $91.8 billion in 2008. The results indicated that the AGB index had higher returns than the S&P 500 and the DJIA for the 2000-2008 period. Similar results were reached by Schnitkey and Kramer (2012) who also constructed an agribusiness index (AgIndex) using a similar methodology as in Clark et al. and concluded that the AgIndex returns exceeded the S&P 500 returns from 2000 until 2011. D’Antoni and Detre (2014) used the agribusiness index created by Clark et al., from 1996 until 2008 to determine how the AGB index performs in conjunction with S&P 500. D’Antoni and Detre applied Copulas and VaR models to their analysis and concluded that a broad-based agribusiness index in combination with the S&P 500 would be unattractive for investors and offer little protection against economic downturns, thus suggesting further research on the subject. First, long-term investors may not be better off holding an agribusiness-only portfolio than investing in other equity indexes such as the S&P 500 and the DJIA. Second, it is necessary to segment and analyze the agribusiness index performance according to different time periods related to the business cycle given that macroeconomic variables can impact the performance of agribusiness firms in a manner different from the way non-agricultural firms respond. Third, since

agribusinesses are a heterogeneous group of companies that range from agricultural machinery, food processors, fertilizer producers, etc., they are subject to more direct supply and demand impacts that may differ from those of broader financial firms. Therefore, the performance of publicly traded agribusiness firms and their implication to portfolio diversification needs to be studied individually.

Chen et al., (2015) used Mean-Value at Risk (M-VaR) and Copulas model to construct the optimal portfolio composition from 37 agricultural assets including five state level U.S. farmland values, 29 agribusiness equities, two commodity futures (corn and oil futures) and the S&P futures index. The portfolio analysis was performed under several risk tolerance assumptions using monthly data for all the 37 assets from 2002 to 2011. Summary statistics of monthly logarithmic returns showed that in some cases agribusiness companies provided higher returns than those of farmland, the S&P futures index and commodity futures at the expense of a much higher risk. In contrast, farmland provided lower returns but were nearly risk-free when compared to equities. In general, the results supported farmland as an attractive investment for low risk-tolerance investors, however, portfolio composition shifted away from farmland to agricultural equities as risk tolerance of investors increased.

2.1.3. Conclusion

The literature on stock-commodity cycles shows that stock and commodities alternate in pricing performance leadership over long time periods (about 3 decades long). Capital investment into agricultural assets (commodities, farmland, agribusiness) has been increasing in the past two decades due to the assumed protection against inflation and diversification benefits they offer in times of economic stress and uncertainty. The diversification benefits of a portfolio depend on the variance and correlation of the returns of its individual assets. However, given the

dynamics of markets, the variance of the returns is not constant, nor is the correlation between the returns of different assets. Econometric models that exist capture correlation across assets in dynamic markets These models can lead to improved estimates of variance (and therefore of the risk) associated with a portfolio and this motivates the use of the DCC-MGARCH model presented later in this thesis.

2.2. Volatility and Dynamic Conditional Correlation Model

A Web of Science search used in early December of 2022 using the keywords "GARCH and agricultural commodities" produced the results shown in Figure 2. Most of the articles found through this search were classified into the fields of economics, agricultural economics policy, business, and business finance, etc. According to the results, the literature on this subject has expanded from 0 publications in 2002 to 452 citations and 14 publications in late 2022, for a total of 1879 citations and 137 publications during the last 21 years (see Figure 2). This exponential development in the literature highlights the growing relevance of using the DCC-GARCH models to better estimate volatility in agricultural commodity markets.

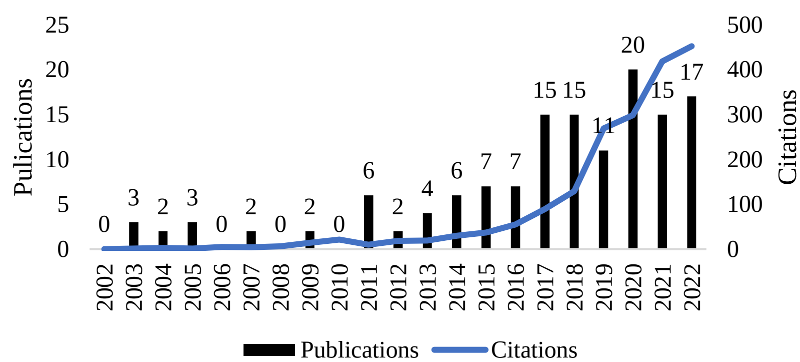

Figure 2. Trend in the number of articles cited/published on “GARCH and agricultural commodities.”
Source: Web of Science, 2002-2022.

The Autoregressive Conditional Heteroskedasticity Model (ARCH) and the Generalized ARCH model (Engle, 1982; Bollerslev, 1986) have been extensively used in literature to analyze

the time-varying variance and the volatility clustering of returns. Volatility clustering refers to the fact that periods of high volatility are followed by periods of high volatility and vice versa. In addition to exhibiting volatility clustering, stock returns may not follow a normal distribution, potentially leading to the underestimation (overestimation) of risk associated with a specific asset or portfolio due to the fat-tailed distribution of financial returns (Sun, 2009), a problem which ARCH and GARCH models can help mitigate by improving the estimated risk.

ARCH and GARCH model applications

Both, ARCH and GARCH, models have been used in the literature to measure risk in financial decisions, including risk management, volatility spillover, forecasting volatilities and correlations of assets including agricultural and non-agricultural commodities (Engle, 2001). Additionally, the literature shows that the ARCH and GARCH models outperform other econometric models such as ARMA and vector regression models in analyzing financial series when the data exhibits volatility clustering or when the homoscedasticity assumption has been violated. For example, Du and Wang (2004) compared a set of different econometrics models (e.g., AR, ARCH, GARCH) to investigate the price movement of wheat futures markets in China, using daily observations from 2000 to 2002. Based on the goodness of fit and forecasting performance, they recommended using the GARCH model over the AR and ARCH models for predicting and analysing the price of wheat in China's futures market. Fałdzinski, et al., (2021) compared the forecasting performance of several GARCH type models with the superior vector regression (SPV) machine learning method for energy commodities. In their analysis they used daily observations of crude oil, natural gas, heating oil, gasoil, and gasoline for the five-year period from 2015 to 2019. The results favored the GARCH models for better predicting volatility in energy commodities when the volatility was measured by the Parkinson estimator.

Concerned with the risk of crop prices in South Africa, the conditional volatility on daily spot prices of yellow maize, white maize, wheat, sunflower seed, and soybeans traded on the South African Stock Exchange was measured by Jordaan et al., (2007) using the GARCH model. Prices for yellow maize, white maize, and wheat start on November 5, 1997; prices for sunflower seeds began on January 7, 2000; while prices for soybeans initiated on April 15, 2002. The last observation for all crops was February 28, 2006. It was found that the price volatility of wheat and soybeans remained constant over time (the price volatility of these two crops was homoscedastic, therefore using a GARCH model was not necessary), proposing these two commodities for farmers who are risk averse, while maize farmers could use financial derivatives like put options to deal with the increased price volatility. More recently, Lestari et al. (2022) analyzed the price volatility of red chili in Indonesia during a thirteen-month period starting on January 2019. After identifying that the data did not meet the assumption of homoscedasticity, the ARCH-GARCH models were utilized with results revealing that the price of red chili in Indonesia is highly volatile. Periods of high volatility typically occur at the beginning, middle and end of the year in response to weather factors and religious holidays.

The causes of price volatility in commodity markets were investigated by Karali & Power (2013). They employed standard GARCH and spline-GARCH[5] models to examine the price volatility in agricultural, energy, and metal futures markets spanning the period from 1990 to 2009. Karali & Power concluded that volatility in commodity prices is affected by changes in inflation, industrial production, and interest rates. Previous research by Yang et al., (2005) revealed that unanticipated futures trading volume could also impact cash price volatility for most commodities traded in US markets. In the same way, Bohl et al., (2018) studied the

[5] See Engle and Rangel (2008)

influence of speculative behaviour on return volatility in Chinese commodities futures markets using a GARCH model. They utilized daily prices from eight commodity future contracts from 2003 to 2017 for soybean meal and soybeans, corn, and cotton from 2004 to 2017, soybean oil and sugar from 2006 to 2017, palm oil from 2007 to 2017, and rapeseed oil from 2012 to 2017. The GARCH model results showed that an increase in speculative behavior can lead to an increase in return volatility of Chinese commodity markets.

Commodity markets are highly volatile (Pindyck, 2004). Volatility in commodity futures market can be caused by macroeconomic variables, trading volume in futures markets, weather events, and other factors. ARCH and GARCH models are often used to estimate volatility and risk. It is expected that any impact on the volatility of an individual asset will modify the relationship of such asset with other assets in an investment portfolio. Thus, it is conceivable that this relationship holds for more aggregate analyses such as in evaluating the pricing performance of farm and nonfarm asset pricing.

2.2.1. Correlation Models

The risk of a portfolio, expressed as variance, depends upon two factors: the variance of its individual assets and the correlation among them. Traditionally, the Pearson correlation is used to estimate the linear relationship between two variables. However, due to its linear nature, it may fail to uncover non-linear relationships, especially when they impact only a small segment of a lager dataset (Bhatta, 2017). The Pearson correlation coefficient is given by:

$$\rho_{x,y} = \frac{\mathrm{cov(x,y)}}{\sqrt{\mathrm{var(x)}}\sqrt{\mathrm{var(y)}}} \qquad \text{(Eq. 1)}$$

where $\mathrm{cov(x, y)}$ is the covariance between x and y, and $\sqrt{\mathrm{var(x)}}$ *and* $\sqrt{\mathrm{var(y)}}$ are the square root of the variance of x and the variance of y, respectively.

The correlation ranges between -1 and +1. A positive correlation coefficient indicates that two variables move in the same direction. On the other hand, a negative correlation between two variables means that as one increases, the other declines linearly; if the correlation coefficient is equal to zero, this implies that there is no linear relationship between the two variables. Historically, it has been thought that commodities have a negative (or close to zero) correlation with stocks. A negative stock-commodity correlation was found by Gorton & Rouwenhorst (2006) when analyzing commodity futures contracts during the 1959-2004 period. These findings suggest that for some time periods, commodities as a separate asset class can lead to a reduced portfolio risk.

Along with a potential negative or low correlation between commodities and stocks, commodities may offer investments benefits. First, commodities are positively correlated with inflation, particularly unexpected inflation (Gorton & Rouwenhorst, 2006). Second, commodities provide equity-like returns. Bodie & Rosansky (1980) using commodity and stock returns from 1950-1976 found that the mean returns on commodity futures were similar to stock returns. Likewise, Greer (2000), after analyzing the returns of stocks and commodities during the period 1970 to 1999 concluded that the returns in both assets were similar as well. These characteristics make commodities worth including in diversified portfolios, especially during times of economic turmoil when investors need to offset potential losses in the broad stock market. Third, commodity price behavior directly reflects fluctuations in market fundamentals (supply and demand) that may not impact other financial assets.

Correlation and diversification are closely related concepts. Assets with low correlation or uncorrelated assets offer risk diversification in Markowitz' efficient portfolios. Although the cited literature so far has suggested a negative (or close to zero) correlation between stocks and

commodities, other scholars noted that this relationship is highly volatile and it fluctuates depending on, among other factors, the different phases of the business cycle (Bhardwaj & Dunsby, 2013). Efforts to model changing correlations has been subject of extensive research. Engle (2002) proposed the DCC Multivariate Generalized Autoregressive Conditional Heteroskedasticity Model (DCC-MGARCH model) to capture the volatility of assets returns and to allow the correlation matrix of asset returns to vary over time. Such updated correlation coefficient estimates can be used to obtain more accurate estimations of portfolio risk.

An early implementation of the DCC-MGARCH model to estimate the relationship between stocks and commodities was done by Büyükşahin et al., (2008). Using monthly returns of commodity and stock indices, Büyükşahin et al., found that from 1992 to 1997 there was an overall positive correlation between the S&P Goldman Sachs Commodity Index and S&P 500. Inversely, this correlation went down to an average of -0.3 from 2002-2007 (statistically significant with α=5 % in both periods) reinstating again the common belief that commodities can offer risk management benefits. Additionally, they concluded that between 2002 and 2007, commodity returns nearly doubled those of stock returns.

The good performance of commodity markets during the first decade of the 2000s was also mentioned by Zapata et al., (2012) and Irwin et al., (2020). Contrary to the period from 2002 to 2007, the 2008 financial crisis marked an inflection point in the stock-commodity correlation. Creti et al., (2013) examined the link between the stock market and commodities applying a DCC GARCH model to determine whether the correlations changed in response to the 2008 financial crisis using data from 25 commodities (energy, raw materials, agricultural, food, etc.,) and the S&P 500 for the period 2001-2011. Results showed that correlations between stock and commodity market are highly volatile and comove over time. Second, the correlation fell in

2008, demonstrating that investors who often chose commodities as a haven are more aware of the advantages of diversification during times of uncertainty in the stock market. Third, the highest correlations were observed after the 2008 financial crisis, concluding that the growth in the stock market influences the demand for industrial commodities causing the two markets to move upwards. Similarly, Baldi et al., (2016) used a volatility impulse response function to analyze the impact of stock market shocks on commodity price volatility. Baldi et al., noticed that after the 2008 financial crisis, volatility spillover dramatically increased, indicating a growing interrelation between financial and agricultural commodities markets. The aforementioned findings corroborate previous literature related to the fluctuation in the stock-commodity correlation coefficient according to the phases of the business cycle.

The economic crisis that ended in 2009 was the beginning of the longest period of expansion of the business cycle in the US economy. During this period, stock market returns largely outperformed commodity market returns. It was not until the early 2020s that the stock market was drastically impacted by the COVID-19. The financial crisis caused by the COVID-19 combined with high inflation and increases in interest rates in 2020s, as well as the low unemployment levels, may have changed the long-lived countercyclical behavior and the dynamics of the correlations in commodity and stock markets.

Chapter 3. Methods

3.1. Stock-Commodity Price Performance

The Relative Price Strength Ratio (RS) will be used to compare the long-run cyclical relationship between stock and agricultural-commodity prices (Zapata et al., 2012). The RS compares the relative performance of two variables: stocks and agricultural-commodity prices, showing the relative price performance to each other. When the RS moves up, it indicates that stock returns are outperforming commodity returns. When the RS is moving down, it indicates that commodity returns are performing better than stock returns. The RS is computed by dividing a stock index over a commodity index:

$$RS = \frac{Stock\ index}{Commodity\ Index} \quad \text{(Eq. 2)}$$

For the stock index, the S&P 500 will be used. On the other hand, commodity indexes will be measured by the PPI, the Bloomberg Commodity Index (BCOM) and the S&P Goldman Sachs Commodity Index (SPGSCI). Although there are currently several commodity indices, for this study only those with more than 30 years of records were considered, since most of the literature suggests that this is the minimum duration of the stock commodity cycles.

Stock-Commodity Econometric Cycles

The Bandpass filter proposed by Christiano-Fitzgerald (CF) is utilized to estimate the cyclical components of the RS cycle. Given a time series $\{x_t\}_{t=1}^{T}$, the Bandpass filter isolates a component of x_t denoted y_t of the series with periods of oscillations between p_l and p_u (p_l and p_u are the minimum and maximum periods of oscillation of the component y_t), where $2 \leq p_l < p_u < \infty$. The CF filter is a finite sample approximation to the ideal bandpass filter and minimizes the mean squared error criterion. In this context, the CF filter, adapts to unit root processes, and provides a good approximation in the case of stationary series.

The minimum and maximum values of the oscillation periods are fix to 18 and 36 years($p_l = 18,\ p_u = 36$). The length of the cycles estimated by the CF methodology is the time it takes to move from peak to peak.

Price Performance Data

Annual average data of the Standard & Poor's (S&P 500) from 1871 to 2022 was calculated from the monthly observations from Shiller (2022), and the corresponding data needed for the annual PPI for all commodities was obtained from Federal Reserve Bank of Saint Louis (FRED) and the Bureau of Labor Statistics (U.S. Bureau of Labor Statistics, 2022). To analyze the performance of the cyclical analyzes during the 2008 financial crisis and the pandemic caused by COVID-19; monthly values of the PPI and S&P 500 from July 2007to June 2010, and from January 2019 to December 2021 were used. The base year for the PPI used in this study is 1982 = 100.

In addition to the PPI, the S&P 500 was compared to two commodity indices, namely, yearly data for the BCOM (1960-2022) and the SPGSCI (1970-2022) indices; data for both indices were downloaded from the Bloomberg terminals located at the LSU E.J. Ourso College of Business. The S&P 500 was chosen as a benchmark due to its comprehensive coverage, representing about 80 % of the total market capitalization of publicly traded companies in the United States (S&P DJI, 2022).

3.2. Dynamic Correlations

To achieve the second objective, this study employs the multivariate dynamic conditional correlation GARCH (DCC-MGARCH) model introduced by Engle & Sheppard (2001) and Engle (2002) to estimate the time-varying correlation between stock and commodity markets. Engle extended the Bollerslev (1986) constant conditional correlation (CCC) model by allowing

the correlation matrix of the standardized residuals to vary over time so that the DCC-MGARCH will yield a value for the correlation at any point in time. Knowing how the correlation between stocks and commodities changes over time is important to determine whether or not commodities provide any diversification benefits in an investment portfolio. The DCC is a two-step model, and it has been extensively used in literature to estimate the time-varying correlation between two series. First, a GARCH (1,1) model is estimated for residual series individually. Then, a time-varying correlation matrix is estimated using the standardized residuals from the first step. The DCC model can be estimated using the following steps:

1. For each series of returns $r_{i,t}$, estimate the conditional volatility $r_{i,t}$, using the GARCH model (Bollerslev, 1986).
2. Define D_t to be a diagonal matrix with conditional volatilities $\sigma_{i,t}$ so that

$$D_{ii,t} = \sigma_{i,t}, \text{ with } D_{ij,t} = 0 \text{ for } i \neq j. \quad \text{(Eq. 3)}$$

3. Standardize residuals by

$$v_t = D_t^{-1}(\mathrm{rt} - \mu) \quad \text{(eq. 4)}$$

   so that these estimated residuals have unit conditional volatility.
4. Define the matrix:

$$\bar{R} \frac{1}{T} \sum_{t=1}^{T} v_t v_t' \ . \quad \text{(Eq. 5)}$$

   This is the Bollerslev (1990) CCC model.
5. Generalize Bollerslev’s CCC to capture dynamics in the correlation and produce the DCC correlations given by

$$Q_t = \bar{R} + \alpha\,(v_{t-1}v_{t-1}' - \bar{R}) + \beta\,(Q_{t-1} - \bar{R}). \quad \text{(Eq. 6)}$$

Notice that the $Q_{ij,t}$ is the correlation between the r_{it} at r_{jt} at time t which are used in plots generated by most computer programs.

Estimates of α and β are obtained by maximizing the log-likelihood function of this model, with the usual restriction that $\alpha + \beta < 1$ at $\alpha, \beta > 0$.

DCC-MGARCH Data

To estimate the DCC across commodities and stock markets, daily returns observations of the S&P 500, the S&P Global Agribusiness Equity Index (SPAGREDP), S&P Global Agribusiness Composite Index (SPAGRDP), the S&P Goldman Sachs Commodity Index (SPGSCI), the Bloomberg Commodity Index(BCOM), S&P GSCI Agriculture Index (SPGSAGP) and returns of the Roger International Commodity Index (RICIGLTR) were obtained over the period from January 6st, 2004 to Oct 28th, 2022 to compare with the S&P 500 and commodity indices and to analyze how this correlation has varied during the different rare events that have impacted the economy during the last 18 years. S&P 500 returns were calculated from daily observations obtained from Yahoo Finance. Standard and Poor's provided the data needed for the S&PGA. Similarly, the Bloomberg terminals located at the LSU E.J. Ourso College of Business provided the remaining data.

Chapter 4. Results

4.1. Stock-Commodity Price Performance

Summary statistics of the price performance data

Prices of stock and commodity markets are illustrated in Figure 3. For the S&P 500 and the PPI, prices start in 1871, while for the two investable commodity indices, the BCOM and the SPGSCI, annual prices start in 1960 and 1970 respectively. In Figure 3 it can be seen that the stock market began to grow exponentially in the early 1980s, ushering in an era of innovation and technological advancement, this growth was interrupted when the dot com bubble collapsed in 2000. Later, the growth in the stock market was also affected again by the financial crisis of 2008 which would be the worst recession since the 1930s. The PPI also shows a significant increase (albeit to a lesser extent than the growth in the stock market) that started shortly before the 1950s and has continued to grow moderately during the subsequent decades. The BCOM shows two price spikes, the first occurring in the mid-1970s and the second in the early 2000s. Lastly, the SPGSCI shows high price variability, especially in the period prior to the year 2000, while the last two decades have been characterized by sudden rises (and falls) in SPGSCI prices.

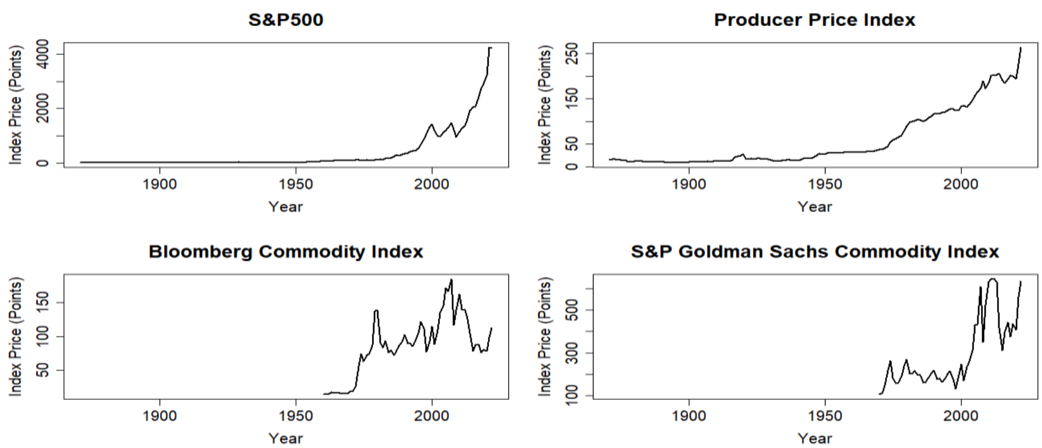

Figure 3. Historical stock and commodity prices of the S&P 500 and PPI (1871-2022), BCOM (1960-2022) and SPGSCI (1970-2022).
Source: Adapted from data available from Yahoo Finance, FRED, Shriller and Bloomberg.

Table 1. Summary statistics for the S&P500, PPI, BCOM, and SPGSCI annual returns (%).

Variable	N	Mean	S.D.	Minimum	Maximum	Kurtosis	Skewness
S&P 500	151	4.50	15.23	-67.88	37.80	2.77	-0.98
PPI	151	1.90	7.78	-45.95	31.73	10.10	-1.11
BCOM	62	3.26	19.32	-45.59	75.42	2.92	0.33
SPGSCI	52	3.47	22.44	-55.86	40.75	-0.09	-0.54

Note: Returns are estimated as natural log returns times 100. The time span covered for S&P 500 and PPI is from 1871 to 2022.The timeframes for BCOM and SPGSCI are 1960-2022 and 1970-2022, respectively.

Summary statistics of annual returns[6] calculated from the indices showed in Figure 3 are summarized in Table 1. From 1871 to 2022, the average annual logarithm returns of the S&P 500 and the PPI were 4.5 % and 1.9 %, respectively. The BCOM and SPGSCI had similar returns, differing by only 0.21 % on average. The results of the standard deviation of BCOM (σ=19.32 %) and SPGSCI (σ=22.44 %) confirm the high variability in commodities, followed by the S&P 500 with σ=15.23 % and finally the PPI with σ = 7.78 %. When summary statistics were computed for the period of 1970 to 2022 for all indices, the average returns for the S&P 500 were 7.55 % (σ=12.94 %), while for the PPI and BCOM the average returns were 3.79 % (σ=5.40 %) and 3.48 % (σ=20.83 %), respectively. This would suggest that commodities have higher risk for the return when periods of comparison ignore the relationship and covariation between them. The minimum and maximum values have a wide range, this is because the logarithmic returns were calculated based on annual average prices, and it is also due to infrequent events, such as the great depression of the 1930s and the financial crisis of 2008. Kurtosis and skewness values are bigger(smaller) than those of a normal distribution.[7]

[6] Log returns are calculated using the following formula: $r_t=\log(P_t/P_{t-1})*100$ where r_t is the rate of return at time t, P_t is the index price at time t, and P_{t-1} is the lag one index price.

[7] A normal distribution has a kurtosis equal to three and skewness equal to zero.

The RS cycles.

The relative price strength ratio (RS cycle) of stock versus commodity markets is shown in Figure 4 spanning the period of 1871-2022. A logarithmic[8] scale is used on the vertical axis to provide a better insight into the countercyclical pattern of stocks versus commodities. The rising arrows shown in Figure 4 indicate periods of better performance of stock markets relative to commodities. Typically, expansions in the stock market are characterized by low interest rates, increased spending by consumers, low unemployment rate, growth in the Gross Domestic Product, etc. Periods when commodities outperformed the stock market are represented by the falling arrows. As seen in Figure 4, stock and commodity markets have moved along a cycle that resembles the business cycle and have alternated in returns leadership nine times since 1877. The countercyclical behavior in stock and commodity markets is time dependent and was noted early by Bannister and Forward (2002) who estimated that the length of the RS cycle was 36 years from peak to peak. Zapata et al., (2012) described the economic and non-economic events that impacted the RS cycle. Moreover, major events (including wars, recessions in stock markets, high inflation rates, oil crises, and farm acts) were triggers for bullish markets in commodities at various times.

Figure 4 indicates that there have been four long periods during which commodities have yielded, on average, higher returns than stocks. For example, the first period when commodities outperformed stocks span from 1907 to 1920. This period covers the panic of 1907 and World War I, being a golden era for agricultural exports. Additionally, the Federal Farm Loan Act of 1916 provided small farmers and ranchers with loans. Agriculture commodity prices jumped to historic highs due to the food demand influenced by the war. As expected, worldwide

[8] A log(10) scale was utilized.

agricultural production recovered after the war ended, leading to a decline in agricultural exports, consequently, a loss in farm revenue (Henderson et al., 2011).

The second period began in 1930 covering the period of the Great Depression and ending shortly after World War II, in 1948. It should be noted that both the stock market and the commodities market saw negative returns in the early years of this period, commodities outperformed stocks in terms of average returns, though. The bills that were enacted during these years include: The Agricultural Adjustment Act (AAA) of 1933, The Gold Reserve Act of 1934 and the “New Deal.” Farmers were provided subsidies in return for limiting their production of particular crops under the AAA. Subsidies were intended to reduce overproduction, allowing crop prices to rise. The Gold Reserve Act of 1934 prohibited the private possession and use of gold as currency. The government called in private gold and then stopped the Treasury from exchanging dollars for gold, causing the dollar to devalue by 40 %. This period was also influenced by World War II. For instance, U.S. agricultural exports increased from $4.3 billion in 1941 to $25 billion by 1944 (Henderson et al., 2011).

The third long period when commodities outperformed stock markets started approximately in 1969 and ended around 1982. This period covers four contractions in the business cycle. It was a period of increased volatility in commodity markets influenced by the collapse of the Bretton Woods regime (Cashin et al., 2002). Another feature that made the 1970s exceptional was high inflation throughout the entire decade. The oil embargo imposed by the Arab countries, members of the Organization of Petroleum Exporting Countries (OPEC), led to the oil crisis of 1973 which increased oil prices up to 400 % approximately from 1972 to 1974 (Carter et al., 2011). Like the first and second commodity bull market, this was also affected by agricultural exports (Hallberg and Herendeem, 1996). For example, grain commodities (e.g.,

rice, corn, wheat.) almost tripled their value in the early 1970s, to some extent, as a consequence of the "Great Grain Robbery".

Figure 4. Historical relationship between stocks and commodity prices.
Source: Adapted from Bannister and Forward, (2002); Zapata et al., (2012)

The increase in demand for commodities by emerging markets (e.g., China and India) was the main driver in the last commodity boom which started in the 2000 and ended about 2009. An increasing world population in combination with a growth in purchasing power in developing countries led to an ongoing rise in global demand for commodities. Along with agricultural and energy commodities, metals also became a price leader during this commodity boom (Carter et al., 2011). The presence of institutional investors caused what is known as financialization of commodities.

Even though during 2010 and 2011 commodities still generated attractive returns, stock returns were higher during these years and would continue to be so for the next decade. The stock market outperformed commodity markets even during the year that the COVID-19

pandemic began, and the subsequent year 2021. However, probably because of the high inflation rates and the Russian-Ukrainian war, among other factors, the stock market lost its pricing performance leadership compared to commodities in 2022.Although inflation in 2022 is still far above the target rate of 2 %, and the stock market has declined by more than 25 % year-to-date as of October 12, 2022, it is too early to predict whether commodity returns will outperform stocks in the coming decade. However, based on evidence from the last 151 years, it can be concluded that cycles in stock and commodity markets do exist and last longer than a decade.

Stock-commodity performance during financial crises

In this section, the effect of the 2008 financial crisis and the COVID-19 pandemic on the RS cycle is analyzed. Figure 5 compares the relationship between stocks and commodity prices (using RS) during the 2008 financial crisis (left) and the COVID-19 pandemic (right) by using monthly values of the PPI and S&P 500 from July/2007-June/2010 and January/2019-December/2021. The financial crisis of 2008 altered the RS cycle's trajectory, marking the end of the commodities bull market and the beginning of the new period of growth in the stock markets.

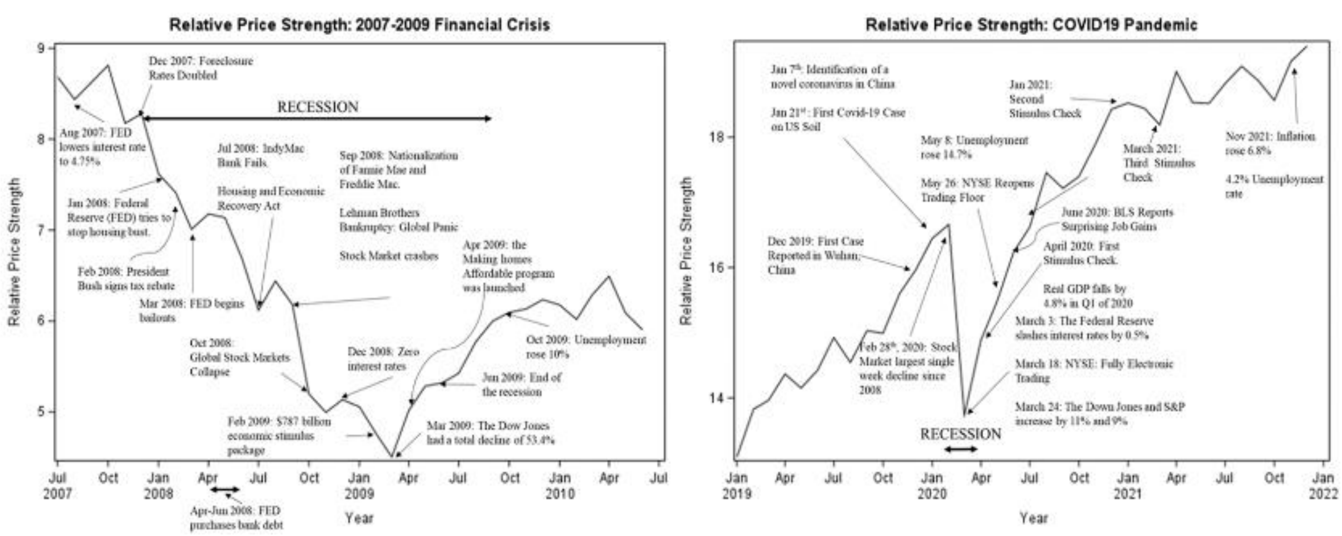

Figure 5. Stock market (S&P 500) versus PPI for all commodities during the 2008 financial crisis and the COVID-19 pandemic.

Although the effects of the crises on unemployment and Gross Domestic Product were more severe during 2020 than during the 2008 financial crisis, prompt health actions and fiscal policies helped the recovery from the COVID-19 crisis at a much faster pace than that of the 2008 financial crisis (note the differences in the “V shapes”). The overriding conclusion is that the coronavirus, a biological agent causing economic stress, did not change the long-term trend of the RS cycle and was less impacted than the 2008 financial crisis.

Econometric estimation of the RS cycle

Figures 6-8 include the results of the Christiano-Fitzgerald bandpass filter applied to the relative price strength (RS) of stocks and producer price index for all commodities (Figure 6), stocks and Bloomberg Commodity Index (Figure 7), and stocks and the S&P Goldman Sachs Commodity Index (Figure 8). Similar to Figure 4, Figure 6 shows the RS cycle over the period 1871-2022. Variability in the RS cycle began to increase approximately from 1930 to the present. The overall upward tendency of the RS cycle observed in Figure 6 (Panel A) confirms the previous summary statistics showing that on average, stock returns outperformed commodities over the last 151 years. However, the Christiano-Fitzgerald econometric cycle (Panel B, Figure 6) demonstrates the cyclical behavior of the relative pricing performance of stock-commodity markets. Based on Panel B (Figure 6), three cycles (from peak to peak) can be fully identified. The first cycle lasted 23 years, and the subsequent cycles had a length of 35 and 34 years, respectively. The average length of the three stock commodity cycles shown in Figure 6 is 31 years. Yet there is a fourth cycle that began 23 years ago; however, at the moment it cannot be ascertained that it has already reached its maximum peak, especially when it is observed that the length of the two previous cycles has been much longer than the length of the very first cycle.

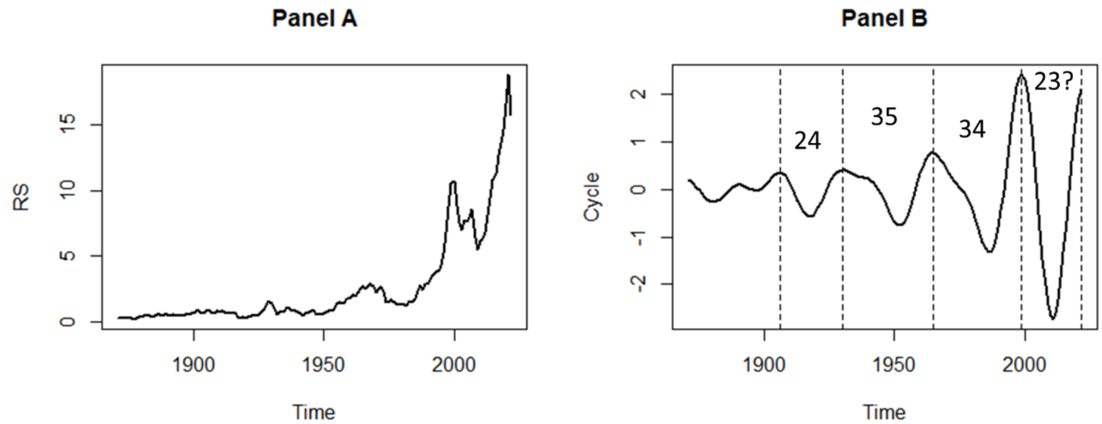

Figure 6. Stock market (S&P 500) versus PPI for all commodities Relative Strength (RS) and the RS CF cycle (1871-2022).

The cycle of stocks relative to commodities shown in Figure 6 has important implications for investors interested in investing in commodities. The summary statistics from Table 1 stated that during the previous 151 years, the average annual returns of the S&P 500 and the PPI were 4.5 % and 1.9 %, respectively. But, when analyzing each phase of the RS cycle it is found that when stocks outperformed commodities (uptrend phases of the RS cycle), stock annual returns are 9.25 % while commodities had annual returns of 0.15 %. Inversely, when commodities outperform stocks (downtrend phase of the RS cycle), stock returns are -1.6 %, and commodity returns equally 4.9 % annually. It is evident from Figure 6 that the benefit of commodity diversification lies in their “cyclical” nature. The abundant literature promoting commodities generally concludes with phrases like adding commodities provides diversification benefits during "contractions in the stock market", which is consistent with what the RS cycle of Figure 6 reveals.

To provide a more adequate comparison between stocks and commodities, in addition to the producer price index, this thesis also examined the long-run linkage between the S&P 500 and two investable commodity indices: the Bloomberg Commodity Index and the S&P Goldman Sachs Commodity Index. Figure 7 displays the relative performance between the S&P 500 and

the Bloomberg Commodity Index. The results of Panel B (Figure 7) confirm that the mid-1960s to the early 1980s and during most of the decade from 2000 to 2010, were periods of high growth in commodity prices. This is consistent with historical data which shows that commodity prices experienced a significant surge during the 1970s due to geopolitical events such as the oil embargo, and again in the early 2000s due to the strong demand from emerging markets like China and India. The length of the cycle shown in panel B (Figure 7) is 34 years, which is equal to the last full cycle in Panel B (Figure 6). However, as can be seen on the vertical axis of both, Panel B (Figure 7 and Figure 8) the amplitude of the cycle is greater when BCOM is used as a proxy for commodities.

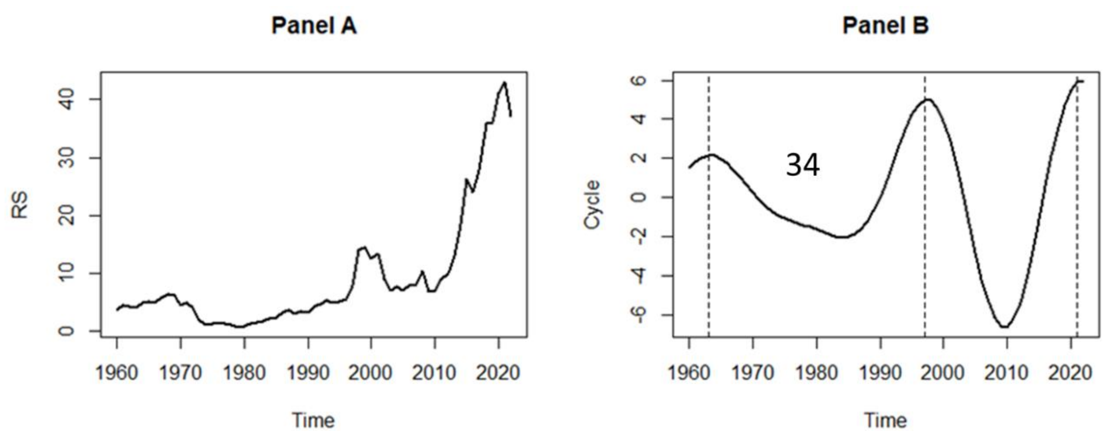

Figure 7. Stock market (S&P 500) versus BCOM Relative Strength (RS) and the RS CF cycle (1960-2022).

Figure 8 (Panel A) shows the price performance of the S&P 500 relative to the S&P GSCI. Launched on April 11, 1991, the S&P GSCI is a well-known benchmark for representing global commodity prices. Even though the annual data available starts in 1970, it can be seen in Panel B that the results are very similar when using the S&P GSCI and the BCOM, which is not surprising given that both indices track many of the same commodities (see Appendix A).

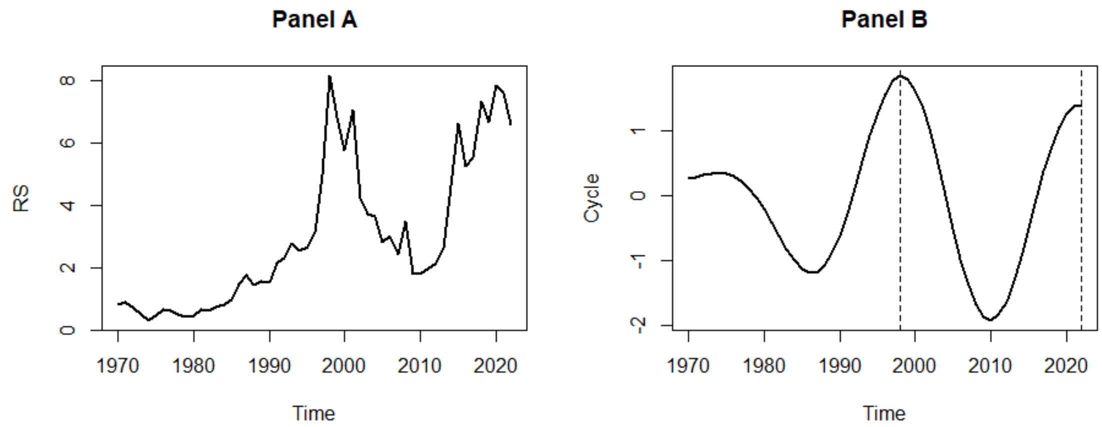

Figure 8. Stock markets (S&P 500) versus the S&PGSCI Relative Strength (RS) and the RS CF cycle (1970-2022).

Overall, Figures 6-8 support previous literature concerning the countercyclical behavior of commodities and the stock market. In the long term, the returns in the stock market exceed the returns in the commodity market on average, however, when considering an investment horizon according to the RS cycle, investors seeking to benefit from commodities can take advantage of their cyclical behavior relative to stock markets by investing in the Bloomberg Commodity Index and the S&P Goldman Sachs Commodity Index for example.

4.2. Dynamic Conditional Correlation GARCH

Summary statistics

Table 2 contains the summary statistics of the daily log returns (%) of the stock market (S&P 500) and six agricultural commodity-related indices. The 4,696 daily observations for each of the indices cover the period from January 2004 to October 2022. The daily returns to the S&P 500 were 0.027 % (about 6.68 % annually). It is evident that the S&P 500 mean returns in the sample size has been lowered due to the poor performance of the stock markets during the current year 2022, the financial crisis of 2008 and the COVID-19 pandemic (see Figure 9). Commodity and agribusiness return ranged from an average of -0.011 % (about -2.74 % annually) for the S&P GSCI Agriculture Index to 0.037 % (about 9.36 % annually) return for the

SPAGREDP, the latter outperformed all the other indices, including the S&P500. Figure 10 shows that all indices suffered a price drop during 2008, but BCOM and SPGSAGP are two examples of commodity indices that have not yet reached previous highs. Although 2004 to 2008 was a bull market for commodities, according to the RS cycle, from 2009 onwards it has been a period of growth for stocks in general. This clarifies why the S&P 500 and the index made up of publicly traded agribusiness firms (SPAGREDP) have outperformed the other indices.

Table 2. Summary statistics and normality test of stock, commodity, and agribusiness indices returns (%) from January 6, 2004, to October 28, 2022.

Variable	**N**	**Mean**	**S. D.**	**Min**	**Max**	**Kurtosis**	**Skewness**	**JB**
SP500	4696	0.027	1.227	-12.765	10.424	13.105	-0.603	33811.3***
SPGSAGP	4696	-0.011	1.309	-7.917	7.155	2.483	-0.112	1212.6***
RICIGLTR	4696	0.010	1.216	-11.117	6.286	5.086	-0.557	5289.8***
SPAGRDP	4696	0.015	0.982	-10.706	9.540	14.606	-0.992	42418.1***
SPGSCI	4696	0.018	1.525	-12.523	7.683	4.922	-0.504	4926.2***
BCOM	4696	-0.005	1.068	-6.402	5.647	2.841	-0.356	1673.8***
SPAGREDP	4696	0.037	1.307	-16.461	10.445	15.485	-1.195	47926.1***

Note: Returns are estimated as natural log returns times 100. *** denotes statistical significance at 1 % level.

Concerning the standard deviation (S.D.) which represents the risk in the indices, the SPAGRDP (σ = 0.982) has the smallest standard deviation of all indices. On the other hand, the highest standard deviation is for SPGSCI (σ =1.525) suggesting the SPGSCI is the riskiest index among all indices. The standard deviations of SPAGREDP and SPGSAGP are quite similar despite the huge differences in their average returns. Additionally, the minimum and maximum values are several standard deviations away from the mean. These extreme values have occurred during periods of high uncertainty and crisis in stock and commodity markets. The values for kurtosis show that two of the indices (BCOM and SPGSAGP) are platykurtic and the other five are leptokurtic, thus suggesting that five out seven indices analyzed have fat tails in the probability distribution of returns. Based on the skewness results, it can be said that only

SPGSAGP and the BCOM are approximately symmetric, the other five indices are moderately to highly skewed to the left. The results from the Jarque-Bera (JB) test are highly significant at a 1 % significance level, consequently rejecting the null hypothesis that the returns are normally distributed (Jarque and Bera, 1980).

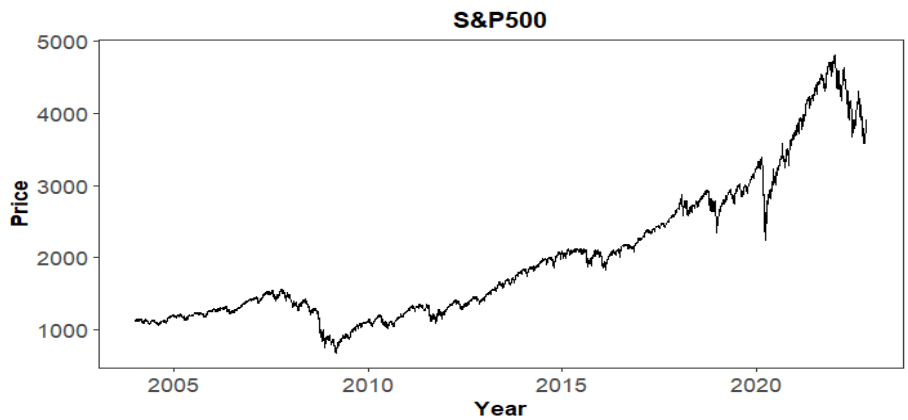

Figure 9. S&P500 daily prices in index points. January/06/2004 to Oct/28/2022.

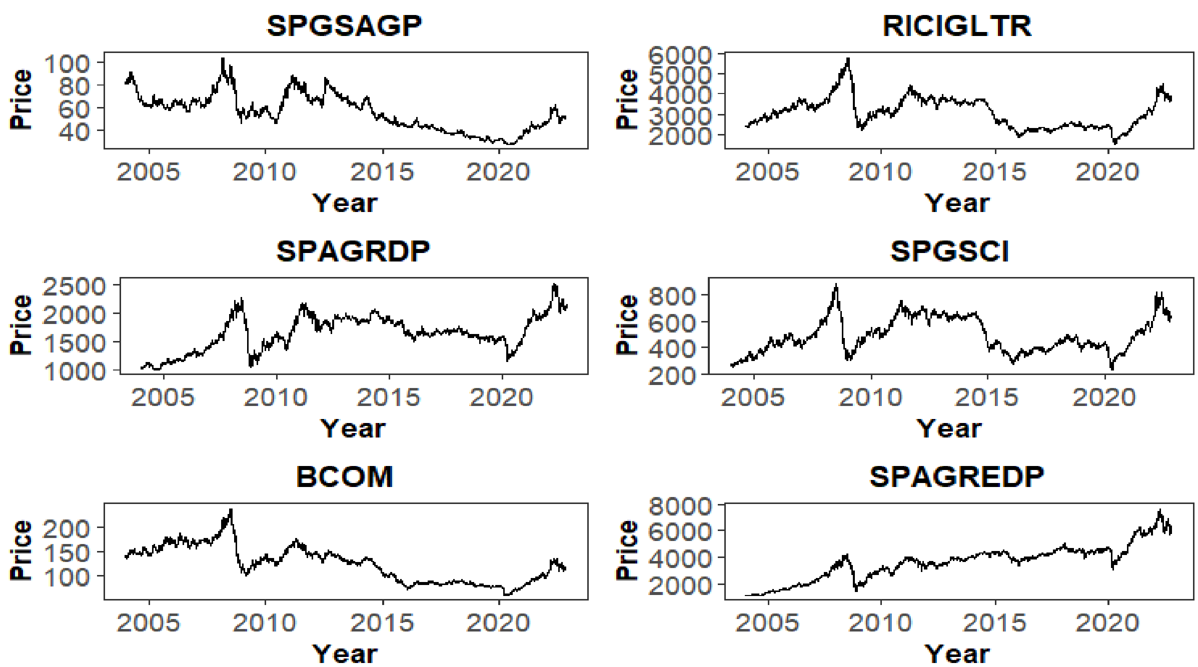

Figure 10. Commodity &Agribusiness daily prices in index points. January/06/2004 to Oct/28/2022.

Time-varying correlations

One of the benefits of using a DCC-MGARCH model is that it allows the conditional correlation to fluctuate over time. Since financial risk management depends on the correlation among assets, having more reliable estimates of correlations and covariance matrices could lead to improved portfolio risk management. According to the results of Table 2, all the indices used in this thesis are not normally distributed. Figure 11 and Figure 12 show the returns to the stock market and commodity indices, respectively. Periods of volatility clustering (e.g., periods of high volatility that are followed by periods of high volatility and vice versa) can be observed in Figure 11 and Figure 12. Periods of high volatility tend to occur during uncertainties in the markets, for example, the clustering of volatility of the markets during the financial crisis of 2008 and when the COVID-19 was declared a pandemic in March of 2020 are particularly prominent.

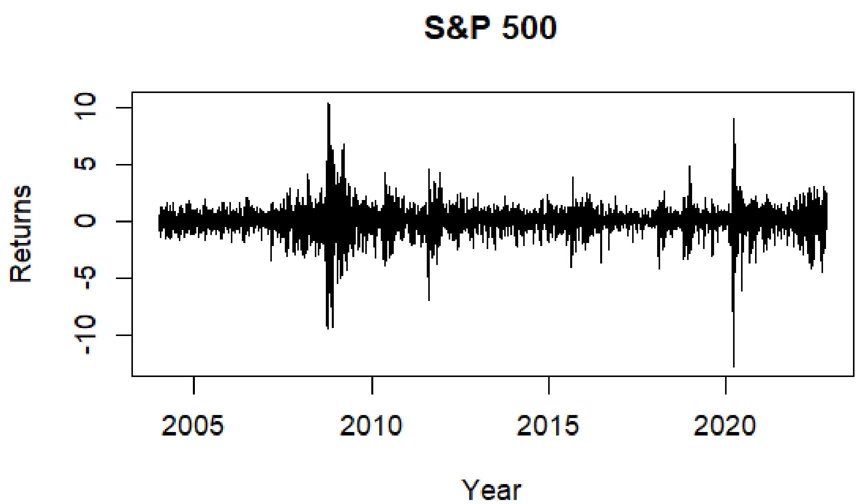

Figure 11. S&P500 daily returns in percentages (2004-2022).

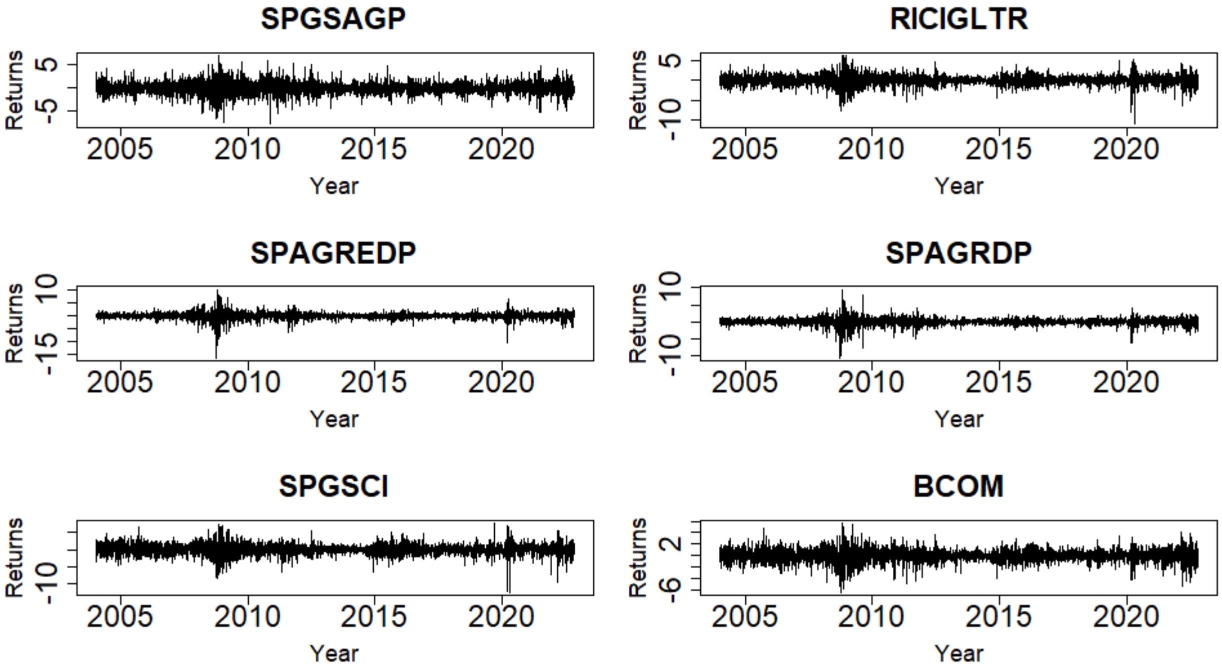

Figure 12. Commodity and Agribusiness Indices daily returns in percentages (2004-2022).

Table 3. Estimated DCC-MGARCH parameters of stock, commodity, and agribusiness indices returns (2004-2022).

	SPGSCI	SPGSAGP	RICIGLTR	SPAGRDP	BCOM	SPAGREDP	SP500
ω	0.0000 (0.000029)	0.0000 (0.000002)	0.0000 (0.000002)	0.0000 (0.000001)	0.0001 (0.000001)	0.0000 (0.000026)	0.0000 (0.000002)
α_1	0.0677 (0.256194)	0.05888*** (0.013803)	0.0558*** (0.016764)	0.0581*** (0.009879)	0.0481*** (0.008144)	0.0886 (0.405960)	0.1356*** (0.013141)
β_1	0.9256*** (0.275690)	0.9333*** (0.015365)	0.9401*** (0.017270)	0.9395*** (0.009816)	0.947*** (0.008613)	0.9052** (0.402171)	0.8426*** (0.017784)
a	0.0258*** (0.006187)	0.0129*** (0.004071)	0.0244*** (0.005041)	0.0314*** (0.004964)	0.0215*** (0.004589)	0.0357*** (0.006487)	
b	0.9688*** (0.008245)	0.979*** (0.007880)	0.9703*** (0.007018)	0.9502*** (0.008216)	0.9728*** (0.006558)	0.9541*** (0.009777)	
Log-L	29248.75	29556.54	30367.03	32271.56	30775.62	32011.27	

Notes: Standard errors of the parameter estimates are reported in parenthesis. *** denotes statistical significance at 1 % level.

The results for the DCC-MGARCH model are reported in Table 3. The ARCH coefficient (α_1) is significant for the S&P500 and four out of six commodity indices. The GARCH coefficients (β_1) are high, ranging from 0.84 (S&P500) to 0.947 (BCOM) and statistically significant (at a 1 % level) for all the indices analyzed. In all cases, the sum of the

conditional variance coefficients ($\alpha_1 + \beta_1$) is close to 1, indicating the long-run persistence of volatility. Additionally, the estimates of the Dynamic Conditional Correlation (a and b) are both statistically significant.

Figure 13 illustrates the time-varying correlation (red graph) from the DCC-MGARCH model and the unconditional correlation (blue dotted line) between stock and commodity markets. The results confirm that the stock-commodity correlation is highly volatile (Creti et al., 2013). For commodities (SPGSCI, SPGSAGP, RICIGLTR, and BCOM), there is a spike in correlations about the end of 2008-beginning of 2009 that reached higher levels than the correlation before the financial crisis, which were around zero. Creti et al., (2013) and Baldi et al., (2016) also noted a rise in the correlation between stocks and commodity markets after the 2008 financial crisis. The growth in this relationship may be explained by two factors: first, the financialization of commodities and the fact that the link between commodities and stock markets may fluctuate according to the phases of the business cycle.

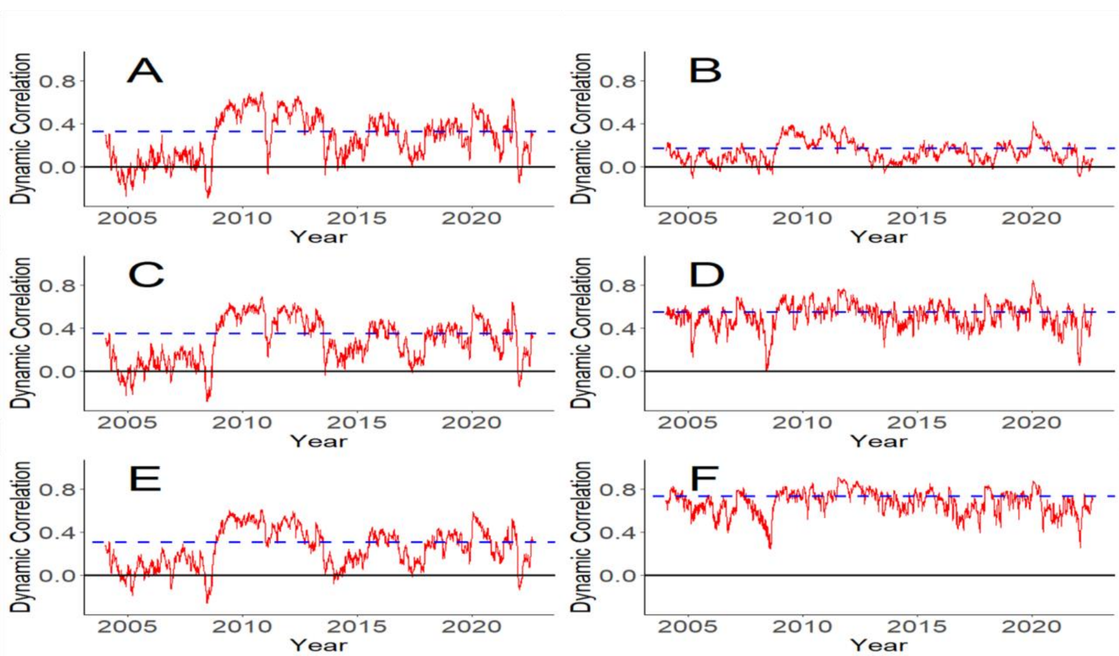

Figure 13. Time-varying conditional correlation between the S&P 500 and (A) SPGSCI (B) SPGSAGP (C) RICIGLTR (D) SPAGRDP (E) BCOM and (F) SPAGREDP.

The financialization of commodities refers to the massive investment capital in commodity markets during the first decade of the 2000s. For instance, Holmes (2006) found that institutional investors had approximately $200 billion tracking the Goldman Sachs Commodity Index and the Dow Jones-AIG Commodity Index. Irwin et al., (2020) calculated that from 2000 to 2012, capital flows into commodity futures markets alone have grown approximately from $100 billion to $450 billion. The increase in correlation after the 2008 financial crisis supports the findings of Domanski & Heath (2007), who had previously stated that as a result of financialization, commodity and financial markets had become more identical.

With respect to the relationship between the S&P 500 and agribusiness indices (SPAGRDP & SPAGREDP), the correlation has been particularly high throughout the entire period, which can be seen in both, the dynamic correlation and in the unconditional correlation. Some of the publicly traded agribusinesses included in these two indices are also included in the S&P 500, which might explain the significant connection. Although the dynamic correlation also declined around 2008-209 and 2021-2022, it appears that these changes in correlation were very brief, and the dynamic correlation quickly returned to its original pre-crisis values in both cases.

In general, the correlation between stock and commodities markets is highly volatile and fluctuates according to the phases of the business cycle. The inflow of capital investment into commodity markets may have caused an increase in the intercorrelation of commodity and financial markets following the 2008 financial crisis. When comparing the S&P 500 to agribusiness indices rather than commodity indices, the connection is stronger.

Chapter 5. Summary and Conclusions

Understanding the risk-return characteristics of farm investments relative to traditional (non-farm) investments is key to financial management. Over the past two decades, interest in farm investing by either individual and/or institutional investors has increased, as summarized in the review of literature chapter. The extent to which farm assets provide diversification opportunities depends on the risk and rewards offered in comparison to the broad financial markets. Both farm and non-farm investments are affected by business cycles but how each investment responds to fluctuations in the business cycles may differ. This thesis research focused on analyzing the cyclical relationship between stock and commodity markets. For the stock market, annual data for the S&P 500 (1871-2022) was collected, while annual Producer Price Index (PPI) data (1871-2022) was used for commodity markets. Given that the PPI is not an investable financial instrument, the annual Bloomberg Commodity Index (1960-2022) and the S&P Goldman Sachs Commodity Index (1970-2022) are used in the analysis to isolate cyclical patterns that reflect actual financial markets pricing performance of commodities. Applying the bandpass filter proposed by Christiano and Fitzgerald (2003) to a measure of pricing performance (called RS), it is found that commodity markets, either at the aggregate level (PPI) or at the more disaggregate level (Commodity indexes), follow a strong cyclical pattern with the broad market, measured by the S&P 500, that lasts about 31 years from peak to peak. This finding is consistent with the findings in previous research (e.g., Zapata et al., 2012; Bannister and Forward, 2002). Naturally, the results point to alternating pricing-performance leadership over which financial markets dominate in pricing performance relative to commodities over long-periods of time, and as found in other research, the length of the alternating leadership in the cycle (from peak to trough) can run for about 15 years. More specifically, the uptrend phase

of the RS cycle indicates that stock returns are outperforming commodity returns. Similarly, the downtrend phase of the cycle indicates that commodity returns are higher than stock returns. Data from the past 151 years provide strong evidence of four occasions in which, on average, commodities have outperformed stocks: 1907-1920, 1930-1938, 1969-1982, and 2000-2009. In essence, commodity booms happen when an unanticipated shock increases the demand for certain commodities, while the supply of those commodities takes time to catch up. Eventually, as supply increases in response to higher prices, the cycle goes into a downturn again, which is often referred to as a "bust" (Büyükşahin et al., 2016). The rise in the price of commodities is associated with wars, inflationary periods, oil prices, and agricultural policies that in one way or another favor the increase in prices. Certainly, the increase in the price of commodities can provide benefits for producers (e.g., farmers) and exporting countries, however, it should not be ignored that it can also have devastating effects on those countries that depend on commodity imports and on the purchasing power of middle- or low-income consumers.

Since 2009, stock returns have dominated those of commodities. However, should this cyclical interplay continue, commodity returns will likely outperform stock returns and will continue to attract investors in the coming years. The ongoing Russian-Ukrainian war could lead to a long period of rising commodity prices. Both countries are very important players in the energy commodities, metals, and grain markets. Even if this war does not escalate to a major world conflict, its end is still uncertain, therefore a precautionary buildup of commodity inventories could trigger the next commodity price boom. Another reason for the next commodity boom could be the increasing food demand caused by growing population. According to a United Nations report, the world population reached 8 billion in November 2022. This growth in the world population directly increases the demand for food commodities.

Whether commodity markets are "the world's best market" (Rogers, 2004) or a market of "disappointing returns" (Irwin et al., 2020) is a debate that will continue to exist. However, this thesis provides strong evidence that the real benefit from investing in commodities ---from an investing standpoint--- lies in their cyclical behavior. Not only do commodities move over time in ups and downs, but such cyclical behavior tends to co-move opposite to the cycle in the stock market. Therefore, an investor who follows the RS cycle in investing can choose investing in commodities for diversification as a hedge. To do so effectively, risk and the phase of the cycle must be accounted for.

One area for future research on this subject is the application of econometric forecasting models to predict cyclical movements between broad financial markets and farm investments. Recent developments in the application of machine learning models to prediction problems in econometrics may offer paradigms for more accurate measurement of the numerous factors that impact the risk-reward relationships between stock and commodity markets. (See for example, Ma et al., 2021). Also note that the cyclical results emerging from this thesis suggest commodity leadership for the near future, and this result is consistent with the current forecast given by some market analysts. For instance, Goldman Sachs projects that the S&P GSCI, its commodities tracking index, would increase by up to 43 % in 2023. The scarcity of metals and energy-related commodities would be the reason for this price spike. Stockpiles are depleting, and markets are constrained as a result of a lack of investment in mining and the search for new oil sources. Once the US and China's economies recover from their recent economic turbulence, Goldman Sachs anticipates that the commodity market will see a boost in prices (Wallace, 2022).

While the writing of these research results was in progress, Goldman Sachs (2022) reaffirmed its prediction that commodity markets will be dominated by underinvestment in early

2023. The high cost of capital caused by the rise in interest rates (as a deflationary action) has discouraged investors from holding commodity inventories, which could drive commodity prices higher. The cost of capital has also been linked to the withdrawal of more than $100 billion from commodity ETFs, active mutual funds, and the Bloomberg Commodity Index. What is even more worrisome according to Goldman Sachs is the underinvestment in production which leads to a reduction of commodity inventories, removing a key buffer against shocks in commodity prices. Underinvestment alone does not generate a price shock in commodity markets; instead, it increases the sensitivity of the commodity markets to demand shocks (e.g., Lyndon B. Johnson’s Great Society in the 1960s, China’s admission to the World Trade Organization in the 2000s).

The second theme of this thesis was to measure the extent to which commodity and non-farm assets correlate to each other in the context of volatile markets. For this purpose, the Dynamic Conditional Correlation (DCC)-GARCH model of Engle (2002) was applied to the relationship between the stock market and six commodity and agribusiness indices using daily returns data for the S&P 500, the S&P Global Agribusiness Equity Index, S&P Global Agribusiness Composite Index, the S&P Goldman Sachs Commodity Index, the Bloomberg Commodity Index, S&P GSCI Agriculture Index and returns of the Roger International Commodity Index over the period January 6, 2004 to October 28, 2022. These indexes are followed by individual and institutional investors when considering investing in farm assets in their portfolios (e.g., Irwin et al., 2020). The estimated parameters of DCC model are highly significant at a 1 % confidence level, suggesting a significant spillover effect in the volatility movements between the two types of assets and that the co-movement alters the risk-reward between the two asset classes. Additionally, the results confirm that the dynamic correlation between stocks and commodity markets is highly volatile, and it has increased since the 2008

financial crisis as a result of the “financialization of commodities.” Understanding the correlation between stocks and commodities is of great importance for companies that rely on commodities prices, such as food and beverage firms that depend on the price of corn, coffee, sugar, soybeans, etc. This is particularly crucial as agricultural commodities play a significant role in agricultural and regulatory policies, as well as subsidies. As noted by Billah (2023), analyzing the food and beverage stocks and agricultural commodity correlation can provide valuable insights for investors and policymakers alike.

One implication for long-term investors is that if both markets have become more correlated because of financialization, there are still substantially different risk-reward interactions. For effective portfolio diversification, this also implies that a strategy that uses cyclical patterns found in this research, combined with the improved measures of correlation from the DCC-MGARCH model, can provide for improved medium to long-term risk and financial management strategies as well as asset allocation decisions. Further research in this area is necessary to fully understand these implications.

Future research should explore the impact of financial crises and the financialization of commodities on the relationship between other asset classes and commodities, such as bonds or real estate. Additionally, investigating how the time varying relationship between stocks and commodities affects different industries, particularly those that depend heavily on commodity prices, would be interesting. Finally, analyzing how global economic and political events influence the correlation between stock and commodity markets may provide valuable global insights.

Limitations

Some limitations of this study are worth noting. First, although we mentioned some historical events that might have had an impact on the cyclical relationship between stock and commodity markets (See Figure 4), the figure may not be as comprehensive as needed for purposes other than cyclicality. Second, the cyclical patterns observed in this thesis are likely specific to the US market and may vary in other countries or regions. However, this limitation may provide for ample future research on the subject. Third, regarding the findings of the DCC-MGARCH analysis, it is worth considering that the impact of financial crises and financialization on the interactions between various asset classes may vary across different time periods and circumstances. Consequently, the generalizability of the results may be constrained by these factors.

Appendix A. Commodity Indices

Roger International Commodity Index	Goldman Sachs Commodity Index	Bloomberg Commodity Index	S&P GSCI Agriculture Index
Aluminum	Aluminum	Aluminum	Cocoa
Azuki Beans	Brent (UK) Crude Oil	Brent Crude Oil	Coffee
Barley	Cocoa	Coffee	Corn
Canola	Coffee	Copper	Cotton
Cocoa	Copper	Corn	Soybeans
Coffee	Corn	Cotton	Sugar
Copper	Cotton	Gold	Wheat
corn	Crude Oil	HRW Wheat	
Cotton	Feeder Cattle	Lean Hogs	
Crude Oil	Gas Oil	Live Cattle	
Gold	Gold	Low Sulphur Gas Oil	
Heating Oil	Heating Oil	Natural Gas	
Lead	Lead	Nickel	
Lean Hogs	Lean Hogs	RBOB Gasoline	
Live Cattle	Live Cattle	Silver	
Lumber	Natural Gas	Soybean Meal	
Natural Gas	Nickel	Soybean oil	
Nickel	Red Wheat	Soybeans	
Oats	Silver	Sugar	
Orange Juice	Soybeans	ULS Diesel	
Palladium	Sugar	Wheat	
Palm/Soybean Oil	Unleaded Gas	WTI Crude Oil	
Platinum	Wheat	Zinc	
Rice	Zinc		
Rubber			
Silk			
Silver			
Soybean Meal			
Soybeans			
Sugar			
Tin			
Unleaded Gas			
Wheat			
Wool			
Zinc			

Appendix B. Largest Agribusiness Companies

Ticker Symbol	Company Name
ADM	Archer-Daniels-Midland Co
ANDE	Andersons Inc
ARTW	Arts-Way Manufacturing Co. Inc.
BAYRY	Bayer AG
BG	Bunge Ltd
BRFS	BRF S.A. (ADR) common stock
CAG	Conagra Brands Inc
CALM	Cal-Maine Foods Inc
CAT	Caterpillar Inc.
CF	CF Industries Holdings, Inc.
DD	DuPont de Nemours Inc
DE	Deere & Company
DOW	Dow Inc
FDP	Fresh Del Monte Produce Inc
FMC	FMC Corp
GIS	General Mills, Inc.
HRL	Hormel Foods Corp
INGR	Ingredion Inc
IPI	Intrepid Potash Inc
KUBTY	Kubota Corp
LNN	Lindsay Corp
MOS	Mosaic Co
NTR	Nutrien Ltd
SOY	SunOpta, Inc.
SQM	Sociedad Quimica y Minera de Chile
TRA	Teras Resources Inc
TRMB	Trimble Inc
TSN	Tyson Foods, Inc.

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Vita

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