Common Cycles in Commodity Prices

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ABSTRACT

This study empirically investigates the short- and long-run co-movement among commodity prices using six commodity group price indices. The commodity group indices used in the study include foodstuffs, livestock and products, fats and oils, raw industrials, metals and textiles. The data for this study was sourced from Commodity Research Bureau (CRB); the frequency of the data is monthly and covers the period from 1951M1 to 2015M6. In order to investigate the short- and long-run co-movement properties of the commodity prices, the study employs the unit root tests, Granger causality test, Johansen cointegration test as well as common cyclical features test. The study reveals that all the variables are stationary in first differences with KPSS test, i.e., all the variables are integrated of same order, I (1). The Granger causality test shows that all variables have at least one unidirectional Granger causality. Johansen cointegration test suggests three cointegration vectors, thus implies long-run equilibrium relationship among the groups of commodity prices. The study shows two common cycles among the groups of six commodity price indices based on the common cyclical features test. The major implication from the findings of the study is that short- and long-run changes in the commodity prices of interest are driven by common factors and any observed change in price of one of the selected commodity prices implies that the other will also change both in the short- and long-run. Therefore, the history of one of the commodity prices can be utilized to make prediction for the others.

Keywords: Common cycles, commodity prices, co-movement.

ÖZ

Bu çalışma ampirik olarak, seçilmiş çeşitli emtiaların fiyatlarındaki kısa dönem ve uzun dönem birlikte hareketleri analiz etmektedir. Çalışmada kullanılan veri seti Emtia Araştırma Bürosu veri tabanından temin edilmiş ve 1951 yılı Ocak ayından 2015 yılı Haziran sonuna kadar olan veriler kullanılmıştır. Çalışma hedeflerine uygun olarak, birim kök testleri, Granger nedensellik testi, Johansen eştümleşme testi ve ortak özellikler döngüsellik testi kullanılmıştır. Birim kok testi sonuçları (KPSS testi) tüm değişkenlerin ilk gecikmede durağan olduğunu göstermektedir. Kısacası tüm değişkenler I(1) düzeyinde tümleşiktir. Granger nedensellik testi de tüm değişkenler arasında en az bir yönlü Granger nedenselliğinin varlığına işaret etmektedir. Johansen eştümleşme testine göre de üç eştümleşme vektörü bulunmakta ve emtia fiyatları arasında uzun dönem ilişkiye dikkat çekilmektedir. Çalışma bulgularına göre ortak döngüsellik testi emtia fiyatları arasında iki ortak döngüye işaret etmektedir. Çalışma sonuçları, emtia gruplarının geçmiş yıllardaki verilerinin tahmin için kullanılabileceği hipotezinin desteklendiğini, dolayısıyla seçilmiş emtia gruplarındaki fiyat değişimlerinin uzun ve kısa dönemde birbirlerini etkilediklerini göstermektedir.

Anahtar kelimeler: Ortak döngü, Emtia Fiyatları, Birlikte Hareket

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Chapter 1

INTRODUCTION

1.1 Background

Commodities are basically defined as the goods that are subjected to trade. The commodity market is a market for buying and selling commodities. The formation of commodity market started in 1848 (during the period of Civil War) with the crises in the US where farmers attempted to avoid the price changes of agricultural products. The markets prevented the fluctuation in prices of such products for centuries in order to control the risk for both producers and consumers. Observing the benefits of controlled risk, the merchants enlarged their business, thus, the commodity market started to function in trading. In the commodity market, the range of goods has been expanded since 1934 when the US Bureau of Labor Statistics (BLS) started to compute a daily Commodity Price Index. A price index for the Spot Market in which goods are sold for immediate delivery is calculated by the BLS in 1952, which measured the price movements of 22 commodities. Base year of the index was the 1947-49 period. In 1981, the US Commodity Research Bureau (CRB) started to calculate the index by using daily data.

The 22 commodities chosen were believed to be the first group that is influenced by the changes in economic conditions. This influence is an early indication of forthcoming changes in business activity. Due to this property, changes in the Spot Market Price Index are accepted to be very important to observe. Therefore, the major purpose of this study is to examine the short- and long-run behavior of prices of the commodity groups in the indexes.

CRB and BLS divide these 22 commodities into two major subdivisions as Raw-Industrials and Foodstuffs. The minor subdivisions of these commodities are Metals, Textiles and Fibers, Livestock and Products, and Fats and Oils. These divisions are not mutually exclusive.

1.2 Aims and Objectives of the Study

The primary aim of this study is to investigate the common cycles in commodity price indexes. The study also seeks to provide answer to the following key questions:

i) Is there any common stochastic trend that leads to long-run co-movement among the selected commodity groups?

ii) Is there a common feature that leads to short-run co-cycles among the selected commodity groups?

iii) What is the direction of Granger Causality among the selected commodity groups, if any exists?

This thesis mainly focuses on the changes in the United States (US) spot market commodity price indices as an indicator of the effects of domestic and international economic fluctuations on the US economy. To understand the overall dynamics influencing the US prices of these commodity groups it would be of utmost importance to look at the production, exports, imports and price changes of commodities in each group in major countries involved for which data are available for the years 2009-2011. This is the period in which the most recent and drastic fluctuations in commodity prices are observed. Therefore, at first, the general description of such economic properties is given in this section. Second step in the study covers the analysis of the commodity price dynamics of the six commodity groups. For this purpose, the time period of the study, 1951-2015, is divided into three sub periods as; 1951-1969, 1970-2007, and 2008-2015. For each period, trends and volatility of the price indexes are analyzed by referring to the possible causes. Afterwards, time series data of the indexes are tested for the stationarity with the use of Augmented Dickey Fuller and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. In addition, Pairwise Granger causality of the variables is also checked to determine the direction of any causality. The next step followed in the study is to check the short-run and long-run behavior of the prices of the commodity groups. Therefore, a vector autoregressive (VAR) model is identified and Johansen Cointegration test is conducted to find out whether any long-run relationship exists amongst the price indexes. Also, common cyclical features test is applied to see the short-run co-movement of the indexes.

1.3 Organization of the Study

This thesis consists of seven chapters. Chapter 1 focuses on background of the study.

Chapter 2 analyzes commodities and commodity markets. Chapter 3 explains commodity price dynamics. Chapter 4 covers the literature review. Chapter 5 explains the methodology. Chapter 6 presents detailed empirical findings of the study and Chapter 7 is the conclusion.

Chapter 2

COMMODITIES AND COMMODITY MARKETS

In this chapter, the main six commodity groups defined by the US CRB and BLS, namely, foodstuffs, livestock and products, fats and oils, raw industrials, metals and textiles are explained. In addition, to understand the overall dynamics influencing the US prices of these commodity groups, production, exports, imports and price changes of the commodities in each group throughout the world are also examined whenever data are available for 2009-2011. 2009-2011 is the period in which the most recent and drastic fluctuations are observed in commodity markets.

2.1 Foodstuffs

First of the main commodity groups we examine is the foodstuffs. According to the CRB Commodity Yearbook (2011), ten types of food whose prices are the most sensitive to economic conditions are hogs, lard, steers, butter, soybean oil, cocoa, corn, Kansas City wheat, Minneapolis wheat, and sugar. There is not any information about steers in the CRB Commodity Yearbook (2011).

Hogs: Main hog producing, exporting and importing countries are given in Table 2.1. Since 2000 the price of lean hog faced the lowest value in August 2009 and the highest value in May 2010. In the world pork market, there are three major producers, namely, China, the European Union (EU), and the US where each of them produced 49%, 22%, and 10% of the world production in 2010, respectively. Furthermore, world consumption of pork increased by 8% in 2010. The largest pork exporters in the world in 2010 are US (33%), the European Union (28%), Canada (19%), and Brazil (10%). On the other hand, the largest pork importing countries are Japan with 20%, Russia with 15%, Mexico with 12%, South Korea and US with 7% each in the same year.

Table 2.1: Hogs producers, exports, imports

Hogs	**Producers**		**Exports**		**Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	49	US	33	Japan	20
	EU	22	EU	28	Russia	15
	US	10	Canada	19	Mexico	12
			Brazil	10	South Korea	7
					US	7

Lard: Lard production is directly related to the production of hog such that the country which has the largest pork production also has the largest lard production. Main lard producing, exporting and importing countries are given in Table 2.2. China ranks the world's largest producer of lard with 43.1% of the world production, closely followed by the United States with 7.4%, Germany with 6.8% and Brazil with 5.2%. Although the US is the second largest lard producer in the world, lard production in the US declined by 2.1% while the lard consumption increased by 19.0% in 2010. At the same time, the US exports 10.7% and imports 2.20% of the overall lard production.

Table 2.2: Lard producers, exports and imports

Lard	**Producers**		**Exports**		**Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	43.1	US	10.7	US	2.20
	US	7.4				
	Germany	6.8				
	Brazil	5.2				

Butter: Demand and supply dynamics of butter determine its price. Main butter producing countries, changes in exports and imports for countries are given in Table 2.3. India is the largest butter producer in the world with 50.8% of the world butter production in 2010, followed by the E.U. (24.2%), the US (8.5%), New Zealand (5.5%), and Russia (2.9%). In the recent years, consumption of butter decreased due to the spread of the news by the scientists regarding the direct relationship between pure butter and cholesterol, the main known cause of heart disease and obesity. In 2010, world imports of butter decreased by 11.6% whereas imports of butter in the US remained the same. World butter exports decreased by 1.1% and also US exports decreased by 10.7% in 2010. As an overall result the average monthly price of butter increased by 18.3% in 2010.

Table 2.3: Butter producers, change in exports and imports

Butter	Producers		Changes in Exports		Changes in Imports	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	India	50.8	World	-1.1	World	-11.1
	EU	24.2	US	-10.7		
	US	8.5				
	New Zealand	5.5				
	Russia	2.9				

Soybean Oil: Soybean oil is generated from the whole soybean. Generally, it is used as cooking oil. Main soybean oil producing countries and changes in exporting for countries are given in Table 2.4. The world soybean oil production increased by 8.0% and future prices of soybean oil increased by 43% in 2010. In 2011 the US comprises 20.6%; Brazil, 15.8%, and E.U, 5.8% of the world's soybean oil production. In this period, the soybean oil production in the US dropped by 3.1%. World's soybean oil consumption increased by 9.2% in the same period where US soybean oil consumption increased by 7.8%. Also in this period, exports of the world's soybean oil increased by 5.8% whereas exports of soybean oil in the U.S. decreased by 16.6%.

Table 2.4: Soybean oil producers, change in exports and imports

Soybean Oil	**Producers**		**Changes in Exports**		**Changes in Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	US	20.6	World	+5.8	NA	NA
	Brazil	15.8	US	-16.6		
	EU	5.8				

Cocoa: Cocoa includes 20% of protein and 40% of both fat and carbohydrates; thus, it has an eminent food value. West African countries have the largest four cocoa producers. These are the Ivory Coast, Nigeria, Ghana, and Cameroon and these countries produce about 2/3 of the whole cocoa output in the world. Main cocoa producing countries and changes in import of US are given in Table 2.5. Ivory Coast is the main producer of cocoa with 33.6% of the world production. The second largest producer is Ghana with 21.0%. After Ghana the top producers are Indonesia with 12.7%, Nigeria with 6.1 percent, Cameroon with 5.6% and Brazil with 4.8%. Cocoa production of the world fell by 6.8% in 2010-2011. In this period European Union has been the major cocoa importer in the world consuming almost 37.1% of the entire output. Cocoa products and cocoa imports of U.S. increased 4.5% in 2010.

Table 2.5: Cocoa producers, change in exports and imports

Cocoa	**Producers**		**Changes in Exports**		**Changes in Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	Ivory Coast	33.6	NA	NA	US	4.5
	Ghana	21.0				
	Indonesia	12.7				
	Nigeria	6.1				
	Cameroon	5.6				
	Brazil	4.8				

Corn: Corn is used primarily as livestock feed in the world. Moreover, corn ethanol can be used as alcohol additive in gasoline, margarine and corn oil for cooking and as food for humans. The main corn producer and exporter countries are given in Table 2.6. Corn is the major crop in the US which is the largest corn producer with 42% of the whole world production, followed by China with 20.6%, and Brazil with 6.3%. Corn production in the world increased by 0.2% as well as the world corn consumption rose by 1.6% due to the strong domestic and foreign demand in 2010-2011. Exports of corn in the US increased by 4.6% and the largest corn export markets for the US are Japan with 29.5%, Mexico with 16.5%, South Korea with 13.6%, Taiwan, and Egypt with each 6% and Canada with 3.9% in 2011.

Table 2.6: Corn producers, exports and imports

Corn	**Producers**		**Exports**		**Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	US	42	Japan	29.5	NA	NA
	China	20.6	Mexico	16.5		
	Brazil	6.3	South Korea	13.6		
			Taiwan	6		
			Egypt	6		

***Wheat*:** Generally, wheat is used as a human food, as wheat flour, making oil, newsprint, gluten, livestock feed, silage or hay and other products. Main soybean oil producing countries, changes in exporting and in importing for US are given in Table 2.7. In 2010-2011, world wheat production decreased by 5.5% due to the severe drought in the world. At the same time, wheat production in the US also fell by 0.4%. The EU is the largest wheat producer with 21.2% in the world, China with 17.7% although its wheat production dropped by 0.5%, India with 12.5%, the United States with 9.3%, Russia with 6.4%, and Australia with 3.9% in 2011. Wheat consumption of the world increased by 1.9% in 2011. At the same time, wheat consumption of the US rose by 3.4%. However, world trade of wheat decreased by 6.7%, wheat exports of US increased by 47.6% while its import decreased by 7.6% in 2011.

Table 2.7: Wheat producers, change in exports and imports

Wheat	**Producers**		**Changes in Exports**		**Changes in Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	EU	21.2	US	+47.6	US	-7.6
	China	17.7				
	India	12.5				
	US	9.3				
	Russia	6.4				

Sugar: Main sugar producing, exporting and changes in imports for countries are given in Table 2.8. The world raw sugar production increased by 5.5% in 2011. Brazil was one of the largest sugar producers with 24.3% of the overall production; next largest producers were India with 15.9%, and the E.U. with 9.1%. In addition, the production of raw sugar in the US increased by 44.9% in 2011. Although world raw sugar consumption increased by 2.7%, the US raw sugar consumption decreased by 1.0%. Brazil was also major sugar exporter of the world in 2011; their exports increased by 10.5% that were comprised of 51.8% of the overall exports. After that, Thailand was the second largest exporter with 9.1% of the total exports and Australia with 7.2%. Both US sugar exports and imports fell around 30% in 2011.

Table 2.8: Sugar producers, exports, change in imports

Sugar	**Producers**		**Exports**		**Changes in Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	Brazil	24.3	Brazil	51.8	US	-30.1
	India	15.9	Thailand	9.1		
	EU	9.1	Australia	7.2		
			US	Change -28.8		

2.2 Livestock and Products

The group of livestock includes hides, hogs, lard, steers, and tallow. Some of them are also under the group of foodstuffs such as hogs, lard, and steers.

Hides: Hides and leather have been used for armor, boots, tents, clothing, buckets, cups, and bottles. At the present, mostly leather is obtained from cowhide, besides deer, snakes, hides of lamb and crocodile. Main hides producing countries are given in Table 2.9. The average monthly cattle hide price increased by 62.5% in 2009-2011. The largest buffalo and cattle producers of the world are the US with 12.3% of the whole production, followed by Brazil (10.5%), and Argentina (4.6%). In this period the world buffalo and cattle production increased by 0.1%.

Table 2.9: Wheat producers, exports and imports

Hides	**Producers**		**Exports**		**Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	US	12.3	NA	NA	NA	NA
	Brazil	10.5				
	Argentina	4.6				

Tallow: Tallow is derived from processing the fat of cattle and is produced as edible or inedible. Products of edible tallow include cooking oil, margarine and baking products while inedible tallow includes candles, soap and lubricants. Main tallow producing and exporting countries are given in Table 2.10. In 2009, the world production of inedible or edible tallow and greases decreased by 0.7% and monthly average price of inedible tallow increased by 32.5% in 2010. The largest tallow and greases producer in the world is the US with 43.5%, followed by Brazil with 7.0%, Australia with 5.8% and Canada with 3.4%. Edible tallow production of the US decreased by 0.6% in 2008. Inedible greases and tallow production of the US fell by

0.4% while its consumption also fell by 10.6% in 2010. The US edible tallow consumption in 2008 increased by 1.4%. In 2010, inedible grease and tallow exports of the US increased by 6%. However, edible tallow exports in the US increased by 2%.

Table 2.10: Tallow producers, exports and imports

Tallow	**Producers**		**Exports**		**Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	US	43.5	US(inedible)	6.0	NA	NA
	Brazil	7.0	US (edible)	2.0		
	Australia	5.8				

2.3 Fats and Oil

The group of Fats and oils covers four commodities: butter, cottonseed oil, lard, and tallow.

Cottonseed oil: Cotton seed oil can be used for cooking and as livestock feed. Main cottonseed oil producing, exporting and changes in imports for countries are given in Table 2.11. The average monthly cottonseed oil price increased by 14.6% in 2010. In the same period world cottonseed production fell by 4.9%. The world largest cottonseed oil producers are China, India, the US, and Pakistan with 29.1%, 25.5%, 9.6% and 10.8% shares of world production, respectively. In 2011 cottonseed oil production in US increased by 29.7%. Although US did not import cottonseed in this period, its exports increased by 20.3%.

Table 2.11: Wheat producers, exports and imports

Cottonseed oil	Producers		Exports		Imports	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	29.1	US	20.3	US	---
	India	25.5				
	US	9.6				
	Pakistan	10.8				

2.4 Raw Industrials

The raw industrials group contains tallow, hides, lead scrap, copper scrap, steel scrap, tin, burlap, zinc, cotton, wool tops, print cloth, rubber and rosin.

Copper: Copper plays an important role in industrial metals because of its unique nature as a good conductor of electricity; and is an excellent resistance to corrosion. Main copper producing countries, changes in exporting and in importing for US are given in Table 2.12. In the period 2009-2011 the world copper production increased by 1.9%. The largest copper producer is Chile which produces 34.1% of the whole copper output of the world, followed by Peru (7.9%), China (7.1%), the US (6.9%) and Australia (5.6%). In this period, refined copper production in the US dropped by 4.8%, consumption fell by 5.6%, imports decreased by 7.2% whereas its refined copper exports increased by 15.0%.

Table 2.12: Copper producers, change in exports and imports

Copper	Producers		Changes in Exports		Changes in Imports	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	Chile	34.1	US	+15.0	US	-7.2
	Peru	7.9				
	China	7.1				
	US	6.9				
	Australia	5.6				

Lead: Lead is well known since ancient times. The usage of lead ranges from the construction sector, bullet making tanks, lining of pipes, storage battery and electric cable sheathing to many others. Lead is also widely used as a protectant in radioactive substances and materials, because of its nuclear nature. Main lead producing countries, changes in imports of US are given in Table 2.13. In 2009, both primary and secondary smelter production of lead in the world increased by 1.4%. China is the major smelter producer of lead; its production comprised 42% of overall world production in this year, followed by the US with 14%, Germany with 4%, and the UK, Australia, Canada, Japan with 3% each. Secondary production, like lead scrap, fell by 1.1%. In the US lead consumption decreased by 1.3% and US lead bars and pigs imports fell by 18.8% in 2009- 2010.

Table 2.13: Lead producers, exports and change in imports

Lead	**Producers**		**Exports**		**Changes in Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	42.0	NA	NA	US	-18.8
	US	14.0				
	Germany	4.0				
	Australia	3.0				
	Canada	3.0				

Steel: Steel has a variety of shapes and sizes, such as pipes, roads, tees, railroad rails, I-beams and channels. Main steel producing countries are given in Table 2.14. The average wholesale price of heavy-melting steel scrap increased by 61.9%. Raw steel production in the world increased by 12.9%; China was the largest producer with 45%, Japan with 8%, and the US with 6% in 2010.

Table 2.14: Steal producers, exports and imports

Steel	Producers		Exports		Imports	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	45.0	NA	NA	NA	NA
	Japan	8.0				
	US	6.0				

Tin: Tin is essential in the automobile industry, in the electroplating and coating of manufactured steels and the likes. Tin is also used as a container in the beverage and food industry. Main tin producing countries, changes in exports and total tin imports for US are given in Table 2.15. In 2010, the average monthly tin price increased by 49.8% and the world tin production increased by 2.7%. China was the largest producer with 37% of the total output followed by Indonesia with 33%, and Peru with 12%. Tin mining in the US is minimal and 80% of its tin imports were from Peru (61% of total imports), Bolivia (19%), Indonesia (10%), China (4%), and Brazil (3%) in 2009. In the same year, the US tin exports decreased by 67.7%.

Table 2.15: Tin producers, change in exports and imports

Tin	Producers		Changes in Exports		Imports	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	37.0	US	-67.7	US	80.0
	Indonesia	33.0				
	Peru	12.0				

Zinc: Zinc is widely used as an alloy with copper, to produce brass, aluminum, and magnesium. Main zinc producing countries are given in Table 2.16. In the 2009-2011 period, the world zinc price increased by 31.0% on average and smelter zinc production increased by 7.1%. The largest zinc producer in the world was China with 29% of the whole smelter production, followed by, Australia with 12%, Canada and the US accounted for 6% each and Mexico with 5%.

Table 2.16: Zinc producers, exports and imports

Zinc	Producers		Exports		Imports	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	29.0	NA	NA	NA	NA
	Australia	12.0				
	Canada	6.0				
	US	6.0				
	Mexico	5.0				

Wool: Wool is used for carpets and furnishing, for insulation in houses and for bedding. Main wool producing countries and changes wool production in the US are given in Table 2.17. In 2009 greasy wool world production decreased by 1.8%. At the same year, Australia is the largest producer in the world with 17.8%, followed by China with 17.7%, and New Zealand with 10%. The US wool production increased by 18.4%.:

Table 2.17: Wool producers, exports and imports

Wool	Producing Countries		Exports		Imports	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	Australia	17.8	NA	NA	NA	NA
	China	17.7				
	New Zealand	10.0				
	US	Change +18.4				

Cotton: Cotton is widely used in clothing, medical products and home furnishing industries. Main cotton producing countries, exports of US and also exports market for US and cotton imports of countries are given in Table 2.18. In 2010-2011, the major countries producing cotton are China with 26%, followed by India, US and Pakistan with 22.6%, 15.9% and 7.6%, respectively. In 2010, the world cotton production decreased by 5.2%. In this year, production also decreased in the US by 4.9 but, in 2011 cotton production in the US showed an increase by 5.7%. Turkey plays a crucial role in cotton imports with 8.1% of world imports, followed by Indonesia, Mexico and Russia with 5.1%, 3.4%, and 1.4%, respectively in 2011. Although US are not the biggest cotton producer in the world it is the major cotton exporter, accounting for 41.3% of the world's total exports. In 2011, China purchased 31.0% of US cotton exports, Mexico, 11.9%, Indonesia, 5.3%, Taiwan, 4.8%, and Thailand, 3.4%.

Table 2.18: Cotton producers, exports and imports

Cotton	**Producers**		**Exports**		**Imports**	
	Countries	**%**	**Countries**	**%**	**Countries**	**%**
	China	26.0	US	41.3	Turkey	8.1
	India	22.6			Indonesia	5.1
	US	15.9			Mexico	3.4
	Pakistan	7.6			Russia	1.4

2.5 Other Commodity Groups: Textiles and Metals

Commodity group of Textiles and Fibers includes cotton, burlap, print cloth and wool tops. There is no information about burlap and print cloth in the CRB Commodity Year Book (2011). Hence, this chapter does not include these commodities. However, the other two commodities of group textiles have placed in raw materials industry.

As we stated before in section 2.4, steel scrap, lead scrap, copper scrap, tin and zinc which also belong to group of metals.

Chapter 3

COMMODITY PRICE DYNAMICS

This chapter analyzes trends and volatility observed in the prices of all commodity groups. In a very broad sense, trend is the general tendency of price changes and volatility refers to variations in prices over time.

The selected 22 commodities are classified into six subdivisions: Foodstuffs, Raw Industrials, Metals, Livestock and Products, Fats and Oils, and Textiles and Fibers. These selected commodities are sensitive to price movements. Although the factors that affect the price of each commodity may differ, we can consider economic and financial crises as common factors affecting the movement of the prices for selected commodity groups. In light of the movements of the data, we can divide our sample into three periods. While the first one covers the period from 1951 to 1969, the second and third are 1970 to 2007 and 2008 to 2015, respectively.

As we can see from Figure 1-6, in the first period (1951-1969), all commodities display a stable behavior. Following the first oil price crisis in 1973, we can observe a significant increase in the prices of all commodities. We may link this increase to the shocks due to the cost-push inflation occurred in the price of commodities during 1973-74 period (Cooper and Lawrence, 1975). In addition, the volatility of macroeconomic variables has fallen dramatically. This was the Great Moderation in several advanced economies from the mid-1980s to 2007 (Summers, 2005). The reduced macroeconomic volatility lowered volatility of inflation which also improved market functioning and reduced economic uncertainty for firms and households. Therefore, the price changes of all commodities were more stable until 2005. At the beginning of third period, the large shocks to all commodities sharply decreased all commodity prices in the mid-2008s due to global recession which started in Dec 2007 triggered by the US subprime mortgage crisis. The reason of this was the subprime mortgage crisis in the United States which has caused global financial and economic crises during Dec 2007-Jun 2009. The emerging economies such as China, India, among others, were also affected by the global crisis and their commodity demand decreased during the global downturn. Despite Federal Reserve’s significant intervention by unconventional monetary policies, the crisis affected the real economy and therefore the prices of all commodities fell sharply in 2008-2009. However, starting from March 2009 the prices of all commodities have started to increase. This was due to recovery of many countries from the global recession.

3.1 Foodstuff

According to the CRB BLS grouping, an index of Foodstuff includes prices of steers, hogs, butter, lard, corn, cocoa, soybean oil, sugar, Minneapolis wheat, and Kansas City wheat.

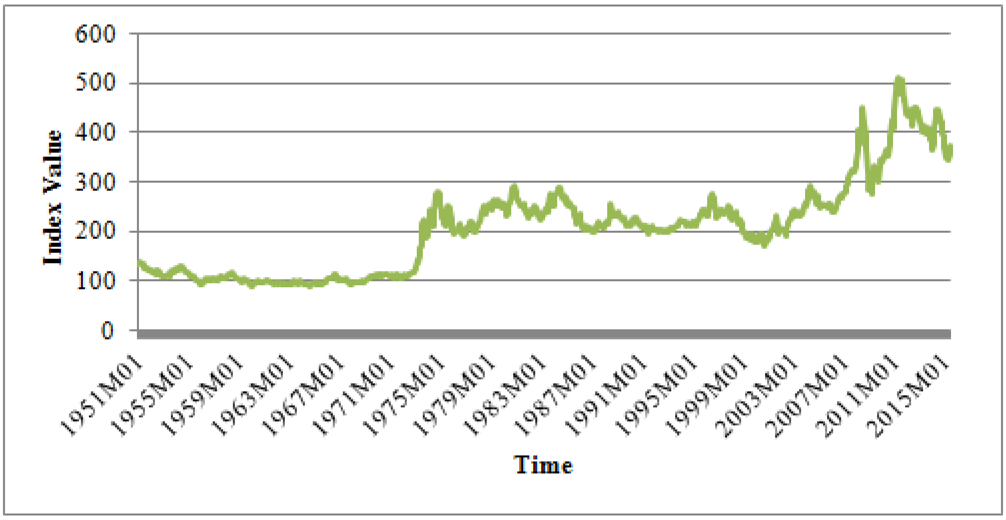

Figure 1: Foodstuffs Sub-Index of Ten Commodities

Figure 1 shows the evolution of foodstuffs index in the sample period. As one can see from the graph, the changes in food prices began to increase after 1971 and the foodstuff price changes have followed an upward trend. The rising prices of foodstuff have several main causes: (1) Increasing demand (demand side), (2) Increasing use of some foodstuffs like corn and maize in the production of Biofuels (price of energy), (3) Increasing agricultural commodity prices as related to increasing oil prices, (4) Low stocks and trade policies implemented, (5) Supply shocks (climatic factors), (6) Increasing cost of inputs and transportation, (7) Population growth (UNCTAD *et al*., 2011).

Foodstuff commodities have higher volatility than the other groups of commodities. Volatility of foodstuff commodity prices is explained by three major market fundamentals. First, natural shocks such as weather and pests have affected the variance of foodstuff production. Second, demand and supply elasticities are relatively small with respect to price, especially in the short-term. Particularly when the stocks are low, prices have to vary quite strongly in order to get demand and supply equilibrium after a supply shock. Third, food production takes time; therefore supply side cannot respond much to price changes at least in the short-term (UNCTAD *et al*., 2011).

The Great Moderation period over 1980-2007 reveals itself with low volatility of the foodstuff price index. In addition, impact of two main foodstuff crises in 2007-2008 and 2010-2011 on the foodstuff prices can also be seen from the peaks in the Figure 1.

3.2 Metal

According to the CRB BLS grouping, Metal index includes prices of lead scrap, copper scrap, steel scrap, zinc and tin. As it is well known, metals are key inputs in many industries. Thus, the dynamics of metal commodity prices are highly related to the worldwide economic activities (Labys, 2006).

As we can follow from Figure 2, price changes of metal commodity group have an upward trend. Volatility of metal prices is low from 1951 to 2005. In the middle of that period, metal prices were negatively affected by oil crisis because of higher input costs. Industry sectors began to use recycling technologies and also substituted other products due to the increase in metal prices. Hence, decreasing price of metals can be explained by the decline in the world demand for metals.

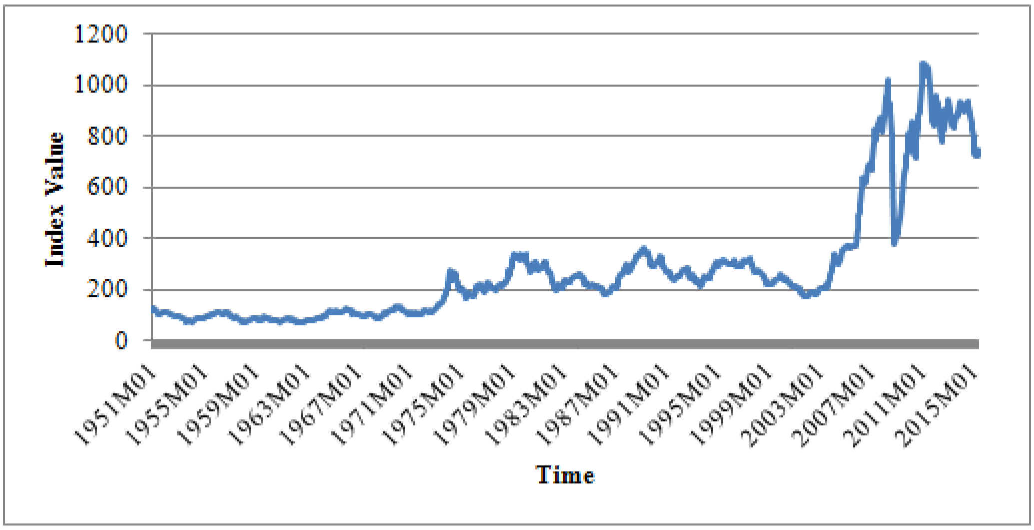

Figure 2: Metals Sub-Index of Five Commodities

Volatility in groups of metals commodity prices has increased between 2001 and 2015 and the price of metals increased dramatically between 2001 and 2008. The main reason of this increase was the advancement of emerging markets demand for metal commodities in different regions, especially China and India. As a result, the world supply of metals could not meet the world demand, and thus metal prices began to increase in this period. In late 2009 period, one can see a sharp decrease in the metal prices because of the contraction in world economy due to the global recession.

3.3 Textiles and Fibers

According to the CRB BLS grouping, Textiles and Fibers index includes prices of cotton, burlap, wool tops and print cloth.

Figure 3 presents the movements in prices of the textiles and fibers commodity group. As we can see from the figure, the group of textiles and fibers have positive upward trend between 1971 and 2015. The main reason for the increase in textiles group prices was the increasing textiles demand from the emerging economies.

Particularly, China's exports of textiles have increased by the end of 2007. However, the worldwide textile demand has been decreased by the unprecedented global economic crisis in 2008. As we can see from the below graph, the decline in the textiles commodity prices following the crisis was not strong.

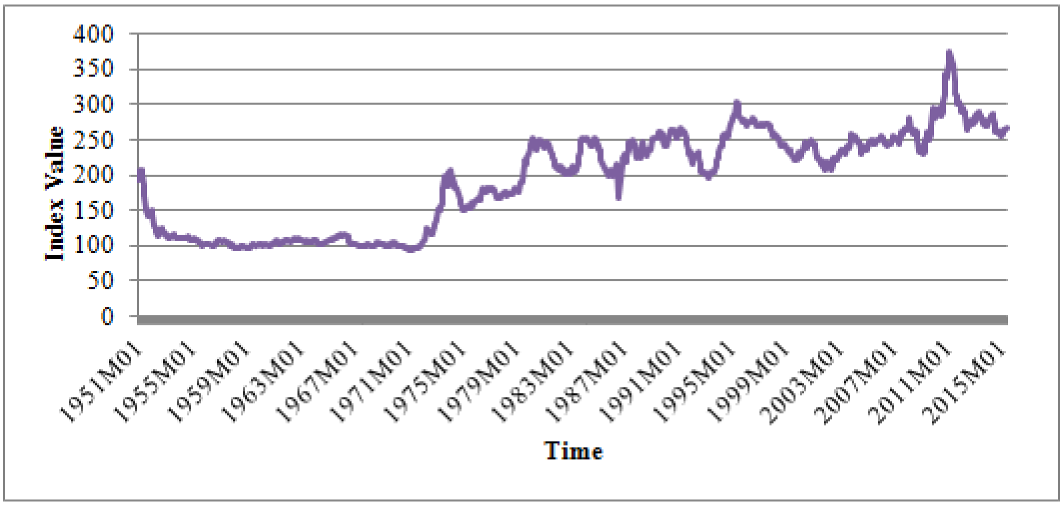

Figure 3: Textiles Sub-Index of Four Commodities

No significant volatility change is observed for the group of textiles and fibers commodity in the sample period, although they become more volatile after 1975. Low volatility of textiles and fibers prices may reflect the inelastic demand for these commodities.

3.4 Livestock and Products

According to the CRB BLS grouping, Livestock and Products index contains hogs, hides, lard, tallow, and steers.

Livestock and products commodity group includes some commodities from the foodstuffs commodity group, such as hogs, steers, and lard as well as soybean and corn. So, naturally the pattern of the graph is very much similar to that of the foodstuffs as can be seen from Figure 4. In addition, the increased world production and global ethanol demand affected the trends of the livestock commodity (Anderson, *et al.*, 2008).

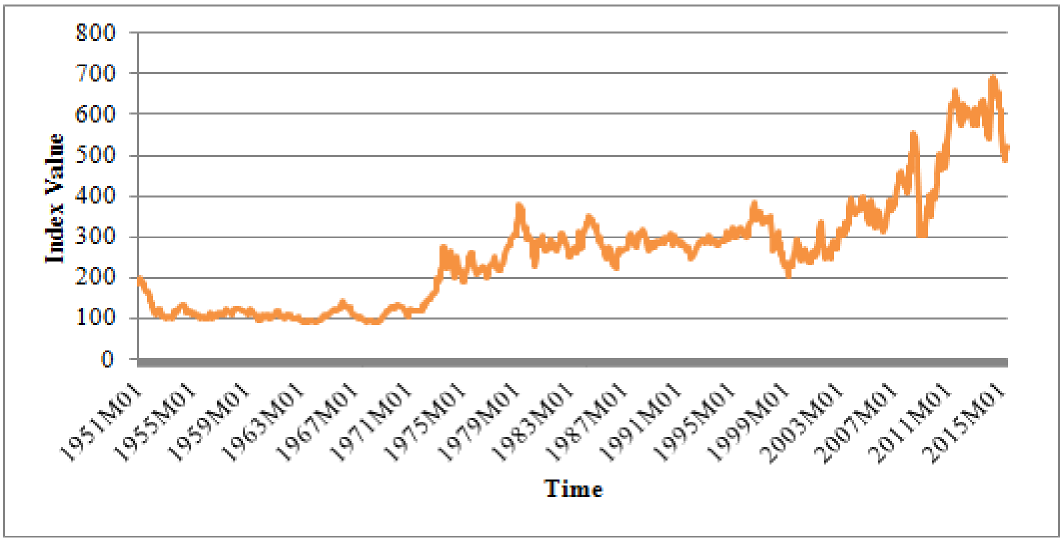

Figure 4: Livestock and Products Sub-Index of Five Commodities

The price volatility of group of livestock commodities increased between 2006 and 2015. The causes of the increased volatility were discussed in Section 3.1.

3.5 Fats and Oils

According to the CRB BLS grouping, Fats and Oil index covers cottonseed oil, butter, tallow, and steers.

From Figure 5, we can see the price changes for fats and oils commodity group. The group of fats and oils index is a combination of commodities in the foodstuffs and textiles index groups. Hence, the commodity of fats and oils has also an upward trend that is driven by the groups of foodstuffs index. Moreover, volatility of groups of fats and oils highly increased between 2006 and 2015. The reason for positive upward trend and increasing volatility were explained in Section 3.1.

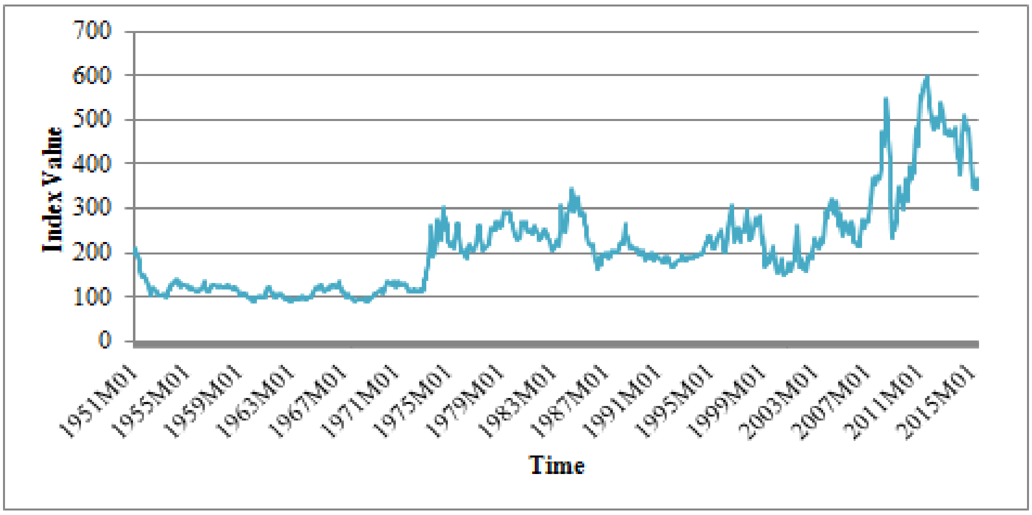

Figure 5: Fats and Oils Sub-Index of Four Commodities

3.6 Raw Industrials

According to the CRB BLS grouping, Raw Industrials index encompasses tallow, hides, lead scrap, copper scrap, steel scrap, tin, zinc, cotton, burlap, wool tops, print cloth, rubber, and rosin.

The group of the raw industrial commodities is a combination of livestock, metals, and textile index groups. As we can see from Figure 6, the raw industrials price index has an upward trend like the livestock, metals, and textile commodity groups. However, the price index of raw industrial commodities mostly driven by the group of metals. As does the metals priced the price volatility of industrial commodities started to increase between the end of 2005 and 2015. The reasons for the increase in volatility were discussed in Section 3.2.

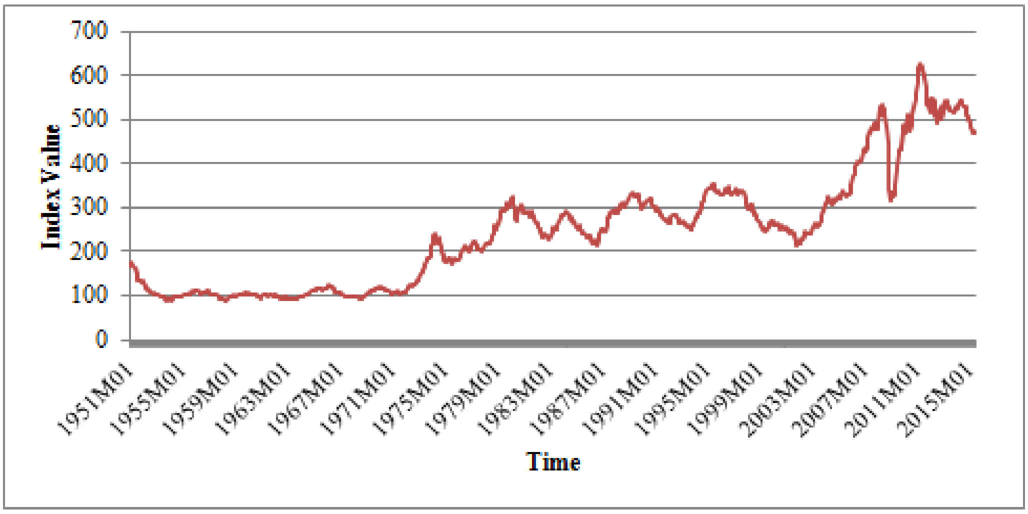

Figure 6: Raw Industrials Sub-Index of Thirteen Commodities

Chapter 4

LITERATURE REVIEW

This chapter focuses on the review of previous empirical work on the topic of interest. There is a broad array of debate among scholars and there has been no consensus regarding the causal effect of commodity price co-movements. This chapter of the thesis discusses various views put forward in the literature on the causes of co-movement of commodity prices.

There is a general belief that three macroeconomic rationales exist behind co-movement of commodity prices. The first view is supported by the studies of Caballero Farhi and Gourinchas (2008) and Kilian and Hicks (2013), and they all argue that the robust growth in emerging economies, leaded by China and India, aids in the explaining the commodity markets co-movement. The second view is the importance of speculations and financialization of traded commodities in either their futures or physical form as posited by the works of Kilian and Lee (2014); Klian and Murphy (2014). The third view held and supported by Frankel (2006); Barsky and Kilian (2004); they asserted that monetary growth is responsible for commodity price co-movements.

Pradhananga (2015) analyzes how the causal links between co-movement in commodity prices and financialization of the commodity futures market for forty-one commodities that include agricultural, livestock, metals, and energy commodities.

The author extracted common factors from these commodity prices using the method of Panel Analysis of Nonstationary and Idiosyncratic Components (PANIC), and Total Open Interest is added to commodity markets to a measure of financialization in the factor-augmented vector error correction (FAVER) model. Because, all commodities are affected by macroeconomic factors, the study includes macroeconomic variables such as; industrial production index, federal funds rate, US inflation, US nominal broad exchange rate and crude oil price. The result of the study provides evidence on the fact that financialization of the commodities futures market led to the recent rise in commodity price co-movements.

Chen (2015) examines the co-movements of commodity sectors such as energy, petrochemicals, nonferrous metals, soft and fats and oils in China. The study attempts to infer the common and individual sector specific factors of the group of commodity prices by using a Bayesian dynamic factor model. The study finds a common factor as major part of the fluctuations of commodity sectors in China. Furthermore, the study also employed a VAR model to investigate whether or not domestic macro fluctuations and global oil price have an effect on co-movement of commodity sectors. It also obtains evidence that the co-movements of commodity sectors are strongly affected by global oil prices rather than domestic macroeconomic fluctuation in short horizons. However, global macroeconomic fluctuations effect co-movements across commodity sectors in long horizons.

Ojeda *et al*. (2015) explore the interrelationships between real gross domestic product (GDP) and real commodity prices in fourteen advanced economies. While Granger causality tests are used to determine the direction of causality, asymmetric Band Pass (BP) filter is applied in order to estimate medium and long-term cyclical components of GDP and commodity prices over the period from 1870 to 2008. According to their findings, although there is a significant relationship between GDP cycles and non-oil commodity price cycles on medium term frequencies, these variables do not show any causality relation. The authors also find evidence that the aggregate demand of developed economies do not affect long and medium-term commodity price cycles.

Chen *et al*. (2014) showed that for five small commodity-exporting countries, Canada, South Africa, Australia, Chile, and New Zealand, commodity prices have predictive power for their Consumer Price Index (CPI) and Production Price Index (PPI) inflation when the inflation targeting monetary policies and the structural breaks are included in the model. They clearly state that this conclusion is robust to the use of aggregated or disaggregated commodity price indexes (where the second one performs better), mixed-frequency data, and the currency denomination of commodity prices. Although the improvements over the AR (1) process are sometimes modest, the commodity indexes perform better than random walk and AR (1) processes.

Ncube *et al*.'s (2014) empirical work shows that commodity price co-movement among petroleum and two groups of commodities. The first group comprises of cotton, cocoa, and coffee while group two comprises of maize, wheat, and palm oil. They use Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) technique on monthly price data for the period of 1980-2014. Results of the study are as follow: the volatility in commodity prices is directly influenced by economic fundamentals, and there is no excess co-movement between the price of commodities and crude oil.

De Nichola *et al*. (2014) examine the degree of co-movement among the nominal price returns of 11 major agricultural, food, and energy commodities between 1970 and 2013. Their study takes into account the time evolution of pair-wise conditional and unconditional correlations between commodity price returns. The authors concluded that the price returns of agricultural and energy commodities were highly correlated; that the whole level of co-movement among commodities increased in recent years, particularly between agricultural and energy commodities, and that after 2007, there was positive relation between stock market volatility and the co-movement of price returns across markets.

Alquist and Coibion (2013) investigated the determinant of commodity price co-movement. The study examines forty commodities from the food, oil, and industrial commodities groups. They used monthly data from 1957 to 2013 and apply the indirect aggregate common factor (IAC) method as estimation technique. Their findings revealed three outcomes. First, each price of the commodity has three different components that capture the distinctive price movements of commodities, global forces in economic and last component interest in specific shocks in the commodity. Second, there is a strong relationship between the IAC factor and business cycle frequencies. The direct commodity shocks negatively affect the global economic activity at business cycle frequencies. Finally, they find that the IAC factor can be used for forecasting of commodity prices. All the results are found to be consistent when compared with a macroeconomic model.

Commodity price behavior is crucial for both developed and developing countries. In this regards, Byrne *et al*. (2013) used non-stationary panel methods and analyzed the determinants and co-movement of commodity prices. The degree of co-movement is statistically significant because of a common factor. Their study reveals that common factor has a reverse relationship between uncertainty and the real interest rate by using Factor Augmented VAR (FAVAR) model. According to their findings, supply and demand shocks have a positive effect on co-movement of commodity prices.

The stochastic behavior of the prices and volatilities of six significant commodity markets are analyzed by Brooks and Prokopczuk (2013). These commodities are categorized as three different markets: energy market (crude oil and gasoline), metal market (gold and silver), and agricultural market (soybeans and wheat). They compare properties of different commodities with the features of the equity market. Observing a considerable amount of heterogeneity in the series' behavior, the findings support the inapplicability of treating different types of commodities as a particular asset class. The study shows that the commodities can diversify equity volatility and equity returns. The economic impacts of the differences across commodities and between model specifications are demonstrated with options pricing and hedging applications. The S&P 500 returns are highly related to the pairs of commodities from the same sub-class. However, this correlation is almost zero across sub-classes.

Nazlioglu and Soytas (2012) analyzed the relationship between world oil prices and twenty-four world agricultural commodity prices responsible for the variation in the relative strength of the American dollar using a panel approach as the estimation technique. They apply panel cointegration and panel Granger causality tests and monthly data running from January 1980 to February 2010. The findings of the study show that there exists a strong effect of world oil prices on agricultural commodity prices. This outcome is contrary to with the results of previous empirical works that support the neutrality of agricultural prices to oil fluctuations. This study also empirically validates the claim of a positive impact of the weak dollar on agricultural prices.

Lombardi *et al*. (2010) examine the interrelationship between macroeconomic variables and two selected commodity prices. The study employs the FAVAR approach as estimation technique and also estimates the impulse responses. The impulse response estimates affirm that industrial production also affects individual non-energy commodity prices as well as the exchange rate. The findings also point out that there was no causality running from oil to non-oil commodity prices. Further conclusion of the study is that individual prices of the commodity are caused by common trend expressed by the metal and food factors.

Reitz and Westerhoff (2007) attemts to generate a new model that is highly related to cyclical commodity price motion. Also, the effects of speculators on commodity price evolution are incorporated into the model. Draper (1985), Smidt (1965), Canoles *et al*. (1998), Weiner (2002), and Sanders *et al*. (2000), use a fundamental and technical analysis mentioned below and find that the speculative trading is the major indicator for the fluctuation in the prices of commodities. By using Smooth Transition Autoregressive- Generalized Autoregressive Conditional Heteroscedasticity (STAR-GARCH) model and monthly data from 1973 to 2003 for lead, sugar, zinc, rice, soybeans, and cotton, the authors show that the coefficients of fundamental and chartist are statistically significant and have expected signs. Also, the models show that the nonlinear trading of heterogeneous speculators can be explained by prominent cycles in commodity prices.

Cashin *et al*. (2002) investigate the magnitude and the duration of the commodity price cycles by using monthly data for thirty-six real commodities which covers the period from 1957:1 to 1999:8. In order to test their claim, they applied Bry-Boschan algorithm to date the cycles. They find that the price booms in commodity markets have shorter time than the price slumps, and also the independence of the durations of commodities' price slumps and booms.

Deaton and Laraque (1992) in their empirical work try to examine the behavioral pattern of commodity prices since it is crucial to decision-makers in the formulation of policies in the developing nations, who are major exporters of these commodities. The study was done using thirteen commodities, such banana, cocoa rice, sugar among others and based on simple competitive storage theory. The study shows a rare existence but high hike in prices, which was also accompanied with a price autocorrelation in normal times. Furthermore, the study suggests that, for the majority of the thirteen commodity prices, the behavior of the prices from year to another is in conformity with the claim of the conditional expectation and also the conditional variance. Nevertheless, the non-linearity of the model does not validate that the theory accounts for the data used in the study.

Pindyck and Rotemborg (1988) tested for the existence of co-movement in raw commodities after controlling for macroeconomic and microeconomic shocks. They applied Ordinary Least Squares (OLS) for seven commodities, which are cotton, wheat, gold, copper, lumber, crude oil and cocoa, to a monthly data covering the period 1960-1985. The features of selected commodities are that "none of the commodities are complements or substitutes, and none of them is used as an input into the production of another". These features are important because the excess co-movement hypothesis (ECM) is not applied to related commodities. The authors also find serial correlation in the residuals from these regressions, and the result shows seemingly unrelated commodities tend to move together after accounting for the impact of macroeconomic variables such as inflation, interest rate, industrial production, etc. Deb *et al*. (1996) find some misspecification in the Pindyck and Rotemberg's approach. Their study did not take into account for potential issues such as heteroscedasticity in the commodity price data and the presence of structural breaks during the sample period. Therefore, Deb *et al*. (1996) applied univariate and multivariate GARCH models, and find much weaker evidence in favor of the ECM hypothesis.

Chapter 5

METHODOLOGY

5.1 Long-Run Co-movement and Common Cycles

This section presents the econometric methodology used in the thesis. The exposition also introduces the terminology used in the rest of the study. The essential key concepts such as the cointegration and serial correlation common features in the first differences and common cycles in the levels of the series are explained.

Let y_t denote and n-vector of I(1) time series with its first difference denoted by Δy_t These series are said to be cointegrated, if there exists a linear combination of the series which is I(0). If this holds, the linear combination is called a cointegration combination while the vector that denotes it is called a cointegrating vector. Independent cointegrating vector can take the form of r (<n) i.e. explaining r as linearly independent cointegrating rank vector. A linear combination of independent cointegrating rank vectors of form n × r matrix, $\alpha' \Delta y_t$ is I (0). A cointegrating space occurs when the range of matrix α which connotes all possible subspace.

Common serial correlation features are defined for the stationary first differences Δy_t. For the serially correlated series, Δy_t, if a linear combination exists that is not serially correlated, then Δy_t are said to have common serial correlation features. The linear combination is known as a cofeature combination; similarly the vector formed from the coefficients of the linear combination is called a cofeature vector. There may exists $s \leq n - r$ combinations that can form independent cofeatures vectors, i.e., s linearly independent cofeature vectors. The n × s matrix $\tilde{\alpha}$, where $\tilde{\alpha}$ 'Δy_t is innovation, form as the linear combinations from the independent cofeature vectors. The $\tilde{\alpha}$ matrix represents the space of all possible cofeatures, which is known as the cofeature space.

Vahid and Engle (1993) introduced to concept of common cofeatures as an extension to cointegration and common stochastic trends.

5.1.1 Moving Average Representation

Moving average (MA) process are stationary, i.e. I(0) processes and the basis of the Wold representation of form is given as:

$$\Delta y_t = \mu + C(L)\varepsilon_t \qquad (1)$$

where C(L) denotes the lag polynomial matrix and L is a lag operato, with

$$C(0) = I_n, \ \sum_{j=1}^{\infty} j \mid Cj \mid \leq \infty$$

also ε_t represents a vector of n × 1, a stationary one-step-ahead linear forecast error in y_t with lagged information of y. Assume that $\mu = 0$ holds for simplicity, noting that the case of $\mu \neq 0$ denotes a time trend in level form. Equation (1) can be rewritten as:

$$\Delta y_t = C(1)\ \varepsilon_t + \Delta C^*(L)\varepsilon_t \qquad (2)$$

where

$$C_i^* = \sum_{j>i} - Cj \text{ for all } i \text{ in particular } C_0^* = I_n - C(1)$$

If we integrate both sides of equation (2), then we obtain:

$$y_t = C(1) \sum_{s=0}^{\infty} \varepsilon_{t-s} + C^*(L)\varepsilon_t \qquad (3)$$

Equation (3) is the multivariate version of the well-known Beveridge and Nelson (1981) trend and cycle decomposition. The series y_t can be decomposed into two main parts, namely pure random walk part and a stationary part. The former is known as the trend component and the latter is known as the cycle component. The elements of y are all stationary, when C(1) is full rank. If the number of independent variables n is greater than rank k of C(1), then it can be decomposed into two matrices of rank k. A common trend representation was developed by Stock and Watson (1988) which is commonly known as the (BNWS) i.e. Beveridge-Nelson-Stock–Watson decomposition:

$$\mathrm{y}_t = \gamma\tau_t + \mathrm{c}_t \tag{4}$$

$$\tau_t = \tau_{t-1} + \delta^{'}\varepsilon_t \tag{5}$$

where,

$$\tau_{t-1} = \delta^{'}\sum_{s=0}^{\infty}\varepsilon_{t-s} \quad \text{and} \quad \mathrm{c}_t = \mathrm{C}^*(\mathrm{L})\varepsilon$$

This vector time series have $r = n - k$ linearly independent cointegrating vectors which for the null space of C $(1)^{'}$. It worthy also mention that the linear combination also includes the cyclical part of y_t, given by

$$\alpha' \mathrm{y}_t = \tilde{\alpha}\mathrm{C}^*(\mathrm{L})\varepsilon_t = \alpha' \mathrm{c}_t$$

Thus, α is a vector that eliminates the common stochastic trends and leaves only the stationary cyclical components. Similarly, $\tilde{\alpha}$ is a vector that eliminates the common serial correlations and leaves a white noise component.

5.2 Common Cycle Test

In this section the test for existence of common serial correlation features or common cycles is explained. The test will be used to examine the existence of serial correlation common features among the six set of commodity price indices. Engle and Kozicki (1993) developed a test of serial correlation common features of variables that are stationary. The two stage least squares regression (2SLS) test is the basis for the test where the instrumental variables in an auxiliary regression are used to capture the pseudo-structure for testing overidentifying restriction. The general idea behind this test is to find the linear dependency of one of the variable's lagged values with lags of other variables. Common cycles in a set of cointegrated variables also follow same logic, but apply to the stationary combinations that are obtained using the cointegration vectors.

In order to investigate the existence of common cycles among the commodity prices, we look for a serially non-correlated linear combination of the first differences of the set of serially correlated and possibly cointegrated variables This is the motivation behind the serial correlation cofeature vector estimator of Engle and Kozicki (1993). A test of serial correlation cofeature can be performed using this estimator.

Let X be a vector of cointegrated time series and Z be the error correction term. Form a matrix W by stacking past of X and lagged error correction term, i.e., $W \equiv \{X_{-1}, \ldots\ldots, X_{-p}, Z_{-1}\}$. Let P_w be the orthogonal projection matrix to the span of the relevant past and M_{w} be the orthogonal projection matrix to the span of corresponding null space of the relevant past. Vahid and Engle (1993) show that the cofeature vector $\tilde{\alpha}$ can be obtained by minimizing:

$$Q(\alpha^{\dagger}) = \frac{\alpha^{\dagger\prime} X' P_w X \alpha^{\dagger}}{\alpha^{\dagger\prime} X' X \alpha^{\dagger}} \quad (6)$$

The numerator is minimized and the first element of the minimand is one, it's obvious that the minimand will the 2SLS coefficient of the first element of Δy_t on the rest of the elements, where instruments are considered as relevant past, referred to as $\tilde{\alpha}_{2SLS}$. Therefore, the objective function estimated at $\tilde{\alpha}_{2SLS}$ forms a Lagrange Multiplier (LM) test statistic for the validity of the instruments which is known to be χ^2 distributed with the number of overidentifying restrictions equal to the degrees of freedom.

Vahid and Engle (1993) introduce a test of *s* linearly independent common serial correlation features based on the canonical correlations between *X* and *W*. The test statistic is calculated as:

$$C(p,s) = -(T-p-1)\sum_{i=1}^{s}\log(1-\lambda_i^2) \quad (7)$$

where the λ_i^2, *i*=1,2,…,s, are the *s* smallest squred canonical correlations between *X* and *W*, *n* denotes the dimension of system, *p* denotes the selected lag order of the differences in the VECM representation, and *r* denotes the cointegration rank. The test is χ^2 distributed with $s^2 + snp + sr - sn$ where degrees of freedom and the null hypothesis tests at least *s* cofeature the representation against *s* cofeature the representation. The test is performed in a sequential manner for *s*=0,1,2,…,*n*-*r*.

Chapter 6

ESTIMATION OF COMMODITY PRICE CO-MOVEMENTS

6.1 Data

The monthly data used in the study covers the period from 1951 to 2015 for the US economy. The source of the data is Commodity Research Bureau (CRB). As stated earlier, the sample consists of commodity groups fat and oils, foodstuffs, livestock, metals, raw industrials and textiles. The variables are analyzed in logarithmic form.

6.2 Descriptive Analysis

This section presents the descriptive statistics of the time series for commodity prices. All data are in monthly frequency and cover the period from 1951M1 to 2015M6. The descriptive statistics are shown in Table 6.1.

Table 6.1: Descriptive Statistics

	Mean	Maximum	Minimum	Std. Dev	JB	p-val. JB
lnfatsandoils	5.260585	6.392989	4.486387	0.458991	21.03257	0.000027
lnfoodstuffs	5.230837	6.238657	4.499810	0.460636	34.0323	0.000000
lnlivestock	5.410379	6.538979	4.478473	0.549027	35.72919	0.000000
lnmetals	5.356431	6.990072	4.252772	0.720363	36.56223	0.000000
lnrawindustrials	5.355416	6.438391	4.492001	0.559198	48.89271	0.000000
lntextiles	5.189120	5.923908	4.528289	0.397572	88.31508	0.000000

According to Table 6.1, *lntextiles*, log of the spot price of burlap, cotton, print, cloth and wool tops, has the lowest mean value 5.18 while *lnlivestock*, log of the spot prices of hides, hogs, lard, steers and tallow, has the highest mean value of 5.41.

On the other hand, the highest maximum value and the lowest minimum value belongs to *lnmetals*, log ofcopper scrap, lead scrap, steel scrap, tin and zinc, which are 6.99 and 4.25, respectively. JB is the Jargua-Berra test of normality and which tests whether the series have normal distribution or not and p-val. JB is its p-value from Chi- square distribution with 2 degrees of freedom. All series are non-normally distributed, because p-val. JB is less than 0.05 and thus we reject the null hypothesis-that series have normal distribution.

6.3 Unit Root Test Results

Stationarity of the series is determined by the unit root test. Augmented Dickey Fuller [ADF] (Dickey and Fuller, 1981) and Kwiatkowski-Phillips-Schmidt-Shin [KPSS] (Kwiatkowski *et al*., 1992) tests are used to test for unit roots. The main difference between ADF and KPSS is the structure of the null hypothesis, the KPSS has stationarity or I(0) as the null hypothesis while the null of ADF is I(1) or nonstationarity. The results of unit root tests are presented in Table 6.2.

Table 6.2: Unit root test result

	Level				First Differences			
	H_0: I(1)		H_0: I(0)		H_0: I(1)		H_0: I(0)	
Series	ADF[a]	ADF[b]	KPSS[c]	KPSS[d]	ADF[a]	ADF[b]	KPSS[c]	KPSS[d]
lnfatsandoil	-4.29***	-1.91	0.73***	11.47***	-32.94***	-32.90***	0.03	0.06
lnfoodstuffs	-2.62	-0.8	0.97***	12.97***	-34.80***	-34.80***	0.06	0.07
lnlivestock	-4.17***	-1.01	0.89***	14.20***	-34.09***	-34.08***	0.05	0.09
lnmetals	-2.77	-0.52	0.74***	13.49***	-22.95***	-22.93***	0.05	0.10
lnrawind	-3.37	-0.36	0.90***	14.67***	-21.41***	-21.39***	0.13*	0.20
lntextiles	-3.43**	-0.58	1.42***	14.13***	-54.26***	-54.25***	0.18**	0.23

Note: *,**,*** indicate significance at the 10,5 and 1 percent levels, respectively.
[a]Test allows for a constant and linear trend; one-sided test of the null hypothesis that the variable has a unit root ; 10, 5, 1 percent critical value equals -3.13, -3.41, -3.97, respectively.
[b]Test allows for a constant ; one- sided test of the null hypothesis that the variable has a unit root; 10, 5, 1 percent critical value equals -2.59, -2.88, -3.45, respectively.
[c]Test allows for a constant and a linear trend ; one-sided test of the null hypothesis that the variable is stationary; 10, 5, 1 percent critical values equals 0.11, 0.14, 0.21, respectively.
[d]Test allows for a constant; one-sided test of the null hypothesis that the variable is stationary ; 10, 5, 1 percent critical values equals 0.34, 0.46, 0.73, respectively.

From Table 6.2, it is clear that *lnfatsandoils* and *lnlivestock* are trend stationary according to the ADF test. This is because that ADF test values are greater than their respective critical values with constant and linear trend. The other series are found to be I(1) by the ADF test. The ADF tests are found to have low power towards stable autoregressive alternatives with roots near unity by Dejong at al. (1989). The KPSS test is known as more powerful in such cases. Thus, we use the KPSS test to confirm the ADF results.

According to KPSS test results reported in Table 6.2, all series are found to be integrated of order one because the test values are greater than the critical values and the null hypothesis that the variable is stationary (trend stationary) is rejected for all variables.

Given the low power property of the ADF test, we base our decision on the KPSS test results and assume that all series are I(1). A long-run relationship may exist among the variables, because of the all series are integrated of the same order (I (1)), we can use the Johansen cointegration test in order to investigate the existence of a long-run relationship. However, we check for any short-run Granger causality among the series before the cointegration analysis.

6.4 Granger Causality Tests

Granger (1969) defines the causality for two variables, X and Y, as follows: if we can predict Y more accurately by using the historical values of both X and Y than we can by using only that of Y, then we can say "X is Granger causal for Y". Ordinarily, the regression analysis does not give any information about causality; it is just related to the correlation between variables. Therefore, Granger causality test is used to determine the direction of causality between variables. In its basic form, the Granger causality test is only applied to stationary series. In the nonstationary case, series will time depend moments and hence existence of any causality can change over time. According to Table 6.2, all variables are integrated order one I(1), which means that these variables are nonstationary. Therefore we have to take first differences of six variables to apply Granger causality test. The Granger Causality test is sensitivity to lag length specification. Accordingly, we a VAR model for determine the appropriate lag length and then we check for the autocorrelations in the residuals for a given lag length by using autocorrelation LM tests and make sure that there is no autocorrelation in the residuals at the selected lag length. The Granger causality test results given in Tables 6.3-6.17 show pair-wise Granger causality among six variables in the short-run.

Table 6.3: Pair-wise Linear Granger Causality Tests for Fats & Oils and Foodstuff

Null Hypothesis	Lags	F-statistic	P-value
Δlnfoodstuffs ≠> Δlnfatsandoils	2	20.836	0.000
Δlnfatsandoils ≠> Δlnfoodstuffs	2	6.474	0.001

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

Table 6.3 shows that there is bidirectional Granger causality between *foodstuffs* and *fatsandoils* at 1% significance level. So that percentage changes in the *foodstuffs* have effect on *fatsandoils* and vice versa. This implies that we can predict the *fatsandoils* by using past values of the *foodstuffs* and the *fatsandoils* as well as we can predict *foodstuffs* by using past values of the *fatsandoils* the *foodstuffs.*

Table 6.4: Pair-wise Linear Granger Causality Tests for Fats & Oils and Livestock

Null Hypothesis	Lags	F-statistic	P-value
Δlnfatsandoils ≠> Δlnlivestock	3	4.465	0.004
Δlnlivestock ≠> Δlnfatsandoils	3	5.652	0.000

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

According to Table 6.4, there is bidirectional Granger causality between *fatsandoils* and *livestock* at 1% significance level. Therefore, percentage changes in the *fatsandoils* have effect on *livestock* and vice versa. This implies that we can predict the *livestock* by using past values of the *fatsandoils* and the *livestock* as well as we can predict *fatsandoils* by using past values of the *livestock* and *fatsandoils.*

Table 6.5: Pair-wise Linear Granger Causality Tests for Fats & Oils and Metals

Null Hypothesis	Lags	F-statistic	P-value
Δlnfatsandoils ≠> Δlnmetals	1	2.185	0.139
Δlnmetals ≠> Δlnfatsandoils	1	22.775	0.000

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause

From the results reported in Table 6.5, we find that *metals* does Granger cause *fatsandoils* at 1% significance level, which means that any percentage changes in *metal*s have effect on *fatsandoils* but in one direction. Evidently *fatsandoils* does not Granger cause *metals*. History of *metals* helps us to better predict *fatsandoils,* but not vice versa.

Table 6.6: Pair-wise Linear Granger Causality Tests for Fats & Oils and Raw Industrials

Null Hypothesis	Lags	F-statistic	P-value
Δlnfatsandoils ≠> Δlnrawindustrials	1	3.099	0.078
Δlnrawindustrials ≠> Δlnfatsandoils	1	19.634	0.000

Note: The symbol '' ≠>'' indicates does not linearly Granger Cause.

From the results in Table 6.6, null hypothesis is rejected for both *fatsandoils* and *rawindustrials* at 10% significance level and there is bidirectional Granger causality between these variables. This means that any percentage changes in the *fatsandoils* have impact on *rawindustrial* or vice versa. Past values of *fatsandoils* help to predict future values of *rawindustrial.* Furthermore, history of *rawindustrial* variable plays important role to predict *fatsandoils*.

Table 6.7: Pair-wise Linear Granger Causality Tests for Fats & Oils and Textiles

Null Hypothesis	Lags	F-statistic	P-value
Δlnfatsandoils ≠> Δlntextiles	1	0.475	0.490
Δlntextiles ≠> Δlnfatsandoils	1	6.380	0.011

Note: The symbol '' ≠>'' indicates does not linearly Granger Cause.

From the results in Table 6.7, while the first null hypothesis, *fatsandoils* does not Granger cause *textiles,* is not rejected at 10% significance level, the second null hypothesis is rejected at 5% significance level. There is a unidirectional Granger causality relation from *textiles* to *fatsandoils*. Therefore, *fatsandoils* can be predicted by past values of the *textiles* and the *fatsandoils*, but not vice versa.

Table 6.8: Pair-wise Linear Granger Causality Tests for Foodstuffs and Livestock

Null Hypothesis	Lags	F-statistic	P-value
Δlnfoodstuffs ≠> Δlnlivestock	1	5.702	0.017
Δlnlivestock ≠> Δlnfoodstuffs	1	0.717	0.397

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

Evidently, Table 6.8 shows us there is a causal relationship between *foodstuffs* and *livestock* in one direction. The results imply that percentage changes in *foodstuffs* have effect on *livestock*, but not vice versa. This implies that information from the past of *foodstuffs* can predict the *livestock*.

Table 6.9: Pair-wise Linear Granger Causality Tests for Foodstuffs and Metals

Null Hypothesis	Lags	F-statistic	P-value
Δlnfoodstuffs ≠>Δlnmetals	1	4.825	0.028
Δlnmetals ≠> Δlnfoodstuffs	1	2.697	0.100

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

From Table 6.9, while the first null hypothesis is rejected at 5% significance level, the second null hypothesis is not rejected at 10% significance level and, then, there is a unidirectional Granger causality from *foodstuffs* to *metal*. This means that history values of the *foodstuffs* can be used to predict value of the *metals* but *metals* does not help to predict values of the *foodstuffs.*

Table 6.10: Pair-wise Linear Granger Causality Tests for Foodstuffs and Raw Industrials

Null Hypothesis	Lags	F-statistic	P-value
Δlnfoodstuffs ≠> Δlnrawindustrial	1	3.222	0.073
Δlnrawindustrial ≠> Δlnfoodstuffs	1	3.937	0.047

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

From Table 6.10, we can say that there is bidirectional Granger causal relation between *foodstuffs* and *rawindustrial* at 10% significance level. Any percentage changes in foodstuffs have effect on values of *rawindustrial* and also vice versa. Therefore, the past values of *foodstuffs* and *rawindustrial* play important role for predicting each other.

Table 6.11: Pair-wise Linear Granger Causality Tests for Foodstuffs and Textiles

Null Hypothesis	Lags	F-statistic	P-value
Δlnfoodstuffs ≠> Δlntextiles	1	3.273	0.070
Δlntextiles ≠> Δlnfoodstuffs	1	2.299	0.129

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

According to Table 6.11, the first null hypothesis is rejected while the second one is not rejected at 10% significance level. This means that there is a bidirectional Granger causal from *foodstuffs* to *textiles* and not vice versa. An increase or decrease in *foodstuffs* can affect the *textiles*. On the other hand, *textiles* do not seem to Granger cause *foodstuffs*. According to this information, we can predict the *textiles* by using past values of *foodstuffs* and *textiles.*

Table 6.12: Pair-wise Linear Granger Causality Tests for Livestock and Metals

Null Hypothesis	Lags	F-statistic	P-value
Δlnlivestock ≠> Δlnmetals	1	0.511	0.474
Δlnmetals ≠> Δlnlivestock	1	16.768	0.000

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

There is a bidirectional Granger cause from *metals* to *livestock* at 10% significance level from the results in Table 6.12. Any percentage changes in metals have effect on values of *livestock*. Therefore, if we take into account past values of *metals* and *livestock* to predict *livestocks,* the results become more accurate than by using only past values of *livestocks.*

Table 6.13: Pair-wise Linear Granger Causality Tests for Livestock and Raw Industrials

Null Hypothesis	Lags	F-statistic	P-value
Δlnlivestock ≠> Δlnrawindustrials	1	3.311	0.069
Δlnrawindustrials ≠> Δlnlivestock	1	14.405	0.000

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

From Table 6.13, both null hypotheses are rejected at 10% significance level. This means that there is bidirectional Granger causality between *livestock* and *rawindustrials*. For this reason, *livestock* can be predicted by using past values of *livestock* and *rawindustrials*, as well as *rawindustrials* also predicted more accurately by using history of *rawindustrials* and *livestock* than just the history of *rawindustrials.*

Table 6.14: Pair-wise Linear Granger Causality Tests for Livestock and Textiles

Null Hypothesis	Lags	F-statistic	P-value
Δlnlivestock ≠> Δlntextiles	1	2.018	0.155
Δlntextiles ≠> Δlnlivestock	1	5.890	0.015

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

Table 6.14 shows that there is a unidirectional Granger causality between *livestock* and *textiles*. The first null hypothesis, *livestock* does not Granger cause on *textiles,* cannot be reject at 10% significance level, while the second null hypothesis; *textiles* does Granger cause on *livestock*, can be rejected at 5% significance level. According to this result, we can say that any percentage changes in *livestock* have effect on *textiles.* This suggests that future values of *textiles* can be predicted via past values of the *livestock* and the *textiles*.

Table 6.15: Pair-wise Linear Granger Causality Tests for Metals and Raw Industrials

Null Hypothesis	Lags	F-statistic	P-value
Δlnmetals ≠> Δlnrawindustrials	1	5.350	0.021
Δlnrawindustrials ≠> Δlnmetals	1	10.682	0.001

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

From Table 6.15 above, there is bidirectional Granger causality between *metals* and *rawindustrials* at 5% significance level. Therefore, any increase or decrease in *metals* can affect and Granger causes the *rawindustrials*. On the other hand, percentage changes in *rawindustrials* have also effects on *metals*. The past values of both *metals* and *rawindustrials* help to predict the values of *metals* more accurately, and vice versa.

Table 6.16: Pair-wise Linear Granger Causality Tests for Metals and Textiles

Null Hypothesis	Lags	F-statistic	P-value
Δlnmetals ≠> Δlntextiles	1	4.444	0.035
Δlntextiles ≠> Δlnmetals	1	14.104	0.000

Note: The symbol ‘’ ≠>’’ indicates does not linearly Granger Cause.

According to the results in Table 6.16, both null hypothesizes are rejected at 5% significance level. This means that *metals* and *textiles* have bidirectional Granger causality. Any percentage changes in metals have affects on the *textiles* and also vice versa. We can use past values of both of *metals* and *textiles* to predict the *metals* as well as *textiles.*

Table 6.17: Pair-wise Linear Granger Causality Tests for Raw Industrials and Textiles

Null Hypothesis	Lags	F-statistic	P-value
Δlnrawindustrial ≠> Δlntextiles	1	8.691	0.003
Δlntextiles ≠> Δlnrawindustrials	1	2.334	0.127

Note: The symbol '' ≠>'' indicates does not linearly Granger Cause.

From Table 6.17 above, there is no evidence of Granger causality from *textiles* to *rawindustrials*. This suggests that information from the past of *textiles* cannot help to predict the behavior of *rawindustrials*. In other words, *rawindustrials* does Granger cause *textiles* at 1% significance level. Therefore, percentage changes in *rawindustrials* have effects on *textiles*, but not vice versa. The past of both of *textiles* and *rawindustrials* help to predict *textiles.*

6.5 Lag Order Selection for the VAR Model

Table 6.18 reports optimal lag length selection criteria for the VAR(p) model of *fats and oils, livestock and products, textiles and fibers, raw industrial, foodstuffs* and *metals.* The table reports the Likelihood Ratio, Final Predict Error, Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn information criterion (HQ). Based on the results in Table 6.18, we select lag order of the VAR equal to using the AIC and HQ criteria.

Table 6.18: Optimal Lag Length Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3012.489	NA	1.57e-11	-7.849840	-7.813486	-7.835846
1	10041.16	13928.87	1.85e-19	-26.10746	-25.85298*	-26.00950
2	10125.23	165.2949*	1.63e-19*	-26.23298*	-25.76038	-26.05105*
3	10150.81	49.88924	1.68e-19	-26.20577	-25.51504	-25.93988
4	10174.93	46.65758	1.73e-19	-26.17474	-25.26589	-25.82489
5	10195.00	38.51550	1.80e-19	-26.13315	-25.00618	-25.69933
6	10217.08	42.04180	1.87e-19	-26.09682	-24.75173	-25.57904
7	10239.28	41.90219	1.94e-19	-26.06078	-24.49757	-25.45904
8	10257.32	33.77733	2.03e-19	-26.01390	-24.23256	-25.32819

Note: * indicates lag order selected by the criterion, each test at the 5% significance level.

6.6 Cointegration Test Results

According to the result of the KPSS test, *lnfatsandoils*, *lnfoodstuffs*, *lnlivestock*, *lnmetals*, *lnrawindustrial*, and *lntextiles* are all integrated of degree 1, I(1), which means that the series are not stationary in levels, but stationary in first differences. Ignoring the nonstationary may cause spurious regression (Granger and Newbold, 1974), if an OLS regression is used to estimate the long-run relationship among the variables. In order avoid the spurious regression problem; one may use the cointegration approach developed by Engle and Granger (1987) (EG). The EG approach tests for cointegration relationship between non-stationary time series variables using a two-step Ordinary Least Squares (OLS) procedure.

If the model includes n variable, there may be, r $0 \leq r < n$, cointegration relationship and the EG approach restricts r as equal to 1. This is however suboptimal and excludes valuable information, if more than one cointegration relationship exists, i.e.,$r > 1$. For this reason, Johansen (1988, 1991) offered Maximum Likelihood Cointegration test via Trace statistics and Maximum

Eigenvalue which allows testing for more than one cointegration relationship. This study includes six variables, therefore Johansen Multivariate Cointegration techniques is the preferred approach, because there may be maximum of five cointegration relationships among the variables.

The results of the Johansen cointegration test are presented in Table 6.19. Johansen trace statistics for no cointegration is formulated as follows

H_0: r = 0 (Series do not have any cointegration relationship)

H_1: r ≤ 1 (Series have less than or equal to one cointegration relationship)

The trace statistics results show that value of the test statistic for $r = 0$ is 162.72, which is greater than its critical value (95.75), so null hypothesis of no cointegration is rejected. The null hypothesis is not rejected at r=3, therefore, the trace test indicates three cointegration vectors among six variables according.

<u>The Maximum Eigenvalue test of no cointegration is formulated as follows:</u>

H_0: r =0 (Series do not have any cointegration relationship)

H_1: r= 1 (Series have one cointegration relationship)

The results for the maximum eigenvalue test show that the value of the statistics for the no cointegration hypothesis is 67.28, which is greater than its critical value (40.07), so the null hypothesis of no cointegration is rejected. The null hypothesis is not rejected at r=3, supporting the existence of three cointegration vectors among the six variables.

The results of cointegration tests show that bothe the Trace test and the Maximum Eigenvalue test indicates three cointegration vectors at %5 level. This implies that there is a long-run (with three cointegrating vectors) relationship among the six variables, and that there is also $6 - 3 = 3$ three common stochastic trends shared by all six variables.

Price index series of the groups of commodities can be decomposed in two ways. First decomposition is done to differentiate between permanent and transitory component and the second decomposition is done to see the common trend and common cycle components.

The six groups of commodities and their permanent components are given in Figure 7. A similar persistent upward trend among these groups is observed. The important point is that these permanent components of the series are determined by the permanent shocks on all the groups of commodities, where a permanent shock means "continuing for a long time into the future." (Campell and Mankiw, 1987). These selected commodities are sensitive to price movements. Although the factors that affect the price of each commodity may differ, we can consider economic and financial crisis as a common factors jointly affecting all commodity prices during the sample period.

Table 6.19: Cointegration Test Results

Statistics/ Series		H_0	H_1	lnfao,lnfood,lnlive,lnmetal,lnraw and lntex
Eigenvalues (λ)	(λ)			
	λ			0.083567
	λ_1			0.053336
	λ_2			0.036167
	λ_3			0.026302
Trace statistics (λ_{trace})				
		r=0	r≤1	162.5672**
		r=1	r≤2	95.28494**
		r=2	r≤3	53.02585**
		r=3	r≤4	24.62415
Maximal eigenvalue Statistics (λ_{max})				
		r=0	r=1	67.28224**
		r=1	r=2	42.25910**
		r=2	r=3	28.40170**
		r=3	r=4	20.55028
5% critical values for λ_{trace}				
		r=0	r≤1	95.75366
		r=1	r≤2	69.81889
		r=2	r≤3	47.85613
		r=3	r≤4	29.79707
5% critical values for λ_{max}				
		r=0	r=1	40.07757
		r=1	r=2	33.87687
		r=2	r=3	27.58434
		r=3	r=4	21.13162
p				2

Note: Table shows result of the Johansen trace and maximal eigenvalue tests of cointegration. p is the order of the VAR model, which is identified by the Akaike Information Criterion (AIC) as 2. *, ** and *** denote 10, 5 and 1 percent levels of significance, respectively.

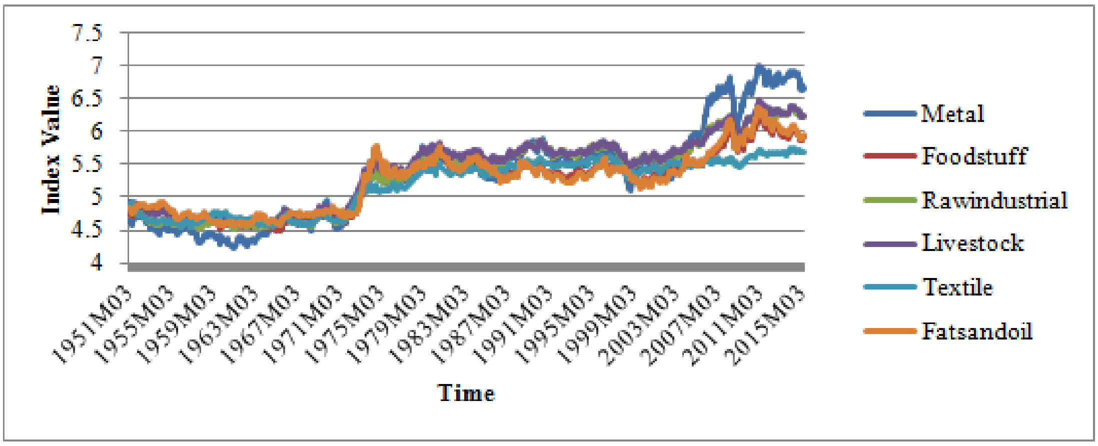

Figure 7: Permanent Components of the Group of Commodities

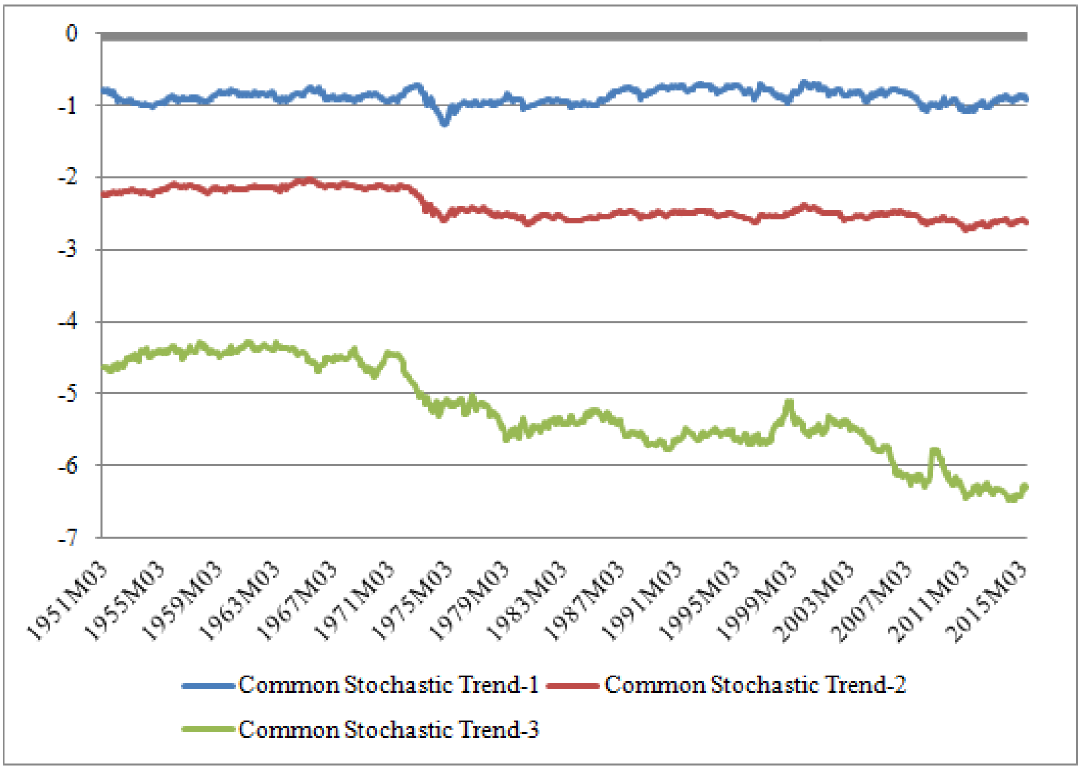

Figure 8: Common Stochastic Trend

As we can see from Figure 7, in period of 1951-1969, all commodities display stable pattern with an average price index of 4.651. In the period of 1970-2007, the average impact of the permanent shocks increased by 17% raising the average index to 5.458. Moreover, the permanent components of commodities were more stable until 2005. After 2005, the impact of permanent shocks on commodities again increased by 10%

raising the average index value to 6.051 in 2008-2015. At the beginning of this period, the permanent shocks on all commodities sharply decreased in the mid 2008s. However, starting from December 2008 the permanent components of commodities have started to increase. This probably is the result of permanent impact of the crisis.

Figure 8 shows common stochastic trends shared by six groups of commodities examined in the study. The figure also reveals that there exists a long-run co-movement pattern among the group of commodity price indices. However, first and second components seem to have a similar pattern relative to the third component. Moreover, the common shocks were more persistent than idiosyncratic shocks of commodities in the whole sample period.

6.7 Short-run Co-movement

We tested the null hypothesis of common cycles among six groups of commodities to see whether the commodities are driven by common serial correlations in the short-run. The test results are presented in Table 6.20. In each case, the probability values of χ^2 distribution of the squared canonical correlation are given. We also report small sample adjusted χ^2 test values. As the sample size is large, small sample tests have the same results as the large sample versions. The null hypothesis that the co feature space dimension is s, i.e., there exists s common cycles among the levels of the series is rejected, as we do not reject the hypothesis that $s > 0$ by a large p-value, more than 66% indeed. According to the result, there are two common cyclical features among the commodity prices at the 5% level of significance, since the the hypothesis that $s > 2$ is rejected at 5% level.

Table 6.20: Common Cyclical Feature Tests

Null Hypothesis	df	Chi2	p-value	Chi2(small sample)	p-value
s > 0	4	2.3802	0.6662	2.3524	0.6712
s > 1	10	13.1015	0.2181	12.9488	0.2265
s > 2	18	41.1749	0.0014	40.6948	0.0017
s > 3	28	92.0807	0.0000	91.0072	0.0000
s > 4	40	152.3550	0.0000	150.5790	0.0000
s > 5	54	332.3970	0.0000	328.5220	0.0000

Note: The tests have χ^2 distribution with $s^2 + snp + sr - sn$ degrees of freedom, where *s* is cofeature space dimension, *n* is the dimension of the system, *r* is the number of cointegration rank in the system, and *p* is the lag order of the VECM.

Figure 9 plots common cycles among the group of commodity prices. The commodity prices are driven by two common cycles which have quite different patterns from each other. The co-cycling behavior of the group of commodity prices might be due to fluctuations in the GDP, the U.S. dollar exchange rate, volatility spillovers, common structural breaks, etc.

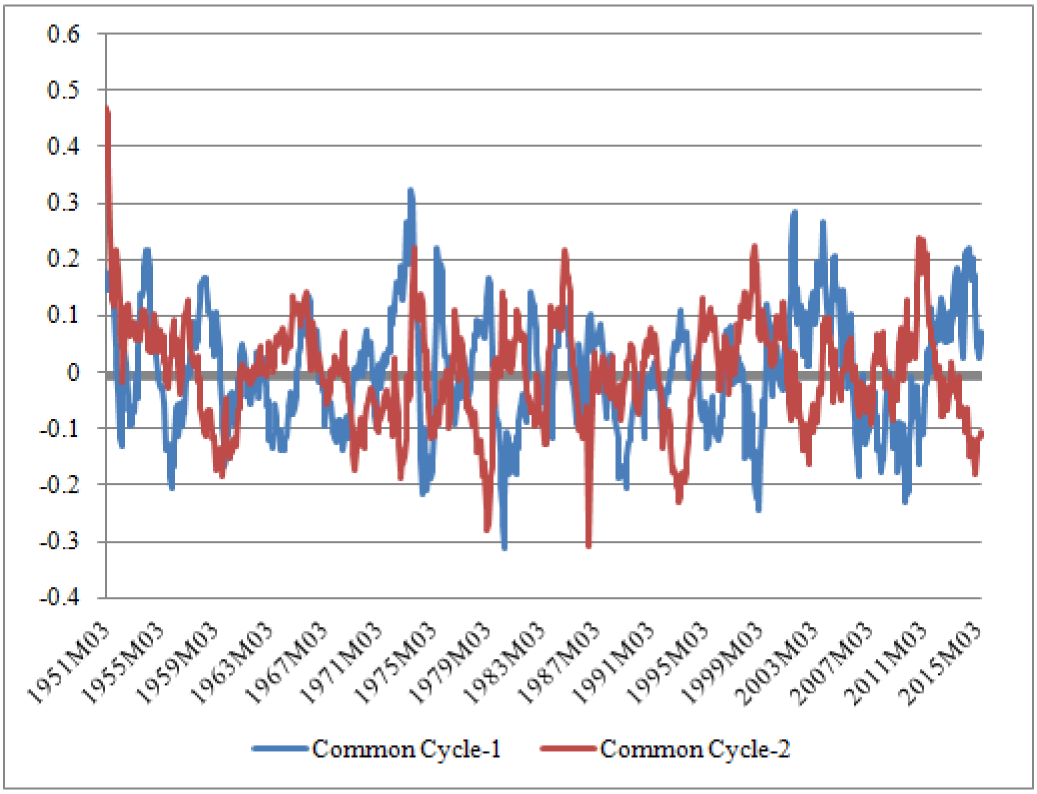

Figure 9: Common Cycle among the Six Commodities

Chapter 7

CONCLUSION

This study analyzed both the short- and long-run co-movement among the six groups of commodity price index in the US. In this respect, first the unit root a test is applied to examine the order of integration of the selected groups of commodity where it is found that they are integrated of order one, I(1). Pairwise Granger Causality tests are also conducted to determine the direction of the short-run Granger causal relationships among the groups of commodities. We then identified a VAR model by selecting appropriate lag length order as two and performed Johansen cointegration tests. Cointegration test showed that three cointegration vectors exist, meaning that three common stochastic trends are shared by all indices in the long-run. Finally, common cyclical feature test showed two common cycle are shared by all six indices in the short-run.

We can summarize the findings as follows:

i) There exist three common stochastic trends among the selected commodity groups.

ii) There exist two common cycles among the selected commodity groups.

iii) Each commodity group is Granger caused by another commodity group in at least one direction. Some groups have bidirectional Granger causality.

Overall results of the empirical analysis imply the following:

- Any increase or decrease in the prices of these six groups of commodity price index results in an increase or decrease in the other commodity groups price indices.
- Any commodity price change occurred in these six commodity groups affects the others in both short- and long-run. The past values of other commodities can be utilized to make prediction for any other commodity group.
- Commodity futures are an asset class for portfolio investors. Hence, it is not recommend to the investors to include all of these six commodity groups to diversify their portfolio as price movements are in the same direction in both the short- and long-run.

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