Notre Dame University-Louaize
Faculty of Business Administration & Economics
Graduate Division

An Empirical Investigation of the Volatility Spillovers among Agricultural Commodity Markets around News Surprises

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of the Master of Science in Financial Risk Management (MSFRM)

NDU-Lebanon
2015

Approval Certificate

An Empirical Investigation of the Volatility Spillovers among Agricultural Commodity Markets around News Surprises

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June 22nd, 2015

DECLARATION

I hereby declare that this thesis is entirely my own work and that it has not been submitted as an exercise for a degree at any other University.

Tamara Nehme

ABSTRACT

Purpose – The objective of this thesis is to empirically test the level of interdependence across commodity markets in terms of return volatility spillover, namely, corn, wheat, soybeans and soybeans oil, and to uncover the impact of macroeconomic announcements on the measurement of integration among those commodities. This will help us to investigate the extent to which different agricultural commodities can be considered as an asset class and to determine whether portfolio diversification across different agricultural commodities can still lead to risk reduction benefits, in the light of the recent liberalization and financialization.

Design/methodology/approach – This thesis applies the modified iterative cumulative sum of squares (ICSS) algorithm to detect structural breaks in the return variance of four selected agricultural commodities. Then, the detected break points as well as the macroeconomic announcement surprises are incorporated in a GARCH (1, 1) process to model the variance of commodity returns. The resulting variances are then combined in a Simultaneous Equation Model (SEM) to spot both the instantaneous and delayed volatility spillovers among agricultural commodity markets as well as the impact of news surprises.

Findings – There is significant evidence of bidirectional volatility spillovers across major agricultural commodity markets. Particularly, it seems that there is more spillover from soybeans and soybean oil markets, to corn and wheat markets, rather than the inverse. In addition, a news surprise originating in the economy has strong impact on the variance of agricultural commodities.

Research limitations– Given the restricted timeframe provided for the thesis completion, the sample size of commodities is restricted to 3,865 observations per variable. This is mainly due to the lack of available data for a common time span, especially for the macroeconomic variables that were only available on a monthly frequency.

Practical implications – The empirical findings of this study have important implications on portfolio diversification and risk management practices. With the recent financialization of commodity markets, investors worldwide are finding it easier to access funds, seek new investment opportunities and follow innovative hedging strategies. However, the results of this dissertation constitute a perfect proof that there is risk proliferation and volatility transmission among agricultural commodity markets. Yet, a thorough examination of the level of integration of those commodities while taking into account the timing of economic surprises could result in portfolio risk reduction.

Originality/value – This thesis uses an innovative combination of econometric tools –the ICSS, GARCH (1, 1) and 3SLS models, in order to examine cross-market volatility spillovers with structural breaks, around macroeconomic news announcements. While most researchers have concentrated their analyses on few macroeconmic release announcements, our research finds that an aggregated index of 39 U.S. data surprises can act as an ideal proxy for economic surprises.

Keywords – Return Volatility Spillover, Agricultural Commodity Integration, Portfolio Diversification, Structural Breaks.

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGMENTS

First, I would like to thank God and Our Lady of Louaize for always blessing me and guiding my path.

My deepest gratitude is to my thesis advisor, Dr. Hassan Hamadi. I have been amazingly fortunate to have a Finance Professor who, since my undergraduate years at NDU, throughout my graduate studies and while supervising my dissertation, sets high academic standards and guides me to meet them. I thank him for being able to see my potentials and not allowing me to work beneath them. While allowing me to work in my own way, he has supported me with his patience and unsurpassed knowledge.

My co-advisor, Dr. Charbel Bassil, has been always there to carefully read and insightfully comment. I extremely appreciate the time he has devoted as well as his valuable knowledge in econometrics that was indispensable to complete this study. I thank him also for the many valuable discussions that helped me understand my research area better.

To all the members of the Faculty of Business Administration and Economics at NDU, particularly to Dr. Elie Menassa and Dr. Roy Khoueiri, I am truly thankful for giving me the opportunity to benefit from this Master program which has widened my knowledge in different aspects of financial risk management, and contributed to my career growth. I am also very pleased and honored for the exceptional experience I acquired while working as a Graduate Teaching Assistant.

I specially thank Mrs. Norma Frayha, the professor who truly made a difference in my academic path. She provided me with academic support and became more of a mentor than a professor. It was through her guidance that I completed my undergraduate degree and was encouraged to apply for graduate studies.

To my parents and my sister Natacha, I doubt that I will ever be able to convey my appreciation fully, but I owe them my eternal gratitude. I dedicate this dissertation to Irini, my Mother.

CONTENTS

CHAPTER 1

INTRODUCTION

1.1. General Background

The main concern of an investor revolves around maximizing profits while reducing risk. In fact, a high risk-adjusted return can be achieved through a careful distribution of funds among different assets, i.e. through tactical portfolio diversification strategies. This theory was developed decades ago based on diversification among weakly correlated stocks in a single market, and later extended to include different asset classes, such as currencies, bonds and commodities, among others. Lately, the financialization of commodity markets in 2004 triggered the interest of many researchers to explore commodity markets. As a result, extensive studies were devoted to assess the level of integration among several commodity markets. Actually, many researchers attempted to disclose the factors affecting commodity markets' performance and to detect the level of interdependence among different commodities. Thorough examination of the nature and degree of cross-commodity interdependence is therefore crucial today to understand the direction of volatility spillovers, if any, between alternative investments. This is of great concern for financial decision making purposes and for investors looking to diversify their portfolio in order to reduce risk.

1.2. Importance of the study

There is no consensus among researchers on whether agricultural commodity markets are in fact integrated and what the impact of such integration on portfolio diversification is. For instance, those who find that agricultural commodity markets constitute a single asset class argue that the risk reduction that was once achieved through diversification is no longer possible. Others claim that a thorough inspection of agricultural commodity markets on the nature of the possible volatility linkages could still yield diversification benefits.

This disagreement among early studies, as well as the different points of view, triggers the need for significant and important additional research in the field. This dissertation proves useful to investors and analysts who are interested in uncovering the conditional risks found in commodity markets and the possible hedging strategies that help in reducing it. This thesis will also serve as a basis for further research and discussions on the return volatility spillover across leading commodity markets.

1.3. Purpose of the Study

Using a distinctive blend of econometric tools, this thesis aims at empirically testing the potential existence of market interdependence across leading agricultural commodities, by:

(a) Investigating the return volatility transmission among corn, wheat, soybeans and soybean oil

(b) Examining the impact of macroeconomic announcement surprises on the instantaneous volatility of the studied commodities

(c) Incorporating the detected structural breaks in the return series, in the estimation of variance distribution

1.4. Layout of the Thesis

The remainder of this thesis is divided into four main chapters. The next chapter, a review of former literature, focuses on offering a strong theoretical background, including the definitions and the development of the theories related to portfolio diversification and risk management. Then it discusses the main findings and methodologies of earlier empirical studies, in order to derive the objective of this thesis and to draw the research question (s). In the light of chapter two, chapter three translates the research question (s) into hypotheses in the form of null and alternative. It also presents the sample to be studied, defines the variables (proxies) and their sources. Then, it lays out the econometric methodology and the appropriate software packages used to test the underlying hypotheses that includes: the Iterative Cumulative Sum of Squares (ICSS) algorithm, the augmented univariate GARCH with structural breaks method, the simultaneous equation model, the two-stage least squares estimator as well as the three-stage least squares estimator. Accordingly, chapter four provides a thorough assessment of the descriptive statistics of the data along with an in-depth discussion of the empirical findings. The last chapter, The Conclusion, wraps up the entire thesis and summarizes the main findings of the study and its resultant implications on portfolio managers. It also states the limitations of this dissertation and argues on the possibility of further research on the topic.

CHAPTER 2

LITERATURE REVIEW

2.1 Theoretical Framework

Early in the sixteenth century, Miguel De Cervantes stated that "it is part of a wise man to keep himself today for tomorrow, and not to venture all his eggs in one basket". Hence, the concept of diversification is age-old and existed long before modern theories. In fact, it did not take its economic sense until 1939 when countries around the world started to recover from the consequences of the Great Depression, and thus, became an essential concept in risk management (Diversification, n. d). In 1952, Harry Markowitz laid down the modern understanding of diversification in the context of finance: "the process of spreading an investment across assets and thereby forming a portfolio" (Ross et al., 2012, p. 439). In other terms, within a diversified portfolio, while some of the holdings might be down and others might be up, the investor is doing fine overall. Hence diversification would require that assets are not moving in the same direction by the same level and therefore the correlations between assets in portfolios should not be very close or perfectly positive.

In his attempt to formulate the concept of diversification mathematically, Markowitz became the father of Modern Portfolio Theory (MPT). The main motivation behind his interest in diversification rests on a fundamental premise in economics: due to the scarcity of resources, all investment decisions are made in the face of trade-offs. The risk-return trade-off facing investors, was heavily addressed in the literature emphasizing that an investor is not only concerned with his portfolio's expected return but also with the associated level of risk. Thus, the main assumption is that investors are utility maximizers and risk averse; i.e. they desire assets with high expected returns and low variability (low risk). Markowitz (1952) examined how an individual security contributes to the risk of the overall portfolio and affects its expected return. He proved that a careful allocation of assets in a portfolio can maximize the expected return for a certain level of risk, or equivalently minimize the risk for a given level of expected return. In other words, an investor can reach the same targeted expected return by selecting different types of investment assets (an efficient portfolio) that jointly have lower risk than an individual security. Therefore, it is crucial to portfolio managers to incorporate the concept of diversification, as it contributes in adjusting both risks and returns, hence quantifying the relationship between risks and returns.

On one hand, the actual return on any risky asset contains a normal part predicted by market participants and an uncertain part resulting from unexpected future news and announcements. The importance of an announcement depends on the amount of information, being expected or surprise, it delivers to the market (Kendall, 1953). Since the Efficient Market Hypothesis, which is concerned with expected announcements, dictates that prices already reflect all available information in the market, speaking about news means talking about the surprise part of an announcement (Rendleman et al., 1982). Moreover, uncertainty is tightly related to the so-called surprise part of an announcement. The systematic risk (or market risk) is the risk that affects a large number of risky assets and cannot be controlled by businesses; while the unsystematic risk (idiosyncratic risk) influences a single firm or industry (Bodie, Kane and Marcus, 2014). Both, the systematic risk and unsystematic risk add up to the total risk. Wagner and Lau (1971) showed that diversification cannot eliminate portfolio risk but it can reduce it up to a certain limit. Hence, while diversification can eliminate the unsystematic risk, systematic risk is not diversifiable. In fact, this limited power of diversification is due to the fact that assets are exposed to common sources of market uncertainty such as inflation rates, exchange rates fluctuations, political instability and war that cannot be eliminated. However, to the extent that the firm-specific influences on two different assets differ, the two effects will offset each other's and increase risk-adjusted returns (Brumelli, 1974).

As a result of the Markowitz theory, the Capital Asset Pricing Model (CAPM) emerged later on and was published by William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966). The CAPM quantifies a linear relationship between the expected return of an asset and its exposure to the market, assuming that the market portfolio is mean-variance efficient. The model draws on the Systematic Risk Principle: since investors are rewarded only for systematic risks and assumed that they diversify their unsystematic risks through diversification, and since rational investors should not bear a diversifiable risk, the expected return of a portfolio does not depend on the total risks, but only on the systematic (undiversifiable) risks endemic to the wider economy. In other terms, risky assets with higher market risk are expected to yield higher returns. Since its preeminence, the CAPM was adopted by many investors as a practical tool to determine the fair price of an asset and the rate of return they deserve for putting their money at risk.

However, the CAPM relies on many assumptions that were deemed to be unrealistic. For instance, it assumes that all information is publicly available and accessible to everyone, implying that investors will have homogeneous expectations with respect to risk and return; whereas in reality many investors have access to insider (private) information (Jaffe, 1974). In addition, the CAPM considers that capital markets are perfect: all assets are infinitely divisible and trade on public exchanges. Also, it assumes that short positions are allowed while in reality, many countries prohibit short sales (Diamond and Verrecchia, 1987). Further, it ignores the restrictions on borrowings by allowing market participants to borrow and lend at a common risk free rate, but this will lead them to reach different optimal risky portfolios (Black, 1972).

Although the CAPM was criticized by many studies for representing a highly simplified and idealized world (Fama and French, 1993; Merton, 1972 and Roll, 1977), it is still considered to be the foundation of all the subsequent asset pricing models. For instance, a good deal of empirical studies showed that the market risk term of the CAPM does not capture all the types of risk; hence, it ignores the multifaceted nature of systematic risk. As a result, Ross (1976) proposed the Arbitrage Pricing Theory (known as APT) as an alternative model for pricing assets. The APT models the expected return of a financial asset as a linear function of multiple macro-economic factors driven by the business cycle such as inflation rates and interest rate fluctuations. Unlike the CAPM, APT explicitly represents systematic risk, but the number and nature of the factors is likely to change over time and among economies. The three-factor model of Fama and French (1993) is a particular example where the expected return of an asset is a function of the market risk (as suggested by CAPM), the firm size (Banz, 1981) and book-to-market ratio (Chan et al., 1991).

The use of the aforementioned asset pricing models and their extensions was primarily restricted to equity markets, especially stocks traded in the USA. But since the world is evolving, portfolios should also evolve as investors have wider choices than before. In fact, the meaning of a well-diversified portfolio has changed over time and a large number of empirical studies recognized the importance of international portfolio diversification. In fact, the issue of international portfolio diversification rose in 1974 when Morgan Guaranty established the first investment of pension fund outside the USA. The advantages of international diversification are due to the fact that different national stock markets may not be highly correlated, exhibit unsynchronized movements and respond to changes in the business cycle in opposite ways (Grubel, 1968; Levy and Sarnat, 1970; Lessurd, 1973; Solnik, 1974; Jorion, 1985 and Levy and Lim, 1994). Since firms operating within the same industry or the same geographical region are subject to the same risks, portfolio diversification was extended to include assets from different stock markets across different countries. While global diversification was primarily limited to developed countries in Europe and the US, many emerging markets in Asia and the MENA region opened their doors later on to foreign investments and became globally accessible to investors due to financial innovation and technology (Bekaert and Urias, 1996).

However, several studies claimed that markets around the world became more and more integrated and increasingly interdependent as a result of the recent globalization, liberalization and deregulation (Beirne et al., 2009). Hence, the risk reduction benefits of international diversification will diminish (Byers and Peel, 1993). For instance, the boom in stock markets and their subsequent crash since 2000 have characterized financial markets worldwide (Angkinand et al., 2010). This strong co-movement has limited the benefits of international portfolio diversification. Therefore, investors considered alternative investment opportunities and broader portfolio diversification across multiple asset classes as a hedge to mitigate increasing risks. Asset allocation was heavily addressed in the literature as an efficient way to avoid excessive exposure to one source of risk. Understanding the nature of the interdependence between different asset classes is important for investors.

Traditionally, the main asset classes were stocks, fixed income securities (mainly bonds) and currencies due to the fact that they respond to risk factors in different ways. In fact, Johnson and Soenen (1997) found that stocks and bonds dominated the portfolios of investors in the period 1984-1995. The tangibility and physical attributes of commodities made them quite different from other asset classes. Moreover, holding physical commodities came at high costs such as storage costs among others. However, researchers were continuously interested in the impact of gold on financial markets and first examined the efficiency of the gold market in the US given its important role as a store value (Tschoegl, 1980; Solt and Swanson, 1981; Aggarwal and Soenen, 1988). Lawrence (2003) found that gold is imperfectly correlated with stocks and bonds and associated this lack of relationship to the fact that stocks and bonds returns correlate with macroeconomic variables, whereas gold returns do not. Jaffe (1989) and Davidson et al. (2003) also found that additional diversification benefits arise from investing in gold. Baur and Lucey (2010) found that investing in precious metals, gold and silver provides a good hedge or safe haven against stock market movements.

Gold was the first commodity to be traded as part of investors' portfolios. Actually, the first Exchange Traded Commodity (ETC) was a Gold ETC listed in 2003 on the Australian Securities Exchange and in 2004 on the London Stock Exchange. Since then, commodities gained an increasing importance as an asset class and investors have been exposed to a wide range of listed ETCs and given access to long and short positions in commodities ranging from livestock to platinum. In the past decade, the behavior of commodities returns and their fluctuations have changed dramatically. A recent literature considers that investors, widely seeking unexplored asset classes as potential new sources of returns and diversification benefits, were rapidly taking positions in commodity futures (Buyuksahin and Robe, 2014). This behavior was triggered by the process of financialization among commodity markets. Obviously, the introduction of those securities (ETCs and futures contracts among others), simplified the access to commodity markets that were previously reserved to a small number of institutional investors, democratized a key asset class and changed the nature of commodities investing (Singleton, 2014). Indeed, investors realized the importance of diversifying across commodities; that is, holding different types of commodities (agricultural, energy, livestock, metal). In fact, introducing commodities in tactical asset allocation strategies has many benefits including the equity-like return of commodity indices (Fuertes et al., 2010) and the role of commodity futures as risk diversifiers and inflation hedges (Bodie, 1983).

Before the early 2000s, the two main types of commodity market participants were the commercial hedgers such as farmers, producers and consumers and the noncommercial hedgers such as hedge funds (Cheng and Xiong, 2014). While noncommercial hedgers pool others' funds and extensively invest them in commodities and commodity derivatives instruments, commercial hedgers hedge the spot-price risk resulting from their commercial activities by trading commodity futures contracts. This suggests that commodity markets were segmented from financial markets and that the aspects of commodity markets are in sharp contrast with the dynamics of typical financial assets. For instance, Gorton and Rouwenhorst (2006) stated that the correlation between commodity markets and the S&P 500 was negligible, especially for short term horizons. Erb and Harvey (2006) also found that commodity markets were not integrated with each other, since their return correlations were very low.

After the year 2000, when equity markets collapsed, market participants started trading commodities as part of their broader portfolio strategy. Since then, commodities and commodity derivatives became a new asset class, particularly after Gorton and Rouwenhorst (2006), Erb and Harvey (2006) and Greer (2000) discovered the existence of a negative correlation between stock returns and commodities returns; hence, potential diversification benefits using commodity futures. In reality, the so-called "financialization" of commodities took effect sometime in the period 2004-2005, when the U.S. Commodity Futures Trading Commission reported an increase in the value of investment inflows to various commodity indices from $15 billion in 2003 to $200 billion in 2008 (CFTC, 2008). Many empirical studies tested and confirmed the presence of a structural break around 2004; hence, the start of the financialization of commodity futures (Irwin and Sanders, 2011; Hamilton and Wu, 2013 and Boons et al.; 2014). This growth in commodity futures investments coincided with the 2007-2008 boom in asset prices, particularly commodity prices. Therefore, a heated debate took place in academia on whether this increased volatility in commodity prices was due to these "financial" flows and to the increased participation in commodity futures markets or it was due to other factors. Tang and Xiong (2012) attributed the increase in commodity price co-movements to several economic mechanisms including the financialization of commodities, the rapid growth of emerging economies, the world financial crisis, inflation and the adoption of biofuel. For instance, the large index investment flow, as well as the development of emerging markets (e.g. India and China) triggered the demand for commodities in various sectors. Under the financialization hypothesis, commodity prices and returns fluctuations are affected by the increased demand for long positions in commodity futures. Moreover, the potential role of commodities in portfolio diversification initiated the curiosity to check whether commodities are considered to be a single asset class or an investor might benefit from diversifying among commodities and therefore the latter may be considered to be different asset classes. Given the considerable effect of macroeconomic announcements on stocks (McQueen and Roley, 1993; Boyd, Hu, and Jagannathan, 2005) and bonds (Fleming and Remolona, 1999; Balduzzi et al., 2001), and since commodities lately emerged as an important asset class traded in investors' portfolios, it is essential, therefore, to establish a link between commodity markets and the economy (Brenner et al., 2009). Despite the intuitive notion that macroeconomic news should influence commodity prices, just as traditional asset markets, it has been a challenge for academics to establish a relationship between macroeconomic announcements and volatility in commodity prices. Daly (2008) described financial volatility, the deviation from an expected value, as an indication of the level of risk. According to Becketti and Sellon (1989), many factors, such as inflation rates variations, monetary policies and interest rates fluctuations, may cause deviations in financial returns and increase volatility. Following the Autoregressive Conditional Heteroskedasticity (ARCH) model pioneered by Engel (1982) and generalized (GARCH) by Bollerslev (1986) a large body of the literature has been devoted to model the time-varying volatility in financial time series. According to Ross (1989), volatility signals the influx of new information. Even if the efficient market hypothesis holds (markets adjust to news perfectly and instantaneously), asset returns may exhibit volatility.

Different theories have discussed the direct effect of macroeconomic news on the volatility of commodity prices. The theory of Dornbusch (1976) claims that, the real price of a commodity, is inversely proportional to the real interest rate. For instance, a contractionary monetary policy (reflected in interest rates rise, inflation decrease, or both) leads to low commodity prices. Intuitively, high interest rates reduce the demand (or increase the supply) for storable commodities through a variety of channels, which can dampen prices. First of all, by encouraging for extraction today rather than tomorrow (think of the rates at which oil is pumped, zinc is mined, forests logged, or livestock herds culled). Secondly, by decreasing firms' desire to carry inventories. When interest rates are high, capital is more expensive and since holding inventories ties up capital, parties are encouraged to minimize inventories; this puts more supply onto the market. Thirdly, by encouraging speculators to shift investments from commodity contracts (mainly spot contracts which do not produce any yield) to yielding instruments such as treasury bills. Finally, by appreciating the domestic currency and so reducing the price of internationally traded commodities in domestic terms (even if the price hasn't fallen in terms of foreign currency).

Anzuini et al. (2013) explains that expansionary monetary policy shocks have a significant impact on commodities and can drive up the broad commodity price index. In other words, an expansionary monetary policy leads to higher commodity prices. Moreover, Elder et al. (2012) explained the intensity, direction and speed of impact of macroeconomic news on the return and volatility of gold, silver and copper futures from 2002 till 2008. They argue that nonfarm payrolls and durable goods orders have the largest impact. Karali (2012) showed that the release of the United States Department of Agriculture (USDA) reports convey new information to the market; hence, the volatility of soybeans, soybeans oil and soybeans meal moves on the release day. Baumet et al. (2014) found that the release of Chinese financial news related to manufacturing and industrial output move commodity markets. On the other hand, Basistha and Kurov (2012) argue that energy prices and stock returns respond to monetary policy shocks in a similar manner. Similarly, Rosa (2014) also showed that energy futures prices and trading volumes are highly affected by monetary policy surprises.

More importantly, King and Wadhwani (1990) investigated the crash of October 1987 and showed that price information diffuse across markets even when the information is market specific. They claimed that markets overreact to the events of another market beyond the influence of fundamentals; hence, they put forward the market contagion hypothesis. With the development of econometric tools, models have been extended to the multivariate dimension (MGARCH). This multivariate aspect triggered the attractiveness of a new research topic: volatility spillovers. Volatility spillover is the transmission of shocks and financial distress from one market/region to another. In other words, the existence of volatility spillovers implies that a shock increases the volatilities not only in its own market, but in other markets as well. Loan et al. (2014) recently explored the different views regarding the definitions of contagion and transmission of shocks. They pointed that the normal interdependence between markets is not causing the shock, but it is propagating it and speeding up its transmission. In others words, when a shock hits a certain market, it does not only affect the market itself, but impacts the volatility of another related market. That's why; studying volatility spillovers can help understanding how information diffuses across markets.

Early studies on volatility spillovers typically focus on equity markets in developed countries, and the transmission of volatility from large to small country markets. According to Eun and

Shim (1989), the US market is the most influential stock market. Theodossiou and Lee (1993) found a high degree of interdependence and a statistically significant mean spillover from stock markets of the U.S to stock markets in Japan, U.K., Canada and Germany. Lin et al. (1994) and Bae and Karolyi (1994) evidenced that when the asymmetric effect of bad news is ignored, the Japanese and the U.S. stock markets exhibit significant transmissions. Brailsford (1996) supported bidirectional volatility transmission between the Australian and New Zealand equity markets. Later on, Morana and Beltratti (2008) claimed that co-movements of prices, returns, volatilities and correlations between the developed markets of the USA, UK, Germany and Japan are increasing over time.

However, as emerging markets gained an important role and as international diversification increasingly relied on investment in emerging markets, former research has considered the linkages between developed markets and emerging markets, and among emerging markets themselves. For example, Cheung and Cha (1998) empirically investigated the relationships between the four Asian Emerging Markets (AEMs): Hong Kong, Korea, Singapore and Taiwan, and the two largest markets in the world: U.S. and Japan. They found that the US leads other equity markets but the four AEMs respond differently to the volatility in the U.S.: the innovations in the U.S. market influences the Hong Kong and the Singapore markets, but not the Korean and the Taiwanese markets. Also, the Japanese market has little impact on the AEMs except on the Korean market. Further, Ng (2000) found significant spillovers from Japan to the Pacific-Basin equity markets. In addition to the studies of the Chinese stock markets by Wang et al. (2004) and Lin and Wu, 2006), Li (2012) showed that China's stock market reforms allowed spillovers from China to the US, Korea and Japan. Moreover, Gunasinghe (2005) found a low volatility spillover effect from the Indian stock market to other regional markets, like Sri Lanka and Pakistan. Similar work was done in the MENA region and Abraham and Seyyed (2006), for instance, observed that information flow from the more accessible Bahraini market to the less accessible Saudi market.

Exchange rate markets also exhibited volatility co-movements and proved to be linked to stock markets. For instance, Engle, Ito and Lin (1990) and Baillie and Bollerslev (1991) evidenced that shocks increased the conditional volatility of the British pound, the Deutsch mark, the Swiss franc and the Japanese yen vis-a-vis the US Dollar. According to Kanas (2000), volatility spills over from stock markets to exchange rates. Similarly, Chiang et al. (2000) pointed out that Asian stock markets are positively related to the value of the national currency. Fang and Miller (2002) supported the existence of a bi-directional causality between the Korean foreign exchange market and the Korean stock market during the Korean financial turmoil of 1997 to 2000. Further, Sabri (2004) showed that stock trading volume and currency exchange rate are the most related indicators of increasing stock return volatility and instability of emerging markets.

After researchers extensively examined volatility spillovers between commodity markets and equity markets using different econometric techniques, it is now well known that markets exhibit more volatile dynamics. Chong and Miffre (2010) studied how commodity futures co-vary with the rest of the portfolio (stocks and bonds) and suggested that commodities are becoming better portfolio diversifiers. In fact, an ample body of the literature was also devoted to study the interdependencies across commodity markets themselves. In the latest years - especially during the period 2006-2009 - agricultural commodity prices exhibited large swings and unexpected extreme fluctuations. Until the year 2007, the evolution of FAO (Food and Agriculture Organization) Food Price Index (FFPI) was quite stable, but it has grown up with an average annual growth of 59% over the period from March 2007 to March 2008. Since the evolution of FFPI reflects the global trends of agricultural commodities, market participants such as producers, consumers and investors have been seriously concerned about the movements of agricultural commodities as well as their co-movements.

In fact, agricultural commodity prices are strictly linked to the market fundamentals such as supply, demand, storage with their relative shocks (e.g. weather, technological progress) (Stevens, 1991). However, the microeconomic theory postulates that commodities can be linked through substitutability and complementarity. On one hand, the relationship of substitutability can be formulated as follows: if the price of corn increases, cattle feeders may use soybean meal instead. On the other hand, if the price of soybean oil increases dramatically and soybeans are crushed to supply such oil, this process also produces soybean meal and may result in a drop in the price of soybean meal. The relationship here is one of complementarity. Further, agricultural commodities are also driven by other macroeconomic factors which horizontally impact different crops at the same time (such as energy and fertilizer prices, exchange rates and interest rates) (Reinbart and Wickbam, 1994). Finally, agricultural commodities are connected via “spreading”

(Malliaris and Urrutia, 1996). Spreading is an arbitrage trading strategy whereby traders are driven by perceived mispricing between products. For example, a trader who finds soybeans cheap, will buy soybeans and sell soybean oil and soybean meal.

Although the previously discussed theoretical grounds claim that "fundamentals" constitute the main linkage among agricultural commodities, the literature on excess co-movements and contagion across agricultural commodity markets is large. An old debate in finance discusses the issue of herd behavior, as a potential explanation of the excess co-movement in commodity markets, besides the impact of fundamentals. For instance, after controlling for macro-economic variables (interest, inflation and exchange rates) and supply and demand conditions to explain co-movement, Pindyck and Rotemberg (1990) found that various unrelated agricultural commodities still moved together. Recently, as a result of the financialization process, whereby 28 commodities have been traded with futures contracts in the US, the price of a commodity is no longer determined solely by its supply and demand, but also by the investment behavior of diversified commodity index investors (Tang and Xiong, 2012). In fact, the most popular commodity investment strategy is to invest in a given commodity index (a basket of commodities such as the S&P GSCI and DJ-UBSCI) that is built on the value of futures contracts to avoid the cost of holding physical commodities. As a result of the growing presence of index investors, any shock to a certain commodity class can cause commodities in the index to move together (Barberis and Shleifer, 2003). Moreover, the adoption of biofuel to reduce the reliance on oil (and fossil fuel) as a main source of energy is a recent development in commodity markets. As a result, oil prices increased and the ethanol industry grew up to constitute one-third of US corn production. Those changes might have caused (1) the price of corn and its substitutes (such as soybeans and wheat) to co-move with oil (2) livestock commodity prices to change since corn is a main source of livestock feed (Wu et al., 2011) (3) planted acreages for corn and soybeans to expand and (4) planted acreage for wheat and rice to decrease since the global cropland endowment is limited (Chen et al., 2010).

Finally, if agricultural commodities are significantly interconnected for any of the various reasons explained above, one might question the benefits of cross hedging as well as cross speculation opportunities using crop yield futures and options contracts. In other terms, if interdependence among agricultural commodity markets is increasing, and different agricultural commodity markets are becoming more integrated, how beneficial is it to diversify across different types of agricultural commodities? Has the financialization of commodity markets removed all boundaries or at least reduced them to a point where an investor would stick to one, rather than various, agricultural commodity? To what extent are the high co-movements between commodities a lasting feature and not a temporary effect of the recent 2008 financial crisis?

The following section is a review of the most important empirical studies concerned with the existence, or absence, of commodity markets interdependence.

2.2 Previous Empirical Studies

While it is not surprising that similar assets are influenced by similar shocks given their potential substitution effects, recent works focused on the joint commodity price movements. In fact, a large amount of empirical studies evaluated the cross-commodity spillovers among separate markets and the level of market integration. As some of the early studies in the field, Chaudhuri (2001) investigated the linkages between oil prices and real monthly commodity prices from January 1973 to May 1996. He found that an index composed of 29 commodities (including food, metals, and other consumption goods) is co-integrated with the price of oil. More precisely, Granger causality is depicted in the direction from oil to the index.

Rezitis (2003) examined the volatility spillover effects across consumer meat prices for lamb, beef, pork and poultry, using monthly data from January 1988 to December 2000. By applying a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach, their work supported the existence of significant linkages between the four retail markets under consideration and evidenced the presence of positive volatility spillover effects across meat markets. Thus, each one of the meat markets under study (for example, pork) forms its own price using information from the other meat markets (that is, lamb, beef and poultry). Following the same methodology, Buguk, Hudson and Hanson (2003) studied price volatility spillovers in US catfish supply chain based on monthly price data from 1980 through 2000 for catfish feed, its ingredients, and farm- and wholesale-level catfish. The estimated univariate exponential GARCH model detected the existence of strong unidirectional spillovers from corn, soybean and menhaden prices to catfish feed, farm, and wholesale catfish prices.

Furthermore, Le Pen and Sévi (2010) considered different measures to test correlations in squared returns and to assess excess co-movements among eight different commodities, including wheat, soybean, cotton, and pork bellies. The monthly prices between 1982 and 2007 were modelled in a set of eight Seemingly Unrelated Equations. The results showed that, even when the issue of heteroscedasticity is considered, excess co-movement in returns still exists. Contrarily, the excess co-movement of volatilities vanished once the effect of fundamentals has been taken out. In his turn, Chng (2008) took interest in the Japanese commodity markets. He applied a Seemingly Unrelated Regression (SUR) to investigate cross-market linkages among softs, precious metals and fuel based futures contracts. The sample consists of daily data for the contracts cycles of natural rubber, palladium and gasoline on the Tokyo Commodity Exchange from 03 July 2000 until 31 March 2008. On the short-run, he found a two-way interaction between natural rubber and gasoline, and a risk feedback from natural rubber to palladium. On the long-run, the volatility of palladium transfers to natural rubber and the traded volume of palladium affect gasoline.

The empirical study of Vivian and Wohar (2012) raised the issue of whether commodities are diverse or form an asset class. The sample data consists of a broad cross-section of 28 different commodities from January 1985 to July 2010. The authors employed a GARCH (1, 1) model to examine the volatility pattern in each regime after including structural breaks. Their results showed weak evidence of volatility breaks since commodity volatility remains high even after accounting for structural breaks. Therefore, they claimed that commodities are still diverse rather than integrated. Concerned with the Philippines commodity markets, Balanay (2013) examined the presence of volatility spillovers out there. The data consists of the monthly prices of the leading meat products (pork, chicken meat and beef) as well as egg products (chicken eggs and duck eggs) from 1990 to 2009. To measure the risks stemming from the fluctuating prices of the products in their own markets and their effects on other markets, she applied an autoregressive conditionally heteroscedastic approach (ARCH). The results indicate the presence of uncertainties in the dressed chicken, chicken eggs, pork and beef markets, since the heat waves are significant. On the other hand, all egg and meat markets in the study receive meteor showers, and that implies the existence of volatility spillovers among those markets.

On a larger scope, Chevallier and Ielpo (2013) followed the methodology pioneered by Diebold and Yilmaz (2012) in order to examine volatility spillovers: (1) within commodity markets (2) between standard assets and commodity markets and (3) between commodities and commodity currencies. Their study covered the sample period 1995–2012. The main findings reveal that volatility spillovers are weaker for commodities than for other asset classes. Particularly, agricultural commodities exhibit the lowest spillovers, whereas precious metals and energy exhibit the largest ones. Finally, different currencies respond to commodity volatility spillovers in different ways. More recently, Grieb (2015) employed the two-stage GARCH-M procedure of Hamao et al. (1990) to study price and volatility spillover effects between nine physical commodity futures contracts (corn, rough rice, soybeans, wheat, feeder cattle, lean hogs, live cattle, crude oil, and natural gas), as well as transmissions to those commodities from Eurodollars, the S&P500, and the U.S. Dollar Index from January 1, 2001 to December 31, 2009. This study documents a strong pattern of price and volatility spillovers within each commodity and from the external markets; that is price innovations for one commodity transfer information to other commodities. Overall, corn proved to be the commodity that most broadly received and transmitted both price and volatility spillovers, followed by crude oil.

On another level, the return and volatility spillover effects were examined in the energy and metals markets. Lin and Tamvakis (2001) undertook the first attempt to study such problem in the energy market. They investigated the information transmission mechanism between two oil markets (NYMEX and IPE) from 4 January 1994 to 30 June 1997 using a univariate and a bivariate GARCH model. They found that there are substantial bidirectional spillover effects when both markets are trading simultaneously. Also, they revealed that NYMEX is the true price leader since its closing prices lead prices in IPE the next morning. Todorova et al. (2013) addressed the transmission of volatility between five non-ferrous (i.e. base, industrial) metals contracts (aluminum, copper, lead, nickel, and zinc) traded on the London Metal Exchange using intraday data over the period June 2006 – December 2012. Their study employed a multivariate heterogeneous autoregressive (HAR) model and detected significant volatility interrelationships in the long-run, rather than in the short- and mid- run.

The rising food prices in the last decade have increased the research interests in agricultural food commodities and have questioned the explanatory power of oil markets. As a result, several studies have been conducted to examine the cross-market linkages and the interdependence between energy and agricultural commodities.

For instance, Abdel and Arshad (2009) examined the linkages between crude oil prices and vegetable oil prices. In their study, they applied the linear co-integration and Granger causality to monthly prices of petroleum, palm oil, soybean oil, sunflower oil and rapeseed oil from January 1983 to March 2008. Their findings suggest that crude oil prices lead the vegetable oil prices. Ciaian and Kancs (2011) also conducted linear co-integration tests between crude oil and food commodity prices. Using weekly prices of corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum and tea from 1994 to 2008, they evidenced that biofuel crops, particularity corn and soybean, became integrated with oil since 1999.

Concerned with nonlinear causal relationships, Nazlioglu (2013) focused on the oil market and three agricultural commodities (corn, soybeans, and wheat). By applying the nonparametric causality method of Dicks-Pancheko (2006) to weekly data from 1994 to 2010, he found that there is a persistent unidirectional nonlinear feedback from the oil prices to the corn and to the soybean prices. Wu et al. (2010) examined the feedback effects from crude oil futures price to corn spot and futures prices in a trivariate volatility spillover model. They employed the T-GARCH (threshold) and BEKK-GARCH models to estimate the trivariate model from January 2, 1992 to June 30, 2009. The results of the three models came as follow: (1) the constant spillover model (containing constant spillover parameters) detected volatility spillovers from crude oil prices to corn cash and futures prices (2) the event spillover model (including differing spillover parameters before and after the introduction of the Energy Policy Act of 2005) indicated an increase in the intensity of spillover effects since Energy Policy Act of 2005 (3) the substitution spillover model (containing time-varying spillover parameters allowed to vary with the ratio of fuel ethanol consumption to gasoline consumption) revealed that when the ethanol–gasoline consumption ratio exceeds a critical level, positive volatility spillovers transmit from crude oil prices to corn prices.

Applying the causality in variance test of Hafner and Herwartz (2006) based on the Lagrange Multiplier (LM) principle , Nazlioglu et al. (2013) tested the volatility spillover between oil and selected agricultural commodity prices (wheat, corn, soybeans, and sugar). The sample consists of daily data from 01 January 1986 to 21 March 2011. This sample period was divided into two sub-periods in order to account for the potential impact of the food price crisis, as follows: the pre-crisis period (01 January 1986 to 31 December 2005) and the post-crisis period (01 January 2006 –21 March 2011). In the pre-crisis period, the variance causality test shows that there is no risk transmission between oil and agricultural commodity markets. However, in the post-crisis period, oil market volatility spills on the agricultural markets —with the exception of sugar. The impulse response analysis also indicates that a shock to oil price volatility is transmitted to agricultural market.

Furthermore, Balcombe and Rapsomanikis (2008) used a Bayesian methodology to study the long-run relationships among international oil prices and Brazilian sugar and ethanol prices. Their study covered the period from July 2000 to May 2006 and used weekly prices. They found that Brazilian oil prices are long-run drivers of sugar prices, which in turn Granger caused ethanol prices. Similarly, Du et al. (2011) applied The Bayesian Markov Chain Monte Carlo methods to weekly crude oil, corn, and wheat futures prices from November 1998 to January 2009. They estimated two types of models: a univariate stochastic volatility model with Merton jump and bivariate stochastic volatility models. Their study confirmed the existence of volatility spillover among crude oil and agricultural commodities (corn and wheat) after the fall of 2006.

Later on, using different methodology, Balcombe and Rapsomanikis (2012) applied the linear and threshold co-integration analysis of Hansen and Sea (2002) on weekly prices of sugar, ethanol and oil from July 2000 to May 2006. They concluded that on the long run, oil prices drive Brazilian sugar prices. Moreover, the paths of sugar and ethanol prices are nonlinear after adjusting for oil price impacts. Methods used in studying commodity markets interdependence vary among researchers, which may lead to similar or contradicting results. Kristoufek et al. (2012) adopted the minimal spanning trees and hierarchical tress to study correlations among food, biofuel and fossil fuel prices from November 2003 to February 2011. Using weekly and monthly prices of crude oil, ethanol, corn, wheat, sugar cane, soybeans, sugar beets, biodiesel, diesel and gasoline, they showed increasing correlations and integration from 2003 to 2011.

The previously reviewed studies illustrate the existence of volatility spillovers between energy and agricultural commodities. This interdependency could be linear or nonlinear, as well as unidirectional or bi-directional. However, another bulk of researches have rejected such conclusions and concluded that there is no oil and agricultural commodity prices linkages. For example, Kaltalioglu and Soytas (2011) applied the Granger causality approach developed by Cheung and Ng (1996) in order to examine the volatility transmission between oil, food and agricultural raw materials markets. Monthly data of three indices were considered for the period January 1980 to April 2008: (1) the Agricultural Raw Material Index (ARMI) containing timber, cotton, wool, rubber and hides (2) the Food Price Index (FPI) encompassing fruits, vegetables, meat, poultry, fish, grocery food and non-alcoholic beverages (3) the Oil Price Index (OPI) measuring the price changes for crude oil. The findings suggest that there is no volatility transmission from oil markets to food and agricultural raw materials. However, a bi-directional volatility spillover is observed between agricultural raw material and food markets.

Moreover, Zhang et al. (2009) examined the causality between energy and food commodities. They studied the linear co-integration between three energy commodities (ethanol, gasoline and oil) and five agricultural commodities (corn, rice, soybeans, sugar and wheat) using monthly prices from March 1989 to July 2008. The results of the estimated VEC model (a simultaneous equations approach) revealed the absence of a long-run relationship between oil and agricultural commodity prices. On the other hand, short run relations were present but not persistent. With a similar research interest, Saghaian (2010) also used VEC models to analyze the causal relationships across five US commodities: corn, soybeans, wheat, ethanol and crude oil. Consistent with the findings of Zhang et al. (2009), the VEC assessment indicated that there were no causal links between energy and agricultural markets. Conversely, crude oil prices Granger caused corn, soybeans, and wheat prices, as shown by the Granger causality tests.

Concerned with the Brazilian commodity markets, Serra (2011) examined the links between crude oil, ethanol and sugar prices in Brazil using a semiparametric GARCH model suggested by Long et al. (2011) as an estimator of the conditional covariance matrix. The sample consists of the weekly international crude oil prices and Brazilian ethanol and sugar prices from July 2000 to November 2009. The findings suggest that there is a long-run relationship between ethanol and crude oil, as well as between ethanol and sugar prices. The results of the parametric BEKK model showed that ethanol prices do not induce sugar prices in the long-run. Instead, crude oil and sugar market shocks transfer volatility to the ethanol market. On a larger scope, Esmeili and Shokooi (2011) conducted linear co-integration analysis on the monthly prices between 1961 and 2005 for: eggs, meat, milk, oilseeds, rice, sugar, wheat, consumer price index (CPI), gross domestic product (GDP), crude oil and food production index. They suggest that crude oil and food prices are not linked directly. Instead, food prices are indirectly affected by crude oil, through the food production index.

Later on, Gardebroek and Hernandez (2013) evaluated the level of interdependence and the dynamics of volatility across oil, ethanol and corn prices in the United States between 1997 and 2011 following a multivariate GARCH approach. They revealed the existence of a high interaction between ethanol and corn markets. However, volatility spillovers are only significant from corn to ethanol prices, but not the other way round. On the other hand, there are no volatility feedbacks between oil and corn markets. The authors also conclude that volatility in energy markets does not stimulate volatility in the US corn market. Bastiani et al. (2013) examined the interaction between prices of ethanol, crops and cattle. They used the monthly prices of ethanol, corn, soybeans, wheat and cattle from January 1987 to March 2012. The results of the Bounded testing and Granger causality showed no evidence of any relation between the commodities under study.

While previous studies such as Cha et al. (2011) focused on the corn market in analyzing the impact of oil on the grain market, Kong (2012) incorporated the ripple effects on major grain markets (rice, wheat, corn and soybean), he applied the bivariate GARCH model and Maximum Likelihood Estimation (MLE) to identify the volatility spillovers between oil and grain prices, using weekly data from 1992 to 2010. A bidirectional transmission of volatility is found both between oil and corn, and between oil and soybean. The volatility of wheat only responds to the volatility stock of oil, but not vice versa. Finally, no volatility transmission was depicted between rice and oil prices. Natalenov et al. (2011) took interest in the co-integration between futures prices of crude oil and futures prices of cocoa, coffee, corn soybeans, soybean oil, wheat, rice, sugar and gold. VECM and TVECM models were applied to monthly futures prices from July1989 to February 2010. The study evidenced that only crude oil, cocoa, wheat and gold are co-integrated, whereas the other commodities (coffe, corn, soybeans, soybean oil, rice and sugar) are not.

In a non-linear framework, Liu (2014) studied the cross-correlations between crude oil and agricultural commodity markets using daily closing spot prices of crude oil and four agricultural commodities (corn, soybean, oat and wheat) from January 3, 1994 to December 31, 2012. Using a statistical test suggested by Podobnik et al. (2009), he found that the linear return cross-correlations as well as the volatility cross-correlations are significant at large lag lengths. The results of the Detrended Cross-Correlation Analysis (DCCA) suggest that the return cross correlations are persistent for corn and soybean and anti-persistent for oat and soybean. However, the nonlinear cross-correlation measure is significant for small time scales and not significant for large ones.

The discussion of the aforementioned studies allows us to conclude that there is no consensus regarding the relationship between agricultural and energy markets: some papers found price links, others did not. That is, the energy-agricultural commodity nexus has become a controversial issue. On another level, a branch of the literature on agricultural commodities devoted its attention to the potential spillovers between major agricultural commodities. Among the early studies in agricultural economics, Anderson (1985) examined the determinant of daily price volatilities in nine American grain and wheat futures markets over the period 1966 to 1980. Using a non-parametric approach and robust statistical methods, he found that futures price changes vary following a regular pattern predicted by seasonality.

After Pindick and Rotemberg (1990) claimed that, over the period from 1960 to 1985, the prices of seven unrelated commodities tend to move together, Malliars and Urrutia (1996) were some of the early researchers to take interest in the co-integration between agricultural commodity futures prices. Their sample consists of the prices of soybeans, oats, corn and wheat for the period 1981 to 1991. Using the error correlation model (ECM) of Engle and Granger (1987), they found that corn futures markets have a long-run impact on the price discovery process in the spot markets of corn, wheat, soybean, soybean meal. Tejeda and Goodwin (2009) empirically studied the impact of corn on grain and livestock prices. They use weekly average prices of futures for corn, soybean, feeder cattle and live cattle from January 1998 till October 2008. By considering a threshold structure in a multivariate time-series model, they found positive dynamic correlations between corn and soybean and feeder and fed cattle prices. On the other hand, corn and feeder prices were inversely related during the period of post mandated ethanol production. Also, we find there are adjustment costs inhibiting price transmission between the crops and the live cattle market, in the form of modifying feeding rations. The results suggest the presence of asymmetric effects, as a result of spillover effects between the markets.

More recently, Lahiani et al. (2013) addressed the volatility transmission among the four major agricultural commodities (sugar, wheat, corn and cotton) over the recent period 2003- 2010. They employed the VAR (1) –GARCH (1, 1) model of Ling and McAleer (2003) and showed that different agricultural commodities exhibit different volatility patterns and respond in different ways to past shocks. Moreover, strong volatility linkages exist between agricultural commodities, particularly, corn proved to have an explanatory power on the volatility of sugar, wheat and cotton. In his turn, Musunuru (2014) employed a multivariate GARCH-BEKK model to study the volatility transmission between corn and wheat using daily returns from 1993 till

2013. The empirical results showed that corn and wheat prices move together and exhibit significant levels of persistence to shocks. The Gaussian distribution reveals bi-directional volatility linkages between corn and wheat.

Furthermore, Gardebroek et al. (2014) examined the dynamics of volatility across major crops in the United States. They followed a Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) approach to assess the level of interdependence and volatility transmission between the corn, wheat, and soybean markets on a daily, weekly, and monthly basis over the period from 1998 until 2012. The estimation results indicate lack of cross-market dependence between corn, wheat, and soybean price returns at the mean level. However, on a weekly and monthly basis, significant volatility spillovers exist across commodities whereby wheat and corn play a major role. Their main conclusion is that, despite the apparent higher financial market integration of some agricultural commodities, agricultural markets did not become more interdependent.

On the other hand, a group of studies have looked into international agricultural price dynamics, as well as the volatility spillover effect at the level of many countries and commodities.

In fact, Goodwin and Piggott (2001) studied market integration in spatially separate regional grain markets, through price linkages. The regional markets considered were for corn and soybean in North Carolina from 2 January 1992 until 4 March 1999. Their results showed that the markets are well integrated. Moreover, price variations adjust faster when the existent threshold points are accounted for in the model. Moreover, Yang et al. (2003) explored price transmissions between the biggest wheat producers, USA, Canada and Europe using daily prices and a sample running from May 1, 1996 to April 30, 2002. They applied the generalized forecast error variance decomposition of Koop et al. (1996) and a generalized impulse response analysis proposed by Pesaran and Shin (1998). They concluded that US wheat prices affect Canadian prices. On the other hand, European prices tend to be autonomous in their price discovery process and slightly influence US-prices.

With a large sample of 4,000 daily observations, Alom et al. (2011) analyzed the relationship of inter-country food price returns between Asia and some Pacific countries. They applied a Multivariate Threshold GARCH (MTGARCH) for Australia, New Zealand, USA, Korea, Singapore, Hong Kong, Taiwan, India and Thailand for the period of 2 January 1995 to 30 April 2010. The authors estimated a two-stage model in order to analyze the spillover effect of food price returns both at the mean and at the volatility level of returns. Firstly, at the mean level of returns, there is weak evidence of significant spillover effects across countries. However, there is strong mean spillover from the USA to the other markets. Secondly, at the volatility (risk) level of returns, there is strong evidence of persistent and are nonlinear cross country effects, and Australia proved to have the least influence on the other markets.

Fung et al. (2013) studies the role of Chinese futures markets in the global context and their price linkages with other global futures markets. They probe to see to which extent China is information-efficient and its leading role in setting the world commodity prices. The sample involves 16 commodity futures traded in China, USA, Japan, Malaysia, and Great Britain from December 2003 until October 31, 2011. The findings suggest that European prices dominate the price discovery process internationally. Moreover, there a bidirectional effect between the US and China. Since there is no significant lead-lag relationships between the Chinese and foreign markets, Chinese commodity futures markets therefore are not led by foreign markets. Finally, the results evidenced that Chinese commodity future markets are information-efficient and likely to be driven by local market dynamics occurring during the daytime trading session.

Adammer et al. (2015) took interest in the international volatility spillover among North American and European agricultural commodity markets. Their study, however, accounts for both the institutional changes in those markets and the impact of the price turmoil after the year 2007. The data consists of the prices of canola, wheat and corn futures between 2000 and 2013. Using co-integration techniques as well as bivariate VECM- and VAR-TDCC-GARCH models, they showed that U.S. and European prices, especially those of corn and wheat have become strongly interlinked between 2007 and 2013. They also evidenced that the US market leads in terms of price transmissions and that Information flows from Europe to the US are indirect. Those results mostly concern the volatility spillovers of corn and canola. A study undertaken by Steen and Gjolberg (2013) covered a large sample of 20 commodities over a period of 25 years (1986-2010). They concluded that variations in price and returns differ across commodities. Moreover, commodity markets became more interdependent with each other and with the stock market after 2004. However, the co-movements stayed relatively stable until 2008. In fact, after the financial crisis of 2008, the interrelationships between commodities turned out to be extensively high.

2.3 Conclusion

In this chapter, an examination of the theoretical grounds and a quick review of previous research concerned with detecting and understanding the co-movements across commodities, were done in order to shed the light on the importance of this topic and its potential implications on portfolio diversification, hedging strategies and risk management.

In short, from theoretical points of view, the concepts of financial diversification and tactical asset allocation as a way to manage the risk of a portfolio, created a link between traditional financial markets and commodities, and across commodities themselves. This interdependency between commodities was mainly triggered by the financialization of commodity markets and the excessive trade of futures contracts in the past decade. As commodities are viewed as an essential financial asset (Alom et al., 2011) to be held as part of a well-diversified portfolio, investors were increasingly seeking diversification and hedging benefits arising from holding different types of commodities. However, the decision making process should not rely solely on the risk-return characteristics of the commodity but also on how the commodity correlate with the rest of the portfolio over time. Therefore, for financial decision making purposes such as portfolio management, measurement of diversification benefits, risk management, and value-at-risk estimation, investors must carefully evaluate the existence and direction of volatility spillovers between alternative investments, particularly between commodity markets, the focus of this thesis.

In the view of the previously discussed empirical studies, it seems that interest in studying cross-commodity volatility spillovers is growing, especially in the light of the recent financialization of commodities. However, we find that there is no consensus with respect to the detected level of integration and interdependence among commodity markets. While many studies saw individual agricultural commodity markets as a single market (highly integrated), others claimed that this degree of integration is time-varying, differs between returns and volatilities and does not exist sometimes. This point is of interest to investors, as it could potentially jeopardize the well-known commodity diversification effects found (among others) in Gorton and Rouwenhorst (2005) and Erb and Campbell (2006). For instance, volatility interactions across commodity markets, if they exist, may lower the effectiveness of diversification strategies.

What seems to be ignored in most of the literature of commodity market linkages is the interdependence among agricultural commodities, as well as the effect that country-specific information and macroeconomic announcements could have on the measurement of integration among markets.

Controlling for such variables in our model allows us to investigate the extent to which different agricultural commodities can be considered an asset class. As it is generally agreed, an asset class should show a high degree of integration, arising from common shocks and common economic fundamentals (Greer, 1997). Therefore in the next chapter we will start with the concept that the impact of macro-economic news on the interdependence among major commodities is not clear and therefore this thesis will bridge this gap in the literature. The answer of this question would allow us to see if major commodities are considered to be a single class of asset or not, since this has a major implication on traders' hedging, risk management and portfolio diversifications. This thesis also understudies the incorporation of structural breaks in the returns of agricultural commodities, because ignoring the existence of structural breaks in the time series could overestimate the level of integration across commodities.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Introduction

As seen in the literature review, there is a gap in the perceived level of interdependence among several commodity markets, and conflicting opinions as to whether portfolio diversification could still be beneficial given evidence of increasing levels of integration. Few studies however consider the impact of macroeconomic announcements in the assessment of linkages among agricultural commodity markets. This may or may not lead to misleading results on the degree of association among commodity markets. Another point that is often ignored is the potential existence of structural changes in the volatility of commodity return, which could have important implications on the level of commodity markets interdependence. This thesis contributes to the existing literature by considering these two points and by adopting a creative blend of econometric strategies to evaluate return volatility transmission among the sampled commodities. To this end, the objective of this thesis is to empirically test the level of commodity markets integration in terms of return volatility spillover, as well as the effect of the announcements surprise on commodities. The chapter is structured in the following manner. Section 3.2 dresses the hypotheses derived from the research questions as well as the expected relationship between the dependent and independent variables. Section 3.3 presents the data used to conduct this study, along with the variables utilized to test the hypotheses. After that, the empirical methodology is outlined in section 3.4. Section 3.5 goes over the statistical package to be employed, and the conclusion is stated in section 3.6.

3.2 Hypotheses

According to the previously established literature and to the formulated research questions, this section presents the testable hypotheses underlying this study.

Ha_0: Agricultural commodity markets are not interdependent and do not exhibit return volatility spillovers.

Ha_1: Agricultural commodity markets are interdependent and do exhibit return volatility spillovers.

The null hypothesis (Ha_0) implies no integration among agricultural commodity markets, such that the volatility in commodity Y is not affected by volatilities in commodities $X_{1,\dots,}X_n$. This can be confirmed by testing the significance of the coefficients for return volatilities in commodities $X_{1,\dots,}X_n$.

Hb_0: Major macroeconomic news announcements do not have statistically significant effect on the volatility of agricultural commodities

Hb_1: Major macroeconomic news announcements have statistically significant effect on the volatility of agricultural commodities

The null hypothesis (Hb_0) implies the absence of news impact on major agricultural commodity markets, such that the volatility in commodity Y is not affected by a macroeconomic surprise. This can be confirmed by testing the significance of the coefficients for the proxies for major macroeconomic announcements.

3.3 Data

This section describes the sample used, defines the variables and the source of the data.

3.3.1 Sample Size

Based on the Friday April 14, 2015 Commitments of Traders (COT) report, which is weekly released by the Commodity Futures Trading Commission (CFTC), the top five most traded agricultural commodities, by value, are: corn, sugar, soybeans, wheat, and soybeans oil. The sample chosen for this thesis comprises the following four commodities: corn, soybeans, wheat, and soybeans oil, for being representative of the agricultural commodity markets and because they all (1) belong to the grains sector (2) trade on the Chicago Board of Trade (CBOT). On the other side, sugar was not chosen because it belongs to the soft sector and trades on the InterContinental Exchange (ICE) which causes a conflict with the trading days of CBOT, inconsistency in the collected data and leads to missing values.

3.3.2 Variable Definition and Sources

Continuous Futures Prices: I use daily futures data for corn, wheat, soybeans and soybeans oil ranging from December 30, 1999 to May 5, 2015, a total of 3,865 observations per variable (one observation is lost in logarithmic returns). Prices for the aforementioned commodity futures are for the nearest expiration contract on CBOT and the data was obtained from Bloomberg Database.

Economic Surprise Index: Based on chapter two, academic studies have found that asset prices respond to regularly scheduled economic announcements and exhibit changes in their return volatility patterns with daily swings far exceeding historical norms. An economic news surprise is an episode whereby actual macroeconomic news data releases exceed or fall short of market expectations (its forecasted value). While most researchers have concentrated their studies on the response of assets to one or few economic data releases, our thesis finds that an aggregated index of U.S. data surprises can be very helpful in anticipating future trends in U.S. economic activity as well as the underlying trends in the transmission of return volatility among agricultural commodities.

In fact, when U.S. economic activity is rising or falling, the tendency of economists to underestimate this move on both the upside and the downside leads to a smoothed and persistent trend in economic surprises. This is due, first, to the fact that the median forecast of surveyed economists might be biased to show little change as it tends to balance both bullish and bearish economic forecasts. Second, forecasters might be slow to adjust their forecasts when economic conditions are changing, perhaps because their expectations are anchored to lagged rather than future economic data. Third, in the face of uncertainty, forecasters might become conservative and not adjust their forecasts quickly enough to changing conditions.

As such, I retrieved the daily data of the Bloomberg Economic Surprise Index from January 3, 2000 (its starting date) until May 5, 2015 from Bloomberg Database. This index is based on Bloomberg News surveys of economic analysts for 39 U.S. weekly and monthly time series reported on a regular basis on the economic calendar[1]. The surprise element is calculated as the percentage difference between the actual economic data release and the median of analysts' forecasts for that release, smoothed with six-month decay. The six-month decay is a weighted average calculated by assigning each release a relative weight with more recent releases given a higher weight. For weekly series such as U.S. Unemployment Claims, the weights over the 24 week period decay linearly from 24 for the most recent release to 1 for the oldest release in the period. For monthly releases, the weights were derived from the weekly weights, where for example, the weight for the most recent month is the same as the sum of the weights for the most recent four weeks (90 = 24 + 23 + 22 + 21).

Four Scheduled Macroeconomic News Announcements: for each of the four listed announcements below, I retrieved the actual news release values and the corresponding market expectations or forecasts spanning from January 2, 2002 to May 5, 2015, from Bloomberg database. The Bloomberg's synchronized survey data on market expectations of macroeconomic news consists of median expectations of the survey panelists. Anderson et al. (2009) tested for the unbiasedness of the Bloomberg forecasted data using standard techniques used in the

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[1] A partial list of the announcements included in the index is available in Appendix I.

literature (Balduzzi et al., 2001) and found that the survey expectations are of good quality (null hypothesis of unbiased data could not be rejected at 10% level).

In this study I use a sample of four macroeconomic news announcements which are most used and influential in the academic studies and press. However, the units of measurement obviously differ across the macroeconomic indicators. For instance, the U.S. CPI indicator is measured by monthly percentage change (MoM%) whereas the U.S. employees on nonfarm payroll indicator is measured by total monthly net change (MoM net change). Hence, to allow for meaningful comparisons across indicators, this study transforms these continuous variables into dummies. We define an announcement as a surprise if its dummy variable takes a value of one (different than zero). The dummy variable takes a value of zero if the forecasted value is equal to the actual value (no surprise), and takes a value of one if the forecasted value is different than the actual value (surprise). Days with missing values are treated as no-surprise days, thus the corresponding dummy variable will be equal to zero in such days.

- **Consumer Price Index:** Consumer prices are a measure of prices paid by consumers for a market basket of consumer goods and services. The yearly (or monthly) growth rates represent the inflation rate. (Bloomberg, 2015)
- **Target Federal Funds Rate:** The federal funds rate is the short-term interest rate targeted by the Federal Reserve's Federal Open Market Committee (FOMC) as part of its monetary policy. In December 2008, the target "fed funds" level was replaced by a target range, and in this thesis, the upper bound of that range is used. (Bloomberg, 2015)
- **Unemployment Rate:** The unemployment rate tracks the number of unemployed persons as a percentage of the labor force (the total number of employed plus unemployed). These figures generally come from a household labor force survey. (Bloomberg, 2015)
- **Non-Farm Payroll:** This indicator measures the number of employees on business payrolls. It is also sometimes referred to as establishment survey employment to distinguish it from the household survey measure of employment. (Bloomberg, 2015)

3.4 Empirical Methodology

The aim of this section is to describe the econometric models used to address the research question. After detecting the existence/absence of structural breaks in the time series using the modified iterative cumulative sum of squares algorithm (ICSS), we derive the volatility of the agricultural commodities from a univariate GARCH (1,1) model. Then, a simultaneous equations model is estimated using a three-stage least squares (3SLS) approach. This model assesses the interdependence between the return volatility of the futures contracts for the four agricultural commodities in question. In each equation, the dependent variable is the commodity's return volatility. At this point, we divide our study into two models. In Model A, the dependent variable of each equation is a function of (1) the current return volatilities of the other commodities (2) the lagged volatilities of the other commodities (3) the 4 dummy variables (section 3.3.2) as a proxy for news surprises. In Model B, the dependent variable of each equation is a function of (1) the current return volatilities of the other commodities (2) the lagged volatilities of the other commodities (3) the Bloomberg economic surprise index (section 3.3.2) as a proxy for announcements surprises. Therefore, the difference between Model A and Model B is in the variables used as proxy for economic news: Model A assumes discrete (dummy) variables whereas Model B makes use of a continuous variable instead of the usual zero-one dummy variable.

3.4.1 Detecting Structural Breaks

According to Hillebrand (2005), breakpoints in the unconditional variance will result in breakpoints in the GARCH; hence, it is important to consider structural breaks in modelling volatility in order to come up with accurate results and to avoid the overestimation of persistency in the series. The iterative cumulative sum of squares (ICSS) algorithm of Inclan and Tiao (1994) is based on the assumption that the series is independently identically distributed. In this study, however, the GARCH series are not independently identically distributed. Accordingly, it is more appropriate to employ the modified ICSS algorithm to overcome the potential issues. The modified ICSS algorithm includes a nonparametric adjustment proposed by Sansó, Arragó and Carrion (2004) to detect structural breaks in the unconditional variance of dependent processes such as the GARCH. We test the null hypothesis of a constant unconditional variance in agricultural commodity returns against the alternative hypothesis of a break in the unconditional variance, at the 5% significance level.

The reasoning underlying the ICSS algorithm is that the time series of commodity returns has a stationary unconditional variance over an initial time period until the occurrence of a sudden break. Then, the unconditional variance is stationary until the next sudden change takes place. The replication of this process through time leads to time series with m breakpoints in the unconditional variance with n observations.

3.4.2 Univariate GARCH model with Structural Breaks

In quantitative financial research, the most commonly used empirical methodology to model and forecast time-varying volatility is the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH). In this thesis, we employ a univariate GARCH to model the volatility of daily futures returns on each of the agricultural commodities under study. What follows is a description of the historical and theoretical grounds of the GARCH model.

The phenomenon of volatility clustering takes place when market data exhibit periods of relative calm and periods of high volatility, whereby large and small errors tend to occur in clusters (Vogelvang, 2005). Although there is no universally accepted explanation of it, this phenomenon can be modelled. To capture such volatility clustering, Engle (1982) introduced the Auto Regressive Conditional Heteroskedasticity (ARCH) model based on the notion that the volatility is not constant; rather, information from the recent past might influence the conditional disturbance variance. Under an ARCH (p) process, recent disturbances affect the variance of the current disturbances and thus the variance of the dependent variable.

Since then, the ARCH model was successfully applied to volatile markets. It was extended later on by Bollerslev (1986) who proposed the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model. In a GARCH (p,q) model, the conditional variance of the coming period is a linear function of a long-term weighted average, previous period(s) squared residuals (the ARCH term) and its own lag (forecasted variance from the last period, i.e. the GARCH term).

A univariate GARCH (1,1) model for the log returns takes the form of:

$$RET_t = \mu + e_t \qquad (1)$$

$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (2)$$

In equation (1), RET_t represents the corresponding log (continuously compounded) returns for the corresponding commodity futures at a certain time t, and e_t follows a student distribution with a variance (σ_t^2) .

In equation (2), σ_t^2 represents the conditional variance of the returns. ω is the average volatility level and is equal to γV_L where $V_L$is the long-run variance rate. e_{t-1}^2 corresponds to the news captured in the error term from the previous period, and σ_{t-1}^2 is the conditional variance of returns from the previous period. The coefficients γ, α and β are the weights assigned to V_L, e_{t-1}^2 and σ_{t-1}^2, respectively and should be positive. The maximum likelihood method will be used to estimate w, α and β. If α + β is less than one then the GARCH model is stable and the volatility of the returns is not persistent.

Next, we make use of two methods to check for autocorrelation in the log returns of commodity futures. In fact, if the log returns of the studied commodity futures show significant partial autocorrelation of order p, then equation (1) can be written as an AR (p) process.

The first method makes use of the correlograms for the autocorrelations (ACF) and partial autocorrelations (PACF) of the series. For an AR (p) process, the partial autocorrelation function is significant up to the order p+1; hence, it is not significant at an order higher than p+1. Thus, to determine p we simply examine the significance of the partial autocorrelation till order 12. The order 12 is arbitrary chosen. In this case, we do not allow autocorrelation (partial autocorrelation) till order 12 but higher order of autocorrelation (partial autocorrelation) will be allowed.

Under the second method, we run the Ljung-Box Q-statistic test of Ljung and Box (1978) which yields a useful picture of the correlation behavior of the residuals. It is a modified version of the Box-Pierce test of Box and Pierce (1970). The Ljung-Box test has an asymptotic X^2 distribution with p degrees of freedom. Therefore, when testing for p^{th} order autocorrelation, the null hypothesis of non-autocorrelation is that the computed autocorrelation coefficients of the disturbances are zero. In other words, we check whether the theoretical autocorrelation coefficients of the residuals are not significantly different from zero. Unlike other tests, such as the Breusch-Godfrey LM-test, that test for autocorrelation at a specific order, the Ljung-Box test offers the advantage of testing the "overall" randomness based on a number of lags. The null hypothesis of randomness is rejected if the p-value is below the significance level.

Therefore, the correlograms for the autocorrelations and partial autocorrelations, as well as the Ljung-Box Q-statistic test given at 1%, 5% and 10% confidence level will allow us to determine the order p.

For instance, if we detect an autocorrelation of order 1 in the log returns, equation (1) will take the form of:

$$RET_t = \mu + \rho RET_{t-1} + e_t \qquad (3)$$

However, standard GARCH models, in which structural breaks are not accounted for, tend to overestimate the persistence of the underlying volatility (Lamoureux and Lastrapes, 1990). Therefore, in order to avoid persistency problems, it is theoretically recommended to augment our univariate GARCH model by incorporating the n detected structural breaks, as follows:

$$\sigma_t^2 = \omega + d_1 D_1 + \cdots + d_n D_n + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (4)$$

Where $D_1 ..., D_n$, are the set of dummy variables taking a value of one for each structural point and zero elsewhere.

3.4.3 Simultaneous Equation Models (SEM)

The simultaneous equation model is a multiple equation model where explanatory variables from one equation can be dependent variables in other equations. A variable is defined as endogenous if it can be explained in another equation which belongs to a complete simultaneous equation model (SEM). So in a SEM we have to deal with endogenous explanatory variables that are explicitly specified in a structural equation. Since endogenous explanatory variables are correlated with the disturbance terms in all the structural equations of the SEM, Ordinary Least Squares (OLS) estimates will be inconsistent, thus, the consistency property of the OLS estimator is lost. Accordingly other but consistent estimation methods will be considered when estimating the parameters of the structural form of the model. This concerns single-equation methods, such as the two-stage least squares (2SLS) estimator, and full-information methods, such as the three-stage least squares (3SLS) estimator (Vogelvang, 2005)

In general, a simultaneous equation model (SEM) takes the following structural form:

$$
\begin{aligned}
Y_{t1} &= \gamma_{11} + \beta_{12}Y_{t2} + \cdots + \beta_{1G}Y_{tG} + \gamma_{12}X_{t1} + \cdots + \gamma_{1K}X_{tK} + \mu_{t1} \\
Y_{t2} &= \gamma_{21} + \beta_{21}Y_{t1} + \cdots + \beta_{2G}Y_{tG} + \gamma_{22}X_{t1} + \cdots + \gamma_{2K}X_{tK} + \mu_{t2} \\
&\vdots \\
Y_{tG} &= \gamma_{G1} + \beta_{G1}Y_{t1} + \cdots + \beta_{GG-1}Y_{tG-1} + \gamma_{G2}X_{t1} + \cdots + \gamma_{GK}X_{tK} + \mu_{tG}
\end{aligned}
$$

Where G is the number of endogenous variables, both dependent and explanatory variables and K is the number of exogenous variables.

In the context of this thesis, two simultaneous equation models will be estimated: model A and model B.

On one hand, model A assumes discrete (dummy) variables as a proxy for announcement surprises and is defined as follows:

$$
\begin{aligned}
\sigma^2_{CORt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_{50}\sigma^2_{WHTt} + \alpha_{60}\sigma^2_{SOYt} + \alpha_{70}\sigma^2_{SOLt} \\
+ \alpha_{51}\sigma^2_{WHTt-1} + \alpha_{61}\sigma^2_{SOYt-1} + \alpha_{71}\sigma^2_{SOLt-1} + \alpha_{81}\sigma^2_{CORt-1} + \alpha_{52}\sigma^2_{WHTt-2} \\
+ \alpha_{62}\sigma^2_{SOYt-2} + \alpha_{72}\sigma^2_{SOLt-2} + \alpha_{82}\sigma^2_{CORt-2} \\
\vdots \\
\alpha_{5k}\sigma^2_{WHTt-k} + \alpha_{6k}\sigma^2_{SOYt-k} + \alpha_{7k}\sigma^2_{SOLt-k} + \alpha_{8k}\sigma^2_{CORt-k} + \varepsilon_t
\end{aligned}
$$

$$\sigma^2_{WHTt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_{50}\sigma^2_{CORt} + \alpha_{60}\sigma^2_{SOYt} + \alpha_{70}\sigma^2_{SOLt}$$
$$+ \alpha_{51}\sigma^2_{CORt-1} + \alpha_{61}\sigma^2_{SOYt-1} + \alpha_{71}\sigma^2_{SOLt-1} + \alpha_{81}\sigma^2_{WHTt-1} + \alpha_{52}\sigma^2_{CORt-2}$$
$$+ \alpha_{62}\sigma^2_{SOYt-2} + \alpha_{72}\sigma^2_{SOLt-2} + \alpha_{82}\sigma^2_{WHTt-2}$$
$$\vdots$$
$$\alpha_{5k}\sigma^2_{CORt-k} + \alpha_{6k}\sigma^2_{SOYt-k} + \alpha_{7k}\sigma^2_{SOLt-k} + \alpha_{8k}\sigma^2_{WHTt-k} + \varepsilon_t$$

$$\sigma^2_{SOYt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_{50}\sigma^2_{CORt} + \alpha_{60}\sigma^2_{WHTt} + \alpha_{70}\sigma^2_{SOLt}$$
$$+ \alpha_{51}\sigma^2_{CORt-1} + \alpha_{61}\sigma^2_{WHTt-1} + \alpha_{71}\sigma^2_{SOLt-1} + \alpha_{81}\sigma^2_{SOYt-1} + \alpha_{52}\sigma^2_{CORt-2}$$
$$+ \alpha_{62}\sigma^2_{WHTt-2} + \alpha_{72}\sigma^2_{SOLt-2} + \alpha_{82}\sigma^2_{SOYt-2}$$
$$\vdots$$
$$\alpha_{5k}\sigma^2_{CORt-k} + \alpha_{6k}\sigma^2_{WHTt-k} + \alpha_{7k}\sigma^2_{SOLt-k} + \alpha_{8k}\sigma^2_{SOYt-k} + \varepsilon_t$$

$$\sigma^2_{SOLt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_{50}\sigma^2_{CORt} + \alpha_{60}\sigma^2_{WHTt} + \alpha_{70}\sigma^2_{SOYt}$$
$$+ \alpha_{51}\sigma^2_{CORt-1} + \alpha_{61}\sigma^2_{WHTt-1} + \alpha_{71}\sigma^2_{SOYt-1} + \alpha_{81}\sigma^2_{SOLt-1} + \alpha_{52}\sigma^2_{CORt-2}$$
$$+ \alpha_{62}\sigma^2_{WHTt-2} + \alpha_{72}\sigma^2_{SOYt-2} + \alpha_{82}\sigma^2_{SOYt-2}$$
$$\vdots$$
$$\alpha_{5k}\sigma^2_{CORt-k} + \alpha_{6k}\sigma^2_{WHTt-k} + \alpha_{7k}\sigma^2_{SOYt-k} + \alpha_{8k}\sigma^2_{SOYt-k} + \varepsilon_t$$

Where for each commodity, $\sigma_t^2$is the expected volatility calculated at time t from the results of the univariate GARCH with structural breaks. CPI_t, UNE_t ,PAY_t and FED_t represent the dummy variables for consumer price index, unemployment rate, non-farm payroll and federal fund rate, respectively.

Since commodity markets may be influenced by delayed volatility spillovers from other markets, rather than be instantaneously affected by volatilities in other markets, this can be captured by using k lags of the volatility of commodity market as explanatory variables in each equation of the model. Accordingly, k represents the number of lags in expected volatility of the commodity market taken as explanatory variables, and α_{ik} is the coefficient of the expected volatility of the corresponding explanatory commodity at time t-k.

On the other hand, model B assumes a continuous index as a proxy for announcement surprises and is defined with the potential existence of k lagged variances, as follows:

$$\sigma^2_{CORt} = \alpha_0 + \alpha_1 I_t + \alpha_{20}\sigma^2_{WHTt} + \alpha_{30}\sigma^2_{SOYt} + \alpha_{40}\sigma^2_{SOLt} + \alpha_{21}\sigma^2_{WHTt-1} + \alpha_{31}\sigma^2_{SOYt-1} + \alpha_{41}\sigma^2_{SOLt-1} + \alpha_{51}\sigma^2_{CORt-1} + \alpha_{22}\sigma^2_{WHTt-2} + \alpha_{32}\sigma^2_{SOYt-2} + \alpha_{42}\sigma^2_{SOLt-2} + \alpha_{52}\sigma^2_{CORt-2}$$

$$\vdots$$

$$\alpha_{2k}\sigma^2_{WHTt-k} + \alpha_{3k}\sigma^2_{SOYt-k} + \alpha_{4k}\sigma^2_{SOLt-k} + \alpha_{5k}\sigma^2_{CORt-k} + \varepsilon_t$$

$$\sigma^2_{WHTt} = \alpha_0 + \alpha_1 I_t + \alpha_{20}\sigma^2_{CORt} + \alpha_{30}\sigma^2_{SOYt} + \alpha_{40}\sigma^2_{SOLt} + \alpha_{21}\sigma^2_{CORt-1} + \alpha_{31}\sigma^2_{SOYt-1} + \alpha_{41}\sigma^2_{SOLt-1} + \alpha_{51}\sigma^2_{WHTt-1} + \alpha_{22}\sigma^2_{CORt-2} + \alpha_{32}\sigma^2_{SOYt-2} + \alpha_{42}\sigma^2_{SOLt-2} + \alpha_{52}\sigma^2_{WHTt-2}$$

$$\vdots$$

$$\alpha_{2k}\sigma^2_{CORt-k} + \alpha_{3k}\sigma^2_{SOYt-k} + \alpha_{4k}\sigma^2_{SOLt-k} + \alpha_{5k}\sigma^2_{WHTt-k} + \varepsilon_t$$

$$\sigma^2_{SOYt} = \alpha_0 + \alpha_1 I_t + \alpha_{20}\sigma^2_{CORt} + \alpha_{30}\sigma^2_{WHTt} + \alpha_{40}\sigma^2_{SOLt} + \alpha_{21}\sigma^2_{CORt-1} + \alpha_{31}\sigma^2_{WHTt-1} + \alpha_{41}\sigma^2_{SOLt-1} + \alpha_{51}\sigma^2_{SOYt-1} + \alpha_{22}\sigma^2_{CORt-2} + \alpha_{32}\sigma^2_{WHTt-2} + \alpha_{42}\sigma^2_{SOLt-2} + \alpha_{52}\sigma^2_{SOYt-2}$$

$$\vdots$$

$$\alpha_{2k}\sigma^2_{CORt-k} + \alpha_{3k}\sigma^2_{WHTt-k} + \alpha_{4k}\sigma^2_{SOLt-k} + \alpha_{5k}\sigma^2_{SOYt-k} + \varepsilon_t$$

$$\sigma^2_{SOLt} = \alpha_0 + \alpha_1 I_t + \alpha_{20}\sigma^2_{CORt} + \alpha_{30}\sigma^2_{WHTt} + \alpha_{40}\sigma^2_{SOYt} + \alpha_{21}\sigma^2_{CORt-1} + \alpha_{31}\sigma^2_{WHTt-1} + \alpha_{41}\sigma^2_{SOYt-1} + \alpha_{51}\sigma^2_{SOLt-1} + \alpha_{22}\sigma^2_{CORt-2} + \alpha_{32}\sigma^2_{WHTt-2} + \alpha_{42}\sigma^2_{SOYt-2} + \alpha_{52}\sigma^2_{SOYt-2}$$

$$\vdots$$

$$\alpha_{2k}\sigma^2_{CORt-k} + \alpha_{3k}\sigma^2_{WHTt-k} + \alpha_{4k}\sigma^2_{SOYt-k} + \alpha_{5k}\sigma^2_{SOYt-k} + \varepsilon_t$$

Where I_t corresponds to the value of the index at time t.

3.4.4 Estimation Methods for a Simultaneous Equation Model (SEM)

We distinguish two types of estimation methods for a SEM: single-equation methods and full-information methods. A single-equation method, such as the two-stage least squares (2SLS) estimator, does not use the information that contemporaneous correlation exists between the disturbance terms of the complete model. Although it is a consistent estimator, the 2SLS is not asymptotically efficient. A full-information method, such as the 3SLS, however, is both consistent and asymptotically efficient.

3.4.4.1 Two-Stage Least Squares (2SLS) Estimator

The structural equations of SEM contain regressors that are correlated with the error term. To understand this correlation: If μ_{t1} increases, then Y_{t1} increases which increases Y_{t2} (assuming $\beta_{21} > 0$) so μ_{t1} and Y_{t2} are (positively) correlated. Because μ_{t1} is unobserved, we attribute all of the increase in Y_{t1} to Y_{t2}, thereby overestimating γ_{11}. Because the source of the bias is the simultaneous determination of Y_{t1} and Y_{t2}, the bias is referred to as simultaneity bias. Accordingly, the OLS estimators are not only biased, but also inconsistent. This endogeneity problem is also revealed by attempting to interpret the coefficients. For instance, the coefficient β_{12} is designed to capture the effect of a small change in Y_{t2} holding X_{t1} constant. Yet a change in Y_{t2}caused by a change in μ_{t2} leads to a change in Y_{t1}, which then feeds back on Y_{t2} through the second equation, which again affects Y_{t1} and so on. We see that β_{21} captures the effects of all the feedbacks and so represents some mix of the effect of Y_{t2} on Y_{t1} and the effect of Y_{t1} onY_{t2}.

To mitigate the bias, it is ideal to replace the endogenous regressors with instruments. The instruments are constructed from the predetermined regressors and the method is termed two-stage least squares (2SLS) estimation, in which:

Stage 1: Regress the endogenous variables on the exogenous variables using OLS. Save the fitted values for the endogenous regressors.

Stage 2: Estimate the structural equations using OLS, but replace any right-hand side endogenous variables with their stage 1 fitted values.

3.4.4.2 Three-Stage Least Squares (3SLS) Estimator

The principle of 3SLS is a combination of the 2SLS and the Seemingly Unrelated Regression (SUR) model. The three-stage least-squares method generalizes the two-stage least-squares method to take account of the correlations across equation disturbances in the same way that SUR generalizes OLS.

The 3SLS estimator involves the following 3 stage procedure:

Stage 1: Regress the endogenous variables on the exogenous variables using OLS. Save the fitted values for the endogenous regressors.

Stage 2: Estimate the structural equations using OLS, but replace any right-hand side endogenous variables with their stage 1 fitted values. Save the 2SLS residuals.

Stage 3: Estimate the variances and covariances of the disturbance terms (cross-equation correlation matrix). Apply the SUR estimator.

The 3SLS is consistent and asymptotically more efficient than the 2SLS. Thus, it yields more desirable results.

Although the 2SLS and the 3SLS were historically estimated following the above stages, estimates are now computed in one formula programmed in econometric software packages.

3.5 Statistical and Econometric Packages

In this thesis, we use Estima's Regression Analysis of Time Series (RATS) software version 7.00 to derive descriptive statistics and run the econometric models described above. "RATS" is known to be a leading econometrics and time-series analysis software package. It's a fast and flexible command-driven tool with menu-driven wizards that allow for easy handling of time series.

In order to estimate the two-stage least squares and three-stage least squares model, we use e-views version 7. "E-Views" offers access to powerful statistical, forecasting, and modeling tools through an easy-to-use object-oriented interface.

3.6 Conclusion

In this chapter, we described the sample and defined the variables and their sources. Moreover, we clarified the methodologies and addressed the econometric tools that will be employed to test the level of integration among agricultural commodities, as well as the impact of announcement surprises. The following chapter is a presentation of the findings, a discussion of the obtained results and a highlight on the hypotheses.

CHAPTER 4

EMPIRICAL FINDINGS

4.1 Introduction

This chapter applies the econometric models described in chapter three to the data collected for the corn, wheat, soybeans and soybean oil futures markets and analyzes the implications of the main results in the context of risk management and portfolio diversification. This dissertation aims at detecting the potential existence of commodity market interdependence and its intensity, while accounting for structural changes in the series of returns. The estimated models will also investigate the impacts of macroeconomic news announcements on the variance of returns for major agricultural commodities. These results will not only consider some macroeconomic news, but also incorporate an index of 39 compiled news and announcements. Then, the obtained results will be compared to the findings of former studies. Ultimately, this study will attempt to check whether the increased interdependence of commodity markets led by the financialization process and greatly mentioned in recent literature, is biased.

4.2 Descriptive Statistics

This section presents and evaluates the summary statistics of the return series for corn, wheat, soybeans and soybean oil.

Table 1 shows a summary of descriptive statistics for the series of logarithmic returns. All four series display facts that are common to many commodities. In terms of the standard deviation, the four series of returns present fairly similar characteristics. The standard deviations are quite high indicating high deviations from the mean. Moreover, all return series have a skewness statistic that is significantly different than zero at the 1% significance level, indicating that the distributions are asymmetric. For instance, the logarithmic returns of corn and soybeans are negatively skewed which indicates asymmetric tail extending towards more negative values, whereas the return distribution of wheat and soybean oil are positively skewed. In terms of the Fisher's kurtosis statistic, there is evidence for excess kurtosis suggesting that the distributions are less flattened than the normal distribution and rather leptokurtic due to volatility clustering.

Statistic	Corn (COR)	Wheat (WHT)	Soybeans (SOY)	Soybean Oil (SOL)
Mean	0.000147	0.000165	0.000192	0.000176
Median	0.000000	0.000000	0.000548	0.000000
Mode	0.000000	0.000000	0.000000	0.000000
Minimum	-0.268620	-0.099728	-0.164989	-0.071377
Maximum	0.127571	0.087943	0.0652514	0.080804
Variance	3.5895	4.1595	2.5445	2.3029
Standard Deviation	1.8946	2.0395	1.5951	1.5175
Skewness (Fisher)[2]	-0.6446 (0.0000)	0.1317 (0.0008)	-0.6840 (0.0000)	0.1312 (0.0009)
Kurtosis (Fisher)	12.5018 (0.0000)	1.8597 (0.0000)	5.5642 (0.0000)	1.8962 (0.0000)
Jarque-Berra Test	25,431.0493 (0.0000)	567.9801 (0.0000)	5,285.9585 (0.0000)	589.9615 (0.0000)

Table 1 Summary Statistics of the Return Series

Thus, skewness and kurtosis measures point out a deviation from normality and the latter is reinforced by the Jarque-Bera test. The Jarque-Berra test for each of the four return series confirms non-normality and is significant at 1% significance level.

Therefore, preliminary statistical analyses illustrate significant asymmetry and kurtosis suggesting that the use of GARCH type models as a tool to model the volatility of returns seems to be appropriate.

4.3 Empirical Findings

4.3.1 Detection of Structural Breaks

The ICSS algorithm detects twenty six and fourteen variance-shifts in the natural logarithm of returns for corn and wheat, respectively. While only eleven shifts are identified in the natural logarithm of returns for soybeans and soybean oil (see Table 2).

[2] We estimate the skewness and kurtosis using Fisher's method because it does not assume that the series is normally distributed.

Commodity Return Series	Structural Breaks	Break Points in the Variance of Returns
COR	26	7/25/2000
		4/19/2001 ; 7/9/2001 ; 7/26/2001 ; 9/21/2001 ; 11/26/2001 ; 12/18/2001
		5/7/2002
		9/15/2006
		10/3/2007
		2/28/2008 ; 9/12/2008
		1/20/2009 ; 6/30/2009 ; 11/11/2009
		6/29/2010
		10/12/2011
		3/29/2012 ; 7/10/2012 ; 10/16/2012
		3/28/2013 ; 5/16/2013 ; 7/15/2013 ; 7/16/2013 ; 9/16/2013
		6/30/2014
WHT	14	6/28/2002
		6/7/2004
		2/23/2005 ; 7/25/2005
		5/10/2006
		2/5/2008 ; 4/9/2008 ; 8/5/2008
		1/23/2009
		10/4/2012
		4/2/2013 ; 4/8/2013 ; 5/15/2013
		2/28/2014
SOY	11	7/15/2003
		5/12/2004 ; 9/8/2004
		2/17/2005 ; 10/13/2005
		6/15/2007 ; 7/24/2007
		3/4/2008 ; 8/1/2008 ; 12/9/2008
		10/13/2009
SOL	11	9/12/2003
		10/20/2005
		3/3/2008 ;9/18/2008 ; 11/17/2008
		4/7/2009 ; 11/19/2009
		10/4/2010
		3/23/2011
		1/18/2013
		2/18/2014

Table 2 Structural Breaks in Unconditional Volatility

Not surprisingly, we found that shifts in variance are more prevalent during periods of economic instability. It also appears that there are common break years for the four series. As suspected, several break points are found during 2008 in the corn, wheat, soybeans and soybean oil, being a clear indicator for the peak in the U.S. subprime financial crisis. Obviously, common breaks are also detected in 2009, during post financial crisis period, most probably marking the beginning of the recovery period, with restored investor confidence in the commodity futures markets.

Even though economic events may coincide with the detected break dates, we do not expect the latter to precisely coincide with actual real events because the agricultural commodity market may respond with a lead or a lag to such events. For example, the structural breaks during 2004 and 2005 in the series of wheat, soybeans and soybean oil mark the beginning of the financialization of commodity markets. However, it seems that corn was leading the financialization process of agricultural commodity markets, since its series encountered several breaks in 2000, 2001 and 2002 (prior to 2004). Other breaks are also identified in the distribution of corn during 2006 and 2007 and this might be a lagged response to the energy policy act of 2005 that contributed to advance the production of corn ethanol.

4.3.2 Augmented Univariate GARCH (1, 1) with Structural Breaks

The results in Table 3 show that the standardized error terms obtained from the estimation of the four equations are not autocorrelated till order 12. In fact, the values are not significant suggesting the acceptance of the null hypothesis of no autocorrelation. Thus, the errors satisfy the condition of independent and identically distributed random variable. The null hypothesis that the errors have no ARCH effects is tested by looking at the STR. For all the four distributions, the STR is not significant leading us to accept the null hypothesis of no ARCH effects. The null hypothesis that the errors have no GARCH effects is tested by looking at the SQSTR. For all the four distributions, the SQSTR is not significant leading us to accept the null hypothesis of no GARCH effects. Moreover, the Jarque-Berra normality test shows that the error terms are not normally distributed; thus the use of a t-distribution for the errors rather than a normal distribution is a must. This is confirmed by the shape parameter that is significant for all the four series. According to these results, we conclude that the volatility of commodity returns is best represented by a GARCH (1, 1) model.

The results obtained from estimating our augmented univariate GARCH (1, 1) with structural breaks are provided in Table 3. We found most parameters to be significant at 1%, 5% and 10% significance levels. In particular, the coefficients for the error terms from the previous period are significant at 5% for corn and 1% for soybeans and soybean oil, except wheat. Another interesting finding is that the ARCH coefficients, which measure the impact of news from previous period on volatility, are positive and significant at the 1% significance level for the four commodities. The significance of the GARCH parameters indicates that the GARCH model in most cases is valid. Moreover, the four GARCH (1, 1) modeling the conditional variance for commodity returns are stable because the sum of the GARCH (1, 1) parameters ($\alpha + \beta$) is less than one. These are respectively 0.0441+0.5387=0.5828, 0.0161+0.3545=0.3706, 0.0368+0.8756=0.9124 and 0.0294+0.8081=0.8375 for corn, wheat, soybeans and soybean oil.

The estimated half-life[3] of shocks is respectively 1.284 day, 0.698 day, 7.561 days and 3.909 days for corn, wheat, soybeans and soybean oil. Thus, the conditional variances from the four models are stationary which implies that a particular shock to commodity markets has only temporary effects on the return volatility of commodity markets. In other words, shocks to corn and wheat markets are short lived and if nothing happened thereafter, the previous level of velocity will be restored in no more than two days. Though, this is not the case of soybeans and soybean oil. Given the fact that shocks are not found to be persistent and the β coefficients are high, this means that agricultural commodity markets react relatively strongly to incoming news but absorb it quickly.

The coefficients for the breaks are high, with high significance at 99% confidence level, except for the soybeans series. This reiterates that structural breaks should be included in the unconditional variance of stock returns. In other terms, the dummies that were added to capture the changes in the variance of commodity returns are significant (see Di) except for few breaks in table 3. This reflects the existence of structural changes in the volatility of commodity returns. Hence, taking into consideration changes in volatility is essential in order to correctly model the volatility dynamics of tourist arrivals to Lebanon. The volatilities calculated using GARCH with incorporated structural breaks are shown in Figure 1. As seen in this figure, the volatility between two break points is almost constant, which is consistent with the assumption behind the modified ICSS algorithm.

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[3] Half-life gives the point estimate of half-life in days given as $\ln(0.5)/\ln(\alpha+\beta)$ for a GARCH model

	RET_COR	RET_WHT	RET_SOY	RET_SOL
Shape Parameter	7.6767 (0.0000)	12.6866 (0.0000)	6.9348 (0.0000)	11.3237 (0.0000)
Serial Correlation till Order 12	15.7935 (0.1490)	7.1704 (0.7851)	15.3305 (0.1679)	8.1511 (0.6997)
STR till order 5	5.8358 (0.3225)	1.7449 (0.8332)	3.4520 (0.6307)	3.4240 (0.6349)
SQSTR till order 5	6.7918 (0.2366)	2.5491 (0.7691)	3.3511 (0.6460)	1.5952 (0.9018)
SSR	3,874.3779	3,862.7331	3,895.3129	3,860.2783
LL	-7,434.2882	-7,902.6507	-6,876.9674	-6,794.5772
AIC	14,930.5762	15,843.3014	13,785.9349	13,621.1544
SBC	15,124.6194	15,962.2311	13,886.0862	13,721.3058
A	0.0441 *(0.0031)*	0.0161 *(0.1096)*	0.0368 *(0.0000)*	0.0294 *(0.0000)*
B	0.5387 *(0.0000)*	0.3545 *(0.0000)*	0.8756 *(0.0000)*	0.8081 *(0.0000)*
Ω	1.0718 *(0.0000)*	1.2539 *(0.0000)*	0.1363 *(0.0606)*	0.2682 *(0.0000)*
d1	-0.5831 *(0.0011)*	1.2159 *(0.0000)*	0.1740 *(0.0403)*	0.2816 *(0.0000)*
d2	0.5389 *(0.0000)*	-0.9299 *(0.0001)*	0.3108 *(0.3491)*	-0.2745 *(0.0000)*
d3	3.2797 *(0.0000)*	0.8460 *(0.0143)*	-0.4508 *(0.2508)*	0.6422 *(0.0000)*
d4	-3.5412 *(0.0000)*	-1.1184 *(0.0011)*	0.0987 *(0.2340)*	1.7381 *(0.0000)*
d5	-0.4650 *(0.0000)*	1.7222 *(0.0000)*	-0.1307 *(0.1438)*	-1.7166 *(0.0000)*
d6	1.1849 *(0.1462)*	10.1433 *(0.0002)*	0.4227 *(0.0427)*	-0.4110 *(0.0000)*
d7	-1.2108 *(0.1428)*	-9.3887 *(0.0007)*	-0.3638 *(0.0634)*	-0.2858 *(0.0000)*
d8	0.7028 *(0.0000)*	3.9237 *(0.0019)*	0.4449 *(0.0407)*	0.1951 *(0.0000)*
d9	1.2353 *(0.0000)*	-4.1531 *(0.0003)*	0.3499 *(0.1829)*	-0.1828 *(0.0000)*
d10	-1.1244 *(0.0007)*	-2.5337 *(0.0000)*	-0.5530 *(0.1007)*	-0.1058 *(0.0000)*
d11	1.5080 *(0.0006)*	10.2121 *(0.0002)*	-0.2884 *(0.0501)*	0.1240 *(0.0000)*
d12	3.9714 *(0.0000)*	-9.3429 *(0.0005)*		

d13	-4.8941 *(0.0000)*	-1.1037 *(0.0034)*		
d14	1.6847 *(0.0172)*	1.2874 *(0.0000)*		
d15	-2.1852 *(0.0020)*			
d16	1.1424 *(0.0009)*			
d17	-1.5372 *(0.0000)*			
d18	2.1983 *(0.0014)*			
d19	-1.5198 *(0.0335)*			
d20	-0.9807 *(0.0023)*			
d21	2.1276 *(0.0712)*			
d22	-1.5378 *(0.2024)*			
d23	59.8291 *(0.0000)*			
d24	-58.7399 *(0.0000)*			
d25	-1.5423 *(0.0000)*			
d26	0.3724 *(0.0080)*			

Table 3 GARCH with Structural Breaks

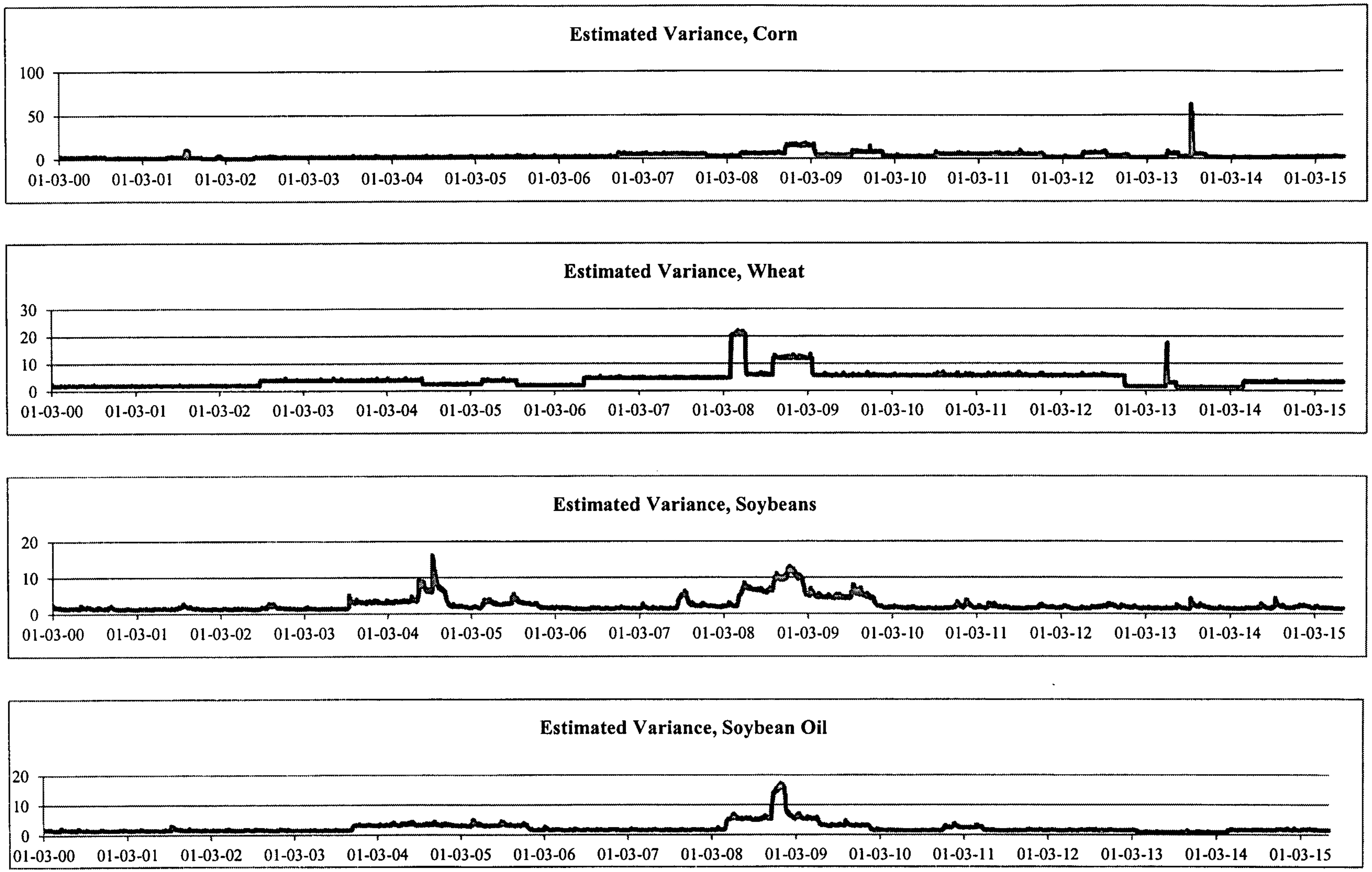

Figure 1 Estimated Variance using GARCH (1, 1) with Structural Breaks

4.3.3 Estimation of Model A with one Lagged Variance

In this section we present the results for the regression of the following simultaneous equation model:

$$\sigma^2_{CORt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_5 \sigma^2_{WHTt} + \alpha_6 \sigma^2_{SOYt} + \alpha_7 \sigma^2_{SOLt} + \alpha_8 \sigma^2_{CORt-1} + \alpha_9 \sigma^2_{WHTt-1} + \alpha_{10} \sigma^2_{SOYt-1} + \alpha_{11} \sigma^2_{SOLt-1} + \varepsilon_t$$

$$\sigma^2_{WHTt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_5 \sigma^2_{CORt} + \alpha_6 \sigma^2_{SOYt} + \alpha_7 \sigma^2_{SOLt} + \alpha_8 \sigma^2_{CORt-1} + \alpha_9 \sigma^2_{WHTt-1} + \alpha_{10} \sigma^2_{SOYt-1} + \alpha_{11} \sigma^2_{SOLt-1} + \varepsilon_t$$

$$\sigma^2_{SOYt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_5 \sigma^2_{CORt} + \alpha_6 \sigma^2_{WHTt} + \alpha_7 \sigma^2_{SOLt} + \alpha_8 \sigma^2_{CORt-1} + \alpha_9 \sigma^2_{WHTt-1} + \alpha_{10} \sigma^2_{SOYt-1} + \alpha_{11} \sigma^2_{SOLt-1} + \varepsilon_t$$

$$\sigma^2_{SOLt} = \alpha_0 + \alpha_1 CPI_t + \alpha_2 UNE_t + \alpha_3 PAY_t + \alpha_4 FED_t + \alpha_{50} \sigma^2_{CORt} + \alpha_6 \sigma^2_{WHTt} + \alpha_7 \sigma^2_{SOYt} + \alpha_8 \sigma^2_{CORt-1} + \alpha_9 \sigma^2_{WHTt-1} + \alpha_{10} \sigma^2_{SOYt-1} + \alpha_{11} \sigma^2_{SOLt-1} + \varepsilon_t$$

The model was estimated using a two-stage least squares method (Appendix II) and the instruments were defined as follows: 2 lagged variances for each corn, wheat, soybeans and soybean oil as well as the four dummy variables representing the news surprise. As we expected in chapter 3, the two-stage least squares estimator did not yield the desired results, so we estimated the same model with the same instruments using the three-stage least squares method. The results are revealed in Table 4. Although the coefficients for the variances of commodities and those of their lags are significant at the 1% significance level (table 4), the coefficients of the dummy variables are not significant in the four equations. This might be due to two reasons: (1) the creation of the dummy variables was done in a very simple way (2) since the scheduled announcements are monthly while the sampled commodity prices are daily, this discrepancy lead to a lot of missing values treated as no-surprise days. Therefore, it is obvious to use a more representative proxy for announcements in order to avoid the oversimplification and overestimation of the dummy variables. An optimal choice so far is the use of the Bloomberg Economic Surprise Index because it is (1) a continuous variable daily computed (2) it comprises 39 announcements instead of 4. The results of this regression are shown and discussed in section 4.3.4.

	COR	WHT	SOY	SOL
C	0.1607 (0.5880)	0.0648 (0.5834)	-0.0067 (0.5888)	-0.0160 (0.5825)
COR		-0.4038 (0.0000)	0.0417 (0.0000)	0.0996 (0.0000)
WHT	-2.4807 (0.0000)		0.1036 (0.0000)	0.2463 (0.0000)
SOY	23.9554 (0.0000)	9.6757 (0.0000)		-2.3869 (0.0000)
SOL	10.0523 (0.0000)	4.0542 (0.0000)	-0.4197 (0.0000)	
COR(-1)	0.8240 (0.0000)	0.3327 (0.0000)	-0.0344 (0.0000)	-0.0821 (0.0000)
WHT(-1)	2.3093 (0.0000)	0.9308 (0.0000)	-0.0964 (0.0000)	-0.2293 (0.0000)
SOY(-1)	-23.4667 (0.0000)	-9.4782 (0.0000)	0.9796 (0.0000)	2.3382 (0.0000)
SOL(-1)	-10.1893 (0.0000)	-4.1096 (0.0000)	0.4254 (0.0000)	1.0137 (0.0000)
Dcpi	-0.0539 (0.8353)	-0.0218 (0.8329)	0.0022 (0.8357)	0.0054 (0.8325)
Dfed	0.4453 (0.1285)	0.1798 (0.1279)	-0.0186 (0.1292)	-0.0443 (0.1328)
Dpay	-1.3647 (0.1921)	-0.5513 (0.1922)	0.0570 (0.1928)	0.1360 (0.1979)
Dune	0.3395 (0.1753)	0.1371 (0.1737)	-0.0142 (0.1761)	-0.0338 (0.1775)

Table 4 Model A Estimation using 3SLS

4.3.4 Estimation of Model B with One Lagged Variance

The following simultaneous equation model is estimated in this section and the corresponding instruments are 2 lagged variances of each corn, wheat, soybeans and soybean oil as well as the economic surprise index. The unsatisfactory results of the 2SLS are shown in Appendix III, while the findings of the 3SLS are represented in table 5 and discussed in this section.

$$\sigma^2_{CORt} = \alpha_0 + \alpha_1 I_t + \alpha_2\sigma^2_{WHTt} + \alpha_3\sigma^2_{SOYt} + \alpha_4\sigma^2_{SOLt} + \alpha_5\sigma^2_{CORt-1} + \alpha_6\sigma^2_{WHTt-1} + \alpha_7\sigma^2_{SOYt-1} + \alpha_8\sigma^2_{SOLt-1} + \varepsilon_t$$

$$\sigma^2_{WHTt} = \alpha_0 + \alpha_1 I_t + \alpha_2\sigma^2_{CORt} + \alpha_3\sigma^2_{SOYt} + \alpha_4\sigma^2_{SOLt} + \alpha_5\sigma^2_{CORt-1} + \alpha_6\sigma^2_{WHTt-1} + \alpha_7\sigma^2_{SOYt-1} + \alpha_8\sigma^2_{SOLt-1} + \varepsilon_t$$

$$\sigma^2_{SOYt} = \alpha_0 + \alpha_1 I_t + \alpha_2\sigma^2_{CORt} + \alpha_3\sigma^2_{WHTt} + \alpha_4\sigma^2_{SOLt} + \alpha_5\sigma^2_{CORt-1} + \alpha_6\sigma^2_{WHTt-1} + \alpha_7\sigma^2_{SOYt-1} + \alpha_8\sigma^2_{SOLt-1} + \varepsilon_t$$

$$\sigma^2_{SOLt} = \alpha_0 + \alpha_1 I_t + \alpha_2\sigma^2_{CORt} + \alpha_3\sigma^2_{WHTt} + \alpha_4\sigma^2_{SOYt} + \alpha_5\sigma^2_{CORt-1} + \alpha_6\sigma^2_{WHTt-1} + \alpha_7\sigma^2_{SOYt-1} + \alpha_8\sigma^2_{SOLt-1} + \varepsilon_t$$

	COR	WHT	SOY	SOL
C	0.3529 (0.0646)	0.1618 (0.0636)	-0.0153 (0.0651)	-0.0406 (0.0641)
COR		-0.4586 (0.0000)	0.0434 (0.0000)	0.1152 (0.00000
WHT	-2.1819 (0.0000)		0.0948 (0.0000)	0.2511 (0.0000)
SOY	23.0201 (0.0000)	10.5600 (0.0000)		-2.6529 (0.0000)
SOL	8.6839 (0.0000)	3.9805 (0.0000)	-0.3773 (0.0000)	
COR(-1)	0.8142 (0.0000)	0.3734 (0.0000)	-0.0354 (0.0000)	-0.0938 (0.0000)
WHT(-1)	2.0280 (0.0000)	0.9295 (0.0000)	-0.0881 (0.0000)	-0.2334 (0.0000)
SOY(-1)	-22.4957 (0.0000)	-10.3194 (0.0000)	0.9772 (0.0000)	2.5925 (0.0000)
SOL(-1)	-8.8467 0.0000	-4.0552 0.0000	0.3843 0.0000	1.0188 0.0000
I	-1.0042 (0.0046)	-0.4606 (0.0059)	0.0436 (0.0046)	0.1157 (0.0064)

Table 5 Model B Estimation using 3SLS

We find important and significant volatility spillovers across the four commodities on a daily basis. On one hand, the variances of both soybeans and soybean oil respond in the same direction to any change in the volatility of either corn or wheat. This is obvious because soybean oil is derived from soybeans and hence the two commodities act as close demand substitutes, have similar input costs and share common market information. This is also confirmed by the negative relationship between their instantaneous volatilities: at the 1% significance level, a unit increase in the variance of soybean oil leads to a 0.38 decrease in the variance of soybeans, and a unit increase in the variance of soybeans leads to a 2.65 decrease in the variance and soybean oil, suggesting that the impact of soybeans on soybean oil is much greater than the impact of soybean oil on soybeans.

Moreover, there is an instantaneous bidirectional volatility transmission from corn and wheat on one hand, to soybeans and soybean oil on the other hand, and vice versa. However, this volatility spillover is more important from soybeans and soybean oil to both corn and wheat, rather than the inverse. For instance, a shock in the soybeans market, leading to a one unit increase in its variance, will cause the variance of corn and wheat to increase by 23.02 and 10.56, respectively at the 1% significance level. Similarly, a one unit increase in the instantaneous variance of soybean oil will lead to a decrease in the variance of corn and wheat by 8.68 and 3.98, respectively. However, innovations in wheat or corn markets have a less important role on the variances of soybeans and soybean oil. Particularly, a unit increase in the instantaneous volatility of corn (wheat) provokes only 0.04 (0.09) and 0.12 (0.25) increase in the variance of soybeans and soybean oil, respectively.

Once we estimate the models with the economic surprise index, we observe that macroeconomic news play an important role in explaining the volatility of the major agricultural commodities. However, there are some differences in estimation results for different commodities. In particular, the results suggest that an economic surprise is important in increasing the return volatility of soybean oil more than that of soybeans. For instance, a one unit increase in the index will lead to a 0.1157 increase in the variance of soybean oil and 0.0436 increase in the variance of soybeans at the 1% significance level. On the other side, an increase in the surprise index will reduce the volatility of both corn and wheat, whereby the impact on corn is larger than the impact on wheat; in fact, a one unit increase in the index will lead to a 1.0042 decrease in the variance of corn and 0.4604 decrease in the variance of soybeans at the 1% significance level. These results are consistent with the previous findings: as a result of a surprise event, the variances of corn and wheat move in the same direction, though different magnitudes and the variances of soybeans and soybean oil move together in the opposite direction.

Moreover, table 5 shows that the coefficients of the lagged variances have an opposite sign to the coefficients of the instantaneous variances, and are all significant at the 1% significance level. For instance, corn and wheat, ancient leaders of agricultural commodity markets, are two competing agricultural commodities. Thus, we would expect to find a negative volatility spillover between those two substitutes. It is clear in table 5 that corn reacts with a lag on wheat, but the volatility falls back to its normal level on the next day. This can be explained in the context of the efficient market hypothesis: once a shock reaches the corn market, the wheat market overreacts to the lagged variance and instantaneously normalizes to its original level.

In short, the null hypothesis of no volatility spillover across agricultural commodities (Ha_0) is rejected and the alternative hypothesis related to the existence of volatility transmission among commodity markets is accepted and supported in this thesis. In addition, the null hypothesis of no macroeconomic impact on the volatility of commodities is rejected. Therefore, in terms of economic news, we find evidence that the incorporation of the surprise index into the estimation yielded significant results and improved the capability of explaining the dynamics of return volatility of the four commodities. Specially, we found that surprise news is most influential on the variance of corn while it has the lowest impact on soybeans.

CHAPTER 5

CONCLUSION

5.1 Main Findings of the Study

In this thesis, we studied the interdependence in terms of return volatility spillover among leading agricultural commodities, particularly corn, wheat, soybeans and soybean oil. We also tested the impact of macroeconomic news surprises on the instantaneous volatility of the aforementioned commodities. In order to capture the impact of structural breaks in the series of returns, we used the modified iterative cumulative sum of squares algorithm. Then, we incorporated the detected breaks in a GARCH (1, 1) model in order to estimate the variance of returns. Given the significance of the coefficients of the breaks as well as the stability of the estimated GARCH (1, 1), we agree that the obtained volatilities can be accurately employed. A system of four simultaneous equations was constructed to detect both the instantaneous and delayed volatility spillover among the sampled commodities. Two different models were estimated using the three-stage least squares estimators: in model A, four dummy variables were used as a proxy for announcements, whereas in model B, a continuous index was used instead.

We find that agricultural commodity markets are indeed interdependent, mainly in terms of risk, with return volatility spilling over across them: some commodities are found to be instantaneously affected by the performance of other markets, while others seem to respond with a delay to events causing volatility fluctuations. It is important to note that bidirectional volatility spillover is found between markets in the sample, with stronger spillover effect running from soybeans and soybean oil, on one hand, to corn and wheat on the other hand. Moreover, it is essential to highlight the fact that macroeconomic news surprises have a significant effect on the four samples commodities.

5.2 Implications of the Study

The empirical findings of this study have important implications on portfolio diversification and risk management practices. With the recent financialization of commodity markets, investors worldwide are finding it easier to access funds, seek new investment opportunities and follow innovative hedging strategies. However, the results of this dissertation constitute a perfect proof that there is risk proliferation and volatility transmission among agricultural commodity markets. Yet, a thorough examination of the level of integration of those commodities while taking into account the timing of economic surprises, could result in portfolio risk reduction, given that (a) risk arising in one market can positively/negatively affect the risk in other markets; (b) some commodity markets may display delayed response to risk originating in other markets.

Another interesting indication of this thesis is that commodity market linkages seem to get stronger at the time of major events. In fact, news originating in one market causing a breakpoint in the variance of returns seems to travel to cause a breakpoint in the variance of returns of another commodity. This phenomenon is obvious among the four commodities with the detected breaks in the variance of corn, wheat, soybeans and soybean oil, falling approximately but not usually in the same years.

Another implication of this thesis is that corn is mostly affected by the economic surprise relative to the other commodities, while soybeans seem to be lastly affected by news. This is interesting to look at when investigating hedging opportunities and trading strategies, but these issues stay beyond the scope of this thesis.

5.3 Limitations of the Study

This thesis remains with some limitations, which nonetheless offer visions for future research. Given the restricted timeframe provided for the thesis completion, the sample size of commodities is restricted to 3,865 observations per variable. This is mainly due to the lack of available data for a common time span, especially for the macroeconomic variables that were only available on a monthly frequency. Though this study attempted to transform the monthly announcements into daily frequency (model A), the results were inaccurate and not significant. Using the index as a proxy with daily frequency, avoids the problem of under/over estimation of news surprises, but it is only available since 2000, which bans the use of a longer time period.

As for the methodologies used in this dissertation, a limitation that could have biased the results is that the return volatility of the four commodities under study is calculated based on the GARCH model. In fact, the identification of the exact model that the series follow takes extensive testing, thus the series might be following a different model.

5.4 Further Research

The findings of this thesis and their implications on portfolio diversification are of considerable importance, and thus deserve further investigation in future studies. One of the possible improvements for this thesis is to include other major agricultural commodities such as sugar in the evaluation of possible return volatility transmission, given their high traded value and volume.

As for the empirical methodology, extensive testing could help identify the exact nature of the returns series volatility – i.e. GARCH, ARCH, EGARCH… as to secure robustness of the results. Moreover, it is ideal to estimate the system of equations using the Generalized Method of Moments (GMM) of Hansen (1982), which is at the heart of semiparametric estimation frameworks.

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APPENDIX I

LIST OF THE SURPRISE ANNOUNCEMENTS IN THE INDEX

1. Wholesale Inventories MoM
2. Change in Nonfarm Payrolls
3. Change in Manufacturing Payrolls
4. Unemployment Rate
5. Consumer Credit
6. ADP Employment Change
7. ISM Non-Manufacturing Composite
8. Factory Orders
9. Wards Total Vehicle Sales
10. Wards Domestic Vehicle Sales
11. Personal Income
12. Personal Spending
13. ISM Manufacturing
14. Construction Spending MoM
15. ISM Milwaukee
16. Chicago Purchasing Manager
17. Pending Home Sales MoM
18. Durable Goods Orders
19. New Home Sales
20. Consumer Confidence Index
21. Richmond Fed Manufacturing Index
22. Dallas Fed Manufacturing Activity
23. Existing Home Sales

APPENDIX II

ESTIMATION RESULTS OF MODEL A USING 2SLS

	COR	WHT	SOY	SOL
C	0.084522 *(0.1371)*	0.031596 *(0.0888)*	0.001286 *(0.9173)*	-0.00866 *(0.2192)*
COR		0.008842 *(0.1171)*	0.027676 *(0.0000)*	2.16E-06 *(0.9992)*
WHT	0.082907 *(0.1171)*		0.008054 *(0.4842)*	-0.00645 *(0.3255)*
SOY	0.584606 *(0.0000)*	0.018144 *(0.4842)*		-0.00553 *(0.5745)*
SOL	0.000141 *(0.9992)*	-0.04479 *(0.3255)*	-0.01704 *(0.5745)*	
COR(-1)	0.85477 *(0.0000)*	-0.0018 *(0.7497)*	-0.02237 *(0.0000)*	0.001447 *(0.4987)*
WHT(-1)	-0.0322 *(0.5438)*	0.985861 *(0.0000)*	-0.00363 *(0.7535)*	0.011727 *(0.0742)*
SOY(-1)	-0.56926 *(0.0000)*	-0.01718 *(0.5091)*	0.97506 *(0.0000)*	0.016681 *(0.0909)*
SOL(-1)	0.072445 *(0.6011)*	0.037001 *(0.4135)*	0.030728 *(0.3080)*	0.981695 *(0.0000)*
Dcpi	-0.00724 *(0.8842)*	0.020365 *(0.2096)*	0.006217 *(0.5655)*	-0.00485 *(0.4307)*
Dune	0.04244 *(0.3770)*	-0.00114 *(0.9422)*	-0.01199 *(0.2514)*	-0.00444 *(0.4555)*
Dpay	0.0213 *(0.9155)*	-0.01048 *(0.8730)*	0.059975 *(0.1695)*	-0.00723 *(0.7713)*
Dfed	-0.04215 *(0.4535)*	0.039567 *(0.0311)*	-0.01601 *(0.1905)*	0.001246 *(0.858)*

APPENDIX III

ESTIMATION RESULTS OF MODEL B USING 2SLS

	COR	WHT	SOY	SOL
C	0.0810 *(0.0322)*	0.0325 *(0.0084)*	-0.0063 *(0.4490)*	-0.0149 *(0.0016)*
COR		0.0091 *(0.0811)*	0.0286 *(0.0000)*	0.0002 *(0.9255)*
WHT	0.0863 *(0.0811)*		0.0082 *(0.4477)*	-0.0117 *(0.0574)*
SOY	0.6005 *(0.0000)*	0.0182 *(0.4477)*		-0.0078 *(0.3926)*
SOL	0.0121 *(0.9255)*	-0.0802 *(0.0574)*	-0.0242 *(0.3926)*	
COR(-1)	0.8608 *(0.0000)*	-0.0020 *(0.7079)*	-0.0221 *(0.0000)*	0.0016 *(0.4330)*
WHT(-1)	-0.0342 *(0.4910)*	0.9883 *(0.0000)*	-0.0028 *(0.7948)*	0.0159 *(0.0097)*
SOY(-1)	-0.5903 *(0.0000)*	-0.0126 *(0.6021)*	0.9787 *(0.0000)*	0.0263 *(0.0044)*
SOL(-1)	0.0586 *(0.6469)*	0.0701 *(0.0923)*	0.0304 *(0.2766)*	0.9759 *(0.0000)*
I	0.0280 *(0.6929)*	0.0212 *(0.3596)*	0.0420 *(0.0067)*	0.0038 *(0.6684)*