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COMMODITIES FUNDAMENTALS AND TIME SERIES FORECASTING MODELS OF DAILY PRICES

by

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ABSTRACT

The present study deals with commodities and time series analysis to create daily price forecasting models and basic daily return risk analysis. The purpose of this work is to investigate the fundamental concepts of commodities and to interpret the interaction between them, as well as how their prices are affected. First, the theoretical background of commodities and their dynamics in the world economy are analyzed. In addition, linear models of daily price forecasting are created and daily returns at risk level are interpreted. ARIMA models are created as prediction models, which are compared for their predictive ability in out of sample forecasting. For this purpose, daily historical closing prices are used until the time 17/7/2020. Risk analysis is performed from the point of view of volatility by finding the number of jumps in GARCH models in the whole sample of daily returns.

ΠΕΡΙΛΗΨΗ

Η παρούσα μελέτη ασχολείται με τα χρηματιστηριακά εμπορεύματα και την ανάλυση χρονοσειρών για τη δημιουργία μοντέλων πρόβλεψης ημερήσιων τιμών και στοιχειώδεις ανάλυσης ρίσκου ημερήσιων αποδόσεων. Σκοπός της εργασίας είναι να ερευνήσει τις θεμελιώδεις έννοιες των εμπορευμάτων και να ερμηνεύσει την αλληλεπίδραση μεταξύ τους, καθώς και τον τρόπο με τον οποίο επηρεάζονται οι τιμές τους. Αρχικά, αναλύεται το θεωρητικό υπόβαθρο των εμπορευμάτων και η δυναμική τους στην παγκόσμια οικονομία. Επιπλέον, δημιουργούνται γραμμικά μοντέλα πρόβλεψης ημερήσιων τιμών και ερμηνεύονται οι ημερήσιες αποδόσεις σε επίπεδο ρίσκου. Ως μοντέλα πρόβλεψης δημιουργούνται ARIMA υποδείγματα, τα οποία συγκρίνονται για την προβλεπτική τους ικανότητα σε εκτός δείγματος πρόβλεψη. Για το σκοπό αυτό, χρησιμοποιούνται ημερήσιες ιστορικές τιμές κλεισίματος μέχρι τη χρονική στιγμή 17/7/2020. Η ανάλυση ρίσκου πραγματοποιείται από την οπτική της διακύμανσης με την εύρεση πλήθους jumps σε GARCH υποδείγματα στο σύνολο του δείγματος των ημερήσιων αποδόσεων.

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1. INTRODUCTION

Commodities is a fascinating topic regarding the financial markets. It is a special asset class that has its roots in the beginning of the western civilization and derives from the need of many individuals to buy and sell vital goods for their needs. Commodity market began as a market for buying and selling agricultural goods from farmers looking to exchange their crops. Then it expaned to other products forming the commodity market we know today.

Commodities are divided into three categories, metals, energy and agriculture, according to their physical properties. These categories include many commodities each one with different characteristics and dynamics. The understanding of the behavior for each commodity will help investors take informed decisions and how they can use commodities as investment or hedging instrument. Another important step would be the prediction of future prices and returns. In this study, we try to achieve that by proposing some ARIMA models for forecasting the daily closing prices.

This master thesis is organized as follows. In chapter 2 there is a general description of the commodities markets, what it is about and what are some unique characteristics of this asset class. Following that in chapter 3 there is brief description of the most important commodities exchanges that operates today, helping many participants to complete their transactions in a regulated environment. The chapter 4 is where we describe thoroughly the fundamentals of commodities and how they interact with its other, as well as their pricing dynamics. In chapter 5 we describe the methodology that we followed regarding the empirical research of commodities and the construction of our ARIMA forecasting models. In chapter 6 we present the descriptive statistics of our data with extensive graphs and tables, to get a better understanding of the commodities prices behavior. In chapter 7 we present two sets of ARIMA forecasting models that we have prepared for each commodity and compare their accuracy using different indicators for the out of sample forecast. Also, we present a basic fundamental risk analysis by measuring the jumps in daily commodity returns. Finally, we have the conclusion, the bibliography and the appendixes where you can find detailed calculations of how we get to our models and supporting material for our analysis.

2. COMMODITY MARKETS

A commodity futures market (or exchange) is, in simple terms, nothing more or less than a public marketplace where commodities are contracted for purchase or sale at an agreed price for delivery at a specified date. These purchases and sales, which must be made through a broker who is a member of an organized exchange, are made under the terms and conditions of a standardized futures contract. The primary distinction between a futures market and a market in which actual commodities are bought and sold, either for immediate or later delivery, is that in the futures market one deals in standardized contractual agreements only. These agreements (more formally called futures contracts) provide for delivery of a specified amount of a particular commodity during a specified future month, but involve no immediate transfer of ownership of the commodity involved (Lerner, 2000).

When measured over the course of centuries, the price of commodities has gone down in real terms, not up. Commodities are produced to be consumed, and they do not naturally produce investment returns. The selection of commodities as a major investment theme is relatively new. Commodities have earned positive returns during periods of high inflation, but these are periods when interest rates are also high, increasing the portion of return due to margin interest. Commodities have performed well in recent years, but their long-term performance has not been so good, especially when compared with equities. Stocks and bonds are purely financial assets. That is, they exist solely to provide a financial return to their owners. They generally produce positive cash flows over their lives. Commodities do not exist to provide investment returns; they are produced to be consumed. Even when they are not good investments, commodities can offer insurance; doing well when inflation is high or when there is a stock market crash or some other wealth destroying event. Commodities have been a somewhat useful hedge against inflation and have tended to perform somewhat above average when equities have performed below average (Dunsby, et al., 2008).

Some of the key differentiators between the commodities markets and other asset classes are the functions of storage, transport and distribution and, in the case of agricultural products, spoilage. As a discrete asset class, commodities are vital to any diversified portfolio due to their unique characteristics. When equity markets fall, commodity markets tend to rise, and vice versa. The price of equities can go to zero – not true of commodities. There is no credit risk on a commodity. Commodity returns are higher than inflation. Bonds and equities are negatively correlated to inflation (this increases with the holding period), whilst the opposite is true of commodities – thus commodities provide an inflation hedge. Commodity prices can rise even if the economy is going nowhere (Taylor, 2013).

The cost of producing a commodity provides a floor for prices. The macroeconomic approach to commodity prices is broader, seeing price as a function of demand and supply and the behaviour of inventories (stocks). To predict the level of consumption, we need to know something about the price elasticity of demand. Typically, if a good is seen as a staple or a necessity, the price elasticity will be low, but what is considered a necessity in one country may be considered a luxury in other parts of the world. Other factors that influence price elasticity include the availability of (presumably cheaper) substitutes and the duration of the change in price. Another relationship to be considered is income elasticity of demand. Although you would expect higher incomes to lead to increased consumption, for commodities such as basic grains it could mean that consumption shifts in favor of more expensive foods, such as meat. The supply side is also difficult to predict. The speed of supply response should also be considered, as well as the uncertainty over stock levels. Of course, other exogenous factors like global liquidity levels, the value of dollar, movements in alternative assets (bonds, stocks), interest rates, investor behaviour or sentiment and changes in the commodity-related financial products available (Bain, 2013).

Despite all the controversy, the fact is that the commodities asset class is an effective way to diversify your portfolio. It is often the case that when commodities prices are in a bull market, the stock market is in the bear phase. A key reason is that companies get squeezed by higher materials prices (Taulli, 2011).

3. COMMODITY EXCHANGES

Exchanges are institutions where the trading of 'paper' takes place, usually futures and/or options linked to a specific underlying asset. Worldwide, there are around 54 major commodity exchanges that trade in more than 90 commodities. A list of all exchanges involving commodities compiled by UNCTAD (2009) is shown at table 1. Commodity exchanges have developed from physical markets where deals were originally transacted in warehouses to futures markets (which were vast buildings, but which are now in essence computer-based 'server farms'), allowing for both hedging and trading. Exchanges introduce stability, transparency and regulations not found in the physical market and are supposed to create a 'safer marketplace' (Taylor, 2013). Some of the most important commodity exchanges are presented below that are the game setters of the global commodities prices.

Acronym	Exchange Name	Country
AEX	Euronext Amsterdam	The Netherlands
ACE	Agricultural Commodity Exchange for Africa	Malawi
AFET	Agricultural Futures Exchange of Thailand	Thailand
AMEX	American Stock and Options Exchange	United States
APX	APX Group (formerly Amsterdam Power Exchange)	The Netherlands, United Kingdom and Belgium
ASCE	Abuja Securities and Commodity Exchange	Nigeria
ASX	Australian Securities Exchange (formerly Australian Stock Exchange)	Australia
BCE	Budapest Commodity Exchange	Hungary
BM&F	Bolsa de Mercadorias & Futuros	Brazil
BMD	Bursa Malaysia Derivative Berhad	Malaysia
BMFMS	Bursa Monetar Finaciara si de Marfuri Sibiu (Sibiu Monetary Financial and Commodities Exchange)	Romania
BNA	Bolsa National Agropecuaria	Colombia
BOTCC	Board of Trade Clearing Corporation (now The Clearing Corporation)	United States
Bovespa	Bolsa de Valores de São Paulo	Brazil
BRM	Bursa Romana de Marfuri (Romanian Commodities Exchange)	Romania
BSCE	Belarussian Currency and Stock Exchange	Belarus
BSE	Budapest Stock Exchange	Hungary
BXS	Euronext Brussels	Belgium
CBOE	Chicago Board Options Exchange	United States
CBOT	Chicago Board of Trade	United States
C-COM	Central Japan Commodity Exchange	Japan
CCX	Chicago Climate Exchange	United States
CFFEX	China Financial Futures Exchange	China
CME	Chicago Mercantile Exchange	United States
COMMEX	Commodity & Monetary Exchange of Malaysia (now part of BMD)	Malaysia
DCE	Dalian Commodity Exchange	China
DGCX	Dubai Gold & Commodities Exchange	UAE

DME	Dubai Mercantile Exchange	UAE
ECEX	Ethiopian Commodity Exchange	Ethiopia
ECX	European Climate Exchange	The Netherlands
EEX	European Energy Exchange	Germany
EXAA	Energy Exchange Austria	Austria
FFE	Fukuoka Futures Exchange (now part of KEX)	Japan
FORTS	Futures & Options on the RTS	Russian Federation
GME	Gestore Mercato Elettrico	Italy
HKEx	Hong Kong Exchanges and Clearing	Hong Kong China
ICE	Intercontinental Exchange	United States
IDEM	Italian Derivatives Exchange Market	Italy
IEX	Indian Energy Exchange	India
IGE	Istanbul Gold Exchange	Turkey
IPE	International Petroleum Exchange (now ICE Futures)	United Kingdom
IPEX	Italian Power Exchange	Italy
ISE	International Securities Exchange (now part of Eurex)	United States
JADE	Joint Asian Derivatives Exchange (now part of SGX)	Singapore
JCCH	Japan Commodity Clearing House	Japan
JFX	Jakarta Futures Exchange	Indonesia
JSE	JSE Securities Exchange	South Africa
KACE	Kenya Agricultural Commodities Exchange	Kenya
KBB	Komoditná Burza Bratislava	Slovakia
KCBT	Kansas City Board of Trade	United States
KEX	Kansai Commodity Exchange	Japan
KICE	Kazakhstan International Commodity Exchange	Kazakhstan
KLCE	Kuala Lumpur Commodity Exchange (now part of BMD)	Malaysia
KLOFFE	Kuala Lumpur Options & Financial Futures Exchange (now part of BMD)	Malaysia
KLSE	Kuala Lumpur Stock Exchange (now part of BMD)	Malaysia
KOFEX	Korean Futures Exchange	Republic of Korea
KRX	Korea Exchange	Republic of Korea
LCH	London Clearing House (now part of LCH.Clearnet)	United Kingdom
LIFFE	Euronext London International Financial Futures Exchange	United Kingdom
LME	London Metal Exchange	United Kingdom
MACE	Malawi Agricultural Commodity Exchange	Malawi
MATba	Mercado a Termino de Buenos Aires	Argentina
MATIF	Euronext Paris	France
MCX	Multi Commodity Exchange	India
MEFF	Mercado español de opciones y futuros financieros	Spain
MexDer	Mexican Derivatives Exchange	Mexico
MGEX	Minneapolis Grain Exchange	United Status
MICEX	Moscow Inter-bank Currency Exchange	Russian Federation
MME	Malaysia Monetary Exchange (now part of BMD)	Malaysia
MX	Bourse de Montréal	Canada
NAMEX	National Mercantile Exchange	Russian Federation
NASDAQ	National Association of Securities Dealers Automated Quotations	United States
NBOT	National Board of Trade	India
NCDEX	National Commodity & Derivatives Exchange	India

NCEL	National Commodity Exchange Limited	Pakistan
NEL	NYMEX Europe Ltd	United Kingdom
NMCE	National Multi-Commodity Exchange	India
Nord Pool	Nordic Power Exchange	Norway
NSE	National Stock Exchange of India	India
NYBOT	New York Board of Trade	United States
NYMEX	New York Mercantile Exchange	United States
NYSE	New York Stock Exchange (now part of NYSE Euronext)	United States
OMX	OMX Group of Exchanges	Sweden
OME	Osaka Mercantile Exchange (now part of C-COM)	Japan
OSE	Osaka Securities Exchange	Japan
PACDEX	Pan-African Commodities & Derivatives Exchange	Botswana
PHLX	Philadelphia Stock Exchange	United States
RMX	Risk Management Exchange (formerly Warenterminbörse Hannover)	Germany
ROFEX	Rosario Futures Exchange	Argentina
RTS	Russian Trading System	Russian Federation
SAFEX	South African Futures Exchange (now part of JSE)	South Africa
SCE	Sofia Commodity Exchange	Bulgaria
SFE	Sydney Futures Exchange (now part of ASX)	Australia
SGX	Singapore Exchange	Singapore
SHFE	Shanghai Futures Exchange	China
SICOM	Singapore Commodity Exchange	Singapore
SPCEX	St. Petersburg Currency Exchange	Russian Federation
TASE	Tel Aviv Stock Exchange	Israel
TAIFEX	Taiwan Futures Exchange	Taiwan, Province of China
TFEX	Thailand Futures Exchange	Thailand
TFX	Tokyo Financial Exchange (formerly TIFFE)	Japan
TGE	Tokyo Grain Exchange	Japan
TME	Tehran Metals Exchange	Iran, Islamic Republic of
TOCOM	Tokyo Commodity Exchange	Japan
TSE	Tokyo Stock Exchange	Japan
TurkDex	Turkish Derivatives Exchange	Turkey
UCE	Ugandan Commodity Exchange	Uganda
UICEX	Ukrainian Interbank Currency Exchange	Ukraine
UFEX	Ukrainian Futures Exchange	Ukraine
USFE	U.S. Futures Exchange	United States
UZEX	Uzbek Commodity Exchange	Uzbekistan
WCE	Winnepeg Commodity Exchange	Canada
WGT	Warszawskiej Gieldy Towarowej	Poland
WSE	Warsaw Stock Exchange	Poland
Y-COM	Yokohama Commodity Exchange (now part of TGE)	Japan
ZCE	Zhengzhou Commodity Exchange	China
ZAMACE	Zambian Agricultural Commodity Exchange	Zambia
ZIMACE	Zimbabwe Agricultural Commodity Exchange	Zimbabwe

Table 1: Commodity Exchanges in the world (UNCTAD, 2009)

The Chicago Board of Trade

The Chicago Board of Trade was created by a handful of savvy grain traders to establish a central location for buyers and sellers to conduct business. Established in 1848, the CBOT is the world's oldest futures and options exchange. The new formalized location and operation enticed wealthy investors to build storage silos to smooth the supply of grain throughout the year and, in turn, aid in price stability. After spending the last decade and a half as one of the largest futures trading organizations in the world and a direct competitor to the Chicago Mercantile Exchange (CME), the CBOT and the CME merged July 12, 2007, to form the CME Group, creating the largest derivatives market ever. The CBOT division of the CME Group is the home of the trading of agricultural products such as corn, soybeans, and wheat. However, the exchange has added several products over the years, to include Treasury bonds and notes and the Dow Jones Industrial Index (Garner, 2013).

The Chicago Mercantile Exchange

The success of the CBOT fueled investment dollars into exchanges that could facilitate the process of trading products other than grain. One of the offshoots of this new investment interest was the Chicago Mercantile Exchange. The CME was formed in 1874 under the operating name Chicago Produce Exchange; it also carried the title Chicago Butter and Egg Board before finally gaining its current name. The contract that put this exchange on the map was frozen pork belly futures, or simply "bellies," as many insiders say. Hollywood and media portrayals of the futures industry often focus on the pork belly market. The CME, a division of the CME Group, is responsible for trading in a vast variety of contracts, including cattle, hogs, stock index futures, currency futures, and short-term interest rates. The exchange also offers alternative trading vehicles such as weather and real-estate derivatives (Garner, 2013).

The New York Mercantile Exchange

Although the futures and options industry was born in Chicago, New York was quick to get in on the action. In the early 1880s, a crop of Manhattan dairy merchants created the Butter and Cheese Exchange of New York, which was later modified to the Butter, Cheese, and Egg Exchange and then, finally, the New York Mercantile Exchange (NYMEX). The NYMEX division of the CME Group currently houses futures trading in the energy complex. Examples of NYMEX-listed futures contracts are crude oil, gasoline, and natural gas. A 1994 merger with the nearby Commodity Exchange (COMEX) exchange allowed the NYMEX to acquire the trading of precious metals futures such as gold and silver under what is referred to as its COMEX division. In March 2008, NYMEX accepted a cash and stock offer from the CME Group that brought the New York futures exchange into the fold, along with the CBOT and the CME. On August 18, 2008, NYMEX seat-holders and shareholders accepted the proposal and the rest is history. The NYMEX division of the CME Group has been fully integrated with the CME and CBOT divisions of the exchange despite being located hundreds of miles away from downtown Chicago (Garner, 2013).

The CME Group

The CME Group consists of the three aforementioned divisions: the CBOT, CME, and NYMEX, which previously stood as independent exchanges. Accordingly, the CME is officially the world's largest derivatives exchange. As previously mentioned, on July 12, 2007, the merger of the CBOT and the CME created the CME Group, but NYMEX was acquired in 2008 to create a powerful and innovative entity. The CME Group currently serves the speculative and risk management needs of customers worldwide. Among the three divisions, the CME Group offers derivative products across nearly all imaginable asset classes. Upon merging, the CBOT and the CME consolidated all floor-trading operations into a single location: the historic CBOT building on 141 West Jackson Boulevard in downtown Chicago (Garner, 2013).

Intercontinental Exchange

Intercontinental Exchange (ICE) is the newest player in U.S. futures trading. In stark contrast to the original models of the CBOT, the CME, and NYMEX, ICE primarily facilitates over-the-counter energy and commodity futures contracts. This simply means that there is no centralized location; nearly all trading takes place in cyberspace. However, ICE continues to operate floor-trading operations in some of its option markets. In addition, the CME Group has followed the lead of ICE and moved a majority of its futures contract execution to electronic means, as opposed to a trading pit with a physical location. ICE was established May 2000, with the mission of transforming OTC trading. By 2001, it had acquired a European energy futures exchange, but it did not dig its claws deep into the heart of the U.S. futures industry until its acquisition of the New York Board of Trade (NYBOT) in 2007, along with the responsibility to facilitate trading in the softs complex. The term soft generally describes a commodity that is grown rather than mined; examples of contracts categorized as soft and traded on ICE in the United States include sugar, cocoa, coffee, and cotton (Garner, 2013).

The New York Board of Trade

The New York Board of Trade (NYBOT) was established in 1998 with the merger of the New York Cotton Exchange (founded 1870) and the Coffee, Sugar and Cocoa Exchange (founded 1882). The NYBOT is the world's ninth largest commodity exchange and the 30th largest futures exchange overall. It sets worldwide reference prices for several key commodities, including cocoa, coffee, cotton, sugar and frozen concentrated orange juice. In January 2007, NYBOT was purchased by ICE and renamed ICE Futures US (UNCTAD, 2009).

The London Metal Exchange

The London Metal Exchange (LME) remains Britain's only independent major commodity exchange. Founded in 1877, the LME specializes in non-ferrous metals and – since May 2005 – plastics. In 2007, with trade of 92.9 million contracts (7 per cent annual growth) it was the world's sixth largest commodity exchange (and the 25th largest futures exchange overall). The LME's role in discovering world metal prices is still predominant. Some analysts had been suggesting that the competing Shanghai Futures Exchange (SHFE) was starting to lead, rather than follow, LME in price discovery, particularly in copper. Contrasting performances between LME and SHFE in 2007 – volume at the former increasing by 6.8 per cent whilst volume at the latter decreased by 47.2 per cent – may weaken such claims. The LME has long been in the process of developing a steel contract. Recent developments have seen the release of two regional physically delivered steel billets contract specifications, with trading to commence in April 2008 (UNCTAD, 2009).

Shanghai Futures Exchange

The SHFE was formed in 1999 after the merger of three Shanghai-based exchanges – the Metal, Commodity, and Cereals & Oils Exchanges. It deals primarily in industrial products, offering futures contracts in copper, aluminium, natural rubber, fuel oil and – since March 2007 – zinc. During 2006, the exchange saw a strong performance, its volumes increasing by 72 per cent to 58 million contracts, making it the seventh largest commodity exchange in the world and the 27th largest futures exchange overall. Over half of the exchange's 2006 volume came from trade in rubber, a sector which posted a 174 per cent rise in volume to become the world's ninth largest commodity derivatives contract. There was also strong growth in aluminium trading and fuel oil trading, which more than made up for a second year of significant decline in SHFE's once highly liquid copper contracts. In September 2007, regulatory approval was granted for the SHFE to list gold futures contracts. That same year, SHFE's trading volumes dipped to 85 million lots and an annual increase of 47 per cent (UNCTAD, 2009).

Dalian Commodity Exchange

Founded in 1993, the DCE was the world's largest agricultural futures exchange by contract volume – its 185 million agri-contracts traded in 2007 places it narrowly ahead of the 154 million traded on the US-based CBOT. In 2006, the DCE also operated the world's most liquid market by volume for corn – the DCE Corn was the world's largest agricultural futures contract with 65 million traded contracts. Moreover, the DCE offered the world's largest market for non-transgenic soybeans and a highly liquid contract for soymeal, the world's third most liquid agricultural futures contract with 32 million contracts traded. The DCE started trading soybean oil futures as of January 2006, and most recently in 2007, linear low-density polyethylene (LLDPE, a raw material in plastics) and palm oil. The exchange's corn and soybean futures prices have become important references for Chinese industry. A broad-based farmer education programme conducted by the exchange, the "1,000 villages, 10,000 farmers" initiative, is training farmers to use this information to form more accurate expectations about future price development across the two crops, improving their planting, harvesting and selling decisions as a result. The DCE's volume has been the largest in China since 2000, although the SHFE – mainly focused on metals – is the largest in terms of notional turnover (UNCTAD, 2009).

Tokyo Commodity Exchange

TOCOM was created in November 1984 through the consolidation of three existing exchanges: the Tokyo Textile Commodities Exchange, the Tokyo Rubber Exchange, and the Tokyo Gold Exchange. In the 24-hour global trading environment, TOCOM has emerged as an influential exchange on a par with exchanges in New York, Chicago and London, dealing in gold, silver, and platinum futures as well as several other precious metals (UNCTAD, 2009).

Overall, the purpose of a commodity exchange is to provide an organized marketplace in which members can freely buy and sell various commodities in which they have an interest (Lerner, 2000). At table 2 you can see the most important commodity exchanges for each commodity category.

Energy • CME Group, which includes New York Mercantile Exchange (NYMEX), which became part of CME in March 2008; • Shanghai Futures Exchange (SHFE), China • InterContinental Exchange (ICE), which acquired the International Petroleum Exchange (IPE) London in 2001 • Multi Commodity Exchange of India • Tokyo Commodity Exchange (TOCOM), Japan • RTS Exchange in Russia • Dubai Mercantile Exchange (DME), UAE
Metals • CME Group, which includes NYMEX and COMEX; • Shanghai Futures Exchange (SHFE), China • Multi Commodity Exchange of India • LME – London Metal Exchange, UK • RTS Exchange, Russia • DGCX – Dubai Gold & Commodities Exchange
Agriculture • CME Group – Chicago Board of Trade and Chicago Mercantile Exchange • Shanghai Futures Exchange (SHFE), China • Zhengzhou Commodity Exchange (ZCE), China • Dalian Commodity Exchange (DCE), China • InterContinental Exchange – Atlanta and London • Tokyo Commodity Exchange (TOCOM), Japan • Kansas City (Missouri) Board of Trade, USA • RTS Exchange, Russia • NYSE Liffe, UK • InterContinental Exchange, Canada

Table 2: Commodity exchanges for every commodity category (Taylor, 2013)

4. FUNDAMENTALS OF COMMODITIES

4.1 Metals

Metals are considered those commodities that has the physical properties of a metal element and are produced by extraction from earth. They divided in two categories based on their value and their use. The first category is precious metals, which include gold, silver, platinum and palladium that are characterized by its high value and scarcity. The other category is industrial or base metals, which include aluminum, copper, zinc, tin, lead and nickel. Their primary use is for industrial purposes, as a base raw material for many applications.

PRECIOUS METALS

Gold

Gold is one of the rarest metals in the world and one of the oldest known to man. While gold has been much used for decorative objects, it also has industrial uses. Its properties include strong resistance to corrosion and good conductivity; it is also malleable and ductile. Gold is easily recyclable because of its low melting point. Its traditional role as a store of value has meant that, according to the World Gold Council (WGC), only 2% of all the gold that has ever been mined has been lost over time (Bain, 2013). Money are flowing into the metal as a store of value, particularly when inflationary expectations heat up or in times of money printing. That’s why gold is considered as a hedge against asset erosion in times of inflation and political unrest. Although gold certainly is used in the jewelry industry and electronics and other industries, it is considered precious due to its traditional role as a medium of exchange (Kleinman, 2013). Gold, like most metals, is measured and weighed in troy ounces. When you want to refer to large quantities of gold, such as the amount of gold a bank holds in reserves or the amount of gold produced in a mine, the unit of measurement you use is metric tons (Bouchentouf, 2015).

Gold has clearly become a mainstream asset class and a credible alternative hard currency, acting as a protection against government policies to devalue their paper currencies in an effort to stimulate their flagging economies (Taylor, 2013). When governments are printing money, gold by default rises (more currency units in circulation require a higher gold price per ounce). In times of instability, gold is considered a store of value. War or a loss of confidence in traditional investments can cause a shift of funds into gold (Kleinman, 2013). Demand for gold will continue to increase, especially as a store of value, driven in part by the weakening paper currency environment that's a result of expansionary monetary policy in the Organization for Economic Cooperation and Development (OECD) countries. As paper currencies come under increased pressure, expect demand for gold to increase (Bouchentouf, 2015). After all, in human perception one of the basic gold's roles is as currency. Thus, if the value of the paper currency is falling, then people could start to request the metal, which should bring the system into balance again. While governments can print money—and most do—they still cannot produce more gold. Its scarcity is certainly a good trait for being an unofficial basis of a currency (Taulli, 2011).

Perhaps no other metal — or commodity — in the world has the cachet and prestige of gold. For centuries, gold has been coveted and valued for its unique metallurgical characteristics. It was such a desirable commodity that it developed monetary applications, and a number of currencies were based on the value of gold. Gold is a very ductile metal, which mean it can be drawn out into a wire effectively. Pure gold (24 karat) is a very malleable metal and has high resistance levels without corroding easily (Bouchentouf, 2015). Unique and therefore precious, gold is its own asset class (Kleinman, 2013).

Gold is mined in both open and underground pits, often alongside other metals, especially lead, zinc and copper. Once the gold ore is extracted, it undergoes extensive and time-consuming processing to remove the gold from the carbon or oxides or sulphides that are also in the ore (Bain, 2013). The process of extracting gold is expensive and time-consuming. It often requires large mines and blasting rock to mine gold. The ore is then transported to a plant that crushes it to get to the gold. Gold is one of the most wasteful commodities (Taulli, 2011). Mine supply typically accounts for nearly 70% of annual gold supply, a low amount compared with other commodities (Bain, 2013). Gold is considered one of the rarest natural resources on earth. Only about 150,000 tons of gold have ever been produced since humans first began mining gold more than 6,000 years ago. And because most gold is recycled every year (about 15%) and never destroyed, a majority of gold is still in use today (Bouchentouf, 2015). While gold mines are the largest part of the global supply, another important source is from scrap. This is the process of converting jewelry into gold bars or coins (Taulli, 2011). Recycling is particularly strong in the United States and southern Europe but fall in the traditional markets of the Middle East, India and East Asia (Bain, 2013).

South Africa was once the dominant global producer of gold, accounting for more than 25% of the world's production and 50% of the in-ground reserves (Kleinman, 2013). But, according to Taulli (2011) since the 1980s, production has steadily declined, partly because of falling profitability, as power and labour costs have risen but also because of ageing mines (Bain, 2013). In 2007, China overtook both South Africa and Australia to become the world's largest gold miner (Bain, 2013) and eventually the largest gold producer is now China (Taulli, 2011). China is the both the world's number one gold producer and second ranking consumer behind India, although recent reports suggest that the world's most populous country may well be about to overtake India to become the top buyer of gold (Taylor, 2013). The other main producers include Australia and the United States (Taulli, 2011). Australia is the second largest producer of gold, followed by the United States and Russia, while South Africa, for many years the world's biggest source of gold, has slipped to fifth place (Taylor, 2013). The next major producers are Canada and Brazil (Kleinman, 2013). So, we can see that gold is widely dispersed geographically, with no one region accounting for more than 20% of production (Bain, 2013).

The increased demand for gold is linked to a number of reasons (Bouchentouf, 2015). There are five main demand sources for gold as Figure 1 shows. First, there is jewelry, which accounts for 40 percent of global consumption (Taulli, 2011) and it is the most important consumer use of gold in the world (Bouchentouf, 2015). This has been falling steadily over the years. Investment is the next largest demand factor and it represents about 25 percent of global consumption (Taulli, 2011). The gap left by the fall in jewelry consumption has been more than filled by strong growth in investment demand for gold. This includes bars and coins as well as the gold held by exchange-traded funds (ETFs). Gold has a number of characteristics that make it an attractive commodity investment, such as high liquidity and global acceptance or recognition (clear quality standards that can be checked), a high value relative to volume (making it easily transportable and reducing storage costs) and the fact that it is virtually indestructible. It is also scarce (especially when compared with currencies – paper money issued by governments). On the negative side, however, relative to currencies, it does not have a body such as a central bank that can monitor its value and take action to support its price. Also interest cannot be earned on a gold investment (Bain, 2013). The third largest category for global gold demand is industrial use, which comes to about 12 percent (Taulli, 2011). Although because of its high price, it is used only as a last resort when a suitable alternative is not available (Bain, 2013). Gold is used because it is nontoxic and an effective conductor of electricity. Some of applications include bonding wire and gold-plated contacts (Taulli, 2011). It can be used in wiring because of its good conductivity, but aluminum and copper are typically used instead as they cost much less (Bain, 2013). Also, it's used as a semiconductor in circuit boards and integrated boards (Bouchentouf, 2015). An additional source of demand in recent years has been central banks, which had been net sellers of gold for decades but since 2010 have become net buyers. Gold is still the world's third largest reserve asset behind dollar- and euro-denominated assets. This is probably a reflection of concerns about the outlook for the dollar and the euro, in particular, with central banks seeking to diversify their reserve holdings (Bain, 2013) . Roughly, 18 percent of the world's supply of gold is not put onto the market. The reason is that this is the amount of the world's gold that is held by central banks (in some cases, the gold has been in vaults for centuries). Finally, gold is also useful in medical treatments, clean energy, and even the aerospace industry (Taulli, 2011). Besides that, because gold resists corrosion, it has wide application in dentistry. It's alloyed with other metals, such as silver, copper, and platinum, to create dental fixtures (Bouchentouf, 2015). Historically, gold was used extensively in medicine and dentistry because of its biocompatibility with the human body, but the availability of much cheaper plastic or ceramic substitutes means it is losing its role in dentistry (Bain, 2013).

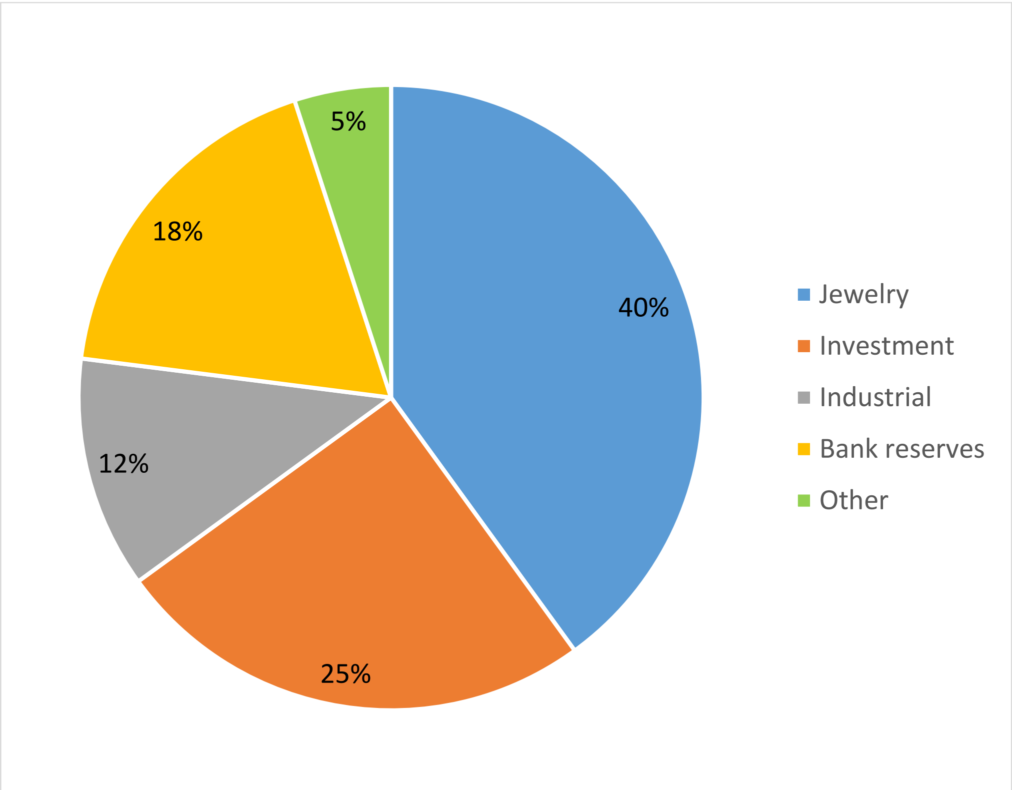


Figure 1: Uses of gold

Traditionally, jewelry making was the primary end-use of gold. India has historically always been the largest consumer of gold jewelry and gold more generally. Culturally, gold has been the principal store of wealth and spikes in consumption have tended to coincide with

Indian festivals and/or the Indian wedding season. Some of the decline in gold's use in jewelry has been a reflection of high prices in recent years as well as the weakness in Western economies since 2008. Whether for reasons of austerity or just fashion, there has been a move away from gold jewelry to cheaper costume jewelry (Bain, 2013).

Although gold has effectively been used as a currency or as a store of value for thousands of years, it began to be formally traded only during the 17th century in London. The gold market is larger and more liquid than almost all other commodity markets; in terms of volumes traded it is more like a large developed-country sovereign bond market (Bain, 2013). Gold trades on many futures exchanges. The main ones include the CME and the Tokyo Commodity Exchange (TOCOM) (Taulli, 2011). London is also a large market, with significant trading also happening in New York, and Zurich (Bain, 2013). Gold now trades freely, in accordance with supply and demand (Kleinman, 2013), across the world with other important exchanges in Dubai, Shanghai, Vietnam, China, India and Pakistan as well as more traditional markets in Europe (Bain, 2013).

There are various factors that influence the price of gold (Taulli, 2011). As with all commodities, textbook economic theory and market fundamentals (the demand–supply balance) can rarely predict exactly the trend in gold prices, but there are a number of relationships between gold and economic indicators that have held in the past. Gold prices are typically inversely correlated with the dollar. This reflects gold's property as a hedge against inflation, particularly hyperinflation, as it will retain its value as well as its appeal as a safe haven in times of dollar uncertainty as currencies are debased (Bain, 2013). So, if there is inflation, or the threat of it, the price of gold is likely to rise. The same goes with economic instability and possible sovereign debt defaults (Taulli, 2011). Furthermore, a falling dollar makes gold and other commodities that are typically denominated in dollars cheaper in terms of other currencies, increasing both demand for gold and the price. Gold prices have also generally done well when other investment assets such as equities (in particular) or bonds are performing poorly; this is partly because gold demand does not have the direct link with the economic or industrial cycle that characterizes base metal and energy demand. The appeal of gold is enhanced when interest rates are low. As holding gold involves only a capital return (no interest), it is less appealing as a savings vehicle if interest rates are high. Geopolitical risk is a further factor that can encourage the consumption of gold and lead to higher prices (Bain, 2013). Also, it is observed that as income growth increases, so has gold demand. However, in the long run, the prices of gold and all other precious metals are sensitive to inflation (Kleinman, 2013). Another reason of price volatility could be that easily accessible scrap supply had already largely been exploited (Bain, 2013), so the availability of gold decreases. The financial crisis certainly came close to bringing down the global economic system. But during the crisis, gold was one of the few investment assets that increased in value. The fact is that the precious metal is considered a safe haven. This has been the case for centuries and will likely continue in the future (Taulli, 2011).

In the future, if concerns about the creditworthiness of major countries escalate, or the American economy slows sharply or the governments fails to tackle their fiscal deficits, gold prices would benefit. However, a marked slowdown in developing countries would negatively affect gold demand and thus prices. A normalization of global monetary conditions and eventual tightening would diminish gold's attractiveness as an investment vehicle. As one of the most actively traded commodities and the one with only limited productive use, gold may suffer unduly from efforts to prevent speculative trading. This could include ever higher reserve requirements in futures trading. There remains a substantial risk of another collapse in gold prices. If economic conditions worsen, investors could be forced to sell off their gold positions to offset losses elsewhere, driving down prices. Conversely, should the global recovery gather pace more quickly than anticipated, investors may decide that gold prices have peaked and seek to take profits to invest them elsewhere, triggering a collapse in prices. Mine supply could become increasingly uncertain, particularly if gold prices fall or mining companies struggle with financing. This is particularly the case as mining costs are expected to increase in the medium term as a result of high energy costs, rising labor costs and potentially more expensive capital investment, as readily available sources of supply are depleted and ores become more difficult to extract (Bain, 2013).

Silver

Silver is considered both precious and industrial (Kleinman, 2013). Silver is a shiny white precious metal. It has many of the same chemical properties as gold, and because it is more plentiful and cheaper its industrial uses are more extensive. Silver is ductile and malleable and has high electrical and thermal conductivity. Historically, it was also used in health products because of its antiseptic qualities. It is found in a pure form, as an alloy with gold or with various other ores (principally copper, lead and zinc). As a result, silver is often mined as part of a wider mining operation focused on gold or copper, for example (Bain, 2013).

While gold production has been declining over the years, this has not been the case with silver (Taulli, 2011). Mine supply has been growing steadily. However, silver mining companies face many of the same issues as their gold-mining counterparts, in particular disruption as a result of labor unrest and falling ore grades in many mines. Nevertheless, supply has continued to grow because of a number of new, relatively small mining projects and larger amounts of silver being extracted in the process of lead/zinc or gold mining (Bain, 2013). Roughly, 77 percent of silver production comes from mines, 20 percent comes from scrap, and 3 percent comes from government stockpiles. However, over the next decade, there are likely to be constraints on the production of silver. The amount of scrap is declining because more silver is being used in electronics products, which are fairly difficult to recycle. Also, government stockpiles are relatively small (Taulli, 2011). Mexico and the United States are the world's largest producers, followed by Peru and Canada. Fourth and fifth in production are Australia and Russia. In recent years, silver consumption has outpaced new production, with the balance being met by above-ground supplies (Kleinman, 2013).

Figure 2: Silver Production distribution

Silver has the highest conductivity of any element, even copper. Silver is also strong yet malleable. Because of these qualities, silver has been a good element for coins. But this usage was eventually phased out in the mid-1960s. Now the only country that uses silver coins is Mexico. There are two main grades of silver. One is pure silver, which has the highest content. Then there is sterling silver or standard silver, which is an alloy of 92.5 percent silver and 7.5 percent copper. Copper helps to increase the durability of silver (Taulli, 2011).

Silver has a number of uses that make it an attractive investment (Bouchentouf, 2015). Some demand sources for silver are for industrial use, for jewelry and silverware, for investment, and for photography (Taulli, 2011). The largest amount of demand for silver comes from industrial applications, which accounts for 46 percent of supply. These include batteries, computer components, medical devices, and surgical instruments. In fact, silver has “green” qualities, such as being a replacement for some applications of lead (Taulli, 2011). Silver has a number of applications in the industrial sector, including creating control switches for electrical appliances and connecting electronic circuit boards, as long as conducting electricity, creating bearings, and welding, soldering, and brazing (the process by which metals are permanently joined together). Because it is a good electrical conductor, silver will keep playing an important role in the industrial sector (Bouchentouf, 2015). That’s why silver is also used in electrical conductors, switches and circuit breakers, batteries and mirrors. Recently, growth in demand for silver has come from the solar energy industry, particularly photovoltaic (solar energy) panels (Bain, 2013). The second biggest component of demand for silver is for jewelry and silverware. This is a fairly steady category. However, if silver prices continue to rise, there may be a decline in demand (Taulli, 2011). Silver has been used in jewelry and coinage for thousands of years and in decorative household items such as cutlery. Today the biggest market for silver jewelry is India (Bain, 2013). Many people believe (incorrectly) that the largest consumer of silver is the jewelry industry. Although silver does play a large role in creating jewelry and silverware, demand from this sector accounted for 25 percent of total silver consumption (Bouchentouf, 2015). Therefore, silverware and jewelry are not the only uses for silver. In fact, silverware is only a small portion of the silver market (Bouchentouf, 2015)! Another category that has been robust is investment demand. Many investors consider silver to be a good alternative to gold. A big reason is that silver is cheaper than gold on a per-ounce basis (Taulli, 2011). Some investors consider silver to be an alternative to a currency (Taulli, 2011). While photography was once a substantial part of silver demand, this has declined substantially over the years. The main reason has been the growth in digital cameras (Taulli, 2011). The photographic industry used to be a major consumer of silver, accounting for about 20 percent of total consumption. In photography, silver is compounded with halogens to form silver halide, which is used in photographic film. With the rise of digital cameras, which don’t use silver halide, becoming more popular than traditional cameras, photography demand for silver went down (Bouchentouf, 2015). Yet, there have been some offsetting factors. For example, in some emerging markets, there has been rising demand for traditional film. Also, there is still a large market for film for professional photographers (Taulli, 2011). Silver is truly a hybrid industrial/precious metal (Kleinman, 2013).

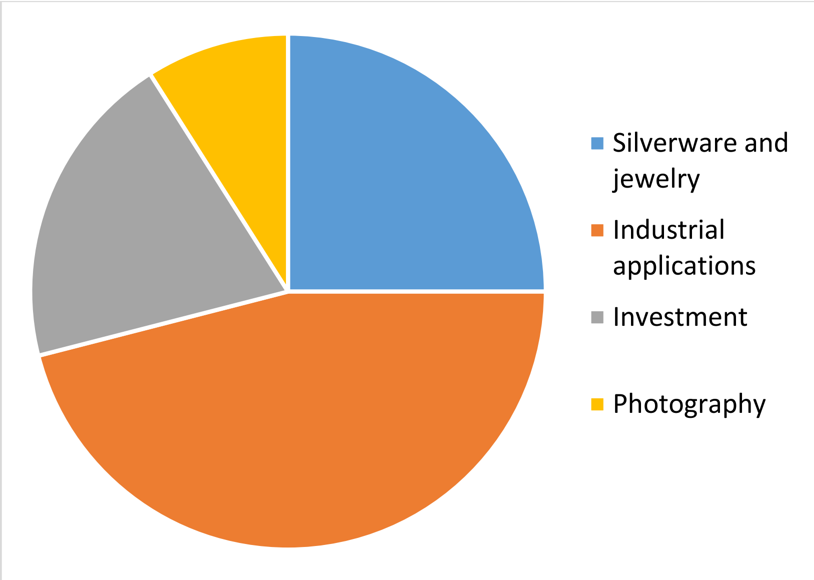


Figure 3: Uses of silver

You can trade silver futures on the Chicago Mercantile Exchange (CME) and the Tokyo Commodities Exchange (TOCOM). Some factors that influence the price of silver are the silver standard, the government silver holdings, and the gold-silver ratio. Today, few governments have silver holdings. As with any commodity, the value of silver is largely affected by supply and demand. However, there is one interesting metric that can provide a relative valuation of the metal. This is done by using the gold-silver ratio. Throughout history, there has been a relatively stable relationship between the two metals. But, when the gold-silver ratio diverges, there may be a buying opportunity. Of course, another key factor has been in the increase in industrial demand. Silver is becoming a key ingredient for high-tech products (Taulli, 2011).

Silver's industrial uses, particularly in a number of new, green technologies, suggest that it will continue to enjoy strong industrial demand in the medium term. In recent years, growing investment demand has driven consumption. This makes the price vulnerable to a loss of investor interest, for example when monetary policy starts to tighten and interest rates to rise. Strong investor interest is leading to higher prices, potentially undermining silver's competitiveness in industrial uses. However, in some applications, there are no suitable substitutes for silver (Bain, 2013). Monitoring the commercial activity in each of these market segments and looking for signs of strength or weakness, will show investment opportunities, because a demand increase or decrease in one of these markets, such as photography, will have a direct impact on the price of silver.

Platinum

Platinum is a grey-white precious metal and one of the rarest elements in the Earth's crust. It is malleable and ductile, has a high melting point, is an excellent electrical conductor and is highly resistant to corrosion. Platinum occurs naturally in a pure form and also alongside nickel and copper ores (Bain, 2013). Platinum is the main part of the so-called platinum group. This group of metals includes palladium, rhodium, ruthenium, iridium, and osmium. They tend to be found in the same mining deposits (Taulli, 2011). Platinum, sometimes referred to as "the rich man's gold," is one of the rarest and most precious metals in the world. Perhaps no other metal or commodity carries the same cachet as platinum, and for good reason: It is by far the rarest metal in the world (Bouchentouf, 2015). Platinum is fairly scarce and is considered a precious metal, because only 80 tons of new production reach the world annually (Kleinman, 2013). To produce 1 ounce, it takes a mine to crush about 10 tons of ore. The process can easily take six months (Taulli, 2011).

Platinum was soon discovered to have superior characteristics to most metals: It's more resistant to corrosion, doesn't oxidize in the air, and has stable chemical properties. Deposits of platinum ore are extremely scarce and, more important, are geographically concentrated in a few regions around the globe, primarily in South Africa, Russia, and North America (Bouchentouf, 2015). The world's largest supplier of platinum is South Africa, which provides about 70 percent of the total. As a result, a disruption in this country could have a major impact. The second largest producer of platinum is Russia. Yet its output has seen wide swings, from 10 percent to 20 percent of the worldwide supply (Taulli, 2011). So, almost ninety percent of the world's production takes place in South Africa and Russia (Kleinman, 2013). North America is also a significant producer of platinum. The country with the world's second largest amount of platinum reserves—an amount that has not been extracted yet—is Zimbabwe (Taulli, 2011).

Some demand sources for platinum are for jewelry, for industrial use, and for investment (Taulli, 2011). Platinum has proven effective for various commercial purposes, such as lab equipment, LCDs, video equipment, and electrodes. But the biggest usage of platinum—60 percent of the world's supply—is for catalytic converters. So the price of the metal is highly related to the global production of cars (Taulli, 2011). Autocatalysts use precious metals to convert the noxious gases in vehicle exhausts into harmless substances (Bain, 2013). Platinum's unique characteristics make it a suitable metal in the production of these pollution-reducing devices. As environmental fuel standards become more stringent, expect the demand from this sector to increase (Bouchentouf, 2015). Slightly less than one-third of total consumption of the metal is in jewelry. Platinum jewelry is particularly popular in China and India (Bain, 2013). At one point, jewelry accounted for more than 50 percent of total demand for platinum. Although that number has decreased, the jewelry industry is still a major purchaser of platinum metals for use in highly prized jewelry (Bouchentouf, 2015). In Japan, platinum is the precious metal of choice, with more of it used for jewelry than gold. A strong economy in Japan is good for platinum prices (Kleinman, 2013). Other uses are in electrical contacts, liquid crystal display (LCD) glass, petrochemicals, oil refining and laboratory equipment. Platinum is also used in dentistry and medicine (Bain, 2013). Platinum is also a key part of batteries and fuel cells for hybrid and electric cars, which should be a long-term growth driver (Taulli, 2011). Because it is a great conductor of heat and electricity, platinum has wide applications in industry. It is used in creating everything from personal computer hard drives to fiber-optic cables. Despite its relative value, platinum will continue to be used for industrial purposes. A change in demand from one of these industries will affect the price of platinum (Bouchentouf, 2015).

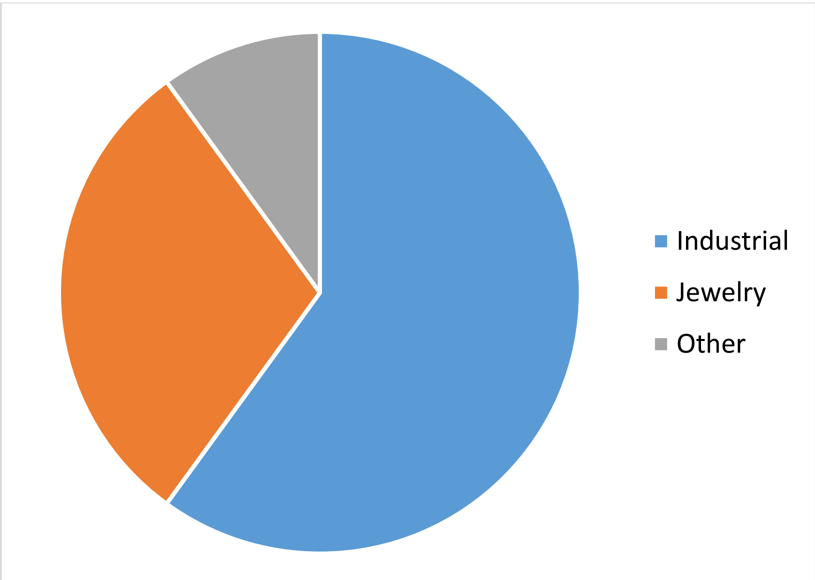


Figure 4: Uses of Platinum

Platinum is traded on the New York Mercantile Exchange (NYMEX) and the London Platinum and Palladium Market (Bain, 2013). Platinum is traded on the CME and the Tokyo Commodity Exchange as well (Taulli, 2011). Platinum's unique characteristics as a highly sought-after precious metal with industrial applications make it an ideal investment (Bouchentouf, 2015). Many times, the platinum price is considered in terms of its relationship with gold (Bain, 2013).

Like all the precious metals, platinum has become more vulnerable to investor sentiment in recent years, as investors account for an increasing amount of the consumption of the physical metal. This will lead to heightened price volatility. Volatile prices create considerable uncertainty for mining companies, given that it takes years to develop a mine and capital costs are typically high. The concentration of mining in a few countries makes the supply of the metal vulnerable to disruption. Developments in the automotive industry are crucial for the future of platinum (Bain, 2013). This is an industrial metal and a precious metal, and the demand for platinum is somewhat dependent on the health of the automotive, electrical, dental, medical, chemical, and petroleum (Kleinman, 2013).

Palladium

Palladium is a rare steely white-coloured metal. It has many of the same properties as the other precious metals: it is ductile and malleable, has good conductivity, has a low melting point and is recyclable. It is also noncorrosive. However, palladium is the softest of the precious metals making it particularly suitable for fine decorative work. It is typically mined in "placer" deposits alongside platinum and other precious metals, including gold. It can also be a by-product of nickel mining (Bain, 2013). Palladium is part of a group of elements called the platinum group metals (PGM), which include platinum, rhodium, ruthenium, iridium, and osmium. While they have many similar properties, palladium has the lowest melting point (Taulli, 2011).

The global supply of palladium is fairly limited. The biggest supplier is Russia, with 45 percent. But this has been declining over the years. To make up for the decrease in supply, South Africa has become a major palladium producer. It now accounts for 29 percent of the world's supply (Taulli, 2011). Because these two countries dominate palladium production, any supply disruption from either country has a significant impact on palladium prices. However, there is no way around the fact that most of the world's reserves of palladium ore are located in these two countries. In fact, perhaps no two countries dominate a commodity as much as Russia and South Africa dominate palladium (Bouchentouf, 2015). North America is an important (and increasing) source of supply, and Zimbabwe has started to increase its production of the metal. Other sources of supply in the palladium market are scrap or investor selling from physically backed ETFs (Bain, 2013).

Palladium, which belongs to the platinum group of metals (PGM), is a popular alternative to platinum in the automotive industry in autocatalysts in petrol-fuelled cars and the jewelry industry. Its largest use comes into play in the creation of pollution-reducing catalytic converters. Palladium's malleability and resistance to corrosion make it the perfect metal for such use and due to the fact that palladium is less expensive per troy ounce than platinum (Bouchentouf, 2015). The most common use is for catalytic converters, which accounts for 57 percent of demand. Palladium may be useful for catalytic converters, but it is not as efficient as platinum. Often confused, palladium and platinum are not interchangeable. Thus, the global demand for cars has a significant impact on the price of palladium (Taulli, 2011). In the EU, there is some substitution of platinum with palladium in lighter diesel vehicles. Its primary use is in autocatalysts in petrol-fuelled cars, but it is also used in the chemical industry, dentistry, electrical components and increasingly in jewellery. Industrial use of palladium rose strongly, despite the difficulties faced by the automobile industry (Bain, 2013). Palladium has also seen strong growth from jewelry with the total worldwide demand being 11 percent (Taulli, 2011).

Palladium is traded on the New York Mercantile Exchange (NYMEX) and the London Platinum and Palladium Market (Bain, 2013). You can also trade palladium on the CME and on the Tokyo Commodity Exchange (Taulli, 2011). Platinum and palladium prices typically move in the same direction and more like those of industrial metals than the other precious metals, gold and silver (Bain, 2013).

INDUSTRIAL/BASE METALS

Aluminum

Aluminum is the third most common element in the earth's crust after oxygen and silicon, accounting for 8 percent of the ground we walk on, while 150 years ago, aluminum was more valuable than gold and platinum (Dunsby, et al., 2008). The primary source of aluminium is from the aluminum ore known as bauxite; this is found worldwide in varying concentrations (Taylor, 2013). Aluminum is a lightweight metal that is resistant to corrosion. Aluminum is generally measured in metric tons (Bouchentouf, 2015).

Primary aluminum processing proceeds in three steps: bauxite mining and milling, conversion of bauxite to alumina and conversion of alumina to aluminum. Aluminum production remains an energy-intensive process, with even modern plants requiring 13 to 16 kilowatt-hours (kWh) of direct electrical energy per kilogram of output. Two tons of alumina are required for each ton of aluminum produced and therefore four to five tons of bauxite produce one ton of aluminum at a purity level of 99.7 percent. The production process of aluminum is shown in Figure 5. Aluminum produced from bauxite via alumina is commonly known as primary aluminum (Dunsby, et al., 2008). This process is highly energy intensive (between 13,000 and 16,000 kWh for each ton of aluminum) and smelters are often built in close proximity to power stations. For a metal, such as aluminum, the operating cost could rise (or drop) drastically due to variations in bauxite or the electricity price. Both price variables represent more than 50 per cent of the production cost changes but the situation is the same (to a lesser extent) with other base metals. As a result, the price of electricity has a strong impact on production costs (Taylor, 2013).

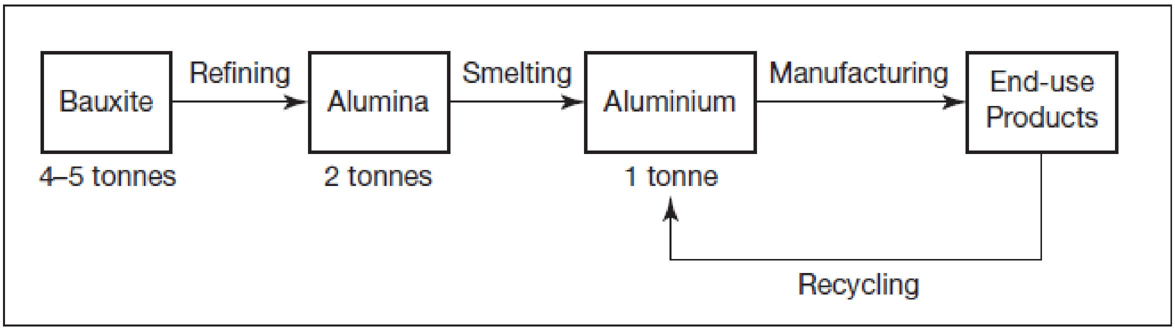


Figure 5: Aluminum lifecycle and production process (Taylor, 2013)

The secondary source of aluminum is scrap, or recycled aluminum. Surprisingly, aluminum recycling is a very old business, which started around 1900. Secondary aluminum accounted for 50 per cent of the supply in 1980 and is now over 70 per cent of the supply since the beginning of the 2000s. Part of this success is due to the fact that recycling of aluminum is less energy intensive (approximately 1/20 of the energy) and therefore cheaper to produce than primary aluminum (Taylor, 2013). Secondary production, or recycling, remains an attractive source of production for aluminum. Recycling aluminum incurs only 5 percent of the energy costs required to convert alumina to aluminum. Currently, recycling global production is significantly higher than the proportions for other metals. Primary and secondary aluminum are frequently but not necessarily alloyed with other metals and then converted into semi-fabricated products (Dunsby, et al., 2008).

Aluminum is mined primarily in tropical parts of the world (Bain, 2013). Bauxite deposits are found primarily in tropical regions, with 80 percent of world production coming from Australia, Brazil, Guinea, China, Jamaica, and India (Dunsby, et al., 2008). The biggest producers of aluminum include China, Russia, Canada, the United States, and Australia (Taulli, 2011). Overall, primary aluminum production is more dispersed than bauxite mining. World primary aluminum production has grown at 5 percent per year since 1995. As with all the metals, the major story is the growth of Chinese primary production. The major supply story over the next 10 years will likely be the continuing shift of production from West to East as new plants come online in China, India, Russia, and the Middle East. Cheap, captive power supply is driving capacity expansion in Russia and the Middle East, while economic growth is driving the expansion in China and India. Notable exceptions to this trend, Iceland and Canada, will likely see capacity increases due to available geothermal and hydroelectric energy sources. While Chinese primary production skyrocketed during the past 10 years, U.S. production fell by one-third. Primary aluminum production has been roughly flat in the other major producing countries, causing their share of world production to fall in the face of China's dramatic growth. On the contrary, the major aluminum recyclers are, unsurprisingly, the United States, Europe, and Japan. In the United States, recycling accounts for a full 60 percent of aluminum production, and in Japan recycling accounts for nearly all aluminum production (Dunsby, et al., 2008).

Demand in the former Soviet Union collapsed after 1990 and remains lower than in the 1980s, boosting export availability. Since 1992 Russia has become the world's largest exporter of primary aluminum and accounted for 26% of total exports in 2011. Canada is the next largest exporter with 11% of the market, with China some way behind with a 3.5% market share. Trade in aluminum has been falling as a share of world consumption from a peak of 66% in 2004 largely because China is self-sufficient. Exports accounted for 50% of total consumption in 2011. Imports of primary aluminum are typically duty-free but trade in semi-finished and finished products is more restricted. The exception to this is the EU, which imposes a 6% tariff on imports of primary aluminum (Bain, 2013).

The consumption picture is dominated by China (Dunsby, et al., 2008). Aluminum is used in the construction industry (more than 20 per cent of demand), packaging (18 per cent), and of course the transportation sectors (largest end user of aluminum with 29 per cent), and with a high level of activity in infrastructure development in emerging countries this increasing price trend looks likely to continue (Taylor, 2013). Aluminum has industrial uses as well, including a role in the construction of buildings, oil pipelines, and even bridges. Building constructors are attracted to it because it is lightweight, durable, and sturdy. In packaging almost a quarter of aluminum is used to create aluminum wrap and foil, along with beverage cans and rivets. In transportation aluminum is used to create the body, axles, and, in some cases, engines of cars. In addition, large commercial aircrafts are built using aluminum, because of its lightweight and sturdiness (Bouchentouf, 2015). As of 1998, end use of aluminum worldwide consisted of: 26 percent transportation (vehicles), 20 percent packaging (foil and cans), 20 percent construction (commercial and residential), 9 percent electric (transmission), and 25 percent other uses (machinery, consumer durables, etc). As of 2004, 37 percent transportation, 22 percent packaging, 16 percent construction, 7 percent electric, and 18 percent other uses. Regarding the set of end uses, GDP, industrial production, and their components would seem to be promising indicators of demand for aluminum (Dunsby, et al., 2008).

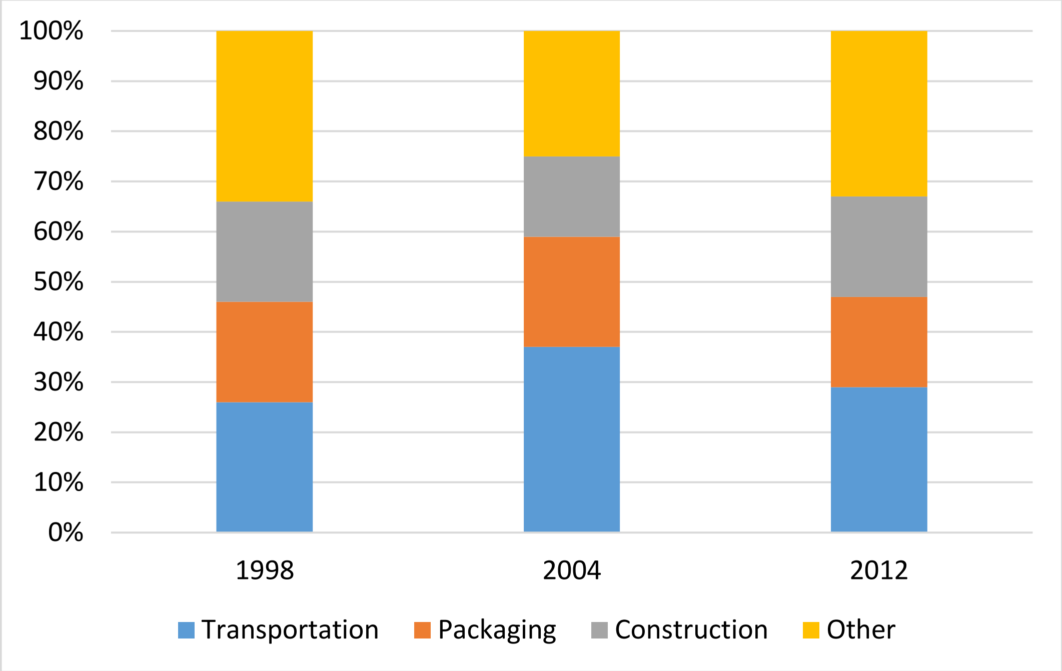


Figure 6: The evolution of aluminum consumption

Although much metal is moved within integrated company systems, primary aluminum is widely traded. Market pricing has been made transparent by the LME, which has traded primary aluminum since 1978. Although metal is still sold directly between producers and consumers on prices fixed for various periods, the setting of those prices is now overwhelmingly influenced by the LME quotations, particularly the 3-months future quotation (Bain, 2013). Primary aluminum trades on the London Metal Exchange (LME) and is quoted in $/metric ton. Contract specifications are for 25 tons of aluminum at 99.7 percent purity. For physical delivery, each lot of metal must be of an LME-approved brand and form residing in an LME-approved warehouse. The minimum quoted tick size is $0.25 on LME Select, but in the ring it is $0.50 (Dunsby, et al., 2008). Aluminum is now traded on a number of exchanges around the world, notably the Shanghai Futures Exchange (SHFE) and also exchanges in Singapore, Rotterdam, Japan and Malaysia (Bain, 2013). Aluminum used to trade in the COMEX division of the New York Mercantile Exchange (NYMEX). However, the COMEX contract was delisted in 2009, after the Chicago Mercantile Exchange (CME) acquired the exchange (Bouchentouf, 2015).

Increasingly attractive alternative to steel (Bain, 2013), aluminum is far more abundant in the earth's crust than copper (Dunsby, et al., 2008) and can be substituted in some applications (Bain, 2013). The risk of upside to aluminum is that aluminum production is highly energy intensive per unit weight, much more so than copper. If energy prices continue to rise, this will have more of an impact on aluminum (Dunsby, et al., 2008). Even when aluminum prices increase, the impact may be delayed for companies. The main reason is that the aluminum industry relies mostly on long-term contracts. Another problem is energy, which accounts for large amounts of the company's costs. Therefore, a spike in the price of crude oil or coal can depress profits from aluminum (Taulli, 2011). In addition, new plants exploiting low-cost power sources should minimize the upward pressure on aluminum prices from higher oil prices. However, Chinese authorities' efforts to restrain power consumption in the sector may slow the pace of supply growth. Aluminum could also benefit from new production standards in the automotive industry (Taylor, 2013).

Aluminum prices have relatively low volatility compared with copper and zinc. The low volatility of aluminum may well be a consequence of its geological abundance (low relative scarcity) in conjunction with the presence of mothballed capacity. Aluminum will remain less volatile than the other metals, benefiting less from the boom in emerging markets but suffering less if the boom should crash. Investing in aluminum may thus provide exposure to the industrial (metal) cycle with a defensive posture. Thus, as long as investment in capacity remains prudent and the industrial cycle stays strong, aluminum is likely to stay strong. Neither of these is guaranteed, however. While the strength of the current commodity markets makes it tempting to forget, growth in supply can certainly exceed growth in demand. Rapidly growing nations such as China may build excessive aluminum capacity, looking to export the excess abroad, until they grow into the available capacity. Similarly, nations with low energy costs such as the Gulf States are ramping up aluminum production to supply export markets. A heavy reliance on export markets, a potential issue in both of those scenarios, leaves aluminum exposed to downward price pressure from a slowdown in the rest of the world. The crisis in the U.S. sub-prime housing market as of mid-2007 may well be a precursor of such a downturn. There are two additional factors that suggest a positive future for aluminum. First, the energy intensity of aluminum means it should benefit more than the other metals from any future increases in energy prices. Second, the larger surge in copper and zinc prices will lead to their substitution by aluminum. Working in the other direction, the rise in aluminum prices may engender switching to plastics. Of course, this will depend on the price of plastics, which are themselves products of the increasingly pricey petroleum complex (Dunsby, et al., 2008).

The global market for aluminum is expected to remain strong for the foreseeable future as retail customers are generally eager to buy lighter and more recyclable consumer goods

(Taylor, 2013). Demand for aluminum will be supported by steady growth in car ownership in countries such as China and India. Alongside its use in construction, consumer goods and packaging, the metal's lightweight properties will ensure that it will be in considerable demand in the production of lightweight, fuel-efficient aircraft and cars. Its easy recyclability will also make it a greener option for end-users. High-energy costs and environmental issues are limiting output growth both in China and globally. These restrictions and the high cost of inputs (both energy and bauxite) mean there will be an increased focus on boosting the use of recycled aluminum instead of refining new metal. Limited bauxite supply could constrain aluminum supply, as importing countries are dependent on a few main exporters. The energy-intensive nature of aluminum production means that production is likely to become more polarized in energy-rich countries. It is also likely to move to lower-wage regions of the world. This combination suggests EU production is in structural decline (Bain, 2013).

Copper

Copper was the first base metal ever discovered and is still widely used (Taylor, 2013). Copper was probably the first base metal to have its properties recognized and to be used extensively by humans. Copper is versatile: it is malleable and ductile; it has superb alloying characteristics; it is resistant to corrosion, strong, durable and recyclable; and it is an excellent conductor of heat and electricity (Bain, 2013). The mining of copper extends back as far as 13,000 B.C. and is actually the first-known industrial metal. As a sign of its importance, copper became the basis of the Copper Age during prehistoric times. Copper was a critical metal for civilizations like the Egyptians and the Romans. It is also an effective conductor of electricity and was essential for the Electric Revolution during the nineteenth century (Taulli, 2011). Copper played a huge role during the Industrial Revolution and in connecting and wiring the modern world. Copper, the third most widely used metal, is the metal of choice for industrial uses. Because it's a great conductor of heat and electricity, its applications in industry are wide and deep. Because of the current trends of industrialization and urbanization across the globe, demand for copper has been — and will remain — very strong, making this base metal a very attractive investment (Bouchentouf, 2015).

Copper occurs naturally in the Earth's crust and is extracted by both open-pit mining (the majority of copper mines) and underground mining (Bain, 2013). Copper miners typically use open-pit mines to process large amounts of low-grade ore. The copper is then crushed and then sent to a smelter. After this, there is a refining process that removes much of the oxygen and impurities. The end-product is cathode and wire rods, which are then sold to copper fabricators (Taulli, 2011). Around 80% of copper mine production is in the form of concentrates (copper sulphide minerals typically containing around 30% copper before concentration), requiring smelting and refining (Bain, 2013). Smelters not associated with a mine—custom smelters—obtain their copper through the market. The mines may either retain ownership of the metal or sell it outright to the smelter. In the former case, smelters receive concentrate treatment ($/ton) and refining charges (cents/pound) from the mines in exchange for converting concentrates to refined metal. The charges vary with the availability of concentrates (Dunsby, et al., 2008). Secondary copper smelters use scrap copper as their feed (Bain, 2013). Recycling plays an important role in copper production, accounting for 10 to 15 percent of total refined copper production worldwide. Secondary copper is the name for refined copper produced through recycling (Dunsby, et al., 2008). Copper is often alloyed with other metals, usually with nickel and zinc. When copper and nickel are alloyed with tin, the resulting metal is bronze; when copper is alloyed with zinc, it results in brass (Bouchentouf, 2015). By 3000 B.C., humans had learned that mixing copper with tin or arsenic yielded a significantly harder material, an alloy that had a low enough melting point to be cast in open hearth pit fires. This was bronze, and with its discovery came the Bronze Age and the continued blossoming of Western civilization (Dunsby, et al., 2008).

There are large amounts of copper reserves in the world. In terms of physical volume, copper is number three in the metals market (Taulli, 2011). South America has emerged as the world's most productive copper region, especially from the Andes Mountains, with Chile being the largest producer (Taylor, 2013). One-third of world-mined copper originates in Chile, with another 5 to 10 percent coming from the United States, Peru, Australia, Indonesia, and China; the remainder is divided among another half-dozen countries. South America, Australia, and Indonesia are the major exporters of concentrate, with much of their copper being refined elsewhere (Dunsby, et al., 2008). Chile remains by far the dominant exporter of all types of copper (Bain, 2013). World refined copper production has grown. This growth has not been evenly distributed. Chile and China are the dominant refiners, and China's production has almost exactly offset the decline in the United States on a percentage basis. More generally, refining in Asia has risen while refining in the West has fallen (Dunsby, et al., 2008).

Copper has been used in jewelry and weapons for as long as 10,000 years (Dunsby, et al., 2008). Copper, the third most widely used metal in the world, has applications in many sectors, including construction, electricity conduction, and large-scale industrial projects.

Copper is sought after because of its high electrical conductivity, resistance to corrosion, and malleability. Copper is used for a variety of purposes, from building and construction to electrical wiring and engineering (Bouchentouf, 2015). Copper's largest end-use is in construction, principally building wire and plumbing (Bain, 2013). However, construction's share of consumption has been falling, with the high cost of copper being one factor that accelerated the substitution of copper by plastics in plumbing applications. Copper also has many crucial applications in electrical and general engineering, coinage and transport. Copper wire is used extensively in the manufacture of electronic equipment. Copper and its alloys still dominate in the production of connectors, but in telecommunications, where new technologies require high-speed data transmission, copper faces competition from fibre optics (Bain, 2013). Aluminum radiators have largely displaced copper in the automotive industry, but use of copper here has started to recover, partly through the introduction of a lightweight alloy radiator and even more by the increased use of electronic components in modern vehicles (Bain, 2013). Copper is also used in heating systems, solar installations, and the desalination of water (Taulli, 2011). Copper is benefiting from environmental legislation and the promotion of renewable energy systems. Approximately ten times more copper is required per megawatt of effective capacity for wind turbines than for coalor gas-fired power stations (Bain, 2013).

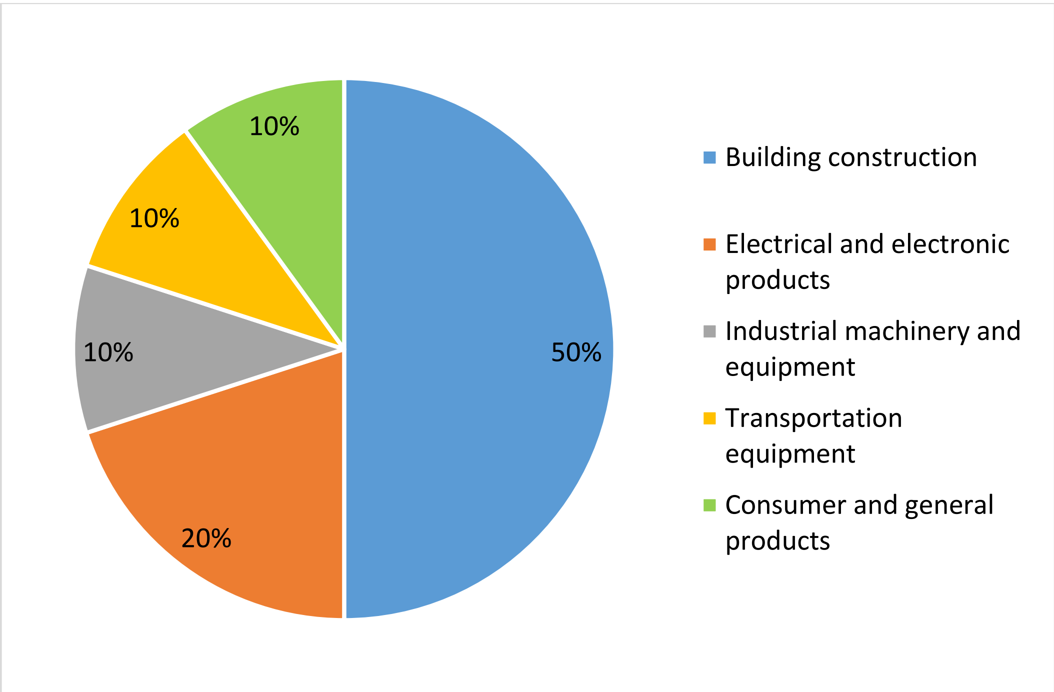


Figure 7: Uses of Copper

Copper is the third most widely used metal, after aluminum (Kleinman, 2013). In Europe and the United States, building and construction account for the bulk of consumption. In Asia, electrical and electronic production is more important, but as countries develop, infrastructure and construction are also absorbing larger amounts of copper (Bain, 2013). China represents 40 percent of global copper consumption. The European Union is ranked second in copper consumption, at 17 percent. The United States is ranked third, with 9 percent (Taulli, 2011).

Copper is the most actively traded of the base metals (Bain, 2013). Copper, the red metal, copper, is traded both in New York and in London at the London Metals Exchange (Kleinman, 2013). The London Metal Exchange (LME) is the dominant price setter along with the Commodity Exchange Division of the New York Mercantile Exchange (COMEX/NYMEX), which is the benchmark for the North American market. The Shanghai Futures Exchange is the main exchange in China. Prices are settled by a bid and offer process. These exchanges also offer futures and options contracts, and provide warehousing facilities that enable market participants to make or take physical delivery of copper in accordance with each exchange's criteria (Bain, 2013). You can also purchase futures contracts on copper on the CME (Taulli, 2011) but the copper contract on the London Metal Exchange (LME) accounts for more than 90 percent of total copper futures activity (Bouchentouf, 2015).

Surging demand for copper is a result of urbanization and rural electrification. With increased prosperity, demand has been rising for air conditioners and refrigerators, electrical appliances and other copper intensive consumer durables, including motor vehicles (Bain, 2013). All in all, copper is a key indicator in gauging the status of the economy. Consider that at the end of 2008, there was a 4 percent drop in copper demand. While this may seem insignificant, it was actually a major event. For savvy investors, the drop-off was a telltale sign that the global economy was falling into a recession (Taulli, 2011). Production of copper varies from year to year for various reasons. Much of the short-term volatility in prices resulting from physical supply–demand imbalances. Demand tends to grow more steadily (Dunsby, et al., 2008). Furthermore, high copper prices have increased copper recycling; this metal is 100 per cent recyclable without any loss of quality. Approximately one third of all copper consumed worldwide is recycled, and these trends are expected to push the copper balance into surplus in the long term (Taylor, 2013). Despite the abundant supply of copper, there are major constraints on the mining of the supply. These include exploration costs, political instability, labor problems, and environmental issues. Apart from these, the age of the mines and the lack of copper scrap causes supply problems, resulting in major swings in prices. One of the big problems for copper companies is that it is tough to cut back on production when there is a recession. As a result, copper companies saw large drops in revenues and profits (Taulli, 2011).

In contrast to its ubiquitous industrial use, copper is a relatively rare element (Dunsby, et al., 2008). Copper is essential to the processes of urbanisation and raising living standards in the developing world, ensuring that long-term demand will prove resilient. Mine production has been particularly vulnerable to unplanned disruption. Strikes, accidents, technical difficulties, low ore grades, planning constraints, tight credit conditions, political risks, and shortages of skilled personnel, equipment and other supplies have all hampered the timely start-up of new projects and the smooth operation of existing ones. There are potential shortages of power and water, both of which are used in, and are crucial to, the copper extraction or mining process, in key producing regions, in particular Chile, Southern Africa and China. If prices remain high and stocks low, there will be rationing of copper, substitution with other metals where possible and the greater use of scrap (Bain, 2013). Copper will likely stay strong as long as the world industrial cycle stays strong and the current cycle is being driven by growth foremost in China and secondarily in other emerging markets in Asia. The main risk is, therefore, a major economic downturn, especially one extending to China. Another risk is that the high price of copper relative to substitutes will lead to substantial demand destruction. This can already be seen in the substitution of PVC for copper pipes for plumbing and the replacement of copper by aluminum in power cables. It will also be seen as copper applications make do with less copper, perhaps by using thinner and smaller components. Finally, another risk for copper is that fully one-third of copper comes from Chile (Dunsby, et al., 2008), that will affect the price and the supply and demand balance, if a disruption will happen there.

Lead

Lead has a blue-white color, is soft, and malleable. When exposed to air, the blue-white color changes to gray. When lead is melted, it turns to a silvery luster. Of course, lead is toxic. Exposure can cause neurological and nervous disorders (Taulli, 2011). It is one of the scarcer non-ferrous metals in the Earth’s crust. Lead has useful properties; in particular, it is highly resistant to corrosion and is malleable, melting and joining easily. Its high density makes it a valuable insulating material for electrical and radiation screening and soundproofing, and its electrochemical properties make it a useful component in storage batteries in motor vehicles and for some back-up power supplies. However, an increasing awareness of the toxicity of lead has led to changes in the pattern of lead consumption (Bain, 2013).

Lead is usually found in ore form with silver, zinc and/or copper and is mined in conjunction with these metals. Only 5% of mined output is from lead-only mines. Mines are now geographically concentrated in China, Australia and the Americas but globally deposits are widespread, which explains why lead has been in use for thousands of years. It is easy to recover by reduction from sulphide or oxide ores. Today, much refined lead comes from secondary sources, particularly recycling. At the primary (mining) stage, lead and zinc are generally produced by the same companies, although new mines tend to have much higher zinc grades relative to those of lead. Many of the new zinc mines are based on copper zinc rather than the traditional lead-zinc-silver deposits (Bain, 2013). Mining is widely integrated with smelting in the United States and Australia. However, there is a large custom smelting industry in Europe, Japan and South Korea, and more recently China, based mainly on imported lead concentrate (particularly from Australia, Canada and Latin America) or secondary production. Recycling (primarily of vehicle batteries) now makes a big contribution to production, particularly in countries where no lead is mined. Another reason for the high level of secondary production in western Europe and the United States is the closure of primary smelting operations for economic and environmental reasons. Outside the United States, secondary producers are more numerous, smaller and more geographically dispersed than primary producers; they serve local markets; and they are closer to end-users (the main source of scrap) (Bain, 2013). The United States is the largest mining producer, followed by Canada, Mexico, Kazakhstan, and Australia (Kleinman, 2013), whereas the main smelting producers of lead are China, the United States, and Germany (Taulli, 2011). As we can see, mine production of lead is highly concentrated. Mine output has been rising over the past ten years but all the growth has been in China; in other parts of the world it has been falling (Bain, 2013).

The primary uses for lead include construction and batteries (Taulli, 2011), while other major uses of lead include car batteries, ammunition, fuel tanks, and as a solder for pipes (Kleinman, 2013). The metal has a broad range of industrial uses, especially in transport, construction and electrical goods. In applications such as cable sheathing, pipe and sheet, it is used as unalloyed metal. It is also used in alloyed form (most importantly in lead battery grids) and in various lead-based chemical compounds, such as lead oxide paste in batteries and pigments (Bain, 2013). However, lead has faced competition from plastics and aluminum in applications such as cable sheathing, pipe and sheet. Substitution in these markets has been offset by the growth of the use of lead in battery manufacture, which now accounts for around 80% of total consumption (Bain, 2013). This growth has been driven by vehicle production and demand for original equipment batteries. An even larger end-use is in replacement batteries where demand will grow alongside growth in the existing stock of vehicles (Bain, 2013). However, new battery technologies are likely to lengthen battery life, ultimately constraining lead demand. Lead, because of its toxic nature, is less used than copper and aluminum. Technology and substitution have reduced the use of lead in many industrial processes, including electronic systems, cable covering, packaging and lead pipes for water and gas (Taylor, 2013).

The United States, Japan, Germany, and the United Kingdom are big consumers. The common link between these countries is a major automotive industry (Kleinman, 2013). There is important intra-European trade in refined lead (and also in lead concentrate) and significant two-way trade in North America but the most important trade flow is with China. Australia is now the largest exporter. China has dominated growth in lead consumption over the past ten years, fueled by the growth in domestic vehicle production. The other factor driving demand in China has been the relocation of battery manufacture to China from higher-cost countries. China's emergence as the leading source of mine supply as well as refined lead output has reduced the trade in lead concentrate, as has the large reduction in smelting capacity in Europe (Bain, 2013).

Lead is listed on the London Metal Exchange (LME) in 25 metric ton contracts quoted in dollars and cents per ton (Kleinman, 2013); under the product symbol PB (Taulli, 2011). Trade in lead concentrate is based on treatment charges, an arrangement for sharing the price of lead between miners and smelters. Concentrates are traded mainly on the basis of annual contracts, typically set in the first quarter of the year. The outcome of these negotiations reflects the balance between mine supply of concentrates and smelter demand, a low treatment charge favouring mining companies and a high charge benefiting smelters. The contracts are set on a basis price plus adjustments that take into account changes in London Metal Exchange (LME) lead prices. As the only futures market for lead, the LME acts as the basis for prices for refined and intermediate products. One feature of the lead market that is more powerful than in other metal markets is the ability of trends in the secondary market to influence prices. Lower lead prices tend to depress the supply of secondary lead (scrap), which in turn leads to reduced supply of total refined lead and thus leads to a renewed tightening of the market balance. The reverse is true when lead prices are high. In this way the secondary market acts as a kind of a pressure valve for the wider market (Bain, 2013).

In the future, there is scope for significant increases in global vehicle numbers, as the vehicles per head figure is low in most emerging economies. However, it appears that lead-acid batteries perform poorly in hybrid and all-electric cars, with producers preferring to use other batteries, notably lithium. At the moment, these eco-friendly vehicles are too expensive to take a large market share, but prices could fall and the technology could improve in the medium term. Steps to reduce pollution and energy intensity in China could have negative consequences for the country's mining and smelting industries, at least in terms of increasing costs. Indeed, concerns about the negative impact of lead production more generally could be a constraint on supply in future years. Prices are likely to be more volatile, despite lead's recession-proof qualities. Automobile sales in developing countries (where all the growth in consumption will be) can be expected to fluctuate more markedly in tandem with the economic cycle, unlike sales in the more mature, largely saturated markets in the Western world (Bain, 2013). Finally, because lead is extremely toxic, there has been a concerted effort to "get the lead out" of many products in recent years (Kleinman, 2013), a factor that will affect the prices and the equilibriums dramatically.

Nickel

Nickel is a silvery-white metal, which can be given a high polish and is the fifth most common element in the Earth's crust (Bain, 2013). Nickel is a ferrous metal, which means it belongs to the iron group of metals (Bouchentouf, 2015). Nickel exhibits a mixture of ferrous and non-ferrous metal properties that can be used in various different industries (Taylor, 2013). It is tough but workable, and resistant to corrosion (Bain, 2013). It can also withstand high levels of heat (Taulli, 2011). These characteristics determine its predominant use as the main alloying metal with chrome in austenitic (iron based) stainless steels and other special steels or superalloys (Bain, 2013). Steel is usually alloyed with nickel to create stainless steel, which ensures that nickel will play an important role for years to come (Bouchentouf, 2015).

The primary production comes mainly from two types of ore deposits, lateritic and magmatic sulfides. Most of the nickel resources on Earth are believed to be concentrated in the planet's core (Taylor, 2013). Nickel mining is a labor-intensive industry, but countries that have large reserves of this special metal are poised to do very well (Bouchentouf, 2015). A variety of diversified miners extracts the commodity. The mining of nickel is quite difficult because it requires sophisticated technologies and mining techniques (Taulli, 2011). The manufacture of austenitic stainless steel accounts for about two-thirds of total nickel consumption. Nickel can constitute 10% or more of austenitic steels, but the most common alloys contain 8% nickel and cheaper grades use as little as 6%. Nickel improves workability by counteracting the embrittling effect of chrome, while maintaining and enhancing corrosion resistance. As a substitute for primary nickel, scrap supply amplifies fluctuations in primary demand. The availability of new scrap depends on output at steelworks and throughput at fabricators in the recent past. When falling sales lead to reduced activity among fabricators, and, as a result, stainless steel output is reduced, new scrap supply (from an earlier period of high activity) is high relative to nickel demand. When, emerging from a recession, fabricating work increases and stainless steel output rises, scrap supply is low relative to demand (Bain, 2013).

Known reserves of nickel are plentiful and geographically well-dispersed, although Australia accounts for 30% (Bain, 2013). Australia has the largest reserves of nickel, and its proximity to the rapidly industrializing Asian center — China and India — is a strategic advantage (Bouchentouf, 2015). The top producers of nickel include Russia, Canada, Australia, Indonesia, Colombia, and China (Taulli, 2011). Russia has dominated mine production for decades, typically accounting for about 15–20% of global output. Canada is another important source of nickel minerals. It exports a high proportion of the nickel matte from its smelters and some of its mine concentrates for refining abroad, which reduces its share of refined nickel production. Canada and Russia are the world's largest exporters of refined nickel. Indonesia is the world's third largest producer and, like the Philippines, an important exporter. China's nickel ore deposits are in geologically difficult areas but this has not deterred the country from increasing mine output and processing in a bid to reduce its stainless steelmakers' dependence on imported refined nickel (Bain, 2013).

The main use for nickel is for stainless steel, which accounts for about two thirds of the global production (Taulli, 2011). When steel is alloyed with nickel, its resistance to corrosion increases dramatically. Because stainless steel is a necessity of modern life, and a large portion of nickel goes toward creating this important metal alloy, you can rest assured that demand for nickel will remain strong (Bouchentouf, 2015). Other uses include coins, batteries, and plating (Taulli, 2011). Nickel is also used, in smaller quantities, to toughen tool steels and some high-strength steels that are not fully corrosion-resistant. Nickel is also an important constituent of some special high-performance alloys (Bain, 2013). Nickel is occasionally used in pure or near-pure forms, most importantly in electroplating, providing a base for other coatings, particularly chrome, and sometimes directly as a final surface treatment. Nickel use in electroplating is more widespread; it has applications in many basic industrial products as well as those involving advanced technology. In the chemicals industry, nickel is used as a catalyst; and it is increasingly used in batteries for portable electronic equipment (Bain, 2013). Sixty-five per cent of the nickel consumed in the Western world is used to make stainless steel. Another 12 per cent goes into superalloys – mostly for the aerospace industry – or non-ferrous alloys, both of which are widely used because of their corrosion resistance. The remaining 23 per cent of consumption is divided between steel alloys, rechargeable batteries, catalysts and other chemicals (Taylor, 2013).

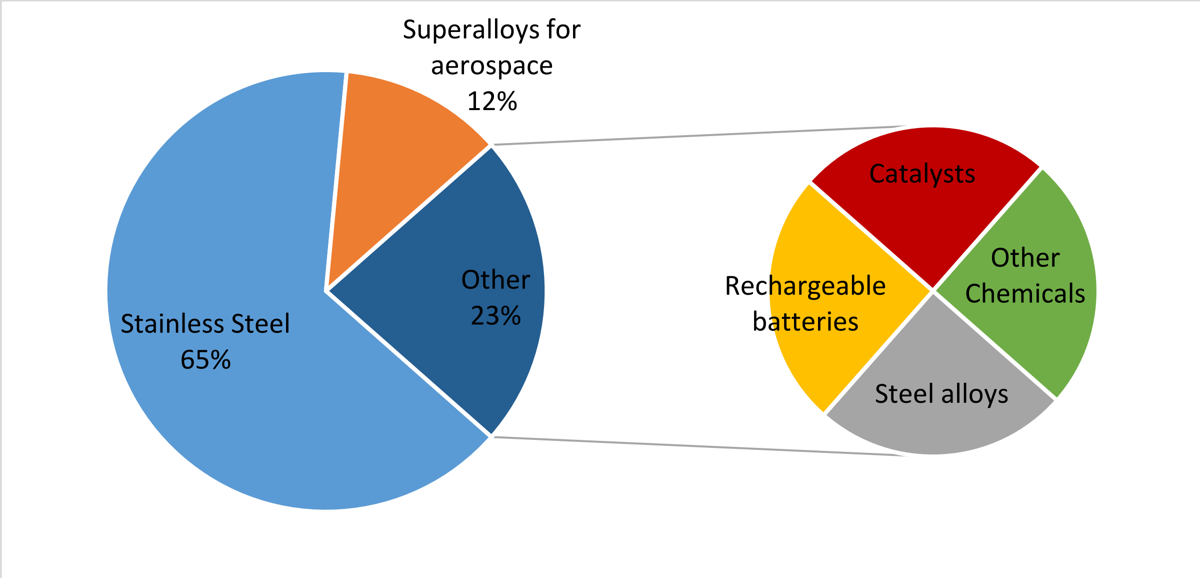


Figure 8: Uses of Nickel

By far, the biggest consumer of nickel is China. It is a key to its economic growth because of the production of stainless steel products (Taulli, 2011). The most significant development of the past few years has been the rise in nickel consumption in China, owing to a rapid increase in stainless steel production capacity. The new capacity was ostensibly aimed at building the country's self-sufficiency in supplies for domestic industries, particularly manufacturers of household appliances such as washing machines and dishwashers. Many new production lines were effectively guaranteed a large share of Asian markets because they were set up in partnership with established international manufacturers, especially those based in Japan and South Korea. Rival producers in other countries, particularly the EU, have had to scale back production in the face of this China-based competition. The EU is the world's second largest nickel consumer (Bain, 2013).

You can trade nickel on the London Metal Exchange (LME), with the product symbol NI (Taulli, 2011). Western nickel producers were hostile to nickel trading on the LME and initially tried to disregard LME prices in their contracts, but over time came to use it as a reference point of last resort. Solid consumption growth is expected to be maintained despite cyclical lows and highs. Stainless steel plays an important role in urbanization and industrialisation – trends that are expected to continue in the developing world (Bain, 2013). The two main factors behind a huge drop in price are the level of surpluses and the substitution effect from nickel pig-iron (NPI), a low grade ferronickel invented in China as a cheaper alternative to pure nickel for the production of stainless steel, that occurs when nickel prices are too high (Taylor, 2013). Moreover, the widespread use of scrap by the steel industry and the use of nickel pig iron in China (predominantly) complicate the supply/demand dynamics of the nickel market (Bain, 2013).

Tin

Tin is one of the earliest metals known to man. During the Bronze Age, tin was added to copper to make bronze – the addition of tin makes the copper stronger and easier to cast (Bain, 2013). Tin has a silvery color, is malleable, and is resistant to oxidation. It is used to help prevent corrosion for other metals (Taulli, 2011). Tin has a low melting point, is resistant to corrosion, and alloys readily with other metals. It is also non-toxic and easy to recycle, attributes that have become increasingly important (Bain, 2013). In modern times, tin is used for food packaging because it is nontoxic (Taulli, 2011).

Indonesia has been the world's leading exporter of tin metal, trading mainly through Singapore. China and Indonesia together accounted for 73% of total mine supply of tin, but output was declining in both countries. Today, tin is mined mainly in Asia and South America. Four countries – China, Indonesia, Peru and Bolivia – accounted for 85% of world output. Known reserves are concentrated in South-East Asia, South America, China and Russia. Outside Asia, the other important producing areas are in South America, particularly Peru and Bolivia and, to a lesser extent, Brazil. Tin is also mined in small quantities in Africa, principally the Democratic Republic of Congo but also Rwanda and Burundi. Until recently, much of the mining was illicit, and undertaken in often dangerous conditions. But there has been a campaign to legalise and improve oversight of the mining of so-called "conflict" minerals in Africa. Australia is also a growing producer of tin with a large number of projects in the pipeline, and increasingly tin mines are being reopened or initiated in more developed countries, including the UK and Germany. As an industry, tin smelting is much more concentrated than mining. China is the world's leading producer of refined tin (Bain, 2013). However, more tin is smelted in Malaysia for export than any other country. It can be volatile at times (Kleinman, 2013). Malaysia and Thailand are important producers of refined tin, but with refining capacity far in excess of local mining capabilities they depend on imported concentrates, primarily from Indonesia. Peru ranks third as a producer of refined tin. Tin supply does, however, still rely on mining and the refining of tin-containing ores (Bain, 2013). Overall, as shown in Figure 9, the biggest producers of tin are China (37%), Indonesia (33%), and Peru (12%), Bolivia (3%). There is no tin production in the United States (Taulli, 2011). Tin consumption in Western industrialised countries is in long-term decline, owing mainly to the migration of electronics manufacturing and other tin-using industries to lower-cost countries (Bain, 2013).

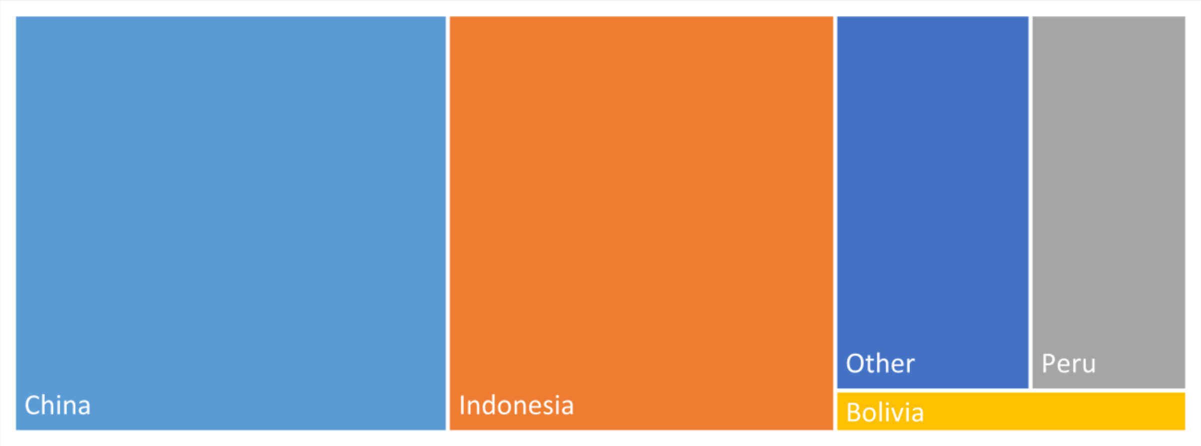


Figure 9: Producers of Tin

Tin is manufactured into a coating for steel containers used to preserve foods and beverages and other forms of electroplating (Kleinman, 2013). The main use of tin is in solder alloys, which are widely used to attach components to circuit boards used in the manufacture of electronic equipment and electrical appliances, and for joining pipes in plumbing systems. Solder's share of tin consumption has slipped recently perhaps because of slower growth in the electronics industry or the manufacture of goods that use less solder. The second most important use of tin is in the production of tinplate (cold reduced sheet steel electrolytically coated with a thin layer of tin). It is used primarily in food packaging, beverage cans and other containers, but it has been losing market share to aluminum for beverage canning, to glass for premium food and beverage products, and to plastics for a wide range of products including chilled foods and paint. Furthermore, where tinplate continues to be used, manufacturers have been experimenting with lighter gauges to cut costs. Although tinplate producers have responded to competition with innovative products and efforts to emphasize tin's recyclability, tinplate is expected to continue to lose market share to other materials. The chemicals industry is the third most important consumer of tin and its market share has been increasing. Tin is used in the manufacture of both organic and inorganic chemicals such as polyvinyl chloride (PVC), silicone resins (where it is used as a catalyst), polyurethane foam and ceramic pigments. However, some of these applications are at risk from legislation to phase out the use of heavy metals, including tin. Production of bronze ranks fourth among end-uses, accounting for around

5% of total consumption, followed by plate glass, accounting for about 2%. Potential new applications for tin include its use in rechargeable batteries, and a potentially significant application may be a nickel-tin-aluminium catalyst for the production of hydrogen for use in fuel cells, in competition with platinum (Bain, 2013).

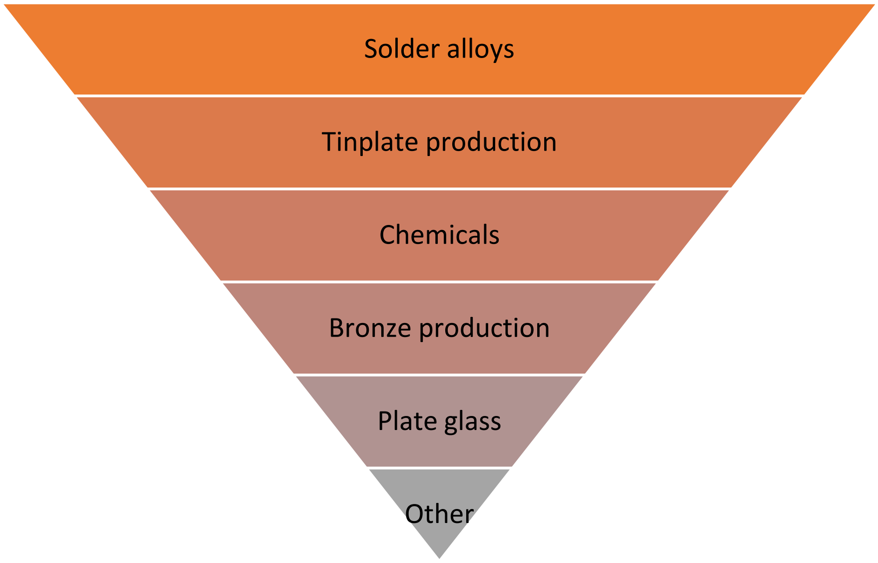


Figure 10: Ranking of Tin uses

The London Metal Exchange (LME) is the focal point for tin prices; trading of its tin futures contract represents a global reference price. Tin producers and their customers commonly agree business based on the LME price. Most (over 95%) of the LME's tin stocks are held in Singapore and Malaysia. The smallest (in volume terms) of the non-ferrous metals markets, the tin market is thinly traded, particularly when compared to the markets for copper and oil, and this adds to price volatility.

In the future, low stocks and the difficulties with mine supply suggest tin prices could rise strongly if consumption growth picks up. China's demand should rise strongly as its electronics industry is aiming to move up the value-added chain. Consumption of processed food is also rising strongly in China, requiring more tinplate packaging. The high concentration of tin mining makes the market vulnerable to supply shocks. It is likely that there will be some diversification of supply in the medium term, possibly in developed countries where investment risk is lower. The average cost of tin mining will rise (with implications for the price) as the easy-access alluvial-based mines become exhausted and companies have to dig deeper mines. In addition, in both Asia and South America, there are increasingly strong environmental lobbies making it more difficult to obtain licenses to mine. The business operating environment in many producing countries, including Indonesia, Peru and Bolivia, is highly uncertain for foreign mining companies, with governments often threatening to raise royalty payments, nationalize part or all of the operation or impose export taxes or quotas. Additional constraints on mining come from the labour market, such as a shortage of mining engineers and increasing union activity by mine workers (Bain, 2013).

Zinc

Zinc is present in the Earth's crust and is found in air, water and soil. Its properties include a resistance to corrosion and a low melting point, and it is a fairly good conductor of heat and electricity. Zinc is also an essential mineral in human well-being; it is found in high concentrations in red blood cells, which helps the functioning of the immune system (Bain, 2013). Zinc is a bit of a mystery. Unlike copper and aluminum, zinc is hardly ever used on its own. It is used to galvanize steel (preventing rust), to make alloys such as brass and bronze, and in various other chemical applications. One of zinc's most familiar applications, zinc oxide, hardly even seems like a metal (Dunsby, et al., 2008). Zinc is a bluish-white color and is a brittle metal. Through metal galvanization, zinc helps to prevent rust and corrosion of other metals like steel or iron (Taulli, 2011). Zinc accounts for roughly 0.007 percent of the Earth's crust on a mass basis, making it only slightly more common than copper. Economically, zinc sulfide is the most important mineral form of the metal with mined ores having concentrations from 1 to 15 percent zinc sulfide (Dunsby, et al., 2008).

The zinc market is one of the major markets in terms of production – fourth behind iron, aluminum and copper. The primary production represents 70 per cent of the total world production, the other 30 per cent coming from recycled zinc. The level of recycling is increasing each year (Taylor, 2013). Zinc is usually mined in conjunction with a number of other metals, notably lead, silver, copper and, less frequently, gold. Approximately 80% of mines are underground operations, 10% open-pit and the remainder a combination of both. In terms of production, large open-pit mines account for as much as 15% of the total, with underground mines producing 65% and combined mines 20% (Bain, 2013). It should be noted that lead and zinc are frequently associated in industry and trade publications. This is because zinc and lead are commonly found together (Dunsby, et al., 2008). Although a handful of countries dominate zinc mine output, there are many small producers in more countries than is the case for many base metals. This is partly because it is often mined as part of a copper-mining operation or there may be combined lead and zinc mines. Smelting is usually located close to the market rather than a mine, and it is even less concentrated than mining (Bain, 2013).

China accounts for one-quarter of the world production of zinc concentrate, with Australia and Peru together accounting for another quarter. The United States, Canada, Europe, Mexico, and India combine for a little more than the third quarter, with the remainder split among several countries (Dunsby, et al., 2008). Unlike other industrial metals, this commodity has sufficient supplies to meet current demand (Taulli, 2011). Worldwide, slab zinc production has grown. China accounts for 30 percent of current slab zinc production, with Europe and Canada together combining for another quarter. Japan and Korea, with their large steel producing and steel-using industries are next. The United States, remarkably, processes very little zinc and is a major exporter of zinc concentrate as well as a major importer of slab zinc (Dunsby, et al., 2008). China is the largest producer of refined zinc with the next single largest producer being South Korea. Significant smelting capacity is located in Europe, with Spain being the largest producer. Usually, smelting takes place near the consuming markets. China is the only exception to this rule with its ten largest smelters accounting for 50% of domestic production. However, even in China, numerous medium-sized or small-scale smelters account for the remaining 50% of output (Bain, 2013).

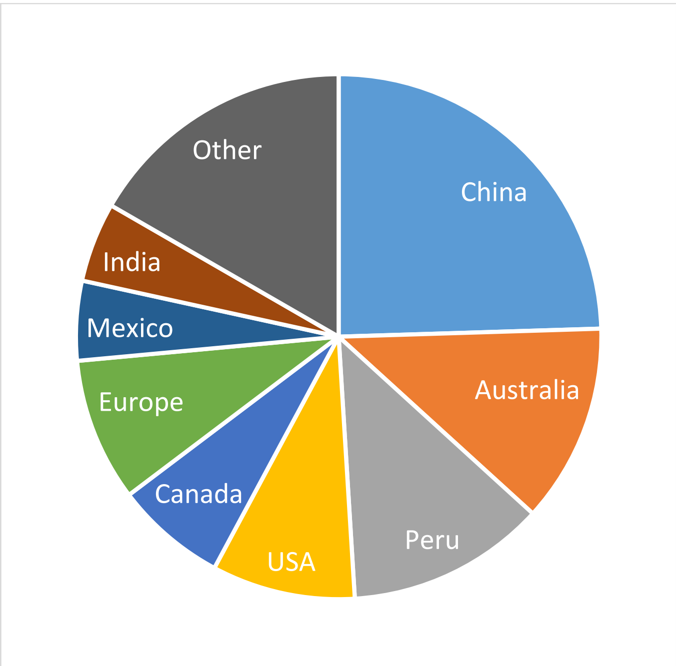


Figure 11: Zinc producing countries distribution

Many of the major trade flows in refined zinc are intra-regional. The United States is by far the largest importer of zinc metal but the bulk of its requirements are met by Canada, the world’s biggest exporter. Similarly, a number of European countries are heavily reliant on imports, notably Germany, Italy and the Netherlands. The region also has a number of leading exporters, namely Belgium, Finland and Spain. Other significant exporters of refined zinc include South Korea, Kazakhstan, India and Peru. Because most refining takes place some way from where zinc is mined, there is a significant trade in zinc concentrate. Countries such as Japan and South Korea and parts of western Europe have to import nearly all the zinc concentrate needed by their smelters. China also has to import zinc concentrate despite being the world's largest zinc miner. Most of the zinc concentrate is traded under long-term contracts, but with some degree of flexibility on quantity and price. This ensures a guaranteed outlet for a mine's production, and allows smelters to fine-tune their operations, by ensuring access to a particular blend of concentrates (Bain, 2013).

Zinc is the fifth most commonly used metal after iron, copper, aluminum, and lead (Dunsby, et al., 2008). Zinc has unique abilities to resist corrosion and oxidation and is used for metal galvanization, the process of applying a metal coating to another metal to prevent rust and corrosion (Bouchentouf, 2015). Zinc is used mainly in galvanising, die-casting and brass (alloyed with copper), which together account for around 80% of its use. Galvanising is by far the largest market and also the fastest-growing in volume terms (Bain, 2013). About 50 per cent of zinc is used for galvanising other metals, coating them to protect iron and steel from corrosion (Taylor, 2013), whether for sheets, structures, fences, storage tanks, fasteners, or even wire (Dunsby, et al., 2008). Another 20 percent of zinc is blended with copper to form brass. Major applications of brass include tubes, valves, fittings, electrical connections, heat exchangers, and ammunition. The automotive, construction, and electrical sectors are particularly important users of brass (Dunsby, et al., 2008). Zinc is also used to a lesser extent in batteries, chemicals and rubber (Bain, 2013), paint pigment, batteries, agriculture fungicides and in some dietary supplements (Taulli, 2011). Another important industry to watch is automobiles. Demand for more durable cars has increased the use of galvanised sheet for body parts in the automotive industry. Construction is the largest consumer of galvanised steel (45% of total zinc use), accounting for over half of the market. Transport accounts for approximately 25%, with consumer goods and electrical appliances at 23% and general engineering at about 7% (Bain, 2013). Chinese end-use growth accounts for more than 60 percent of worldwide growth (Dunsby, et al., 2008).

Figure 12: Zinc primary uses

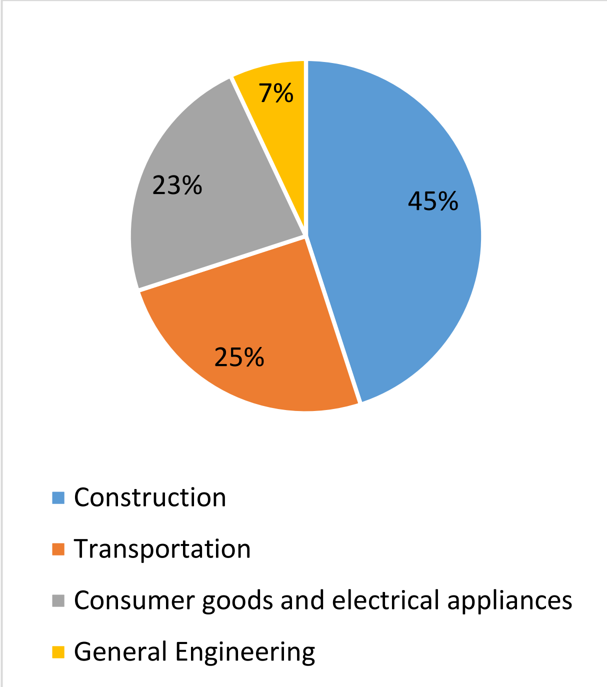


Figure 13: Zinc end uses

Zinc trades on the London Metals Exchange (LME) (Dunsby, et al., 2008). The London Metal Exchange (LME) is the main futures market for zinc. The metal is also traded on the Shanghai Futures Exchange and on exchanges in the Netherlands, the United States and Singapore. Pricing on the LME provides the benchmark for sales of refined metal and concentrates throughout much of the world (Bain, 2013). Competition, to a large extent, comes from aluminum, magnesium, and plastics (Dunsby, et al., 2008), affecting the price of zinc, due to substitution.

In the future, the risk of a Chinese slowdown exposes a deeper truth: zinc follows the world industrial cycle. While China may present an obvious risk, a slowdown in any of the major areas of the world poses a problem for strong zinc prices. In the medium term, zinc will have to be recovered from less attractive sources as the better mine deposits become tapped out. This natural decline will be at least somewhat mitigated by technological progress, which helps to expand the set of economical mines. Another factor that should help to contain zinc prices is recycling: unlike the products of the petroleum complex, zinc can be recycled. Relative to aluminum, though, zinc is less readily recycled because of the dispersive nature of its uses. Since zinc is also less commonly available in the ground, this will likely mean an increase in the price of zinc compared with that of aluminum. If the price of zinc rises too high, however, substitution will occur. Aluminum, magnesium, and plastics are all possible substitutes for zinc. Admittedly, all these materials are currently experiencing strong prices (Dunsby, et al., 2008). Apart from this, there has been some switching away from galvanised steel in vehicles to aluminium, which is lighter in weight and thus more fuel-efficient. Supply has improved but low prevailing prices and the risks associated with future demand could lead to lower investment in the zinc industry in future. Small-scale projects, of which there are many in the zinc industry, often owned by junior mining companies that can struggle to obtain financing, could be particularly vulnerable (Bain, 2013).

4.2 Energy

Energy commodities are those that are used to produce energy, mostly by burn, or to create other derivative products with many applications. The main energy commodities are crude oil, brent oil, gasoline, heating oil and natural gas.

Crude Oil

Crude oil, also known as petroleum, was formed millions of years ago by the remains of plants and animals that inhabited the seas. It is thought that the majority of these organisms were single-celled and as they died their remains fell to the sea bed and were covered with sand and mud creating a rich organic layer. This process repeated itself over and over and the layers eventually developed into sedimentary rock. Over time increased pressure and heat from the weight of the layers caused the organic remains to slowly transform themselves into crude oil and natural gas, among other things (Dunsby, et al., 2008). Crude oil is a hydrocarbon, composed mostly of hydrogen and carbon. It is typically found in underground or undersea reservoirs (Bain, 2013). Oil is the biggest business in the world. If anything, it has been the driver of industrialization and modernization. Even with higher oil prices, oil is still a cheap source of energy—especially in terms of its power and efficiency. A barrel of oil equals the manual labor of a person for eight days (Taulli, 2011). Crude oil is undoubtedly the king of commodities, in both its production value and its importance to the global economy (Bouchentouf, 2015).

The most common way to produce crude oil is to use drilling rigs to create an oil well that will extract oil from a crude oil field. Oil wells can be located onshore or offshore (Dunsby, et al., 2008). It is extracted by a number of methods, using either the natural pressure in the reservoir or pumps. As the oil becomes more difficult to extract, recovery-enhancing techniques such as injecting water or gas can be used. The extraction of less conventional crude from oil sands or oil shale requires more of a mining-style approach (Bain, 2013). In the simplest of terms, oil is still extracted from the ground in crude oil form and then shipped or piped to refineries where the crude oil is refined into oil products. Once refined, the finished products would either be destined for domestic use or in some cases they went for export (Taylor, 2013). The oil industry first classifies crude based on its production location. The important physical characteristics of crude oil are whether it is light or heavy and whether it is sweet or sour (Dunsby, et al., 2008). Crude oils are typically classed as high or low sulphur. Typically the lower the sulphur, the higher the value of the crude. Crude oils are also classed as light or heavy. The higher the gravity (or the lighter the crude oil), typically the higher the value of the crude (Taylor, 2013). Historically, lighter oil has commanded a price premium as it is more suited to the production of petroleum in the refinery (Bain, 2013). A number of factors influence how much crude a country is able to pump out of the ground daily, including geopolitical stability and the application of technologically advanced crude-recovery techniques. Daily production may vary throughout the year because of disruptions resulting either from geopolitical events such as embargos, sanctions, and sabotage that put a stop to daily production or from other external factors, like weather (Bouchentouf, 2015).

Crude oil by itself is not very useful; it derives its value from its products. Only after it's processed and refined into consumable products it become so valuable (Bouchentouf, 2015). Refining is the act of taking crude oil and processing it to make finished petroleum products that we use on a daily basis such as gasoline, heating oil, diesel, and jet fuel. The quality of the crude oil used in the refining process is important in determining how much processing is needed to achieve an optimal mix of products. Each type of crude oil has a unique distillation curve dependent on the kinds of hydrocarbons that make up that crude. The amount of carbon atoms in the crude oil determines its density or weight. Gases typically have between one and four carbons, whereas heavier grades of crude oil can have 50 carbons. Both the weight and the distillation curve of a specific crude oil are important to refiners who need to separate the different components of the crude oil to make various products such as gasoline, heating oil, diesel, and jet fuel (Dunsby, et al., 2008). Crude oil is refined into various products such as petrol, middle distillates and fuel oil. Petrol consists of aviation and motor petrol, and light distillate feedstock (LDF). Middle distillates consist of jet and heating kerosene, and gas and diesel oils. Fuel oil includes marine fuels (bunkers or oil used in maritime transport) and crude oil used directly as fuel. Other products are liquefied petroleum gas (LPG), solvents, petroleum coke, lubricants and bitumen. The market for crude consists primarily of refiners, many of which are integrated downstream into the distribution and sale of petroleum products, or upstream into exploration or production, or both. Historically, crude oil refining took place in consuming countries, as crude oil is cheaper to transport than its products. Although more refining is now taking place in producing countries. Refining has generally been less profitable than other parts of the oil business (Bain, 2013). The oil industry is a multidimensional, complex business with many players that often have conflicting interests (Bouchentouf, 2015).

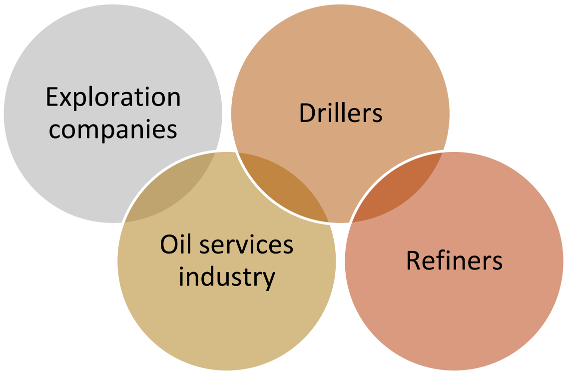


Figure 14: Oil market participants

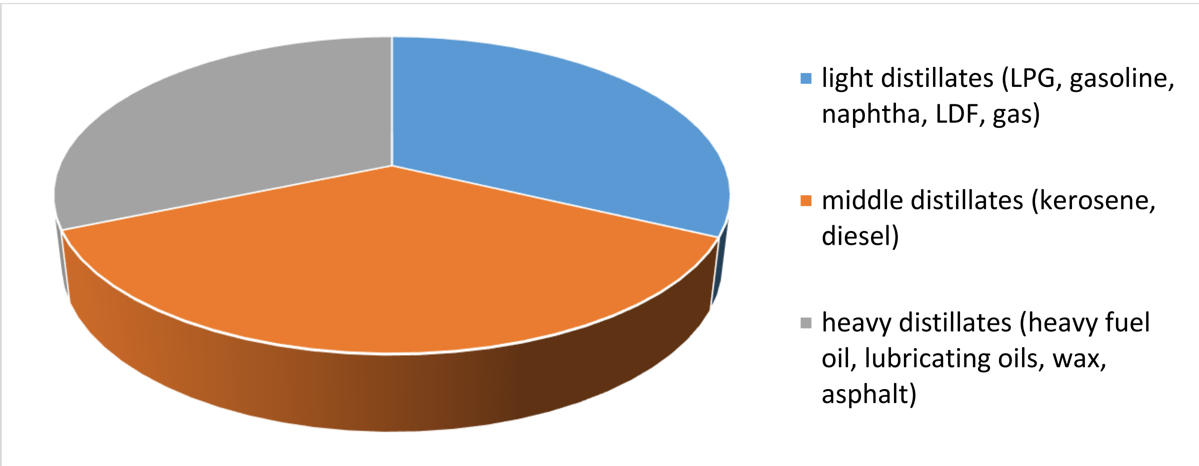


Figure 15: Oil distillates (Bain, 2013)

The vast majority of the world's untapped crude oil is to be found in the Middle East, with over 50 per cent of the world's proven reserves. Areas such as West Africa and the Former Soviet Union (FSU) also hold vast reserves, as well as the continent of South America. Crude oil is also to be found all over Asia but usually in vastly smaller quantities (Taylor, 2013). An oil reserve is a known supply of oil held underground that is economically recoverable. Proven reserves are oil reserves that are reasonably certain to be able to be extracted using current technologies at current prices (Dunsby, et al., 2008). Having large deposits of crude does not mean that a country has exploited and developed all its oil fields. There is a big difference between proven reserves and actual production. A country may have large deposits of crude oil, but it isn't necessarily able to produce and export crude oil for a profit (Bouchentouf, 2015).

Crude oil is literally a fossil fuel — a fuel derived from fossils (Bouchentouf, 2015). Alternative energy sources are substitutes for crude oil or petroleum products and are not made from fossil fuels. The most popular bio-fuels are ethanol and biodiesel. Ethanol is currently made from both sugarcane and corn. Biodiesel is produced from vegetable oils such as soybean oil, canola oil, or palm oil. Other alternative sources such as wind power, solar energy, wave power, nuclear energy, and methane hydrates can also be considered partial substitutes for crude oil products. While some of these alternative sources of energy have been around for some time and others are still being tested for real world application, the global marketplace continues to search for energy sources to compete and possibly take the place of nonrenewable crude oil (Dunsby, et al., 2008).

Oil producers are classified according to two groupings. The first and most famous of these is the Organization of Petroleum Exporting Countries (OPEC). OPEC members hold the majority of the spare oil production capacity in the world and use it to change their production levels dependent on both prices and demand for crude oil. The 12 member states are Algeria, Angola, Indonesia, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, the United Arab Emirates, and Venezuela. The other producer group is non-OPEC, which consists of all oil producers that are not members of OPEC. By 1980 the rest of the world had surpassed OPEC in oil production. The major characteristic of non-OPEC producers is that the large majority of them are net oil importers. Most of the non-OPEC oil production is run by private oil companies, with the notable exception of Mexico. In addition, production costs tend to be higher for non-OPEC countries than for OPEC countries, making them more vulnerable to price collapses. OPEC is important to the world because as a whole those countries have the most spare production capacity available. Since OPEC institutes production quotas for its members, production tends to run below total capacity. This enables OPEC to react to changes in the global oil market quickly. Unexpected increases in demand that raise the price of oil can be met by increases in the OPEC production quota. If there is a long-term supply loss from a non-OPEC country, OPEC is able to use spare capacity to make up this shortfall if necessary. This ability makes OPEC the swing producer in the global oil market, and at times the market is at the whim of OPEC's decisions (Dunsby, et al., 2008). OPEC still yield tremendous power and can have a major impact on the price of crude oil (Taulli, 2011).

Oil is used in a variety of applications. It can be burned to power a car, generate electricity, or heat a home. It also can be used as a raw material to create plastics, petrochemicals, and many other products (Dunsby, et al., 2008). Oil still dominates as a source of commercial energy. Energy accounts for the bulk of crude oil consumption, of which transport and power generation are the largest. Non-energy uses of oil, mainly feedstock for plastics, synthetic fibres and rubber, account for less than 10% of demand. Transport accounts for around half of the oil consumed globally, with industry (including manufacturing, agriculture, mining and construction) accounting for approximately one-third. Household and commercial uses account for the remainder. Despite the rise in consumption of biofuels and compressed natural gas, petroleum products remain dominant in the transport industry (Bain, 2013). Crude oil is the most traded nonfinancial commodity in the world today, and it supplies 40 percent of the world's total energy needs — more than any other single commodity. Despite many calls to shift energy consumption toward more renewable energy sources, the crude reality is that petroleum products are still the dominant resource worldwide. Crude oil's importance also stems from the fact that it's the base product for a number of indispensable goods, including gasoline, jet fuel, and plastics. Oil is truly the lifeblood of the global economy (Bouchentouf, 2015).

Globally the largest consumers of oil have traditionally been industrialized countries such as the United States, England, Germany, and Japan. Asia Pacific region has had a large expansion in demand during the past 20 years. A large portion of this demand increase in Asia has come from China. China, South Korea, and India have shown huge increases in demand for oil whereas industrialized countries such as Germany and France have actually exhibited a decline in oil demand. This is partly because the industrialized countries are using energy more efficiently than the emerging economies. In addition, manufacturing has been moving out of countries such as the United States and Germany and into China and South Korea. As these emerging economies such as China, India, and Brazil continue their growth, their consumption of oil will continue to increase. It is not unreasonable to suppose that these countries may have a growth pattern similar to that of the United States after the Great Depression. Although China and India are the most populous countries in the world, their global share of oil consumption is extremely small. As their economies grow and consumption increases, demand for energy is sure to grow as well. This will create competition for oil imports between the industrialized countries and these emerging economies (Dunsby, et al., 2008). The United States and China are currently the biggest consumers of crude oil in the world, and this trend will continue throughout the 21st century (Bouchentouf, 2015). Although global consumption figures might remain within a tight trading band, the consumer profile is likely to change. Specifically, you can expect oil consumption in OECD and developed countries to remain stagnant — and, in some cases, experience a decrease — and consumption in emerging market nations to increase (Bouchentouf, 2015). Typically, oil consumption follows the path of GDP growth (Bain, 2013).

Crude oil is the undisputed heavyweight champion in the commodities world. More barrels of crude oil are traded every single day than any other commodity (Bouchentouf, 2015).

There is more international trade in oil than in any other commodity, in both volume and value, and oil exports account for around 60% of production. Crude oil still predominates, but trade in products is rising. Most oil is transported by sea (via tankers) or overland through pipelines (Bain, 2013). Physical barrels of products or crude can be traded on a fixed price basis, but are typically traded and priced off a series of price quotes established during a date range relevant to the time of loading or delivery. The actual price quotations that are used are defined at the time of the physical or paper (such as swaps) transaction (Taylor, 2013). Countries that export crude oil have seen their current account surpluses reach record highs. These windfall profits are having a tremendous effect on the economies of such countries (Bouchentouf, 2015).

The NYMEX WTI crude oil contract is arguably the most important commodity contract listed today, and it makes up a large part of the S&P GSCI Index, the most widely followed commodity index. The Chicago Board of Trade was formed in 1848, but crude oil futures were not introduced until 1983. It is arguably with the introduction of crude oil futures that the modern age of commodity investing began. Both of the two most liquid futures contracts on crude oil are those of the light sweet variety. The first one is West Texas Intermediate (WTI), traded on the New York Mercantile Exchange (NYMEX). WTI crude oil is produced in the United States and is of very high quality, making it ideal for refining into gasoline. The second contract is Brent crude oil, which is traded on the Intercontinental Exchange (ICE). Both WTI crude oil and Brent futures, traded on the NYMEX, were launched in March, 1983 (Dunsby, et al., 2008) and they are also traded in London on ICE Futures Europe (Bain, 2013). The WTI is a light, sweet crude, preferred by refiners due to its low sulfur content. Most of the world's supply is sour (high-sulfur) crude, but because the sulfur content varies widely, the contract based on WTI is one of the two pace setters for world oil prices in general (Kleinman, 2013). Oil futures were traded in the past on open outcry exchanges. When the International Petroleum Exchange (IPE) was acquired by ICE in 2005, the London trading floor was closed down and all the volume was transferred onto screen-based trading via the ICE platform. The last bastion of open outcry trading for the oil markets, but the reality is that the success of the screen-based ICE platform forced NYMEX to follow suit. This is the main benchmark in the Americas. Unlike Brent, WTI has real physical deliverability (not just linked to an underlying physical contract) with the delivery point in Cushing, Oklahoma (Taylor, 2013). Traditionally, WTI traded at a small premium to Brent, but in 2009 this relationship reversed (Bain, 2013). The futures markets are particularly sensitive to daily crude oil production numbers, and any event that takes crude off the market can have a sudden impact on crude futures contracts (Bouchentouf, 2015). There are also enormous international traded markets for finished products (Taylor, 2013).

As mentioned previously, the various prices of crude oil and oil products are set on the international exchanges. This effectively sets what is known as the ‘flat price’. The oil markets are typically traded as a series of curves across the various crudes and products linked by differentials to each other. The oil products curves move in much the same way as and at fluctuating levels to the crude oil contracts. Oil is driven as much by politics as it is by fundamentals and by regulation as much as it is by speculation. Oil markets are essentially very ‘mature’ nowadays, with the price highly defined and tracked every second of the day all around the world (Taylor, 2013). Spot and futures markets exist in the principal crudes traded internationally. Because oil comes in a changing variety of types, no single crude can be taken as fully representative of the market price (Bain, 2013).

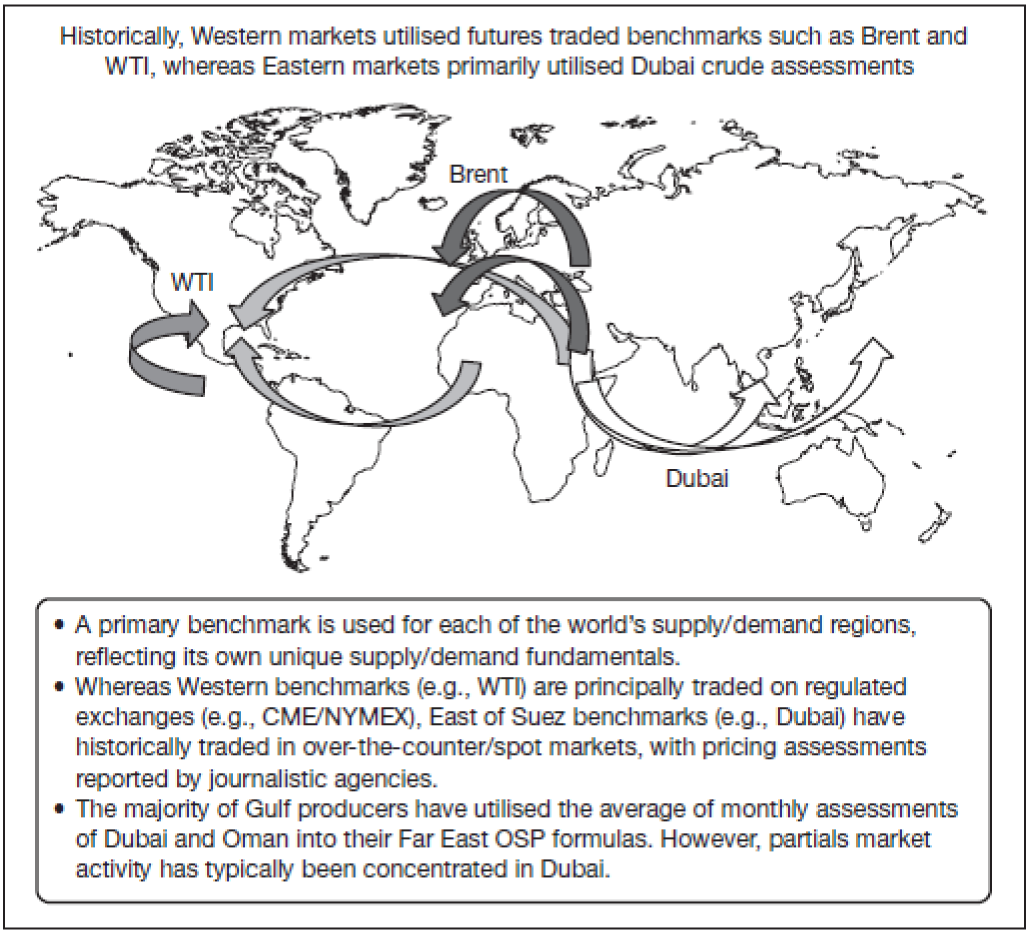
A growing problem is a mismatch between the nature of refining capacity and the sort of crude oil available, due to supply inconsistency. Unforeseen disruptions to supply in recent years include adverse weather, civil and labour unrest, politically motivated sanctions, accidents and unanticipated maintenance. Seasonal demand swings influence the supply/demand balance and the price of oil. Normally, prices increase in the fourth quarter when demand is boosted by stock-building for the northern hemisphere winter months, and decrease in the spring months when space-heating demand falls. However, this is slowly changing as emerging-world consumption increases. Oil projects are becoming increasingly complex and are subject to delay. Costs are also much higher and some projects face environmental obstacles or technological constraints. Transport needs will determine long-term demand, as there are substitutes for oil in almost all its other uses. If a cost-effective, easily accessible alternative to running cars on oil is found, global oil prices would collapse (Bain, 2013).

Brent Oil

Brent crude oil consists of a variety of crudes produced from the North Sea and includes Brent Crude, Oseberg, and Forties. It is not as light or sweet as WTI but it is ideal for the production of gasoline and distillates. The name Brent is taken from the Brent goose, but it is also an acronym for the formation layers (Broom, Rannoch, Etieve, Ness, and Tarbat) of the Brent oil field (Dunsby, et al., 2008). Brent Crude is also liquid and active, based on the European North

Sea variety but a benchmark for much of the oil traded in Europe and Asia. The dominant benchmarks for crudes are Brent Blend (North Sea crudes, seaborne oil) (Kleinman, 2013).

Brent oil future listed on the ICE (Dunsby, et al., 2008), which trades an active Brent Crude Oil, contract (Kleinman, 2013). Brent has myriad jargon and names that follow it. The futures contract is now simply referred to as ICE Brent but the underlying contract is actually called 'BOFE', an acronym for a basket of crude oils that are deliverable into the physical contract. These are Brent, Oseberg, Forties and Ekofisk. This provides the main benchmark for crude oil delivered within Europe, for crude exported from West Africa and for Arabian Gulf deliveries to Europe. It is also used widely now for sweet crude oil produced in Asia (Taylor, 2013). Brent is currently used as the basis for the pricing of nearly 70% of the global trade in oil (Kleinman, 2013).



Source: Dubai Mercantile Exchange

Figure 16: Benchmark crudes and where they are used

Gasoline

Gasoline has become a topic of conversation and is a commodity that many people are constantly aware of. Yet, it is also the most complicated of all the energy commodities (Dunsby, et al., 2008). Unleaded gasoline is a complicated mixture, which relies primarily on crude oil (Taulli, 2011). Gasoline is the main product produced from refining crude oil. When a barrel of crude oil is refined, it produces about 20 gallons of gasoline, a yield of 47 percent (Dunsby, et al., 2008).

Because summer is the heavy driving season, there's an increase in demand for gasoline products. Thus, all things equal, unleaded gasoline tends to increase in price during the summer (Bouchentouf, 2015). During the summer, refineries are often close to maxing out their capacity due to the strong demand for gasoline. This results in little open refining capacity in the summer; therefore, unplanned refinery outages due to fire or other mechanical issues can create quite a stir in the gasoline markets. Refinery outages in the summer cut into gasoline production expectations, so price rises in order to entice other refineries to increase gasoline production. This rise in price also acts to attract additional imports and to curb gasoline demand. Since refining capacity growth has not increased as fast as gasoline demand, both imports and storage help meet the production shortfall that occurs during the summer months. Gasoline imports can come in the form of finished gasoline or blending components which are then combined to make finished gasoline. During the winter when it is cold and snow is building up, gasoline demand decreases. This allows refiners to build up storage. Once the winter maintenance season ends, usually in February or March, gasoline production is increased to build supplies up in anticipation of the summer demand period. Throughout the summer, storage decreases as gasoline demand exceeds production and imports. Gasoline storage typically hits its lows for the year coming out of the summer demand season and from the refinery maintenance that occurs in October and November. Gasoline demand rises over the summer vacation period, with peak demand occurring in the months of July and August. The lowest demand for gasoline occurs in the winter, usually during the month of February. Weather affects demand in the gasoline market to some extent, but not to the degree that it does so for heating oil (Dunsby, et al., 2008).

Gasoline is facing competition from many other fuels. The main alternative transportation fuel is a form of fuel ethanol. Ethanol, also known as grain alcohol or ethyl alcohol, is an alcohol-based fuel made from the simple sugars of various crops. Globally, ethanol is primarily made from sugarcane or corn, although it can be made from wheat, sorghum, and other starch crops. Fuel ethanol has been around for a long time. Today the largest use of ethanol is as a fuel and fuel additive. The common ethanol gasoline mixture consists of 10 percent ethanol and 90 percent gasoline, called E10. This is the current fuel available in major metropolitan areas. Fuel ethanol contains more than a third less energy content per gallon than conventional gasoline, resulting in fewer miles per gallon for fuel ethanol. So blending approximately 10 percent ethanol with gasoline will result in higher overall demand, because a full tank of gasoline will now contain less energy than it did before ethanol was added to the gasoline pool (Dunsby, et al., 2008).

Unleaded gasoline is traded at CME. Futures prices for unleaded gasoline might appear to be too cheap when compared to the pump price, but they are based on the wholesale price for delivery at New York Harbor. The price you pay at the pump has all those costs added to get it to the station, including local and national taxes (Kleinman, 2013). The demand for gasoline isn't absolutely inelastic, however — you won't keep paying for it regardless of the price. A point will come at which you'd decide that it's simply not worth it to keep paying the amount you're paying at the pump, so you'd begin looking for alternatives. But the truth remains that you're willing to pay more for gasoline than for other products you don't need (Bouchentouf, 2015). The higher price is caused by both the strong demand for gasoline and the high cost of production. Of all the finished products made from crude oil, demand for gasoline is the highest. In addition, the processing costs are higher since gasoline is one of the lightest products and it requires further refining and additives to meet various requirements. The peak demand for gasoline occurs during the summer months of July and August. Other large price increases for gasoline can occur during April and May if gasoline stocks are low for that time of year. This is necessary to increase the profit margin and entice refiners to produce as much gasoline as possible in order to build stocks before the summer demand season begins (Dunsby, et al., 2008).

Unleaded gasoline is by far the most important product, accounting for almost half of the yield from a barrel of crude (Kleinman, 2013). Due to the close relationship between unleaded gasoline and crude oil, the prices often follow each other. But there are times when there are divergences, especially during events like hurricanes. For example, there may be a large amount of crude oil on the market yet a major storm could disrupt refineries and distribution systems. So as crude oil prices fall, unleaded gasoline prices will do the opposite (Taulli, 2011). Prices of products in the petroleum complex are highly correlated. Although the correlation is not perfect, the prices of these products generally do move together. There are risks on the supply side from slow increases in refining capacity and further specification changes. Unless there are major changes made to refining capacity, public transportation, or a cheaper alternative fuel is discovered, gasoline prices are likely to rise over time (Dunsby, et al., 2008).

Heating Oil

Heating oil is one of the many products produced from refining crude oil. It is classified as a distillate along with diesel, jet fuel, and kerosene. All of the distillates have a similar chemical make-up, and in some areas heating oil is the same product as diesel fuel with the exception of a few additives. When refined, one barrel (42 gallons) of crude oil produces approximately 10 gallons of diesel and heating oil along with 4 gallons of jet fuel. Slightly higher yields of these distillates may be possible through further refining or use of different crude oil grades (Dunsby, et al., 2008). Heating oil—also called oil heat—is flammable petroleum that has low viscosity. The primary uses include energy for furnaces, much of it for homes. Heating oil is stored in tanks, which are typically in basements or garages. Much of the demand is from October to March (Taulli, 2011).

Heating oil is used to heat both residential homes and commercial buildings and is very safe to use for heating. Since heating oil is used as a heating fuel, it is highly dependent on the winter weather. A warm or above-average winter would result in lower than normal seasonal demand for heating oil. In the other case, an extremely cold winter can cause a spike in both the demand and the price of heating oil. Traders in the heating oil market are very focused on both short-term and long-term forecasts for winter weather. Because heating oil is considered a middle distillate along with diesel, jet fuel, and kerosene, the demand factors for these other products are also important. For example, strong demand for diesel may pull supply away from the heating oil market as refiners focus on yielding more diesel fuel from their distillates pool. Both jet fuel and kerosene are the lesser known distillates, but each can have an impact on the supply and price of heating oil (Dunsby, et al., 2008).

Heating oil can also be used as a substitute for natural gas in power generation. Some power plants have the ability to burn either natural gas or heating oil to generate power. Plant managers will make this decision based on which fuel is cheaper for them to burn and still generate the same amount of electricity. Natural gas is almost always the cheaper fuel, but in the past heating oil has been cheaper for short periods of time when natural gas prices spike due to short supply or high demand. Another possible substitute for heating oil and diesel is biodiesel or bioheat. Biodiesel is fuel created using biological sources; in this case vegetable oils such as palm oil, canola oil, and soybean oil are used. The biodiesel can be used in pure form or blended with regular diesel to achieve a fuel mix (Dunsby, et al., 2008).

Heating oil futures trade on the New York Mercantile Exchange (NYMEX) and heating oil was the first successful energy contract on the exchange (Dunsby, et al., 2008). For many years, the NYMEX heating oil contract was the second-most liquid energy contract, although in recent years, it has been overshadowed by natural gas. It is also known as the number-two fuel oil and accounts for about 25% of the yield of a barrel of crude (Kleinman, 2013). Heating oil is also traded on the CME (Taulli, 2011). Heating oil price volatility does increase during the winter months. These price spikes all occur during the winter months in conjunction with extreme cold weather (Dunsby, et al., 2008).

In the future heating, oil prices will have a closer relationship with its substitutes, such as natural gas, as price will continue to create competition between the fuels in some sectors. Heating oil prices will continue to be volatile in the winter months. Demand for both diesel and jet fuel will grow globally with the need to transport both goods and people. Supply issues such as refining capacity must be addressed in order to produce enough distillate to meet demand over the long term. Overall, prices will continue to be correlated with both crude oil and gasoline. In the longer-term, higher prices should prevail to attract companies to invest in future refinery and pipeline infrastructure to increase supply of refined products.

Natural Gas

Natural gas is a nonrenewable fossil fuel found in large deposits within the earth. In fact, natural gas is sometimes found not too far away from crude oil deposits (Bouchentouf, 2015). Natural gas is hydrocarbon gas and it is found in underground rock beds or with other hydrocarbons (oil and coal deposits). Natural gas was formed during the same process that created petroleum. Plant and animal remains from millions of years ago formed organic material. Over time this organic material was trapped under rock and exposed to pressure and heat. The pressure and high temperatures changed the organic material into petroleum, coal, and natural gas. At low temperatures more oil was formed than natural gas, and at high temperatures more natural gas was formed. It is composed primarily of methane (Dunsby, et al., 2008) and is found alongside fossil fuels and coal beds. As a source of energy, natural gas has many advantages. It is cheaper than crude oil and it is environmentally friendly. Consider that a natural gas plant will generate about half the amount of carbon emissions than a coal plant (Taulli, 2011). Historically, gas was not considered commercially viable and the gas produced by oil drilling was just burnt off or flared. By the 1970s, it was recognised that gas was a viable commodity in its own right, and "associated" (with oil) gas is now transported from oil wells by pipeline. Non-associated gas is derived from pure natural gas fields, and coal bed methane is extracted from coal-bearing rock formations (Bain, 2013).

The purest form of natural gas is almost pure methane, which is called dry natural gas (Dunsby, et al., 2008). When other hydrocarbons are present at a level of over 10 per cent, the natural gas is 'wet' (Taylor, 2013). Natural gas has a long history, although techniques to capture, process, and utilize it are more recent. Like crude oil, natural gas is produced by drilling for a gas deposit and extracting the natural gas through a well. Natural gas produced through the basic drilling and well system is known as conventional natural gas because it is easy, feasible, and economic to produce. Natural gas can be found in deposits that contain gas and oil, gas and coal, or just gas. Deposits that contain gas and oil have the natural gas on the top since it is lighter. After production, natural gas goes through a processing plant, where it is cleaned and brought to pipeline quality specifications. The natural gas that is produced directly underground is not the same form of natural gas that is used by the consumer. Pipelines require natural gas of a specific quality in order to operate properly (Dunsby, et al., 2008). Gas must be processed following extraction to remove impurities. The byproducts of the extraction process – ethane, propane and butane – are then viable for commercial sale in their own right (Bain, 2013).

Unconventional natural gas is much harder and more costly to produce than conventional gas. It may also use technological methods that are not fully developed. As these technologies become more advanced and the price received for natural gas production increases, then what is unconventional gas today may be considered conventional gas in the future (Dunsby, et al., 2008). As the technology has become available, gas has started to be extracted from less accessible rock formations. These "unconventional" gases include tight gas, which is extracted from low-permeability rock formations, and shale gas, which is extracted from shale formations. These gases cost more to extract because of the advanced technology used and the amount of energy involved (Bain, 2013). Shale is a rock; a very fine grained, organic-rich, sedimentary rock. Geologists have known for years that natural gas may be found in shale rock but until a short time ago it could not be cost-effectively extracted (Taylor, 2013).

Natural gas, oil and coal resources are known as finite or non-renewable, given the millions of years required for their formation (Taylor, 2013). Natural gas reserves are a supply of natural gas held underground. Unfortunately, unlike crude oil, there is no reliable data for total (proven and unproven) recoverable global natural gas reserves. Further exploration for global natural gas reserves and technological advances in production of unconventional sources are likely to increase the total reserve base in the coming years. This increase is likely to lead to an increase in price also. The costs of research, new technology, and exploration continue to rise. If the prices paid to producers do not increase with these costs, production will be shut in when it becomes unprofitable and exploration will stop (Dunsby, et al., 2008).

A few large producers dominate gas production (Bain, 2013). The US and countries of the former Soviet Union are currently the largest producers of natural gas. Other major global producers include Canada, Iran, Norway, Qatar, China, Algeria, Saudi Arabia and Indonesia. The Middle East holds 41 per cent of world reserves, while an additional 34 per cent is located in the former Soviet Union, with only 9 per cent held in the OECD countries (Taylor, 2013). Russia has the world's largest reserves, followed by Iran, Qatar and Turkmenistan. Other countries with large reserves include oil-producing countries in the Middle East and Africa (Saudi Arabia, Iraq, the United Arab Emirates, Algeria and Nigeria) and Australia (Bain, 2013). There have been various attempts, led by Russia and Iran, to create an OPEC-style gas organisation, and Qatar, Venezuela, Nigeria, Libya, Indonesia, Egypt and Algeria have taken part in periodic discussions with them about the gas market. However, an organisation that can influence prices by co-ordinated changes in output does not seem feasible with the dislocation in global gas markets (Bain, 2013).

Natural gas as an energy source is used in a variety of ways. It can heat homes and businesses, generate electricity, cook food, or serve as an industrial fuel or heat source (Dunsby, et al., 2008). In terms of percentage of total consumption, the residential, commercial, and transportation sectors have been largely unchanged. The industrial sector decline occurred at the same time that prices of natural gas increased. Natural gas costs became too high to sustain profitability, and some industrial plants (such as in the aluminum smelter industry) were mothballed as a result. The electrical generation increase occurred as new generation plants fueled by natural gas came online and replaced older plants fueled by oil and other fossil fuels. Natural gas use in generation has grown as the fuel is considered environmentally friendly and has a high heat content, which is important when determining the heat rate of a power plant (Dunsby, et al., 2008). Of all the natural gas that is produced, industry (including utilities) uses about two-thirds, and homeowners use one-fourth (Kleinman, 2013). Gas is increasingly the fuel of choice to supply electricity, provide heating and cooling, and support economic growth. Now it is used mostly for heating and cooking although some gas is used to power gas and steam turbines for electricity generation in preference to coal (Taylor, 2013). The electricity-generating industry is by far the largest consumer of gas, followed by buildings (where gas is used to power boilers generating hot water and space heating, primarily in the OECD) and industry (metal refining, petrochemicals, iron and steel). Gas now accounts for just over 20% of the feedstock for power generation globally. There is growing consumption in the transport industry, but this accounts for only a tiny proportion of total consumption (Bain, 2013). It's not a widely known fact, but natural gas is used in a number of vehicles as a source of fuel. These vehicles, known simply as natural gas vehicles (NGV), run on a grade of natural gas called compressed natural gas (CNG). This usage accounts for only about 5 percent of total natural gas consumption, but demand for NGV may increase as a viable (cheaper) alternative to gasoline (a crude oil derivative). The primary consumers of this commodity are the industrial sector, commercial interests, residential elements, transportation, and electricity generation. The industrial sector is the largest consumer of natural gas, accounting for almost 40 percent of total consumption. Although industrial uses of natural gas have always played a major role in the sector, their significance has increased during the last several years and will continue to do so. Residential use accounts for almost a quarter of total natural gas consumption. The use of natural gas for cooking purposes has steadily increased as technological developments have allowed for an efficient and safe use of natural gas. About 40 percent of the energy consumed by commercial users, such as hospitals and schools, comes from natural gas, accounting for about 15 percent of total natural gas consumption. Because commercial users include establishments such as schools, hospitals, restaurants, movie theatres, malls, and office buildings, demand for natural gas from these key drivers of the economy rises during times of increasing economic activity (Bouchentouf, 2015).

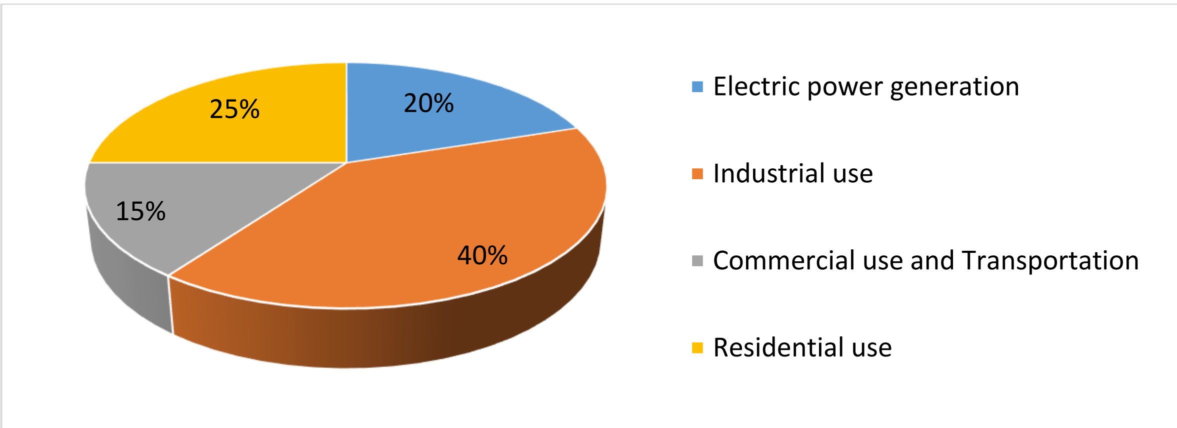


Figure 17: Natural gas consumption

Since natural gas and oil are both hydrocarbons, it is reasonable to suppose that they may be substitutes within some sectors. In homes and businesses, heating equipment is able to burn heating oil or natural gas as fuel, but not both. Homeowners cannot just flip a switch on the burner depending on which fuel is cheaper to burn. One sector in which fuel switching does occur is electrical generation. Dual-fuel generators allow utilities to choose between an oil-based fuel (such as residual fuel oil, kerosene, or heating oil) and natural gas. Heating oil is priced under natural gas a few times during the winter when natural gas prices spiked due to heating demand. It is during these times that utilities may find it more profitable to burn heating oil in their dual-fuel power plants if they are able to switch. Keep in mind that utilities have other factors to consider when determining the economics of switching. These include the cost to switch the plant to a different fuel, taxes, and cost of extra emissions produced by burning a dirtier fuel. Utilities will not switch fuels if it is beneficial for just a day. They will look at the cost of either fuel over a medium to longer time frame to determine which fuel is more beneficial (Dunsby, et al., 2008).

Historically the natural gas was released either intentionally or unintentionally during coal-mining activities. It was realized that this natural gas could be captured and either used to fuel mining activities or injected into a natural gas pipeline for resale (Dunsby, et al., 2008). Gas is not easy to transport and it was not until the 1960s when high strength steel pipelines were developed that gas could be transported over long distances. As a result, many countries did not develop the infrastructure to use natural gas (Taylor, 2013). As demand for natural gas increases, you need to be able to transport this precious commodity across vast distances (for example, across continents and through oceans). Transporting it is difficult to do when it’s in a gaseous state (Bouchentouf, 2015). Transportation of natural gas across the ocean on vessels is not a simple process (Dunsby, et al., 2008). Natural gas is frequently cooled for ease of transportation and storage (Taylor, 2013). In order to be transported, natural gas must go through a liquefaction process, creating liquefied natural gas (LNG). The liquefaction process reduces volume and allows it to be shipped efficiently across oceans (Dunsby, et al., 2008). Liquefaction takes place when natural gas is cooled under high pressure, condensed and then reduced in pressure for storage (Taylor, 2013). Liquefied natural gas (LNG) is a clear liquid that is created when natural gas is cooled to around −160°C. The volume shrinks hugely, making the gas easy to store and transport (Bain, 2013). Japan and South Korea together account for nearly half of all LNG imports (Taylor, 2013).

Natural gas futures are traded on NYMEX (now part of CME) and to a lesser extent on ICE (Taylor, 2013). The natural gas futures contract is the second-most popular energy contract on the CME, right behind crude oil (Bouchentouf, 2015). Gas is one of the few commodities for which there is no global benchmark price forming the basis of most international trade. This is partly because of the difficulty in transporting gas. Traditionally, long-term sales contracts would be signed between producer and consumer countries and a pipeline would then be constructed to fulfil these obligations. The price would be indexed through a formula (typically involving a time lag) based on international oil prices. It is not possible to generalise about gas prices in the way that is possible for many commodities. This is because of the differences in regional markets (Bain, 2013).

Demand peaks in the winter months of January and February because of strong demand for residential and commercial heating. It rises again in the summer months of July and August on electrical generation demand driven by air conditioner use. The one thing in common in these two cases is the weather. Winter weather drives demand for natural gas as a heating fuel, whereas summer weather drives demand for natural gas as a generation fuel. These changes in demand from month to month in turn affect the price. The seasonality of natural gas consumption is exhibited in the futures curve, where the highest-priced months of January and February are also the two months with the highest demand. Storage is used in the winter to meet the strong demand for natural gas, because during that time domestic production and imports fall short of demand. Natural gas storage has both a withdrawal and an injection season. Natural gas consumption is dominated by its use to heat residential and commercial buildings. This results in the need to withdraw natural gas from storage during peak demand in the winter and inject it into storage during the spring, summer, and fall months. The injection season occurs from April through October and is associated with the non-heating season. The withdrawal period occurs between November and March during the heating season (Dunsby, et al., 2008). In the short run, the price of natural gas is heavily impacted by the weather (Taulli, 2011). Natural gas price volatility has been very exciting in the twenty-first century. As discussed previously, the use of natural gas as a heating fuel and to power air conditioners through electrical generation makes demand reliant on weather patterns. Many of the price spikes are the result of below-average winter temperatures in the natural gas consuming areas (Dunsby, et al., 2008). The long-term trend is that more natural gas will be required to generate electricity. This increased demand from a critical sector will keep upward pressures on natural gas prices over the long term (Bouchentouf, 2015).

The future of natural gas looks bright. On the demand side, increased need for cleaner-burning fuel will help feed demand, along with strong growth in many emerging economies (Dunsby, et al., 2008). Natural gas burns cleanly and produces 30 per cent less carbon dioxide than oil and 40 per cent less than coal (Taylor, 2013). The carbon emissions associated with the combustion of gas are lower than for coal or oil, so gas is perceived to play a major role in efforts to control (and reduce) such emissions globally. The energy policies of large economies will determine the future for gas. It remains to be seen whether governments take measures to reduce carbon emissions which would favour gas relative to other hydrocarbons. The promotion of renewable energy would also benefit gas, as it is perceived to be the best alternative fuel to act as a back-up power source in periods of low generation by renewables (Bain, 2013). Also, increased industrial demand should put upward price pressures on natural gas. Transportation sector is a really important industry to be watched for technological developments. If natural gas grabbed a slice of the transportation market, which now accounts for almost two-thirds of crude oil consumption, prices for natural gas could increase dramatically (Bouchentouf, 2015). Further exploration and production will continue as strong global demand from electrical generation and industrial sectors will support prices. Compared with oil, the natural gas market is still in its infancy. Many questions must be answered regarding the supply side of the market, specifically the amount of global reserves available. It will continue to be essential to watch how the prices of natural gas and its fossil fuel substitutes, oil and coal interact (Dunsby, et al., 2008). Although there is no shortage of untapped gas reserves, many of these reserves will be expensive to tap, given the increasing complexity of extraction. This has implications for long-term supply and prices. Unconventional gas production is expected to continue to increase its share of global production (Bain, 2013).

4.3 Agriculture

Agricultural commodities are the primary commodities in the world that derive from the cultivation of land. They can be classified in three categories, grains, softs and livestock. The grains complex consists of corn, wheat, soybeans, soybean oil, soybean meal, rice and oats and are used as basic food source for humans and animals. The softs complex consists of coffee cotton, sugar, cocoa, lumber that has a softer nature. Finally, the livestock commodities are feeder cattle, live cattle and lean hogs, which are the meats.

GRAINS

Corn

Corn is a unique grain with no close counterpart in the plant world. The origins of corn remain controversial. There is no historical evidence of wild corn as we know it today. It is not able to survive in the wild, as it has no way of distributing its seeds, or kernels. It must be planted and cultivated each year by humans in order to produce a crop (Dunsby, et al., 2008). Corn is an important food source for both humans and animals and, unlike other grains, can be grown in a wide variety of climates and conditions, making it an important cash crop. Beyond feedstock, corn has other important applications and is processed into starches, corn oil, and even fuel ethanol (Bouchentouf, 2015).

Corn production is not smooth from year to year. Corn production depends on two things—acreage harvested and yield per acre. The number of acres harvested is a function of the amount initially planted. Some planted acreage may not be harvested due to poor performance of the crop, pest infestation, or extreme weather events that would destroy the crop. Crop yield is the main driver of production, and it is dependent on weather during the critical tasseling and pollination stages. The yield is upward sloping as a result of technological advances in farm machinery, fertilizer, and genetically modified seed, among other things. It is noticeable that yield from year to year can be extremely volatile. The volatility in yield occurs because the crop is vulnerable to stress during the tasseling and pollination stages. Yield changes greater than ±10 percent from one year to the next are not uncommon (Dunsby, et al., 2008). Weather has a major impact on corn, especially during June and July. If the weather is severe, then there will likely be a spike in corn prices. However, prices will likely hit their lows in the fall because of the harvest (Taulli, 2011).

In the grain market, the supply comes all at harvest whereas demand is spread throughout the year. This creates supply in excess of immediate consumption. That’s why storage is an extremely important concern in the grain markets. Grains are largely stored in grain elevators located near major rivers and ports for shipping. A series of bins, tanks, or silos that are able to store grain in bulk and then empty it into trucks, barges, or railcars for shipment to end users (Dunsby, et al., 2008).

Corn is grown in more countries than any other crop and on all continents except Antarctica. It can thrive in many climates (Dunsby, et al., 2008). Approximately 35 million hectares of land are used exclusively for the production of corn worldwide, a business that the

U.S. Department of Agriculture values at more than $20 billion a year (Bouchentouf, 2015). Worldwide production of corn is dominated by the United States. The next largest producer of corn is China, while European Union and Brazil follow (Dunsby, et al., 2008). Historically, the United States has dominated the corn markets — and still does, thanks to abundant land and helpful governmental subsidies. China is also a major player and exhibits potential for becoming a market leader in the future. Other notable producers include Mexico, and India (Bouchentouf, 2015).

Corn started as a primary food source for humans, but today it's mainly used as animal feed. As livestock feed, corn is important for its high-energy value (Dunsby, et al., 2008). Corn is the predominant carbohydrate source used for animal feed (Kleinman, 2013). The key reason is that corn has a high starch content (Taulli, 2011). Corn is also utilized in starch form in consumer and industrial products. Paper products, adhesives, and thickening agents are just a few of the ways we use corn starch (Dunsby, et al., 2008). Corn's use for culinary purposes is perhaps unrivaled by any other grain, which makes this a potentially lucrative investment (Bouchentouf, 2015). We consume corn as food in kernel form and in products such as corn flakes, tortillas, and popcorn. Corn also yields other products such as vegetable oil and high fructose corn syrup (Dunsby, et al., 2008). Besides being a food for people and animals, corn is also used for the fuel known as ethanol (Taulli, 2011). Corn has been grabbing headlines since 2005 for its use as a fuel in the form of ethanol. Ethanol is an alcohol-based fuel made from the simple sugars and starches of various crops (Dunsby, et al., 2008). Around 40 per cent of all US corn production is now used as inputs for the refining of biofuel (Taylor, 2013). This versatility makes it one of the most important crops in the world (Dunsby, et al., 2008).

Not only is the United States the largest worldwide producer of corn, it is also the largest exporter of corn. Japan is by far the largest importer of corn followed by South Korea. Both countries do not produce many coarse grains. However, because they are large meat producers, it is necessary to import corn for feed use. Both Argentina and South Africa are large exporters of corn. Worldwide corn consumption is highest in the United States and is followed by China, the European Union, Brazil, and Mexico. Demand for corn is dominated by its use in livestock feed for animals such as cattle, hogs, and poultry (Dunsby, et al., 2008).

Different corn futures trade in many different countries. The most liquid corn future trades on the Chicago Board of Trade (CBOT) (Dunsby, et al., 2008) and comes nearest to representing a global benchmark, but there are many other regional and national exchanges, in China and Latin America in particular. It is also traded on the London-based Euronext-LIFFE (Bain, 2013). The most direct way of investing in corn is to go through the futures markets. A corn contract, courtesy of the Chicago Mercantile Exchange (CME), helps farmers, consumers, and investors manage and profit from the underlying market opportunities. Corn futures contracts are usually measured in bushels (as with the corn contract the CME offers). Large-scale corn production and consumption is measured in metric tons (Bouchentouf, 2015).

Corn is subject to seasonal and cyclical factors that have a direct, and often powerful, effect on prices (Bouchentouf, 2015). From September to November, corn generally has a lower price because of the high amounts of corn on the market. Then from December to May, the prices tend to increase. In fact, this may continue throughout the summer. The reason is the potential for bad weather (Taulli, 2011). In some countries, the commodity is known as maize (Taulli, 2011). Maize prices are chiefly determined by the balance between American supply and demand (domestic and overseas), but they are also influenced by availability in Argentina and China. Low stocks and high prices will constrain consumption, with other grains being substituted for maize, particularly in animal feed (Bain, 2013). The corn market does compete with other grains for use in the feed sector. Other feed grains available to livestock producers are sorghum, barley, and oats. In addition, when corn is expensive as compared with wheat, livestock producers have the ability to feed wheat to their animals. Corn also competes with sugar for its use in the sweetener market, especially in soft drinks (Dunsby, et al., 2008). However, higher prices will encourage the planting of maize and consumption growth can be expected to resume strongly once stocks start to be rebuilt (Bain, 2013).

The future outlook for corn demand looks strong with increasing use of corn to make ethanol for fuel. The demand for corn from ethanol production will not change until additional and cheaper sources of ethanol are established. The two common stressors for agricultural plants are drought and heat (Dunsby, et al., 2008) that will constantly create more volatility (Kleinman, 2013). Another aspect that should be considered is the fact that corn needs more fuel and fertiliser than other crops and, as input costs rise or credit facilities disappear, farmers in many countries, especially in South America, may turn to other commodities (Bain, 2013). This will reduce the corn crop and eventually the entire supply, driving the prices up.

Rice

A member of the grass family, rice produces seeds that are used for human consumption (Bain, 2013). Rice is a grain that represents the main staple for billions of people in Asia, the Middle

East, and Latin America. Rice is the second-most produced grain, with the biggest being corn (Taulli, 2011).

Rice crops require a large amount of rainfall (Taulli, 2011). It is usually an annual crop, but in some countries (India, for example) a winter and a summer crop can be sown. It thrives in areas with heavy rainfall; the traditional method of cultivation involves flooding the fields with water (paddies), which helps to repel weeds and pests. There are many varieties of rice, but almost all are grown for human consumption, which accounts for about 90% of (milled) production. Some lower-quality rice and surpluses that cannot be marketed may be sold for animal feed (Bain, 2013). But there have been pressures on the rice supply because of droughts and flooding in areas where it is grown. Another supply constraint has been the surge in the prices of other grains, like corn and wheat. The result is that farmers have been pushing production of these commodities. This in turn has lowered the plantings of rice crops. The production of rice is labor-intensive. So production is most economical in low-wage countries, like Thailand and Vietnam. However, this makes rice subject to major governmental control and if there are key changes in policy, this could have a big impact on rice prices (Taulli, 2011). In advanced commercial farming, high yielding seeds and agrochemicals are used extensively and mechanization enables harvests to be swiftly and efficiently gathered. However, falling water tables and rising salinity may affect production in the future (Bain, 2013).

The Middle East is a major rice market that is growing as domestic production is limited by lack of water. Asia accounts for about 90% of global production, but output is increasing in Africa. The high priority given to agriculture by many Asian governments has encouraged private as well as public investment in rice farming, and the use of better cultivation techniques and improved varieties. Improved irrigation has reduced vulnerability to drought, although water is becoming scarcer in some producing areas. In Bangladesh, rice occupies three-quarters of the crop area. The United States is a high-quality rice producer and a major exporter (Bain, 2013).

The leading rice exporters are Thailand, Vietnam, India, Pakistan and the United States, but internationally traded rice accounts for only around 7% of total rice production a year. Most rice is transported in milled form, but this does not store well and has to be bagged for shipment. Freight and handling costs are accordingly higher than for wheat or corn, which are generally shipped in bulk. Indonesia’s needs sometimes dominate the international rice market. The Philippines is another important player in global trade China’s imports are almost entirely high-quality fragrant grades, sourced exclusively from Thailand. Perhaps more important for the rice market and international prices are the stocks held in the main exporting countries (Bain, 2013).

Rice is culturally important in South and East Asia, and food habits are slow to change, especially in rural areas. However, in more developed Asian countries, such as Japan and South Korea, rice consumption per head is steadily declining. In many developing countries outside Asia, where the grain is not a traditional staple food, consumption is growing in line with rising incomes and the availability of improved varieties. China typically accounts for about 30% of global rice consumption. Rice is the staple food in rural Bangladesh but is giving way to wheat in urban areas. India is the second largest rice-consuming country. Demand is increasing as the population grows, but consumption varies widely. In recent years population growth has been offsetting the impact of declining consumption per head as diets diversify. Rising disposable incomes have increased demand for high quality non-indigenous varieties such as fragrant rice. (Bain, 2013).

Investors can trade futures on rough rice on the CME. Rough rice is rice that comes after a harvest (Taulli, 2011). Rice futures are traded on the Chicago Board of Trade, and there are important exchanges in Thailand, Vietnam and Pakistan (Bain, 2013).

Rice is politically sensitive in much of Asia, and in many countries rice farmers and consumers are a major political force. Accordingly, governments are alert to price fluctuations and are active players in procurement for domestic consumption or export. They are also quick to impose trade restrictions if there are concerns about supply or prices. Limited production prospects in the Middle East and a growing market will lead to higher imports. Middle Eastern countries concerned about supplies are also starting to invest in farmland in a number of countries in Africa and Asia. Consumption per head will continue to decline in parts of Asia, especially in China, Japan and South Korea, as diets diversify to include greater quantities of meat and other convenience (wheat-based) foods (Bain, 2013).

Soybeans – Soybean oil – Soybean meal

Soybeans are part of the oilseed family of legumes. Oilseeds are crops that are grown mainly for their vegetable oil and protein meal content. Within the oilseeds complex, soybeans are the most important in terms of world production and trade (Dunsby, et al., 2008). Soybeans are a species of legume (others include peas, beans, lentils, alfalfa, and so on), originally from East Asia; it is only in the past couple of centuries that they were introduced in other parts of the world. Historically, soybeans have been grown in temperate parts of the world, typically with hot summers, but now they are cultivated in tropical and subtropical parts of the world, particularly India. Aside from being able to sell the beans for consumption, soybean crops improve soil fertility by adding nitrogen from the atmosphere. The plant has an edible bean that is valued for its nutritional qualities; it is one of the few plants that can provide a complete protein (Bain, 2013). Soybeans have been cultivated for centuries, starting in Asia. Soybeans are a vital crop for the world economy, used in everything from producing poultry feedstock to creating vegetable oil (Bouchentouf, 2015).

Soybean production is cyclical (Bouchentouf, 2015). Soybeans are often grown in rotation with corn. There is a close relationship between the two, with farmers often deciding to expand one crop or another in a particular year based on their relative prices (Bain, 2013). Within the soy complex there are two separate production stages. The first stage is the production of soybeans (Dunsby, et al., 2008). The most critical time for the soybeans crop is during pollination, or the fertilization phase, which comes in July. If there is adverse weather, it could reduce the crop (Taulli, 2011). Once the crop has been harvested, the soybeans are exported, sent to a local processor or used directly for human consumption (Bain, 2013). The second stage of production occurs when the soybeans are processed into soymeal and bean oil. Soybeans are a raw product that must be processed to create protein meal and vegetable oil. This occurs at a soybean processing plant and is called crushing. Crushing facilities are often located near production regions and major transportation areas. This allows countries to import soybeans and process them as soon as they are received and then send the soymeal and bean oil to various other regions. Logistically, many countries find it is easier to import soybeans and do the crushing themselves instead of importing soymeal and bean oil (Dunsby, et al., 2008). Globally, 90–95% of soybeans are processed (either in the country of origin or in the importing country), with the remainder being used for human consumption (Bain, 2013).

Worldwide, there are four large soybean producers: Argentina, Brazil, China, and the United States. These countries account for approximately 90 percent of world soybean production. Since these four countries account for the majority of worldwide soybean production, they must also be responsible for the soybean export market. This is true with the exception of China, whose vast population still consumes more than China can produce. This leaves Argentina, Brazil, and the United States with the bulk of the export market. The climate, soil, and topography in the Midwest and in the southeastern parts of the United States are ideal for soybean production. This has allowed it to become the world’s largest soybean producer and exporter (Dunsby, et al., 2008). Sixty percent of U.S. production is used domestically, and the balance is exported (Kleinman, 2013). This is quite an achievement when you realize that soybeans are a relatively new crop in the United States compared with corn and wheat (Dunsby, et al., 2008). A number of countries have started to expand soybean cultivation in recent years, but their output remains small compared with that of the Americas (Bain, 2013). In Brazil, soybeans are planted in November and December, and they are harvested in March through May. Argentina follows a similar planting and harvesting schedule for its main soybean crop. Some farmers in Argentina plant soybeans double cropped with winter wheat. These farmers plant in January after the winter wheat harvest, and they harvest the soybeans in May and June. This double crop represents a small amount of soybean production in Argentina. The crop marketing year for soybeans in Brazil extends from February through January. In the U.S., the soybean marketing year is September through August with planting in May and June, and harvest in September through October. Since harvests in these large producing countries do not occur at the same time, this creates a more stable soybean supply year round. In the United States, the crop marketing years for soymeal and bean oil are from October through September. This lags the soybean marketing year by one month to allow for the time it takes to put the new soybean harvest through the crushing process. As with other agricultural crops, the amount of soybean production relies on the acreage harvested and the yield. Yields can vary depending on the weather during the growing season (Dunsby, et al., 2008). Nearly all the US crop is now genetically modified. Initially, the modifications were made to reduce the need for herbicides and pesticides, but now they are improving the nutritional quality of the soybean. Soybeans are the second most planted field crop in the United States. Although the United States remains the largest producer for now, its scope for further expansion is less than in Brazil. China and India have also been trying to increase output in an effort to meet rising domestic demand. In China, soybeans are primarily grown in the northeast, but there are limitations on available land and water. In India, yields are typically low, but production has been growing strongly. However, the soybean crop is entirely summer-sown and therefore dependent on monsoon rains. Ukraine has significantly increased output and is becoming an important supplier to the international market. As soybean is a spring-sown crop, farmers there have been planting it in preference to winter-sown rapeseed, which is often susceptible to winterkill (Bain, 2013).

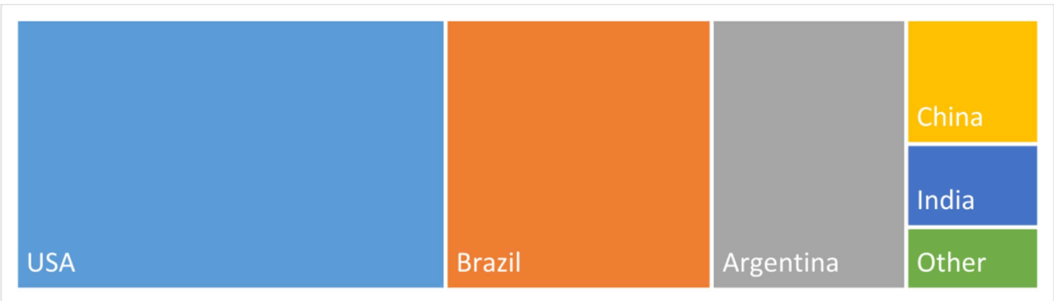


Figure 18: Soybean producing countries

A small amount of whole soybeans are used for seed and human consumption. The majority of soybeans are crushed for the meal and oil. Soybean oil, also known as vegetable oil, is derived from actual soybeans. The vegetable oil is called soybean oil, soyoil, or bean oil and is used primarily for human consumption. It is used for cooking purposes and has become popular in recent years with the health-conscious dietary movement. Bean oil is mainly consumed by humans in a number of foods such as cooking oils, salad dressing, margarine, and various bakery products and food spreads. More than 90 percent of total use comes from human consumption (Dunsby, et al., 2008). In addition to its gastronomic uses, soybean oil is becoming an increasingly popular additive in alternative energy sources technology, such as biodiesel (Bouchentouf, 2015). Biodiesel is a diesel fuel made from vegetable oils such as soybean oil, palm oil, and rapeseed oil. In addition, bean oil does have some industrial applications in products such as paints, putty, epoxy, and adhesives. (Dunsby, et al., 2008). Most soybean oil (over 90%) is edible oil, with the remainder being used by the biodiesel industry and in the manufacture of products such as soaps, plastics and crayons. It is the most important vegetable oil, accounting for about 20% of global consumption, but it has been losing market share to (typically cheaper) palm oil (Bain, 2013). Palm oil competes directly with soybean oil and canola oil, but it generally trades at a discount because of health concerns about saturated fat in tropical oils. Palm oil is attractive to countries with expanding, low-income populations (Kleinman, 2013).

Of the two soy products, soymeal is considered the more valuable and is the most significant protein meal produced in the world. It has the highest percentage of protein meal produced from any of the major oilseeds (Dunsby, et al., 2008). Soybean meal, like soybean oil, is an extract of soybeans. Basically, whatever is left after soybean oil is extracted from soybeans can be converted to soybean meal. Soybean meal is a high-protein, high-energy content food used primarily as a feedstock for cattle, hogs, and poultry (Bouchentouf, 2015). Soybean meal is used almost entirely for animal feed, with a small percentage (typically about 2%) used to make soy flour and proteins. The demand for soybean meal for animal feed has been an important factor in soybean oil production and, ultimately, consumption (Bain, 2013). Its closest competitor in the protein meal market is rapeseed meal (also known as canola meal), which accounts for slightly more than 10 percent of worldwide protein meal consumption. Another protein meal, fish meal, can also be a significant competitor as it has protein content comparable to soymeal. Soymeal and bean oil are created by processing the raw soybeans, a process called crushing. These products along with soybeans make up the soy complex (Dunsby, et al., 2008).

The largest consumers of soymeal are the European Union, the United States, and China. Soymeal is an excellent source of protein and is used extensively in the feed industry for cattle, hogs, poultry, and aquaculture (Dunsby, et al., 2008). EU consumption of soybeans depends to some extent on European grains harvests, as their use in animal feed increases if the availability of grains is low or prices are high. Imports of soybeans to make oil will also increase if regional output of other oilseeds, rapeseed in particular, is low. The EU can be an important import market in years when its own grain or oilseed crops suffer weather-related damage. EU countries import soybeans particularly for their protein content. Consumption in the United States has been growing steadily in recent years, partly because it has stepped up its exports of meat and partly because of recent demand for soybean oil for biodiesel. Although Argentina is only the world's third largest producer of soybeans, it has a highly developed crushing industry and is the world's largest exporter of soybean meal and oil. This reflects a government policy to encourage domestic processing – the export tax is lower on soybean meal and oil than on raw soybeans. However, Argentina's domestic consumption is low and as a result it is an important exporter (Bain, 2013).

Like the other major agricultural products corn and wheat, the benchmark future contracts for soybeans, soymeal, and bean oil all trade on the Chicago Board of Trade (CBOT). Each contract has different specifications with regard to contract size, tick size, value, and delivery specifications. Different soybean, soymeal and bean oil futures contracts are traded on global exchanges, but none are as liquid as those on the CBOT. Bean oil has a large amount of substitutable commodities, unlike soymeal, so its price may respond to be competitive with those oils (Dunsby, et al., 2008). The futures market in Chicago is the main indicator of soybean price changes. Soybeans are also traded on exchanges in South Africa, China, Japan, India and Argentina (Bain, 2013). The soybean market is a large market and presents some good investment opportunities. The most direct way to invest and trade soybeans is through the CME soybean futures contract (Bouchentouf, 2015). Financially, it is generally the most volatile of all the grains, although, technically, it is not a grain but a legume (also known as an oilseed) (Kleinman, 2013).

Growth in consumption has been particularly strong in the developing world, where rising incomes have led to greater meat consumption and thus demand for animal feed (Bain, 2013). Demand for soybeans in the form of soymeal and bean oil has grown excessively during the past 25 years. One reason is that the increase in world wealth can cause a diet change that incorporates more meat. This results in more livestock being raised and a correspondingly higher demand for soymeal to feed them. In addition, given that soybeans are a new crop as compared with corn and wheat, there has been demand from new products that use soymeal and bean oil in the food and industrial sectors (Dunsby, et al., 2008). In the medium term, increased meat consumption in the developing world should sustain growth in soybean demand. This will depend on continued growth in per head income, particularly in China and India. The protein in soybeans is a useful addition to vegetarian and vegan diets. However, the presence of trans fats in soybean oil has reduced its popularity in processed foods in recent years (Bain, 2013). The long-term prospects for the soy complex are supportive. Increased wealth and demand for meat products will continue to support demand for soymeal. Worldwide demand for bean oil to create biofuels will increase as interest rises in greener fuels. In addition, government mandates in a variety of countries on biofuel consumption along with tax incentives for biofuel production will continue to support this specific sector. Production in countries such as Argentina and Brazil, which still have available arable acreage, will increase. This increase in acreage will be needed to meet future demand increases. In other countries such as the United States and China, competition for acreage between soybeans and other crops such as corn will also lend support to the soy complex (Dunsby, et al., 2008).

Oats

The oat is a cereal grain, which is grown for its seed. Nearly 90 percent of oats is used for oatmeal. But the commodity is also useful to feed horses, chicken, and other livestock. Oats are even a part of various dog foods. Oats are usually planted in the spring, but may be planted in the summer months. Over the years, demand has been declining. Instead, the focus has been on soybeans and corn (Taulli, 2011).

The oat market is generally a slower-moving, more thinly traded market. Oats is the only major crop that the United States imports, primarily from the Scandinavian countries, Argentina, and Canada. Milling quality (used in oatmeal and other forms of human consumption) and feed oats are the two major varieties of oats (Kleinman, 2013). You can trade oats futures on the Chicago Board of Trade (CBOT) of the CME (Taulli, 2011).

Wheat

Wheat is the staple food of mankind. It is a cereal grain and globally the most important grain for human consumption. Cereal grains are grasses cultivated for their grains or seeds, and they provide more food energy to humans than any other crop. Other cereal grains include corn, rice, barley, oats, and rye. The calories that have fed the population boom of the world have largely come from these grains (Dunsby, et al., 2008). Wheat is a grass grown widely throughout the world, but particularly in temperate climates. Certain varieties can, however, cope with widely varying temperatures and levels of rainfall. There are a number of wheat types, each traditionally associated with different products, although modern milling and baking technologies are blurring the distinctions (Bain, 2013). The leading producers include China, the European Union (EU), and the United States. It helps that wheat can be planted in many types of climates but wheat does require a heavy amount of rainfall (Taulli, 2011).

Wheat is the second most widely produced agricultural commodity in the world (on a per-volume basis), right behind corn and ahead of rice (Bouchentouf, 2015). Annual wheat production comes to about 20 billion bushels (Taulli, 2011). Countries have different marketing years depending on when they begin to harvest the new crop. In wheat, the international marketing year is from July through June. Wheat is grouped into two categories based on its growing season: winter wheat and spring wheat. Winter wheat is planted in the fall and becomes established before a period of dormancy during the winter. When spring comes, the winter wheat resumes its growth until an early summertime harvest. In areas where the winter is harsh, spring wheat is planted during the spring. It then is harvested in the late summer or early fall. Each wheat class is important as it has characteristics that are important to food manufacturers for specific products. Worldwide there are different classes (dependent on the country it is grown in) and varieties of wheat, but any wheat produced can be classified as either winter wheat or spring wheat (Dunsby, et al., 2008). Wheat production, like that of corn and soybeans, is a seasonal enterprise that’s subject to various output disruptions (Bouchentouf, 2015). As with other agricultural crops, the weather is an important factor in the final crop yield for wheat (Dunsby, et al., 2008). The supply of wheat depends on weather conditions, although investment in the sector – such as fertiliser, pesticides, irrigation and good storage – can also have an effect. In general, higher-protein hard wheats, which are grown in a short summer season under relatively dry conditions, have lower yields than other types, while varieties grown for animal feed have higher yields (Bain, 2013). Worldwide production of wheat has begun to take a back seat to production of corn and soybeans. Over the last decade its area harvested has declined by more than 7 percent. During this same time the area harvested for corn has increased over 7 percent and soybeans area harvested has increased over 36 percent. Wheat production has lost its luster as demand for corn and soybeans has increased at a faster pace than demand for wheat. In addition, declining returns relative to other crops have helped entice farmers to switch away from planting wheat. However, an important factor affecting the production dynamics is the fact that while corn farmers tend to buy their seed from dealers each year, wheat farmers use saved seeds from prior production (Dunsby, et al., 2008).

The majority of the world's wheat production is grown as winter wheat in the Northern Hemisphere (Dunsby, et al., 2008). Unlike other commodities that are dominated by single producers no single country dominates wheat production (Bouchentouf, 2015). The EU is the world's largest wheat producer of which approximately one-third is grown in France. Other large wheat producers include Germany, the UK, Poland, Romania, Italy and Spain. The EU often produces more than it needs, but wheat remains popular among farmers: it is easy to grow, yields are good, and it is readily marketed. The EU actively supports wheat farming and has taken protectionist measures in the past to prevent cheap imports (Bain, 2013). The next largest wheat producer is China, the Chinese government also actively supports wheat farmers. India's harvests are variable and sometimes it becomes a net importer, but it is the world's third largest producer (Bain, 2013). Together, the advanced developing countries of China and India are the two largest producers in Asia. (Bouchentouf, 2015). The production of wheat in the United States is extremely important to the worldwide market. This is because the United States is the largest exporter of wheat. Approximately half of the country's production is exported each year (Dunsby, et al., 2008). The United States produces a wide variety of types and classes of wheat, each of which is exported as well as consumed domestically (Bain, 2013). Other countries, such as Australia and Canada, are also important with regard to their levels of wheat production. Although they may not be the largest producers, these two countries are large exporters of wheat; historically, they export more than half of their production each year (Dunsby, et al., 2008).

World wheat trade accounts for only 20% of total production. The wheat market, unlike those for barley, corn or soybeans, is widely based geographically. It is almost unknown for a single country to account for more than 10% of total wheat imports. The EU is a leading wheat exporter but lacks the high-protein wheat needed in the baking industry as well as high-specification durum wheat. High internal prices make the EU an attractive market for medium-quality and feed wheat produced in the Black Sea region, although these shipments are subject to import restrictions. The United States is always the biggest wheat exporter no other country can match the range of types and grades it produces and the efficient storage, transport and handling systems keep costs down and enable large amounts to be moved at short notice. The country is the “residual market supplier” and its transparent export prices (closely related to prices on American futures markets) represent a target against which other exporters compete (Bain, 2013). Most of the wheat consumed in China is produced within the country; China imports only a small amount of wheat (Dunsby, et al., 2008). With its huge demand, fluctuating production and uncertainty about the exact levels of reserve stocks, China can have a major impact on world wheat markets but it is not a regular importer. Small amounts of wheat are currently imported annually for use in blending with domestic grains. Countries in the Middle East and North Africa where bread is a staple food are important players in the wheat trade, importing significant quantities, particularly from Black Sea exporters such as Russia, Ukraine and Kazakhstan. Egypt is usually the largest wheat-importing country. Although efforts are being made to increase domestic production, it still falls short of demand, which is sustained at great expense by heavy bread subsidies. With high consumption per head and limited production, Algeria is heavily dependent on wheat imports, and Turkey’s imports can also be substantial. India is an occasional purchaser depending on the state of domestic supply and stocks. Pakistan is normally close to self-sufficiency but has to resort to imports occasionally. In Bangladesh, consumption of wheat is growing strongly, helped by the government’s open-market sales, which offer wheat at a marked discount to people on low incomes. Domestic production is increasing only slowly, and imports are substantial. Indonesia is a major importer as it produces no wheat and demand for noodles and bakery products is increasing along with economic growth. With small domestic markets and no production or export subsidies, wheat farmers in Argentina and Australia depend much more on trade than their northern hemisphere counterparts. Some can, however, turn to other products so output is responsive to world prices as well as to the weather (Bain, 2013). Unlike the corn export market, which is dominated by one player—the United States—the wheat market has a number of exporters. The United States happens to be the largest wheat exporter, but it faces competition from Canada, Russia, Argentina, and Australia. This competition is healthy for the market and allows importers several choices from which to buy their wheat. In addition, since wheat is planted and harvested at different times during the year, a production shortfall in one region may be made up easily by upcoming harvests in other regions. This diversity of exporting countries provides stability to wheat trade and prices. The result is lower price volatility for wheat than in the corn market, because the corn market relies on one country’s production for the majority of the world export market (Dunsby, et al., 2008).

Wheat is still a dominant commodity, ranked second in food production. Of the world production, about two-thirds is for food consumption, with much of the rest for livestock feed. But there are other uses including seeds (Taulli, 2011). Wheat is primarily consumed in the form of flour used to bake breads, cakes, crackers, pasta, and other edibles. The wheat milling byproducts bran, germ, middling, and shorts are also produced. These milling byproducts are used by feed manufacturers in the production of livestock feeds (Dunsby, et al., 2008). Wheat is also used for industrial purposes, primarily to make starch. An emerging use of wheat, particularly in the EU, is in making ethanol (Bain, 2013). Since wheat is primarily consumed in the form of flour, other cereal grains and starchy food substances can be considered substitutes. Besides wheat, flour can be made from many other crops such as corn, barley, rye, and rice. Wheat flour is considered superior because of its gluten content. Other flour alternatives such as corn flour, bean flour, and rice flour are important because of their use in specific cultures (Dunsby, et al., 2008).

Wheat consumption per capita has been in decline for almost 20 years. This is in comparison with corn, where per capita consumption has been rising during the same period of time. One of the reasons is that as diets become more diversified and disposable income rises, demand for more expensive foods such as meats, fruits, and vegetables replaces demand for wheat. Keep in mind that wheat is still primarily consumed as a food source. On the other hand, corn is used in a variety of applications outside of food such as industrial uses and ethanol. The lack of additional uses for wheat results in slower growth in demand over time (Dunsby, et al., 2008). Globally, human consumption per head is falling, but increases in human consumption are still recorded in many developing countries in some cases because of government subsidies, especially in North Africa. In India and Bangladesh massive amounts of wheat and rice are supplied through subsidized public distribution systems. Population growth and rising sales of flour-based convenience foods underpin world food-wheat consumption. Growth in consumption is largely in developing countries in South Asia, the Middle East, Latin America and North Africa; consumption in the most advanced economies is more or less unchanged (Bain, 2013). Worldwide consumption of wheat is dominated by China. This is not surprising considering that it is the most populated country in the world. Other large consumers of wheat include the EU, India, Russia, and the United States. Together they constituted almost 70 percent of worldwide wheat consumption. Not surprisingly, all of these countries are also the ones with the highest levels of production. They do not rely on imports for their domestic consumption needs. Instead, with the exception of China, they are also some of the market's largest exporters (Dunsby, et al., 2008).

As with the other agricultural commodities discussed in this chapter, the CME offers a futures contract for those interested in capturing profits from wheat price movements (Bouchentouf, 2015). The benchmark wheat future is the Chicago Board of Trade (CBOT) wheat future (Dunsby, et al., 2008). The Chicago contract is the highest volume contract in the world (Kleinman, 2013).

The future outlook for wheat prices is mixed. Demand should remain steady, yet the supply side could have many changes. The most likely change comes from increasing competition for acreage from other crops such as corn and soybeans. Farmers that have the ability to plant multiple crops on their land will choose the crop with the highest profit margin. This battle for acreage will result in more competition between products for land and the potential for higher price correlation among crops. Overall wheat prices should lag gains in other crops as demand growth will be slower. As with other crops, the weather will play an important part in determining yields and thus production for each year's harvest. Poor weather will lead to price spikes similar to those seen in the past (Dunsby, et al., 2008). Also, transport improvements and larger supplies from newer exporting countries, such as Russia, mean that the world wheat economy can function smoothly with much smaller stocks, while shortages of water will limit growth in wheat production, especially in China and other rapidly urbanizing and populous developing countries. Growth in food use will remain sluggish and mainly concentrated in developing countries in Asia, particularly India, and Latin America. In the longer term, food-wheat consumption growth may begin to slow as more meat is included in diets in parts of Asia and North Africa. The use of wheat as feed is linked to pricing and availability. The EU and Russia will remain big users, but processors in other countries could switch back to corn and other products (Bain, 2013).

SOFTS

Coffee

Coffee beans are not actually beans but are the seeds within a fruit (or cherry) of a tropical tree grown in a large number of countries across Asia, Africa and Latin America. Two principal varieties of coffee are traded internationally: arabica and robusta (Bain, 2013). Coffee is the world's premiere caffeine delivery device. It provides about 54 percent of the world's total caffeine, followed by tea and soft drinks. The coffee plant is a woody evergreen shrub or tree that is grown in subtropical and tropical climates. Coffee beans are the seeds of this plant (Dunsby, et al., 2008). Coffee is the second most widely produced commodity in the world, in terms of physical volume, behind only crude oil (Bouchentouf, 2015).

There are two major types of coffee: Arabica and Robusta. Arabica coffee is generally considered superior to Robusta, which is often described as having a harsh taste. About two-thirds of world production is Arabica, and one-third Robusta (Dunsby, et al., 2008). Arabica coffee is the most widely grown coffee plant in the world, accounting for more than 60 percent of global coffee production. It's the premium coffee bean, adding a richer taste to any brew, and, as a result, is the most expensive coffee bean in the world. Because of its high quality, it serves as the benchmark for coffee prices all over the world (Bouchentouf, 2015). Arabica is more aromatic but takes more time to cultivate and is more complex (Taulli, 2011). Arabica trees grow at high altitudes, often on volcanic soils, and because they are more difficult and costly to grow, the beans trade at a premium (Bain, 2013). Robusta accounts for about 40 percent of total coffee production. Because it's easier to grow than Arabica coffee, it's also less expensive (Bouchentouf, 2015). As the name implies, Robusta is stronger and has higher caffeine levels (Taulli, 2011). Robusta trees grow at lower altitudes and the beans, while stronger, are considered to have less flavor (Bain, 2013). It takes approximately four years for a coffee bush to produce a useful crop (Kleinman, 2013). This long lead time can create periods of supply–demand imbalance, as farmers plant coffee when prices are high but then do not produce a crop for several years, by which time circumstances may differ (Dunsby, et al., 2008). Farmers typically sell their beans to local co-operatives or buyers, who sell them on to exporters for roasting or processing in the consuming country. Roasters then sell directly to retailers. Coffee roasting is a concentrated activity; nearly 40% of the world's coffee is traded by four companies and 45% is processed by three coffee-roasting firms. Most processing takes place in end-user countries and they still dominate. The dominance of a few multinationals in the coffee business has reduced the power of coffee farmers to influence prices or the market more generally.

Many countries produce both varieties. There are a lot of smallholders growing coffee as well as large farms and estates, particularly in Latin America and Kenya (Bain, 2013). Coffee is produced in approximately 70 countries, but the world's largest coffee producer by far is Brazil. This makes the price of coffee sensitive to weather conditions in Brazil. About two-thirds of world coffee production is Arabica. The countries of Western Africa and Vietnam produce mostly Robusta coffee. Although Brazil produces mostly Arabica coffee, it is actually the world's second largest Robusta producer, behind Vietnam. A bit more than 20 percent of

Brazil's crop is typically Robusta. The producers of Arabica coffee are located in Central America, Africa, and South America. Brazil is the world's largest producer of Arabica coffee by far (Dunsby, et al., 2008). The potential dangers to the Brazilian harvest are frosts from early June to August in the south, and drought from September to December in the north, by far the more important producing region. The biennial cycle of the country's arabica trees also affects the size of the harvest. Colombia, Peru, Ecuador, Mexico and Central America are all important coffee-growing regions, but Colombia's output has fallen in recent years, partly because of adverse weather and partly because of a rejuvenation programme, the rewards of which will come later (Bain, 2013). Recently, the second largest producer of coffee has been Vietnam, surpassing Colombia, which has historically been the second-biggest producer. This represents quite a change to the coffee supply dynamic, given that as of the mid-1980s Vietnam was only a trivial producer of coffee. The value of Colombia's production is still greater, however, as it produces premium Arabica beans whereas Vietnam's production is primarily Robusta (Dunsby, et al., 2008). The Central American countries of Costa Rica, Mexico, Guatemala, Honduras, and El Salvador are also important producers, as are Uganda, Indonesia, and Vietnam (Kleinman, 2013).

Producing countries export most of what they grow (Dunsby, et al., 2008). Vietnam is now the world's largest coffee exporter (reflecting very low domestic consumption) and second largest producer. Africa, where coffee farming has been starved of investment and at times hit by civil disturbance, now accounts for little more than 12% of exportable supply (Bain, 2013). Brazil and Columbia account for one-third of the world's exportable supplies (Kleinman, 2013).

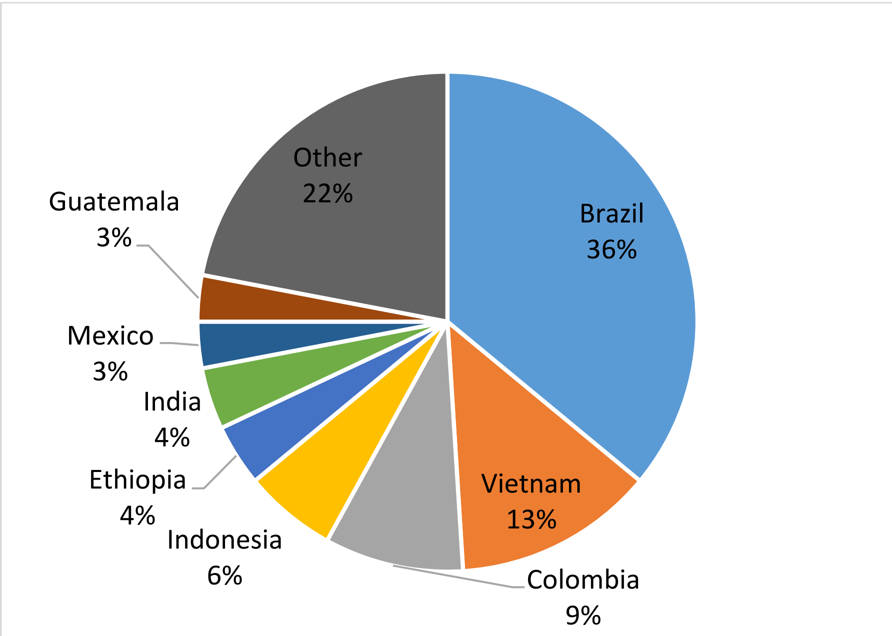


Figure 19: Coffee production by country (Dunsby, et al., 2008)

Coffee consumption is believed to be more inelastic, with a major price increase needed to curtail demand. Americans consume close to double what the Germans drink (they are number two), followed by the Chinese, the French, the Japanese, and then those from the other major EEC countries. Consumption trends need to be followed closely (Kleinman, 2013). Arabica coffee has the highest consumption (70 percent) and price. Yet both Robusta and Arabica coffee prices tend to track each other (Taulli, 2011). Consumer preferences are also impacted by changes in culture or even in advertising. Companies like Starbucks have helped to increase the demand for coffee (Taulli, 2011).

Coffee trades on two major exchanges (Dunsby, et al., 2008). Coffee is traded in London, but the most active contract is in the United States, which is also the major consuming nation (Kleinman, 2013). The main international futures markets for coffee are in New York (arabicas) and London (robustas) (Bain, 2013). The New York Board of Trade (NYBOT) lists a contract for washed Arabica deliverable from a predetermined set of countries. The same goes for Robusta coffee that trades on the Euronext-Liffe exchange. Like the NYBOT contract, this contract also specifies a set of countries whose growths are deliverable (Dunsby, et al., 2008). Investors can also purchase coffee futures on the CME (Taulli, 2011). Arabica trades at a premium to Robusta, and the two prices tend to move together. There is no long-term discernible trend in the price of coffee (Dunsby, et al., 2008).

For decades (between the 1960s and 1980s), coffee prices were controlled by International Coffee Agreements (ICAs), which sought to manage exports in a bid to maintain prices at a level acceptable to both consumers and producers. Intervention ended in July 1989, and prices were subsequently hit by large increases in coffee production in Brazil and Vietnam. Coffee prices proved surprisingly resilient during the subsequent global economic downturn, largely because of disappointing crops which meant that the market was in deficit for five years between 2007/08 and 2011/12 (Bain, 2013). Because of seasonality, cyclicality, and geopolitical factors, coffee can be a volatile commodity subject to extreme price swings (Bouchentouf, 2015). A major impact on coffee pricing is from supply disruptions due to weather (Taulli, 2011).

The outlook for global coffee consumption is for sluggish growth, with lower growth in most OECD countries (Europe in particular) than in non-traditional markets (mainly in the developing world) for some time (Bain, 2013). The steady increase in coffee supply and the only moderate increase in demand make it unlikely that there will be a secular demand/supply imbalance that will put upward pressure on the price of coffee. More likely, the price of coffee will remain trendless or mildly increasing and will continue to have weather-related price spikes. Given that coffee is produced in many different countries and that many of these countries are poor, there is likely to be continued upward pressure on supplies. If so, it will be difficult for coffee to show a strong upward trend in the future (Dunsby, et al., 2008). Supply should continue to grow as many countries have rehabilitation schemes in place or on the drawing board aimed at boosting yields and cutting costs. Furthermore, the legacy of several years of historically high prices has allowed farmers to invest in better crop maintenance and expand planted area (Bain, 2013).

Cocoa

Cocoa is the fundamental ingredient in all things chocolate: milk chocolate, dark chocolate, and cocoa powder, among other things. It is the seed a of the cacao tree a tropical understory tree that grows only in wet environments near the equator. It originates from South America, but today it is mostly grown in Africa. It has been the exclusive delicacy of royalty, it has served as currency, and it has become what it is today—an everyday treat for people worldwide and an important cash crop for many developing countries (Dunsby, et al., 2008). Cocoa production, which is dominated by a handful of countries, is a major agricultural commodity, primarily because it’s used to create chocolate (Bouchentouf, 2015).

Cocoa is grown mainly in tropical parts of the world, close to the equator and predominantly on smallholdings. Cocoa trees need plenty of rain and sun and protection from strong winds (Bain, 2013). The cacao tree is unusual in that it produces both flowers and seeds at the same time; thus, where rainfall is adequate, it can produce more than one crop during the year (Dunsby, et al., 2008). The main producing countries have two crops a year: a main one and a subsidiary crop, usually called the mid-crop. The world’s main crop is produced from October to March (Dunsby, et al., 2008). Once trees reach maturity, which takes 3–4 years, yields increase for some years and then reach a plateau, which can be maintained for up to 30 years, before going into decline. As a result, cocoa production tends to be inelastic in response to price as it takes several years to establish a commercially productive plantation. However, yields can be improved through increased use of fertilizers and pesticides. Cocoa farmers typically sell their beans to a local co-operative or buyer, which then sells the beans on to grinders. These can be either local companies or foreign buyers, which then ship the beans abroad – or, increasingly, foreign-owned companies operating in the cocoa-growing countries. Cocoa beans are cleaned, roasted and ground to produce cocoa liquor. The liquor is then processed to give two intermediate products: cocoa butter and cocoa powder (Bain, 2013). The marketing year for cocoa runs from October to September (Dunsby, et al., 2008).

Cocoa production is highly concentrated in certain parts of the world, principally West Africa, Indonesia and Brazil (Bain, 2013). The cocoa tree is a tropical plant that grows only in hot, rainy climates. As a result, the major producing countries are Brazil, The Ivory Coast, Ghana, Malaysia, and Nigeria (Kleinman, 2013). The largest by a wide margin is Cote d'Ivoire (Ivory Coast) which produces just under 40 percent of all cocoa. The importance of Cote d'Ivoire to the supply of cocoa makes events there important for the price of cocoa. A bad crop, perhaps due to dry weather, would certainly push the price of cocoa up worldwide. Also, Cote d'Ivoire has had periods of political instability (Dunsby, et al., 2008) and since cocoa is found in areas that involve political instability, like the Ivory Coast, the commodity has seen much volatility over the years (Taulli, 2011). Additionally, lower labor costs in producing countries have been an incentive for foreign companies to invest in local processing (Bain, 2013).

The number-one and number-two export destinations for cocoa are Europe and North America. Because cocoa is a luxury good, consumption is generally related to a country's wealth (Dunsby, et al., 2008). Over 85% of world cocoa output is exported, either as raw beans or as processed products, as most producing countries are small final consumers of the commodity. Exceptions include Brazil, which in some years is a net importer, Mexico and Colombia. The leading exporters –Côte d'Ivoire, Ghana, Indonesia, Nigeria and Cameroon – accounted for 83% of all cocoa bean exports. Historically, cocoa-producing countries exported most of their cocoa beans for processing in their end markets, particularly in Europe and the United States. However, in recent years there has been an expansion in cocoa-bean grindings in producing countries as they try to move up the value chain (Bain, 2013). The leading importing nations are (in order) the United States, Germany, France, the Netherlands, and the United Kingdom (Kleinman, 2013). Traditionally, the bulk of stocks were held in importing countries, particularly western Europe's main entry ports, but this has changed in recent years with the growth in processing in producing countries (Bain, 2013). Cocoa production for import and export purposes is measured in metric tons (Bouchentouf, 2015).

Consumption is not measured directly but is inferred from grindings—that is, how much cocoa bean enters processing (Dunsby, et al., 2008). Cocoa butter is extracted from the beans for use in cosmetics and pharmaceuticals, but its primary use is for the manufacture of chocolate (Kleinman, 2013). More than 98% of cocoa ends up in chocolate, other confectionery, bakery products and drinks, with the pharmaceutical and cosmetic industries taking the rest (Bain, 2013). Cocoa is consumed primarily in countries of relatively high income. It was first brought to Europe as a luxury drink in the seventeenth century. The five leading importing nations, mentioned above, account for about two-thirds of the world's consumption (Kleinman, 2013). The growth in cocoa demand in emerging countries is proving more robust, but this is from a low base. Rising cocoa consumption in developing markets is, however, influencing the balance of demand between cocoa butter and cocoa powder, leading to a shift in demand from butter, which is used in richer products like chocolate confectionery, to cocoa powder, which is used in products like chocolate biscuits, cakes and drinks (Bain, 2013).

Cocoa futures are traded on the London (Euronext-LIFFE) and New York (NYBOT) stock exchanges, and these provide a reference point for the physical trade in cocoa (Bain, 2013). The main difference between the contracts is that the NYBOT contract is denominated in U.S. dollars and the Euronext contract is denominated in British pounds sterling. Accounting for the currency difference, the Euronext contract typically trades at a premium because of warehouse location and the quality of the cocoa deliverable at par. It also has a moderately higher open interest (Dunsby, et al., 2008). Having benchmarks set in London or New York makes it harder for producers or buyers to manipulate prices in local markets (Bain, 2013).

Cocoa is one of the few agricultural commodities to suffer in an economic downturn, reflecting its status as a luxury item rather than an essential food (Bain, 2013). As with coffee, the cocoa market is subject to seasonal and cyclical factors that have a large impact on price movements. It can be pretty volatile (Bouchentouf, 2015). Production is more volatile than consumption but much more steady than production in, say, coffee (Dunsby, et al., 2008). In the past couple of decades, cocoa prices have been hugely volatile. This is partly because supply is concentrated in only a few producers, so adverse weather or civil unrest (which disrupts output or trade) in any of the large producers leads to market shortages. Financial investors in the cocoa market have also contributed to price volatility. The activity of investment funds on futures markets has in recent years played a big role in short-term price movements (Bain, 2013). Aside from spikes, the price of cocoa has increased only very slowly (Dunsby, et al., 2008).

The outlook for cocoa supply is positive (barring unforeseen shocks such as adverse weather), constraining the potential for sharply higher prices in the medium term. Slow global growth in recent years and price-conscious consumers have led to some switching by confectionery-makers from cocoa butter to cheaper vegetable-oil substitutes (Bain, 2013). In recent years, perhaps following in the footsteps of coffee, there has been increased interest in higher-quality, single-country cocoa. This could potentially lead to a double or multi-tiered market in the future. Other recent developments are the introduction of organic cocoa and, again as with coffee, fair trade cocoa, which guarantees a minimum price to the grower. Looking forward, as with all commodities, there will be price spikes. In cocoa, they will likely be related to weather and possibly also to political unrest. Increasing world wealth and newly found health benefits bode well for demand, which should grow steadily, as it has. Supply should increase as producing countries increase acreage devoted to cocoa, but it will be limited by the fact that cocoa can be grown only in equatorial regions. Thus, the long-term outlook for price is flat to modestly increasing (Dunsby, et al., 2008).

Sugar

Sugar is a crystalline of carbohydrates. The main ingredients are sucrose, lactose, and fructose. Of course, the result is a sweet flavor (Taulli, 2011). Sugar is made by plants to store energy that they don't need immediately, similar to the way animals store fat. All plants produce sugar using photosynthesis, but only sugarcane and sugar beets store enough for commercial production. Once processed, the end product produced from both crops is nearly identical (Dunsby, et al., 2008). The two main sources for sugar come from sugarcane and sugar beets. Of these, sugarcane accounts for roughly 70 percent of global production (Taulli, 2011). Sugarcane is a perennial grass that looks like bamboo and is grown in tropical and semitropical climates. Sugar beets are an annual crop grown in the more temperate climates of the Northern Hemisphere. Sugar is a pure carbohydrate that supplies energy to the body. It plays an important role in the world's food supply (Dunsby, et al., 2008).

The two main types of sugar grown in the world are cane and beet. Both produce the same type of refined product (Kleinman, 2013). Sugar cane is a grass grown in tropical and subtropical parts of the world. It can be cut manually or by machine. It is taken to a processing plant where it is milled and the juice extracted. Sugar beet is grown in temperate parts of the world and is an annual plant with a tuberous root that has a high concentration of sucrose. It can also be harvested manually or mechanically (Bain, 2013). During the past 25 years, approximately 70 percent of world sugar production has come from sugarcane and 30 percent from sugar beets. More recently, those percentages have shifted to account for more sugar from sugarcane and less from sugar beets. This is because the cost of producing sugar from sugarcane is cheaper than from sugar beets. Sugarcane and sugar beets go through different processes in order to arrive at the end product, refined sugar (Dunsby, et al., 2008). At the processing plant, the sugar is extracted by diffusion. Sugar cane, the main source of supply, requires more processing than beet and this sometimes takes place in the destination country (Bain, 2013). The raw sugar is yellowish brown in color and can be bleached to make crystal sugar or refined to create white refined sugar. When raw sugar goes through a sugar refiner, it is purified even further to white refined sugar. This is the sugar commonly found in Europe and the United States. White refined sugar is usually dried and packaged as granulated sugar. Sugar beets and sugarcane can also be processed into sugar-based ethanol for transportation fuel. Of the two, sugarcane is the most cost effective input for making ethanol (Dunsby, et al., 2008). Around 70% of total production is traditionally during October to March, with the peak beet lifting and processing period occurring in October- December, and cane cutting taking place in January-March. Southern hemisphere crops, mainly cane, boost supply in the second and third quarters. Cane crops are harvested 12–18 months after planting and cut for up to seven years before replanting. If the weather is good, some countries can harvest more than once a year. The balance comes from sugar beet, which is sown in the spring and harvested from October onwards, mainly in the temperate zones (Bain, 2013).

Sugar is grown in more than 100 countries around the world (Kleinman, 2013). The world's largest sugar producers are Brazil, the European Union, China, and India. They account for more than 50 percent of world production. Of the four, the European Union is the only country to produce most of its sugar from sugar beets. Other smaller but important sugar producers include Thailand, Australia, Pakistan, Mexico, and the United States (Dunsby, et al., 2008). More specifically, Cuba, India, Thailand, Brazil and China are the leading cane producers, whereas Russia, USA, Europe, Japan, and the EEC are the major beet producers (Kleinman, 2013; Taulli, 2011). A few countries spanning subtropical and temperate zones, such as the United States and China, produce beet and cane. The contribution of cane to supply has risen sharply in recent years, following steep increases in Indian and Brazilian output and a decline in EU beet production. More recently, the rate of cane sugar expansion has slowed because of competition for the raw material from Brazil's ethanol sector (Bain, 2013). Brazil is the largest producer of ethanol using sugarcane (Dunsby, et al., 2008). Furthermore, Russia's efforts to reduce dependency on imports with larger domestic crops is sustaining the size of the global beet crop (Bain, 2013). India is the world's second largest sugar producer, but annual production can vary enormously depending on the monsoon (Bain, 2013). Since sugar production is concentrated in only a few regions, it is vulnerable to weather (Taulli, 2011).

Four major players – Brazil, Thailand, Australia and Guatemala – typically account for around two-thirds of world exports, with the rest coming from medium-sized and smaller suppliers, which helps to reduce supply volatility. India and EU can also be important suppliers in years of good harvests. Exports consist mainly of raws (unrefined cane sugar) and whites (mainly refined from beet but including some refined raws). Raw sugar exports were traditionally dominated by Brazil, Australia, Thailand, Guatemala, South Africa and Cuba, and white sugar by Brazil, the EU and Thailand and, in good crop years, India. In some years, India is an important supplier to the global market, but in other years it restricts exports to contain internal prices. Russia, the United States, Japan, South-East Asia, the Middle East, western Europe and China have traditionally been the largest net importers. However, Russia has made some progress in boosting domestic beet supply and is no longer such a large presence in the market, partly because it uses its own stocks when it can, particularly when prices are high. Indonesia has also made progress on reducing its import volumes but so far has failed to reach its goal of self-sufficiency, while Pakistan has gone from being a net importer to a small net exporter in some years. Efforts by importing countries to reduce their reliance on imports mean that world trade in sugar as a share of production is declining, apart from years in which one of these countries experiences a major crop shortfall (Bain, 2013). In addition, the countries that utilize the sugar import market have changed over time. At this time the sugar import market is made up of many developing countries that will lower their consumption when prices increase. Brazil has been a model for the rest of the world in weaning itself of energy imports. It helps that Brazil has a large amount of available land and the right climate for growing sugarcane to make ethanol. Ethanol is a biofuel made from the fermentation of sugars and is used as an alternative to gasoline. The low-cost production of ethanol using sugarcane will allow Brazil to have a foothold in the global ethanol industry for many decades to come (Dunsby, et al., 2008). The EU is in a good position to expand beet output with its equable climate, high yields, rapid harvest and modern, efficient processing chains, and the demand is likely to be there if ethanol production expands. However, growing opposition to the use of food crops to make biofuels could curtail this incentive for beet production, although it may indirectly benefit the region’s sugar production. Thailand has significantly increased sugarcane production and milling in recent years. This expansion is the result of harvest mechanisation and increased milling capacity, and Thailand is now the world’s second largest exporter. China typically produces more sugar than Thailand and has also been increasing output, but output still falls short of consumption and the country is a net importer. The government will continue to encourage domestic crop expansion, but suitable land could prove a constraint (Bain, 2013).

Consumption of sugar divides between household use and indirect industrial use in soft drinks, confectionery and manufactured foods. Indirect use accounts for over two-thirds of consumption in Europe and North America and over 80% in some East Asian countries. The split in the developing world varies widely, but growth is principally in indirect use, as processed food and soft-drink consumption increases (Bain, 2013). Also, the expansion into biofuels has increased demand for raw sugar from sugarcane to make fuel ethanol (Dunsby, et al., 2008). India is the world's largest consumer of sugar, although growth in consumption in recent years has been much slower than in China. Consumption in India, though, can vary from year to year depending on the size of the domestic crop and prices. Demand in the Middle East has been growing steadily in recent years, despite high prices, and in much of Sub-Saharan Africa (apart from South Africa and its sugar-producing neighbours) demand for sugar has long outstripped supply (Bain, 2013). The highest consumer of sugar is Brazil, in terms of per-capita consumption. A key driver for sugar demand has actually been for energy production. Brazil uses a large amount of sugarcane for ethanol. Interestingly enough, the higher oil prices go, the more attractive this fuel becomes, due to substitution effect (Taulli, 2011). Usually, most sugar is consumed in the country in which it was grown and produced under government pricing arrangements (Kleinman, 2013).

Of course, sugar is used to manufacture food products. There are substitutes for sugar. One is high fructose corn syrup. If sugar prices get to extreme levels, consumers will usually move over to the sugar alternatives, which will affect the demand for sugar. There are both natural and chemical sweetener substitutes for sugar, although sugar retains about a 70% share of world demand for sweeteners. Chemical sweeteners, such as saccharin and aspartame, as well as an expanding number of synthetic chemical products, are typically much stronger than sugar. High-fructose corn syrup is a more natural alternative to sugar that has been widely adopted in the United States. However, chemical sweeteners are typically less versatile and cannot be used at extremely high temperatures, making them unsuitable for baking. They can also affect taste. Nevertheless, their low calorific value and intensity of sweetness can help with weight reduction or control programmes and make them popular with diabetics. There are also cost advantages in using artificial sweeteners rather than sugar in food processing. Furthermore, substitutes for sugar have been widely adopted in the manufacture of soft drinks where taste is more easily masked or in countries where sugar prices are so manipulated that they are price competitive. Technological advances are extending some of the substitutes' properties, gradually enlarging their share of sweetener use, especially in soft drinks (Bain, 2013).

Sugar has a market structure that is completely different from that of the other commodities (Dunsby, et al., 2008). Government sugar subsidies have a significant impact on the fundamentals of the world sugar market. Nearly every country in the world that produces sugar has some form of subsidy, either directly or indirectly. This makes sugar the most subsidized commodity in the world. Direct subsidies can be in the form of domestic market controls such as production quotas and guaranteed prices, export controls such as export subsidies, or import controls such as import tariffs or quotas. Indirect subsidies occur in the form of income support and debt financing or additional long-term support programs such as government ethanol programs. The result of these sugar subsidies is overproduction of sugar and a sugar surplus in the world market. This occurs because subsidized producers overproduce and then dump their excess sugar on the world market for whatever price they can get. The price received is often a fraction of the cost of production. This dumping of sugar on the market is why the world market for sugar is often referred to as the world dump market and the price received is called the dump price. Compared to actual supply and demand, the dump market for sugar is fairly small. Approximately 20 percent of world sugar production is openly traded on the world dump market. Some countries do not allow or minimize access to the dump market for both consumers and producers. This distorts the market even further in that consumers may be required to pay the domestic price, which is higher than the dump market price. In addition, countries can limit their sugar production by not allowing producers to sell excess sugar on the dump market. This will make them produce only what the government will pay for, because additional production would not be of any value (Dunsby, et al., 2008). Historically, subsidised production led to high global stocks, which hovered at around one-third of global consumption. India in particular required high stocks to feed a vast and complex distribution system, and the EU and China both maintained stockpiles in an effort to regulate their internal markets. Transparency in the sugar market has improved hugely as a result of efforts, mainly during the 1990s, to liberalise trade, privatisation and deregulation. However, government policies in some countries still distort domestic prices or prices paid by end-users. In the EU, a reform programme designed to be compliant with WTO rules – curbing subsidised output and exports – has resulted in significant restructuring in the industry, which has emerged smaller but more efficient. However, the region is now a net sugar importer (Bain, 2013).

There are many varieties of sugar futures. But the most common one for futures investors is Sugar No.11, which is based on the world benchmark contract for raw sugar (Taulli, 2011). There are two active sugar futures in the world, one for the delivery of raw cane sugar and one for the delivery of white refined crystal sugar. The raw sugar future is traded on the New York Board of Trade (NYBOT). It is the world sugar #11 future and has been trading since 1914. The London International Financial Futures Exchange (LIFFE) trades the white sugar future. In terms of liquidity the NYBOT sugar #11 future is the premier sugar future. It has approximately 10 times the open interest and significantly more daily volume than the

LIFFE white sugar future (Dunsby, et al., 2008). You can, also, trade the sugar futures on the CME (Taulli, 2011).

Sugar has had a volatile trading history (Taulli, 2011). The world market for sugar as well as the corresponding futures contract does not bear any relationship to the true global supply and demand conditions. This is because nearly every sugar-producing country in the world intervenes in its production, consumption, and trade of sugar. Only approximately 20 percent of global sugar production is traded on the open market. The rest is consumed or stored in the country in which it is produced. This makes it extremely hard to derive a true assessment of the fundamentals that drive the world sugar price. The sugar on the open market is heavily subsidized, and often the price received is lower than the cost of production. The future of the sugar market is dependent on world governments' curtailing subsidies and other sugar support programs (Dunsby, et al., 2008). The sugar that is not subject to government restrictions is freely traded among nations, corporations, and traders. This free market is typically 15% to 25% of world production. A 5% change in production can mean a 25% change in free market supply (Kleinman, 2013). Investor interest in the market has been cited as an important factor in the strengthening of prices, but there are others such as years of underinvestment in the sector (because of low prices), rising demand for sugarcane from the biofuel sector, protectionist trade policies and strong economic growth (Bain, 2013).

As adoption of ethanol as fuel increases, Brazil will divert some of its sugar exports to ethanol exports. Demand growth for sugar will come from alternative markets such as ethanol because refined sugar is facing increasing competition from non-sugar substitutes.

The price for sugar on the world dump market should continue to be influenced by changes in government subsidies for sugar. Overall, the price should remain steady, but production shortfalls due to weather events could lead to price spikes (Dunsby, et al., 2008). Sugar consumption, which is often supply-led, weakens but continues to grow during times of high prices. A recovery in supply and a return to lower prices could unleash a rapid acceleration in consumption, particularly in the beverages and manufactured-food industries of developing countries. Growing concerns in the developed world, and increasingly in the developing world, about obesity and the rising incidence of diabetes associated with sweet foods (although sweet foods are not always sugar-based) could act as a constraint on sugar consumption. Cane (and to a lesser extent beet) can also be used to make biochemical – acting as a substitute for petrochemicals – and bioplastics. As cane is a renewable input, these industries are likely to grow, putting more pressure on cane suppliers and potentially leading to higher prices (Bain, 2013).

Cotton

Cotton is the world's most important textile (Dunsby, et al., 2008). Cotton has been around for thousands of years. Today, cotton is still important and it is the most widely used natural fiber for clothing (Taulli, 2011). Cotton is the soft fiber seed casing of the cotton plant that is grown worldwide in tropical and subtropical regions. The fiber is spun into thread and used to make a textile or cloth. Its economic importance in many countries around the world resulted in cotton being known as white gold (Dunsby, et al., 2008).

Farmers plant cotton during April and May, when the soil and weather are generally the best. But if there is adverse weather during this time, then it can wreak havoc on the cotton crop (Taulli, 2011). Cotton plants require a sunny growing period with at least 160 frost-free days and an ample supply of water. Wild cotton is a perennial plant, but cultivated cotton must be planted annually. Today's cotton plant was created using a combination of genetic modification and specific breeding of a variety of wild cotton species. These modifications have enabled the cotton plant to be resistant to some insects, to require less fertilizer, and to make the cotton fiber better for textile processing (Dunsby, et al., 2008). Cotton grows around the seeds of the plant in a protective pod or boll and is almost pure cellulose, which means that is soft, breathable and absorbs moisture easily. Cotton used to be picked manually in what was an arduous process, but now most picking is mechanised. Once harvested, the cotton is combed to remove the seeds. Cotton is typically spun to make a yarn or thread. The intermediate processing stages are many: spinning, weaving, knitting, dyeing, finishing, the manufacture of clothing, and so on. Cotton is graded by country of origin, staple length, fineness and maturity. Objective grading criteria have been introduced, of which the micronaire ranking of fibre quality is the most significant. (Bain, 2013). All parts, not just the cotton fiber, of the cotton plant are valuable. . The cottonseed part of the cotton plant is an oilseed like soybeans. Cottonseed is crushed to produce its three products: cottonseed oil, cottonseed meal, and hulls. Both the cottonseed oil and cottonseed meal have uses similar to those of soybean oil and soybean meal. The cottonseed oil is used primarily for human consumption in the form of cooking oil, salad dressings, and other food products. Cottonseed meal is a protein source used for livestock feed (Dunsby, et al., 2008).

World production of cotton is dominated by China, the United States, India, and Pakistan. These four producers account for approximately 70 percent of world production. Each country may have a different crop marketing year depending on its planting and harvest schedule (Dunsby, et al., 2008). The American government subsidizes cotton producers and exporters; in recent years this has proved controversial, with Brazil and African countries challenging the subsidies. EU countries, particularly Spain and Greece, also offer subsidies, but output is small and thus this has not been the subject of debate. China offers incentives to producers, but as it is a net importer of cotton this is not deemed to be a market-distorting activity. India and many African producers offer minimum support prices to farmers, but the level of subsidy is generally low. Production in Eastern Europe and central Asia declined after the break-up of the Soviet Union, but it has since recovered in Uzbekistan, Turkmenistan, Tajikistan and Kazakhstan and is typically price competitive (Bain, 2013).

World cotton trade has two major players—the United States and China. The United States is the single largest exporter of cotton, as its textile and clothing production has been declining but its cotton production has been increasing. China is the largest importer of cotton as its textile production has had tremendous growth (Dunsby, et al., 2008). Now, China and India are the biggest importers of cotton, and the growth has been strong (Taulli, 2011).

The cotton fiber is used to produce fabric, and the seed is used for cooking oil (Kleinman, 2013). Approximately 60% of cotton consumption is in the manufacture of clothing, notably jeans, shirts and t-shirts. A significant proportion is used to make household textiles: towels, table linen, bedding, curtains and upholstery fabrics (Bain, 2013). It is used in hundreds of textile products, including bed sheets, and bath towels (Dunsby, et al., 2008).

China is now the largest consumer of cotton with the India being the second (Bain, 2013). Other major consumers (some are users for manufacturing) of cotton are Pakistan, Turkey, Brazil, and the United States (Kleinman, 2013). These countries then re-export the finished apparel and household goods back to the United States, which is the largest exporter of raw cotton. One reason is the expansion of the textile industry in this region. Cotton production there is high, creating a potentially lower input cost to the textile mills (Dunsby, et al., 2008).

Futures and options are traded on the ICE Futures exchange in New York. There are around 20 cotton exchanges around the world, in both producing and consuming countries, where raw cotton is traded (Bain, 2013). You can, also, purchase futures contracts for cotton on the CME (Taulli, 2011). In terms of both volume and open interest, the cotton futures on the New York Board of Trade (NYBOT) are the most liquid in the world (Dunsby, et al., 2008).

Price changes in the U.S. cotton market seem to be largely driven by export demand. The movement of the textile industry away from the United States to China and other Asian countries has fueled the expansion of cotton production in China. Other smaller cotton producers such as Brazil and Uzbekistan have emerged as swing cotton producers. A large amount of their excess production goes to the export market. This results in more competition and supply in the cotton export market, benefiting importers with lower prices (Dunsby, et al., 2008). Cotton prices are affected by trends in other industrial raw material prices, by the prices of possible substitutes (wool and man-made fibres), developments in the textile sector, the value of the dollar, and the demand and supply fundamentals associated with cotton. While cotton competes with other natural fibres such as wool, flax, jute and bamboo, more serious competition has come from synthetic (petroleumbased) and artificial (cellulose-based) fibres, affecting the pricing dynamics of cotton as substitutes. Today, the use of cotton in products such as net draperies, sportswear, hosiery and technical textiles is small. In many other products – woven shirts, for example – cotton is often blended, usually with polyester (Bain, 2013).

Cotton is a sustainable fibre (in that it comes from a crop that can be grown again, whereas most man-made fibres are based on petroleum, a finite resource), which should boost its attractiveness in the medium term (Bain, 2013). Cotton's future remains mired between the competition for acreage among agricultural products and demand for textile products. As population and global wealth increase, demand for clothing, household goods, and other textile products will increase. This demand increase will come at a time of lower available acreage for cotton, as it faces competition globally from food crops such as corn, soybeans and other oilseeds, and wheat. Still, cotton production will be dependent on the weather, and price spikes will occur. Overall cotton prices should remain steady to higher going forward in order to buy acreage each year as needed for production (Dunsby, et al., 2008).

Lumber

Woods are classified as hard or soft. Softwoods account for 85% of total lumber consumption. Most harvesting of lumber is done by the mill on land leased for timber rights by private parties or the government. The bark is removed, and logs move to the head saw (Kleinman, 2013).

There are two types of wood in the lumber industry: softwood and hardwood. Softwood comes from trees whose seeds, known as conifers, are protected by cones. Examples of softwood trees are pine, fir, larch, spruce, and hemlock. For the most part, softwood is easy to saw and nail. Because of this, it is the primary source of lumber production used in construction. The main areas for lumber production are the Baltic area in Europe and North America. Hardwood comes from trees whose seeds, known as angiosperms, are protected by a covering. An acorn comes from a hardwood tree. The main trees are broad-leaved. Examples of hardwood trees are deciduous trees like oak. Hardwoods are primarily used in furniture manufacturing.

Hardwoods are also used for wood flooring, construction, panels, and kitchen cabinets (Taulli, 2011).

The processing of lumber is time-consuming. A tree must be felled and the branches removed. From this, logs will be created and trucked to sawmills. Depending on the demand, the lumber will be cut into various sizes. Then the lumber is either shipped via truck or rail. Freight can constitute 20 percent to 30 percent of the overall price of lumber. Of the construction market, housing is the biggest user of lumber. You can trade lumber on the CME (Taulli, 2011).

LIVESTOCK

Lean Hogs

Hogs, along with goats and sheep, are the oldest known domesticated animal food source. Today's hog farming is high-tech big business. Long gone are most of the small family farms. In their place are massive buildings containing thousands of hogs under a common roof. The rigorous application of scientific and management principles has driven a spectacular leap forward in pork production productivity (Dunsby, et al., 2008).

Over the past 20 years, the hog industry has undergone some major innovations. Hog producers typically have hog factories, which are state of the art facilities. They are made to minimize disease and to boost the size and grade of the hogs. The factories also protect the herd from adverse weather conditions. The hog industry has also been sensitive to changes in the American diet. There has been a move to steadily reduce the fat component of hogs. The farms are mostly large so as to benefit from economies of scale, as well as leverage when negotiating with packers (Taulli, 2011). The preslaughter phase of hog production is usually combined into what's called the "farrow-to-finish operation." In the hog industry, the backgrounding phase does not exist. In other words, the hog generally stays on the same farm from birth to finish (Kleinman, 2013).

A rancher will breed hogs twice a year, which results in more consistent production of baby piglets. The breeding is done with matching boars or by artificial insemination. A female hog will give birth to nine to ten piglets after a four month gestation period. They will have a high-grain diet—including corn, barley, oats, and oilseed meal—that maximizes weight and growth. Within six months, the hogs should be ready for slaughter (Taulli, 2011). By 26 weeks of age, the piglet has grown into a 260 pound hog and is ready for slaughter. Roughly 25 percent of hog weight is lost during the slaughter process, leaving a carcass weight of about 200 pounds. In addition, 10 percent of the pig crop is commonly lost to death and disease before slaughter (Dunsby, et al., 2008). Of this carcass, about 20 percent will be ham, 20 percent loin, 15 percent belly, 10 percent picnic (a ham-like cut), 5 percent spareribs, and 5 percent butt (Taulli, 2011). Most beef is sold as fresh meat; however, a large portion of pork is processed further and becomes storable as ham— smoked, canned, or frozen (Kleinman, 2013). Each batch of hogs requires about 42 weeks to progress from previous crop weaning to current crop slaughter, and each sow spends about 20 weeks between successive farrowings. Thus, an efficient operation could see a sow produce three litters per year (Dunsby, et al., 2008). During the accumulation phase of the cattle cycle, ranchers are building their herds by holding back cows. This method can temporarily create a short supply of market-ready animals, but it is bearish longer term. During liquidation (for example, in times of drought, which kills off the grazing pastures, or high feed prices), cows are sent to market. This is bearish from a supply and price standpoint in the short run but bullish longer term. This tactic works the same way for hogs as cattle. During the expansion phase, an increased number of gilts and sows (female breeders) are withheld from slaughter to become part of the breeding herd. During contraction, females are culled from the breeding herd, and the female portion of the total slaughter rises (Kleinman, 2013).

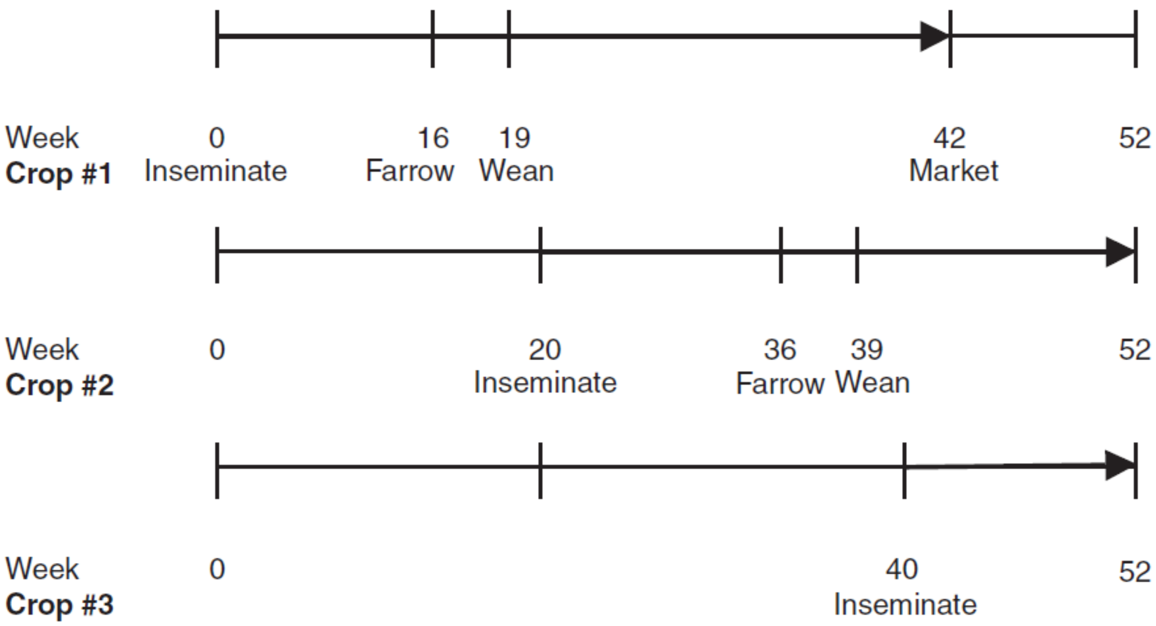


Figure 20: Hog Production (Dunsby, et al., 2008)

The packers are that firms process the hogs from the nation's farms and convert them into portions fit for our tables, earning profits by buying hogs from farmers and selling the processed ensemble, known as the pork cutout, to wholesalers and retailers. The packer industry has undergone substantial consolidation over the last 20 years with more than 50 plants closing and the top 3 packers increasing their share of total slaughter capacity from 35 percent to 55 percent. This consolidation has seen the scale of individual packing plants grow dramatically and has seen substantial improvements in productivity, such that processing is now seen as a distinctive source of comparative advantage for the U.S. pork industry. At the same time, in order to secure consistent supplies for their plants, packers have changed the way they source market hogs by integrating backward into hog production and developing long-term contracting relationships with independent producers (Dunsby, et al., 2008).

The hog market is fairly concentrated in the United States. The United States is the largest exporter of pork in the world. Interestingly enough, the largest amount goes to Japan. Other major importers include Canada, Mexico, Hong Kong, and China (Taulli, 2011). United States has become an importer of pork. The United States imports nearly 10 percent of all domestically slaughtered hogs from Canada (Dunsby, et al., 2008).

The lean hog futures contract (which is a contract for the hog's carcass) trades on the CME and is used primarily by producers of lean hogs — both domestic and international — and pork importers/exporters. Perhaps no other commodity, agricultural or otherwise, exhibits the same level of volatility as the lean hogs futures contract. One of the reasons is that, compared to other products, this contract isn't very liquid: It's primarily used by commercial entities seeking to hedge against price risk. Other commodities that are actively traded by individual speculators as well as the commercial entities (such as crude oil) are far more liquid and, therefore, less volatile (Bouchentouf, 2015). Since it started to trade in 1997, the lean hogs contracts have been extremely volatile. A key reason is that the market is fairly illiquid and involves large commercial players. Another important driver is the outbreak of viruses. Because of the fears of consumers, the futures of lean hogs plunged (Taulli, 2011).

Notice a high degree of seasonality in hog prices. Hog markets have a long history of cyclical prices, commonly known as the hog cycle. In fact, lean hogs are one of the most seasonal of all futures contracts. This is at least partially due to natural seasonal variation in reproductive fitness and weight gain. The source of these manmade cycles is the 10-month delay between the decision to invest by breeding a sow rather than sending it to the slaughterhouse and the return on the investment in the form of a marketable pig crop. Farrowings are lowest during the heart of winter and highest in mid to late spring, yielding low supplies of marketable hogs in early summer and high supplies just before the holiday season. Natural patterns of weight gain reinforce the reproductive cycle as hogs grow fastest in the spring and fall. Enclosed, temperature-controlled barns have mitigated but not eliminated nature's own hog production cycle (Dunsby, et al., 2008). Hog prices tend to be the highest in the summer months because the December through- February time frame is traditionally a low-birth period. Also, the demand for pork tends to peak during the summer months. The rule of thumb is that high feed prices result in liquidation and low feed prices result in accumulation. The other variable here is the market price of the finished product. If sale prices of cattle or hogs are high, then more money can be spent on feed (Kleinman, 2013). If the prices of the agricultural commodities used to feed the hogs increase, it will usually lead to higher hog prices. In fact, if feed prices are high, producers will usually increase the slaughter of hogs so as to lower costs. This is the same with the beef industry but the process tends to be quicker (Taulli, 2011).

Demand for meat tends to be relatively inelastic, so an increase in the price of hogs driven by feed cost would have a moderate downward impact on overall meat consumption and production. Another upward price risk would be stricter enforcement of environmental regulations (Dunsby, et al., 2008). When a country achieves a higher level of income, the demand for red meat increases. Exports to Asia have become a much more important factor in recent years, and unexpected new export business can, at times, result in price spikes. China is a major soybean (and at times corn) importer due in large part to its large and expanding hog industry. Beef, pork, chicken, turkey, and fish are substitutable commodities to a major extent, affecting the price dynamics (Kleinman, 2013). As for future trends, if ethanol from corn or biodiesel from soybeans develop into significant sources of energy for fueling cars, the price of these two commodities may be expected to rise. Since feed composed of corn and beans constitutes the largest component of hog costs, the price of hogs ought to rise as well. This applies to broilers and cattle as well, however (Dunsby, et al., 2008).

Feeder Cattle – Live Cattle

Cows are a special breed because they're low-maintenance animals with high product output: They eat almost nothing but grass, yet they produce milk, provide meat, and, in some cases, create leather goods. This input to output ratio means that cows occupy a special place in the agricultural complex (Bouchentouf, 2015). Cattle provide meat and dairy for food, leather for clothing, raw muscle power for transportation and farm work, and, in many poorer countries, serve as a store of wealth (Dunsby, et al., 2008). There are many definitions for livestock, which is also known as cattle. But in a broad sense, it refers to animals that are domesticated for some type of commercial purposes (Taulli, 2011).

Raising cattle is a more complicated process than raising hogs. First, the time from gestation to slaughter in cattle runs 30 months, whereas the life cycle for slaughter hogs runs 10 months. Thus, cattle production requires more long-term planning and, consequently, one might expect longer cattle cycles and more financial hedging on the part of farmers. U.S. cattle are awarded one of eight grade designations based on age, the degree of fatness, and the firmness of muscling. For farmers and feedlots the Choice to Select price spread has a strong bearing on feeding decisions. The larger the spread, the more attractive it is to feed cattle longer to achieve a higher grade. For traders the ratio of Choice to Select slaughter can be informative, inasmuch as a higher ratio of Choice to Select suggests less current (older) supplies of fed cattle and more pressure for slaughter (Dunsby, et al., 2008). In cattle feeding, the feeder's cost accounts for, in many cases, more than half of the total cost of production. Higher feeder costs lead to lower placements into feedlots (Kleinman, 2013). Simultaneously, marketing agreements and alliances between producers and packers have grown substantially. These longer-term arrangements guarantee steady, consistent quality throughput for packers while lowering price risk and providing access to quality premiums for producers. Some in the industry are concerned that these new pricing arrangements are reflective of increasing monopsony power amongst the packers. It is not clear that increased concentration is bad. The spread between the retail price faced by consumers and the farm price received by producers can be decomposed into two parts: the farm-to-wholesale spread and the wholesale-to-retail spread. If packers wield increasing market power, the farm-to-wholesale spread would likely increase, and the wholesale-to-retail spread would likely fall (Dunsby, et al., 2008). Today, most cattle feeders just accept the risk of the marketplace. They feed cattle and hope for a decent price in four or five months to reward them for their efforts (Kleinman, 2013).

The United States is the major producer of beef, accounting for nearly one quarter of world production during the past 10 years. Other major producers include Argentina and Brazil (together about as large as the United States), Europe, and China. Unlike the case with hogs, the location of beef cattle production in the United States has remained relatively constant over time (Dunsby, et al., 2008).

Physical live cattle trade is mostly very local, with U.S. live exports and imports going to and from Canada and Mexico. Historically, imports from Canada consist of feeder cattle destined for feedlots and live cattle destined for packing plants. Mexico exports primarily lighter cattle for finishing in U.S. feedlots or stocking/pasturing operations. Ultimately the major players drawing cattle into the United States are the large, efficient packing facilities that need a continual supply of live animals. As cattle are far more expensive to transport than beef, most of the movement of meat occurs after processing. The major exporters of beef are the Brazil–Argentina–Uruguay axis, the Australia–New Zealand axis, the United States and Canada, and India. Perhaps surprisingly given its dominant production position and its massive exports, the United States on its own has been a net importer of beef for more than 25 years. In fact, the United States is the world's largest importer of beef. This is partly because many of these imports are re-exported, as the United States imports low-quality beef for processing and then sends it back out again. Russia, the European Union, and East Asia are the other major importers worldwide. China imports virtually no beef, probably a political rather than an economic outcome (Dunsby, et al., 2008).

Two futures contracts exist for the cattle trader and investor: the live cattle and the feeder cattle contracts. Both trade on the Chicago Mercantile Exchange (CME). The market for the live cattle contract can be fairly volatile (Bouchentouf, 2015) and it is by far the more liquid contract (Dunsby, et al., 2008). Per pound, feeder cattle trade at a premium to fed cattle. This differential arises because the dollar cost per pound of gain is typically higher for raising feeder cattle than for converting feeder cattle to fed cattle (Dunsby, et al., 2008).

Demand for live cattle typically falls during May and June. The reason is that this is when a large amount of supply comes onto the market. There is also the influx of other meats, like poultry and pork (Taulli, 2011). Tough winter weather can result in death loss and weight loss, which can reduce supply permanently or temporarily. At times, when the temperatures in the major feeding regions get extremely cold, cattle eat more and gain less. Animals that were to be ready for market at a certain date are "pushed back," creating a temporary shortage, and there is a glut later when they reach market weight. This fundamental is more important for cattle than hogs because the majority of hogs are now fed indoors (Kleinman, 2013). Although it does not happen every year, feeder cattle sales tend to peak in the fall, with the end of the grazing season. At the same time, calf/cow operators tend to sell off unproductive cows, which increases the total beef supply and depresses prices (Kleinman, 2013).

Furthermore, a rise in grain prices, as biofuels and ethanol play a more significant role in energy supply, will drive up feed costs and, therefore, the price of cattle. The impact of higher grains costs merits further elaboration. When the price of grain rises permanently, this must pass through to feeder cattle and live (fed) cattle prices in the long run. Feeder cattle prices rise to reflect grain consumption by pregnant and lactating cows as well as any grain supplementation of the calves. Fed cattle prices rise to accommodate both the increase in the price of feeder cattle and the grain fed directly to the feedlot animals. In the short run or when the price of grain rises only temporarily, we often see a fall in the price of feeder cattle. This is because retail prices are relatively sticky, more or less fixed in the short run, so the cost increase in the price of grain must be shared between the players somewhere along the chain of production. Ranchers receive less for their animals, feedlot operators see their margins fall if not turn negative, and packers see their margins fall as well. Accompanying these shifts in prices, ranchers are inclined to keep feeder cattle on pasture longer, passing along heavier, more mature animals. Meanwhile, feedlot operators pass along lighter, less mature, lower-grade animals. In fact, feeder cattle can even trade at a discount to fed cattle in these situations. It is not too surprising, then, that even temporary surges in grain prices can halt expansions or cause outright contractions of the breeding population. Thus, culled beef and dairy cows enter the market and fewer heifers are retained (Dunsby, et al., 2008). There are some risks to that rosy view of high prices for beef in the future. Continued growth of the cattle industry in Argentina, Brazil, and Uruguay may put some downward pressure on beef prices, relative demand for beef could fall as a result of the perception of beef as less healthy than other possible meat choices (Dunsby, et al., 2008).

5. METHODOLOGY

The research objective of this study is to try to create forecasting models in order to predict daily prices and daily returns of different commodities. To achieve that we collect the appropriate data and proceed creating linear ARIMA models, following the Box-Jenkins method for time series forecasting (Box, et al., 2016). Finally, we try to forecast closing prices with the models and compare the results with our out of sample data.

The two primary sources for raw data collection was yahoo finance and investing.com. We collect the daily closing prices of the 30 investigated commodities from the beginning of available data until 17/7/2020. This way we have a big sample with high frequency historical data to perform our analysis. We keep the 90% of our sample as in-sample data to create our models and we exclude the last 10% to perform out of sample forecasting and compare the results with the forecasted prices and the actual out of sample prices, in order to determine the accuracy of our prediction. In the table 3, you can see all the commodities, the sample sizes and the observations we kept out of sample for model forecasting accuracy evaluation with the corresponding dates. So, we end up having 30 time series for analysis for 30 different commodities.

Commodities	Total historical daily closing prices observations	Out of sample observations (last 10% of the sample)	In sample observations	Date of the first observation (first price)	Date of the last observation (last price)
METALS					
Precious					
gold	5.108	511	4597	27/12/1979	17/7/2020
silver	5.166	517	4649	28/2/2000	17/7/2020
platinum	5.267	527	4740	28/4/1997	17/7/2020
palladium	5.202	520	4682	27/3/1998	17/7/2020
Industrial/Base					
aluminum	902	90	812	21/11/2016	17/7/2020
copper	6.234	509	4584	30/3/2000	17/7/2020
lead	2.946	296	2651	7/7/2008	17/7/2020
nickel	2.946	295	2651	7/7/2008	17/7/2020
tin	2.946	295	2651	7/7/2008	17/7/2020
zinc	3.033	303	2730	18/2/2008	17/7/2020
ENERGY					
crude oil	5.095	510	4585	22/3/1998	17/7/2020
brent oil	8.182	818	7364	27/6/1988	17/7/2020
gasoline rbob	4.018	402	3616	4/10/2005	17/7/2020
heating oil	5.114	511	4603	1/3/2000	17/7/2020
natural gas	5.113	511	4602	28/2/2000	17/7/2020

AGRICULTURE					
Grains					
corn	10.447	1045	9402	27/12/1979	17/7/2020
rice	5.058	506	4552	21/3/2000	17/7/2020
soybeans	7.914	791	7123	2/1/1990	17/7/2020
soybean oil	10.462	1046	9416	27/12/1979	17/7/2020
soybean meal	7.875	788	7087	2/1/1990	17/7/2020
oats	5.082	508	4574	15/3/2000	17/7/2020
wheat	5.080	508	4572	23/3/2000	17/7/2020
Softs					
coffee	10.229	1023	9206	27/12/1979	17/7/2020
cocoa	10.184	1018	9166	27/12/1979	17/7/2020
sugar	10.213	1021	9192	27/12/1979	17/7/2020
cotton	5.225	523	4702	8/12/1999	17/7/2020
lumber	10.228	1024	9204	27/12/1979	17/7/2020
Livestock					
lean logs	10.256	1026	9230	27/12/1979	17/7/2020
feeder cattle	5.109	511	4598	28/1/2000	17/7/2020
live cattle	10.244	1024	9220	3/1/1980	17/7/2020

Table 3: Data structure of commodities time series

To analyze the closing prices we used two software, MS Excel and Eviews. We calculate the descriptive statistics of both closing prices and daily log returns of the 30 commodities and create graphs as an initial overview of the data, in order to see the bigger picture and understand how they behave. We used log daily returns, as they are not different from simple returns, due to their high frequency, and will help us later in the time series analysis. This initial stage of analysis was performed using MS Excel and is presented extensively in the descriptive statistics chapter.

The second step was to create the actual models to forecast daily closing prices. To do that we used Eviews, importing all the available daily closing prices data and then we followed the Box-Jenkins method for time series forecasting (Box, et al., 2016). First, we checked the stationarity of our data for each commodity separately and we figure that data are becoming stationary using first differences. One way to understand that was to use autocorrelogram and partial autocorrelogram of time series of daily closing prices. We observe that with first differences the bars of each graph was within the limits. Another way to support this, was to perform unit root tests using different methods at significance level of 5%. The three tests that we used was Augmented Dickey-Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and Phillips-Perron (PP) test. Again, when we used first differences the data were becoming stationary and almost all commodities passed all the three tests that we used. So, all the models that we will create will have first degree of differencing (d=1). The results of the commodities that passed the tests are presented at the table 4.

	Stationarity – Unit Root Tests		
	ADF	**KPSS**	**PP**
Aluminum	●	●	●
Corn	●		●
Brent Oil	●	●	●
Coffee	●	●	●
Copper	●	●	●
Crude Oil	●	●	●
Feeder Cattle	●	●	●
Cocoa	●	●	●
Gasoline	●		●
Gold	●	●	●
Heating Oil	●	●	●
Lead	●	●	●
Lean Hogs	●		●
Live Cattle	●		●
Lumber	●		●
Natural Gas	●	●	●
Nickel	●	●	●
Oats	●	●	●
Palladium	●	●	●
Platinum	●	●	●
Rice	●	●	●
Silver	●	●	●
Soybean Meal	●		●
Soybean Oil	●		●
Soybeans	●		●
Sugar	●	●	●
Tin	●	●	●
Wheat	●	●	●
Zinc	●	●	●
Cotton	●		●

Table 4: Unit root test results of all commodities that passed the test at significance level 5%

Following that procedure it was the time to choose the AR/MA terms p (the number of lag observations) and q (the size of the moving average window). Unfortunately, ACF and PACF correlograms were not very helpful in determining these terms so we followed another approach to select the AR/MA terms and create the ARIMA models. We decided to create two sets of ARIMA models to forecast daily closing prices. The first one was based on selecting AR/MA terms that was statistically significant at significance level 5%. Additionally, these AR/MA terms should present a stable AR/MA structure based on Inverse Roots of AR/MA Polynomials circle graph by Eviews, with all the roots being inside the circle and all be statistically significant at the Ramsey RESET stability test, at significance level of 5%. Also, we performed residuals diagnostics with ACF and PACF plots indicating that there is no serial correlation in the residual errors, leaving no temporal structure in the time series of forecast residuals for any of the models. With all these requirements satisfied we end up to the first set of 30 ARIMA models, one for each commodity. We call these models “Custom ARIMA models”. The other set of ARIMA models created based on AR/MA terms proposed by the Eviews Add in “Automatic ARIMA selection” using an automated process of finding the roots, based on the Akaike criterion. These AR/MA terms did not have the same strict requirements as the previous set and we have accepted models that did not satisfy some of the above requirements. Therefore, we have another 30 ARIMA models, one for each commodity. We name these models “Eviews Add in ARIMA models”.

After the identification of the two sets of the ARIMA models, we perform an out of sample forecast for the closing prices of each commodity. In an effort to compare these two sets of models between them we initially perform a Diebold-Mariano test (Diebold & Mariano, 1995) that compares the forecast accuracy of two forecast methods. Then we compare four forecasting accuracy indicators, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil Inequality Coefficient, in order to see which model performs the best in an out of sample forecasting of two forecast methods.

We also perform a basic risk analysis of commodities based on their volatility and GARCH models. We calculate the jumps of their daily returns and compare them with each other. In addition, we present the number of positive and negative jumps for each commodity, trying to explain in a basic level the risk involved in daily returns.

6. DESCRIPTIVE STATISTICS

For the examined period of each commodity, we calculate the descriptive statistic for each one as a first, basic level of our initial analysis. As theory and commodities' fundamentals describe, we observe that generally commodities are doing good when economy is down and vise versa. There is an indication for this that almost all commodities prices climbed during the recent economic crisis and during other unstable times in the past. Therefore, we confirm the notion that wants commodities as alternative investments during bad times.

Gold presented an upward trend through the years of our sample, confirming its strong reputation as value preserving asset. The base metals present very little trends, remaining almost stable with small flunctuations of their prices. This can be described by its own nature that are industrial metals, used as raw materials to many necessary applications. Soybeans, soybean oil and soybean meal prices tend to move together as they are products that derive from the same raw material soybeans. The agricultural commodities seem to have a great level of seasonality, because they always are affected by weather and seasonal demand.

Generally, daily returns of all commodities present a high level of volatility. They tend to become extremely volatile in times of small or big crisis. In 2020, they present great volatility, due to the COVID-19 outbreak and the instability and uncertainty that it has brought to the markets. An interesting fact regarding daily returns of almost all commodities, is that they present a high level of kurtosis (excess kurtosis) which is a common phenomenon in finance described as "fat tails". By definition, a fat tail is a probability distribution, which predicts movements of three or more standard deviations more frequently than a normal distribution (Nath, 2015). It is worth mentioning that the average daily return is not positive for all commodities and it is also very small. Daily returns seem to be stationary indicating no trends and no seasonality.

You can see the graphs and the descriptive statistics for each commodity in the following pages.

6.1 Metals

Gold

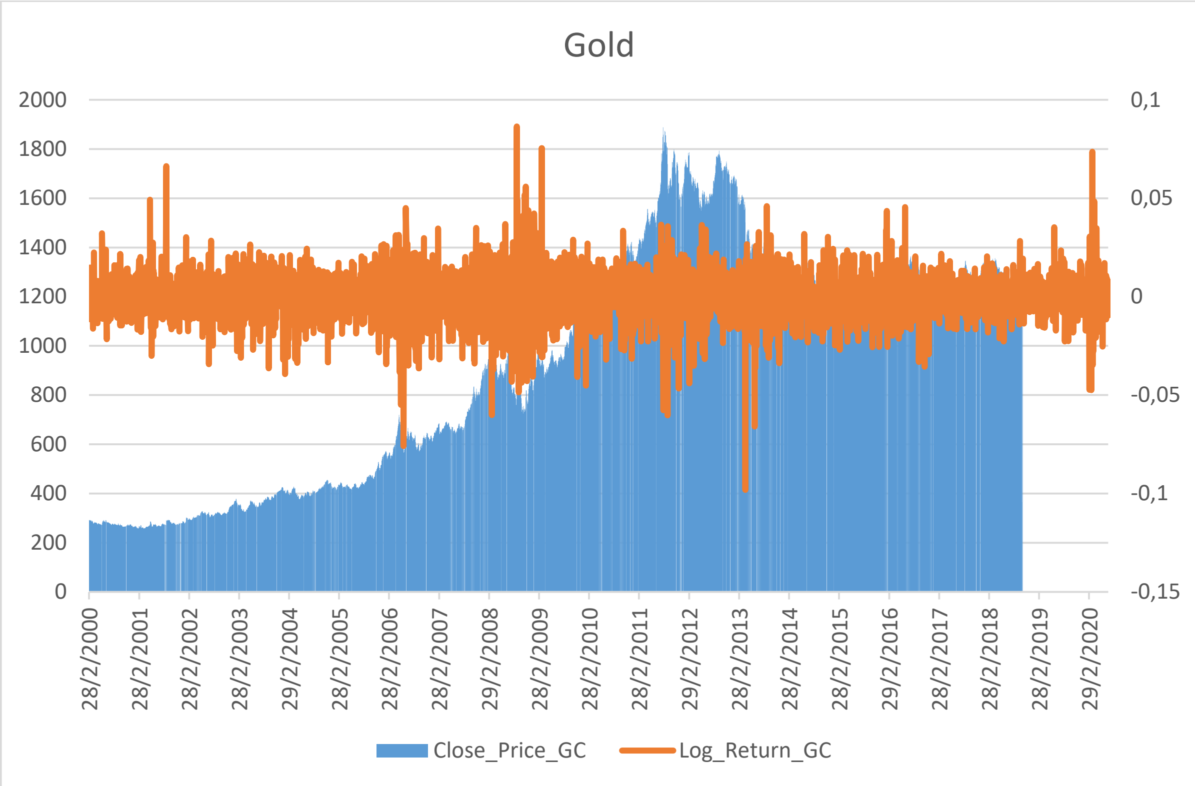


Figure 21: Gold daily closing prices and log returns graph

Close_Price_GC	
Mean	962,7964371
Standard Error	6,618243862
Median	1117,549988
Mode	273,100006
Standard Deviation	473,0076992
Sample Variance	223736,2835
Kurtosis	-1,335345025
Skewness	-0,115991729
Range	1633,599945
Minimum	255,100006
Maximum	1888,699951
Sum	4917964,201
Count	5108

Table 5: Gold daily close prices descriptive statistics

Log_Return_GC	
Mean	0,000357113
Standard Error	0,000155371
Median	0,000367221
Mode	0
Standard Deviation	0,01110332
Sample Variance	0,000123284
Kurtosis	5,799334489
Skewness	-0,193217229
Range	0,184637449
Minimum	-0,098205791
Maximum	0,086431657
Sum	1,823776993
Count	5107

Table 6: Gold daily log returns descriptive statistics

Silver

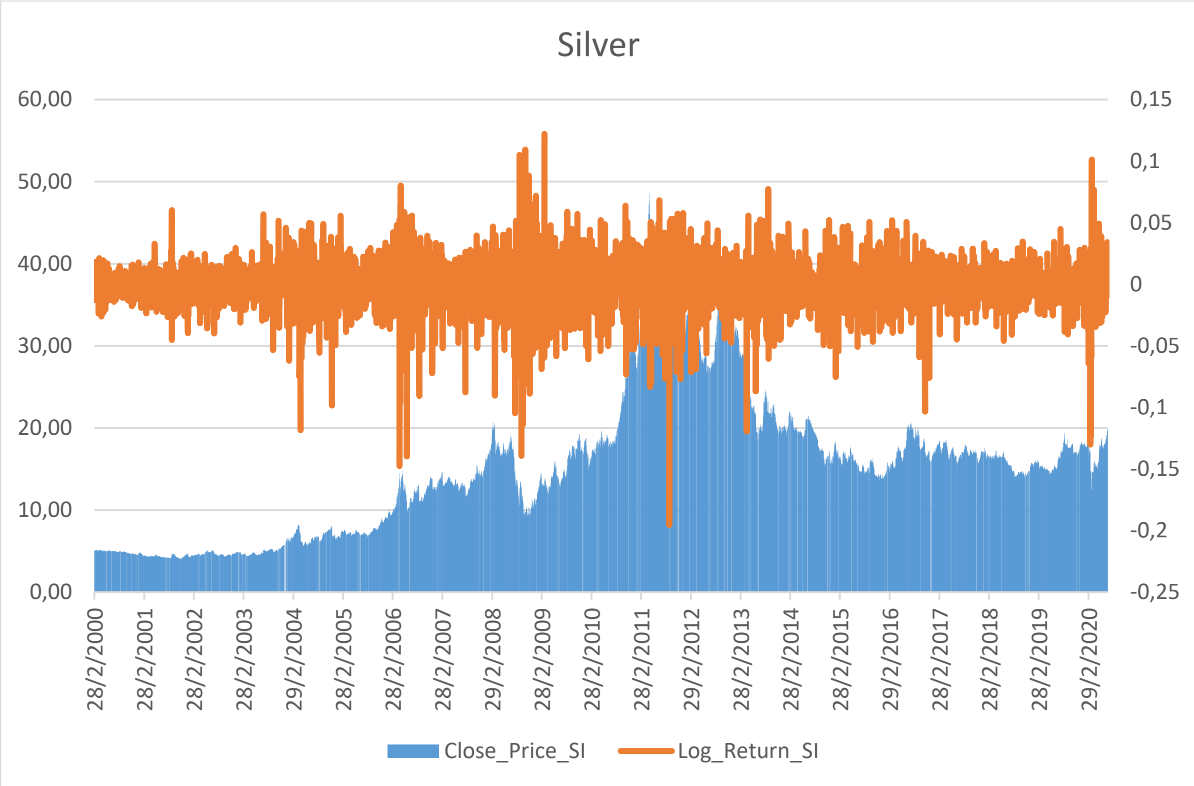


Figure 22: Silver daily closing prices and log returns graph

Close_Price_SI	
Mean	15,07485231
Standard Error	0,116426024
Median	15,2915
Mode	4,923
Standard Deviation	8,368107794
Sample Variance	70,02522805
Kurtosis	0,707439269
Skewness	0,849008576
Range	44,558
Minimum	4,026
Maximum	48,584
Sum	77876,68705
Count	5166

Table 7: Silver daily close prices descriptive statistics

Log_Return_SI	
Mean	0,000264067
Standard Error	0,000267311
Median	0,000994332
Mode	0
Standard Deviation	0,019211089
Sample Variance	0,000369066
Kurtosis	8,473049901
Skewness	-0,957511731
Range	0,317415196
Minimum	-0,195456789
Maximum	0,121958407
Sum	1,36390822
Count	5165

Table 8: Silver daily log returns descriptive statistics

Platinum

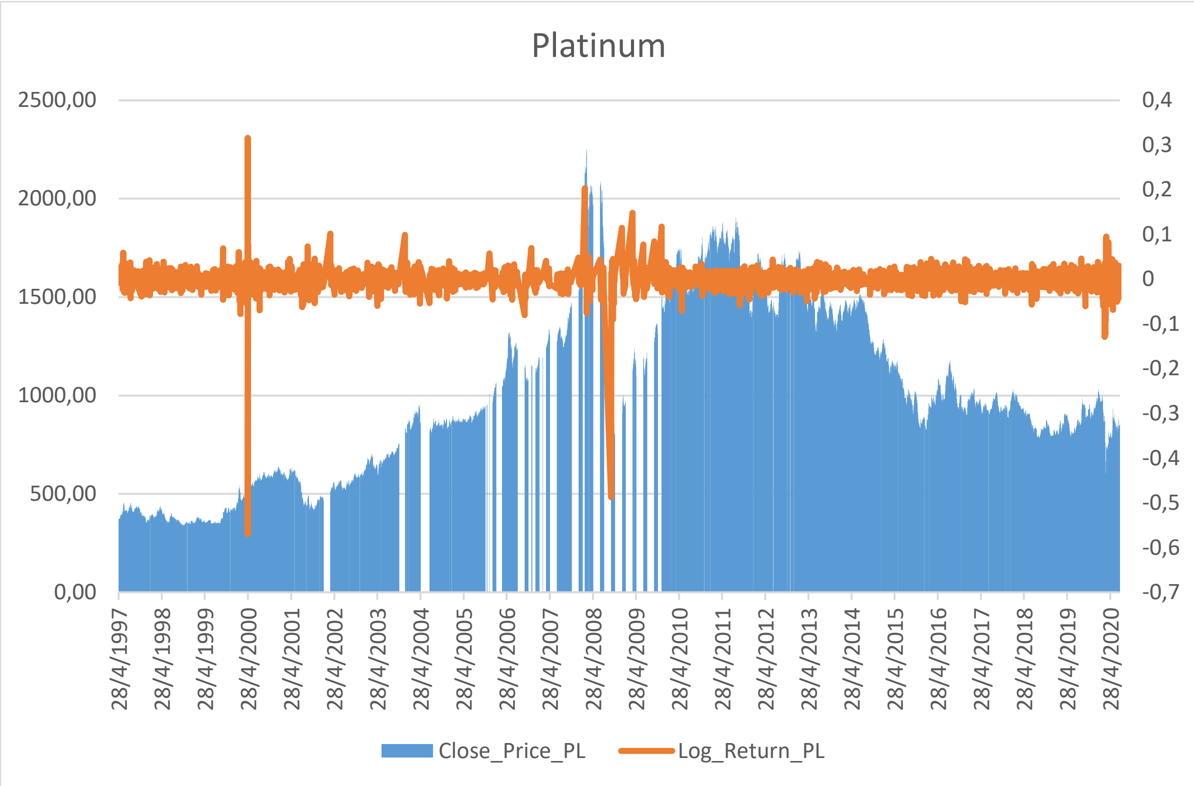


Figure 23: Platinum daily closing prices and log returns graph

Close_Price_PL	
Mean	978,149307
Standard Error	5,923755622
Median	913,5
Mode	352
Standard Deviation	429,9112333
Sample Variance	184823,6685
Kurtosis	-0,756687844
Skewness	0,394676506
Range	1914,700104
Minimum	336,399994
Maximum	2251,100098
Sum	5151912,4
Count	5267

Table 9: Platinum daily close prices descriptive statistics

Log_Return_PL	
Mean	0,000156978
Standard Error	0,000261214
Median	0,000807159
Mode	0
Standard Deviation	0,018955603
Sample Variance	0,000359315
Kurtosis	258,1985751
Skewness	-7,215773813
Range	0,885922308
Minimum	-0,570415821
Maximum	0,315506487
Sum	0,826645044
Count	5266

Table 10: Platinum daily log returns descriptive statistics

Palladium

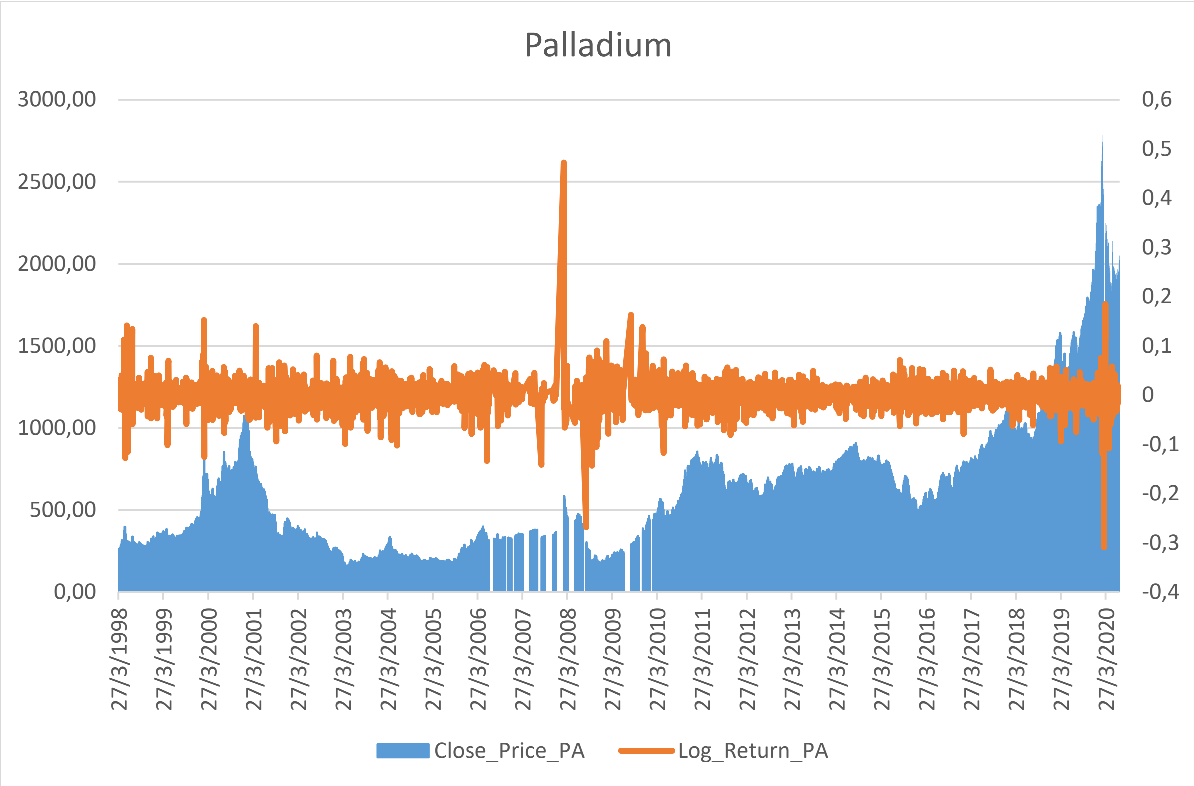


Figure 24: Palladium daily closing prices and log returns graph

Close_Price_PA	
Mean	640,2716551
Standard Error	5,935289889
Median	595,25
Mode	342
Standard Deviation	428,0821403
Sample Variance	183254,3188
Kurtosis	3,373265852
Skewness	1,666071545
Range	2635,600098
Minimum	148,5
Maximum	2784,100098
Sum	3330693,15
Count	5202

Table 11: Palladium daily close prices descriptive statistics

Log_Return_PA	
Mean	0,000398033
Standard Error	0,000328756
Median	0,00080997
Mode	0
Standard Deviation	0,023709185
Sample Variance	0,000562125
Kurtosis	43,34573723
Skewness	0,758436591
Range	0,781492
Minimum	-0,309487191
Maximum	0,472004809
Sum	2,070169809
Count	5201

Table 12: Palladium daily log returns descriptive statistics

Aluminum

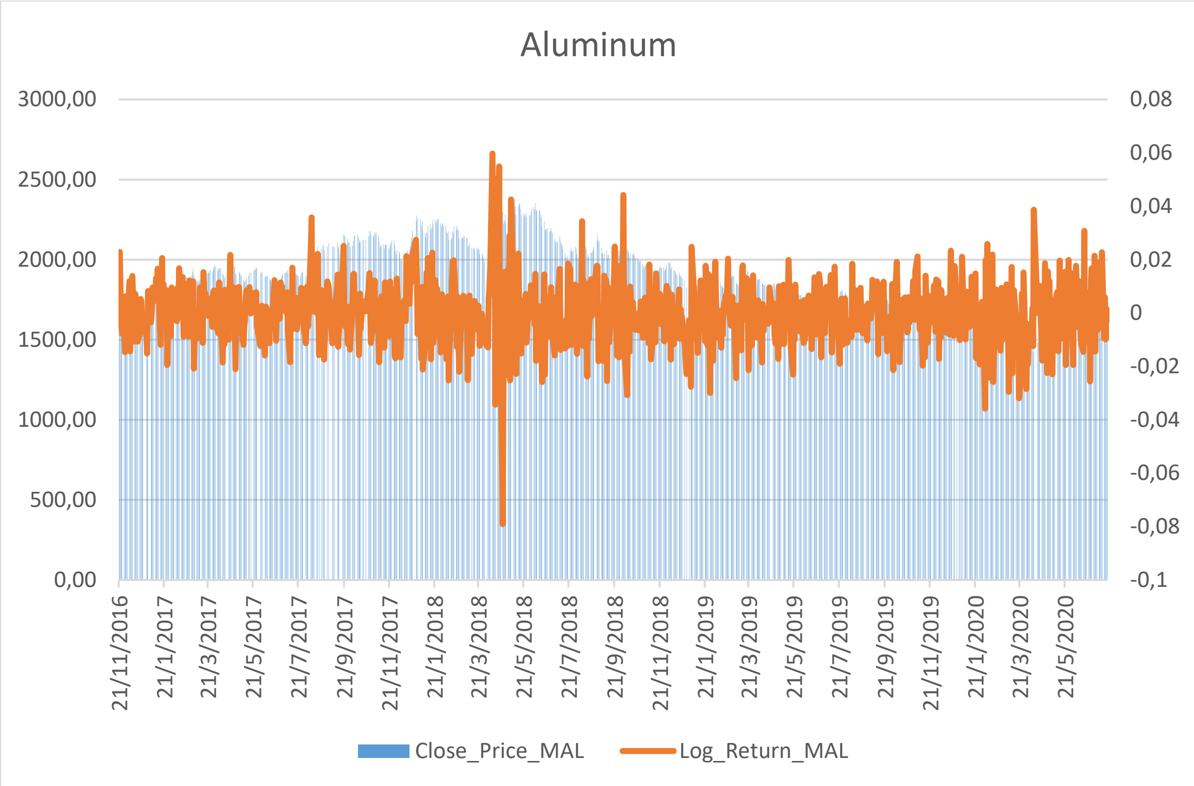


Figure 25: Aluminum daily closing prices and log returns graph

Close_Price_MAL	
Mean	1898,415676
Standard Error	6,757287909
Median	1879,375
Mode	1899,75
Standard Deviation	202,9437552
Sample Variance	41186,16778
Kurtosis	-0,194438891
Skewness	0,175345695
Range	1121,5
Minimum	1426,5
Maximum	2548
Sum	1712370,94
Count	902

Table 13: Alumium daily close prices descriptive statistics

Log_Return_MAL	
Mean	-0,000039643
Standard Error	0,000404092
Median	-0,00011849
Mode	0
Standard Deviation	0,012129495
Sample Variance	0,000147125
Kurtosis	3,446758187
Skewness	0,106700399
Range	0,138850237
Minimum	-0,079104181
Maximum	0,059746056
Sum	-0,035718083
Count	901

Table 14: Aluminum daily log returns descriptive statistics

Copper

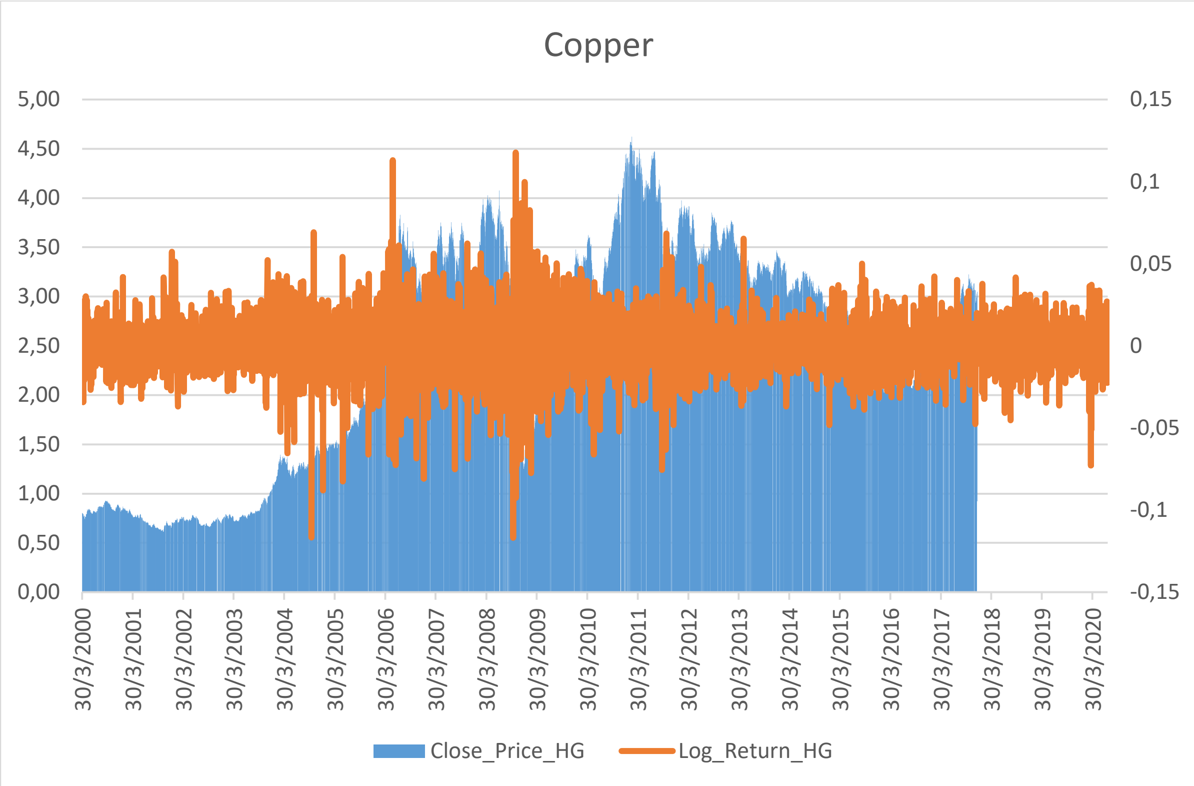


Figure 26: Copper daily closing prices and log returns graph

Close_Price_HG	
Mean	2,450289515
Standard Error	0,014768716
Median	2,678
Mode	0,765
Standard Deviation	1,05397321
Sample Variance	1,110859527
Kurtosis	-1,022833189
Skewness	-0,357701074
Range	4,019
Minimum	0,604
Maximum	4,623
Sum	12479,3245
Count	5093

Table 15: Copper daily close prices descriptive statistics

Log_Return_HG	
Mean	0,000252372
Standard Error	0,000240008
Median	0,000160801
Mode	0
Standard Deviation	0,017126546
Sample Variance	0,000293319
Kurtosis	4,524633591
Skewness	-0,169766902
Range	0,234625057
Minimum	-0,116932531
Maximum	0,117692526
Sum	1,285078929
Count	5092

Table 16: Copper daily log returns descriptive statistics

Lead

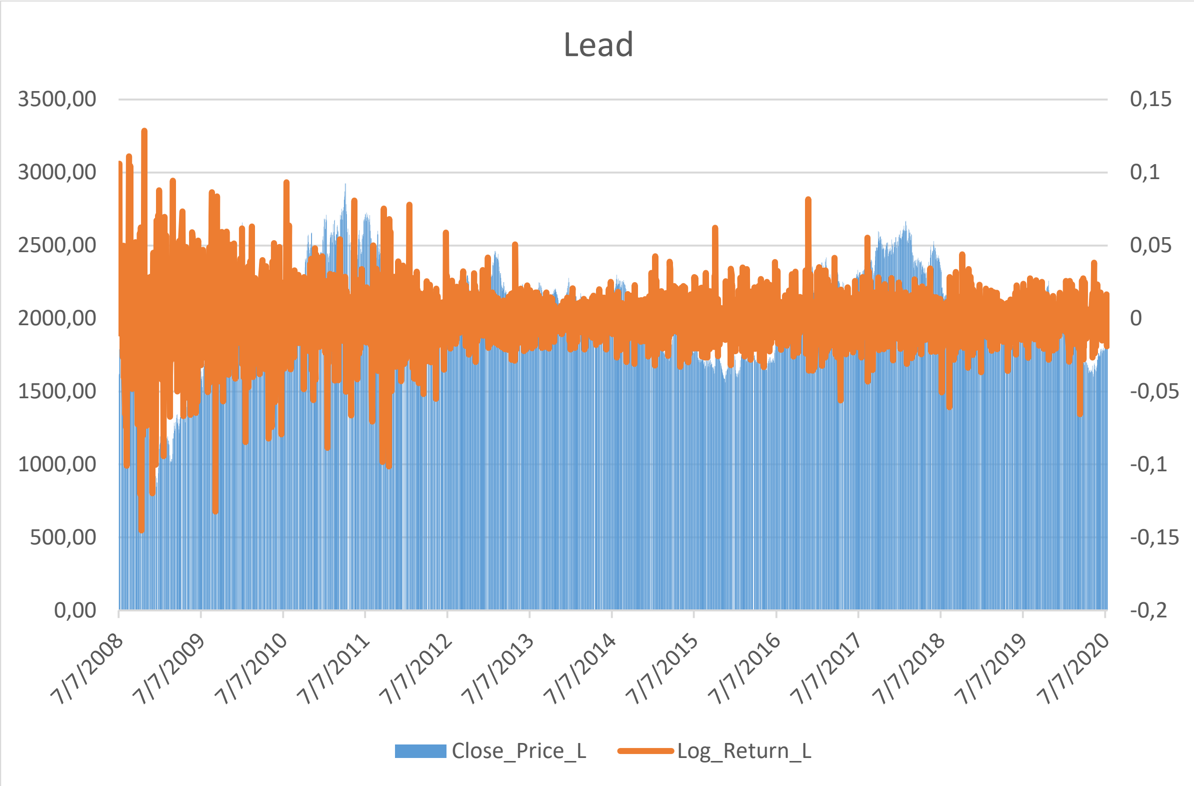


Figure 27: Lead daily closing prices and log returns graph

Close_Price_L	
Mean	2044,462067
Standard Error	5,755403551
Median	2065,875
Mode	2060
Standard Deviation	312,386424
Sample Variance	97585,27791
Kurtosis	1,035237469
Skewness	-0,552538306
Range	2078
Minimum	848
Maximum	2926
Sum	6022985,25
Count	2946

Table 17: Lead daily close prices descriptive statistics

Log_Return_L	
Mean	0,000040146
Standard Error	0,000379479
Median	0,000209666
Mode	0
Standard Deviation	0,020593531
Sample Variance	0,000424094
Kurtosis	6,039099348
Skewness	-0,2197763
Range	0,273827906
Minimum	-0,145157026
Maximum	0,12867088
Sum	0,118231103
Count	2945

Table 18: Copper daily log returns descriptive statistics

Nickel

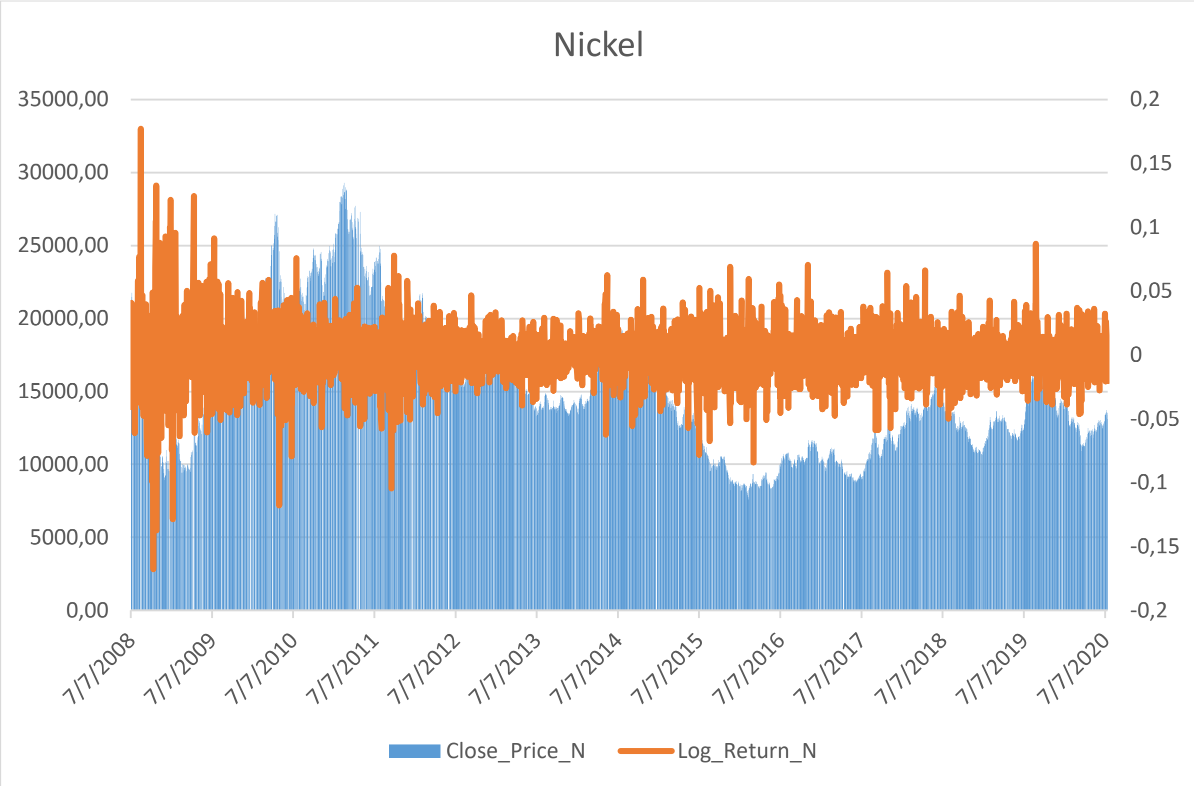


Figure 28: Nickel daily closing prices and log returns graph

Close_Price_N	
Mean	15012,04421
Standard Error	81,43251995
Median	14139,25
Mode	16225
Standard Deviation	4419,91834
Sample Variance	19535678,13
Kurtosis	0,102873631
Skewness	0,734410214
Range	21696
Minimum	7590
Maximum	29286
Sum	44225482,25
Count	2946

Table 19: Nickel daily close prices descriptive statistics

Log_Return_N	
Mean	-0,000156229
Standard Error	0,000406972
Median	0
Mode	0
Standard Deviation	0,022085499
Sample Variance	0,000487769
Kurtosis	6,080706745
Skewness	0,107363471
Range	0,344837924
Minimum	-0,167778145
Maximum	0,177059779
Sum	-0,460093789
Count	2945

Table 20: Nickel daily log returns descriptive statistics

Tin

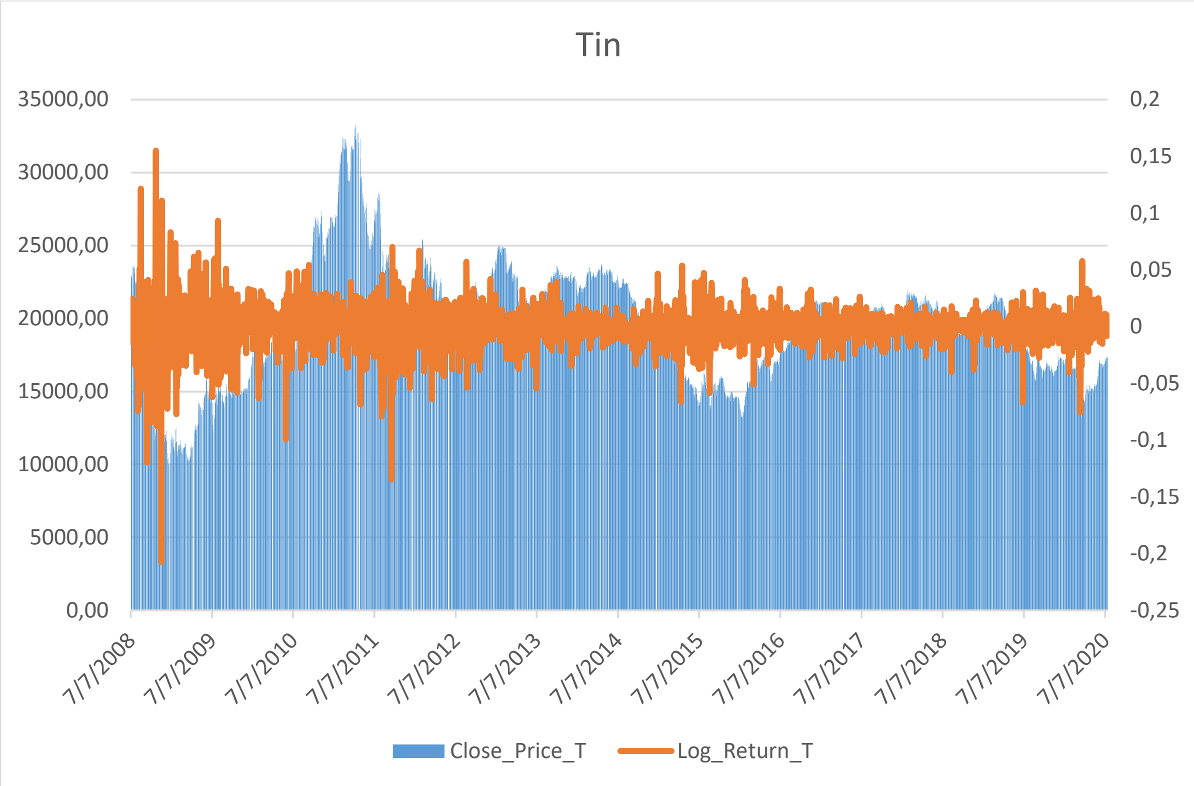


Figure 29: Tin daily closing prices and log returns graph

Close_Price_T	
Mean	19468,91217
Standard Error	70,28084715
Median	19571,75
Mode	14825
Standard Deviation	3814,638248
Sample Variance	14551464,97
Kurtosis	0,990912634
Skewness	0,42948997
Range	23399
Minimum	9870
Maximum	33269
Sum	57355415,25
Count	2946

Table 21: Tin daily close prices descriptive statistics

Log_Return_T	
Mean	-0,000093491
Standard Error	0,000324319
Median	0,000399583
Mode	0
Standard Deviation	0,017600082
Sample Variance	0,000309763
Kurtosis	14,5147476
Skewness	-0,70161093
Range	0,362120497
Minimum	-0,207253998
Maximum	0,154866499
Sum	-0,275331752
Count	2945

Table 22: Tin daily log returns descriptive statistics

Zinc

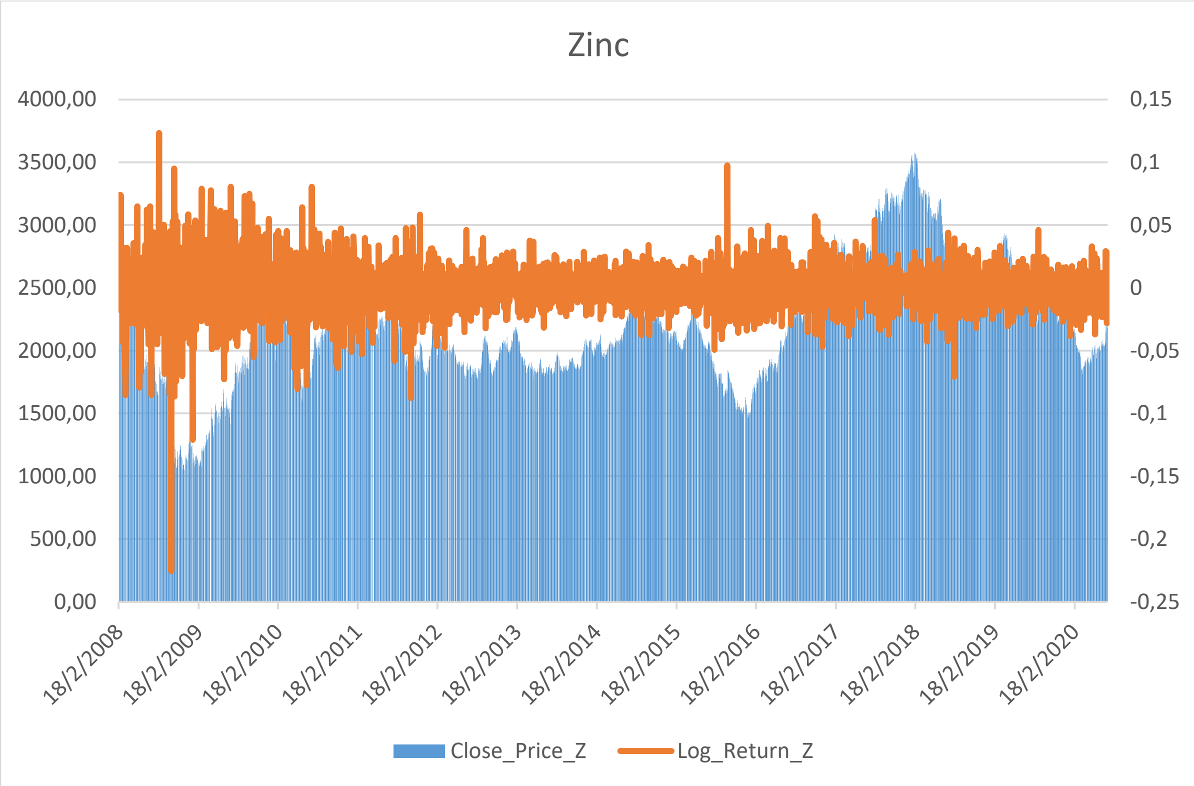


Figure 30: Zinc daily closing prices and log returns graph

Close_Price_Z	
Mean	2188,973304
Standard Error	8,330680341
Median	2137
Mode	1916
Standard Deviation	458,7928864
Sample Variance	210490,9126
Kurtosis	0,503330873
Skewness	0,411536392
Range	2532,5
Minimum	1047
Maximum	3579,5
Sum	6639156,03
Count	3033

Table 23: Zinc daily close prices descriptive statistics

Log_Return_Z	
Mean	-0,000023912
Standard Error	0,000354563
Median	0,000266657
Mode	0
Standard Deviation	0,01952352
Sample Variance	0,000381168
Kurtosis	8,708517258
Skewness	-0,483030122
Range	0,348728831
Minimum	-0,225445748
Maximum	0,123283083
Sum	-0,072501915
Count	3032

Table 24: Nickel daily log returns descriptive statistics

6.2 Energy

Crude Oil

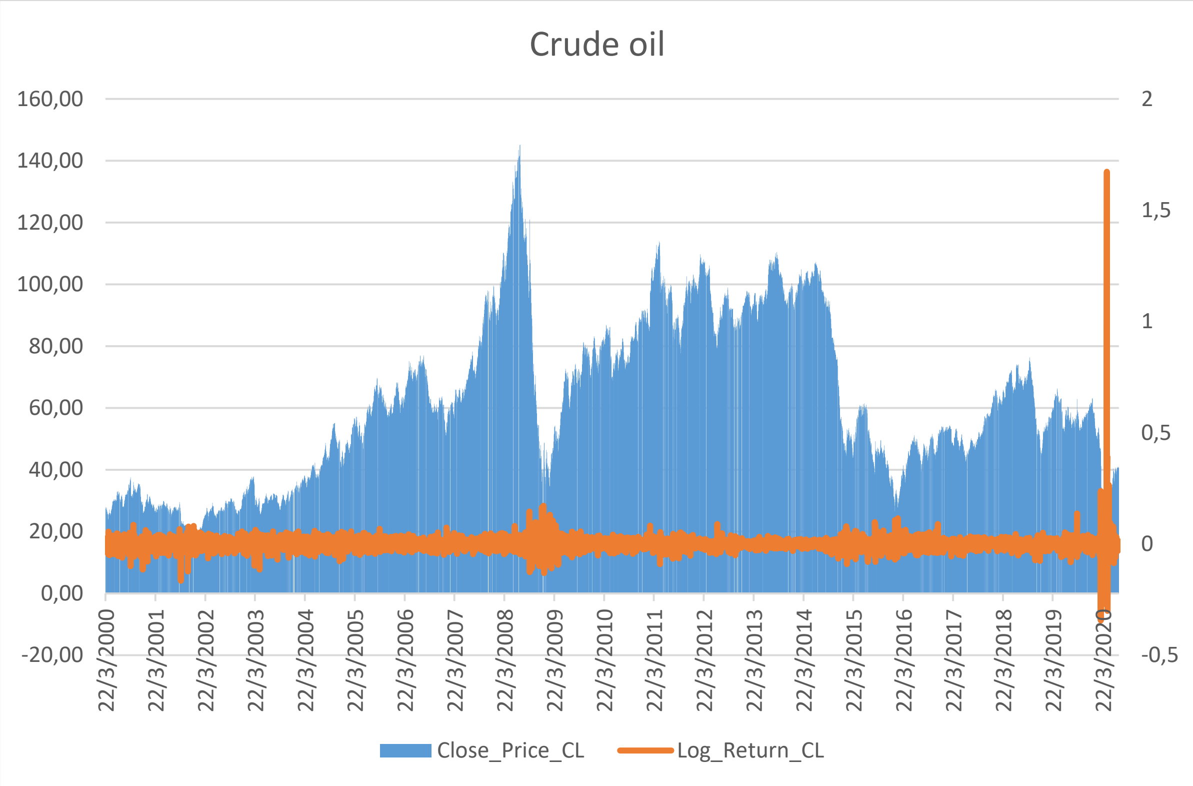


Figure 31: Crude oil daily closing prices and log returns graph

Close_Price_CL	
Mean	61,4361715
Standard Error	0,366701138
Median	58,1499995
Mode	26,860001
Standard Deviation	26,17742761
Sample Variance	685,2577163
Kurtosis	-0,678723464
Skewness	0,39667881
Range	147,899993
Minimum	-2,72
Maximum	145,179993
Sum	313078,7299
Count	5096

Table 25: Crude oil daily close prices descriptive statistics

Log_Return_CL	
Mean	0,00052905
Standard Error	0,000507503
Median	0,000841663
Mode	0
Standard Deviation	0,036225184
Sample Variance	0,001312264
Kurtosis	901,526587
Skewness	19,42479454
Range	2,017511797
Minimum	-0,343995028
Maximum	1,673516769
Sum	2,695509742
Count	5095

Table 26: Crude oil daily log returns descriptive statistics

Brent Oil

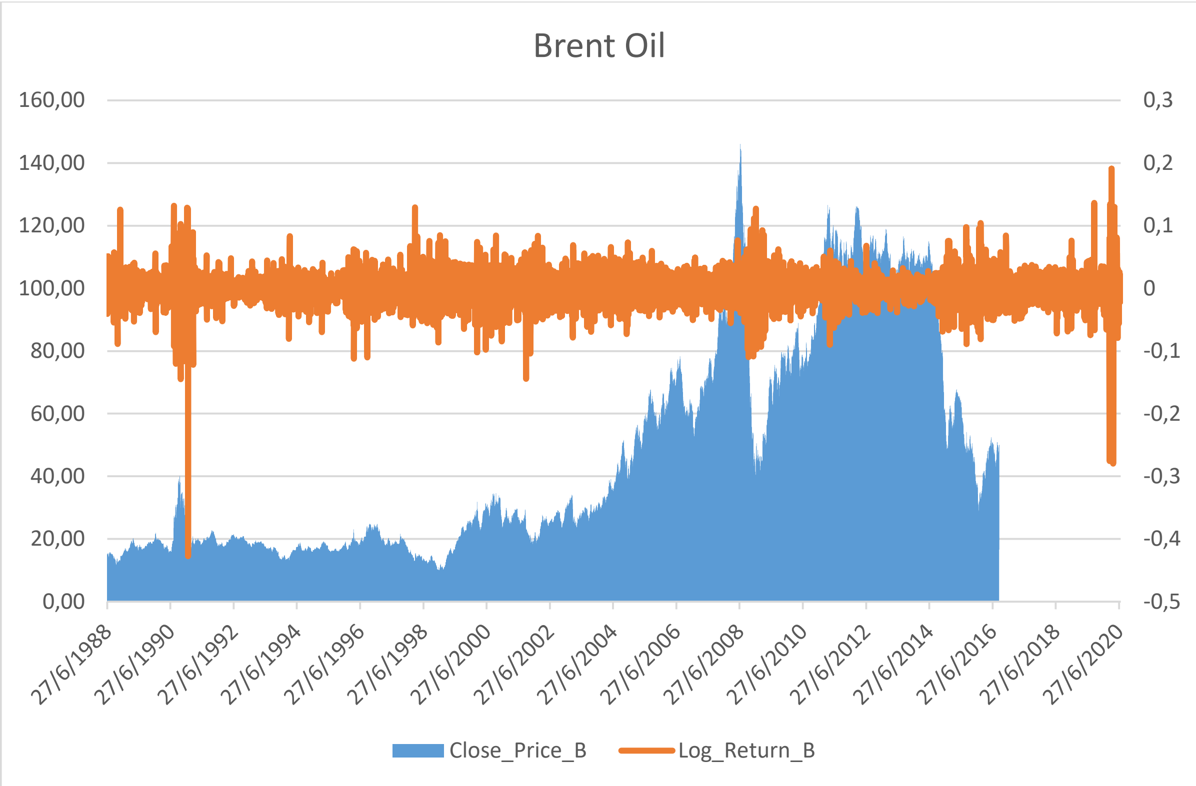


Figure 32: Brent oil daily closing prices and log returns graph

Close_Price_B	
Mean	48,07152286
Standard Error	0,362681711
Median	35,315
Mode	17,5
Standard Deviation	32,8061596
Sample Variance	1076,244108
Kurtosis	-0,543263082
Skewness	0,800710902
Range	136,44
Minimum	9,64
Maximum	146,08
Sum	393321,2
Count	8182

Table 27: Brent oil daily close prices descriptive statistics

Log_Return_B	
Mean	0,000128316
Standard Error	0,000255297
Median	0,000745212
Mode	0
Standard Deviation	0,023091285
Sample Variance	0,000533207
Kurtosis	23,5484408
Skewness	-1,204710868
Range	0,617997301
Minimum	-0,427223289
Maximum	0,190774012
Sum	1,049755897
Count	8181

Table 28: Brent oil daily log returns descriptive statistics

Gasoline

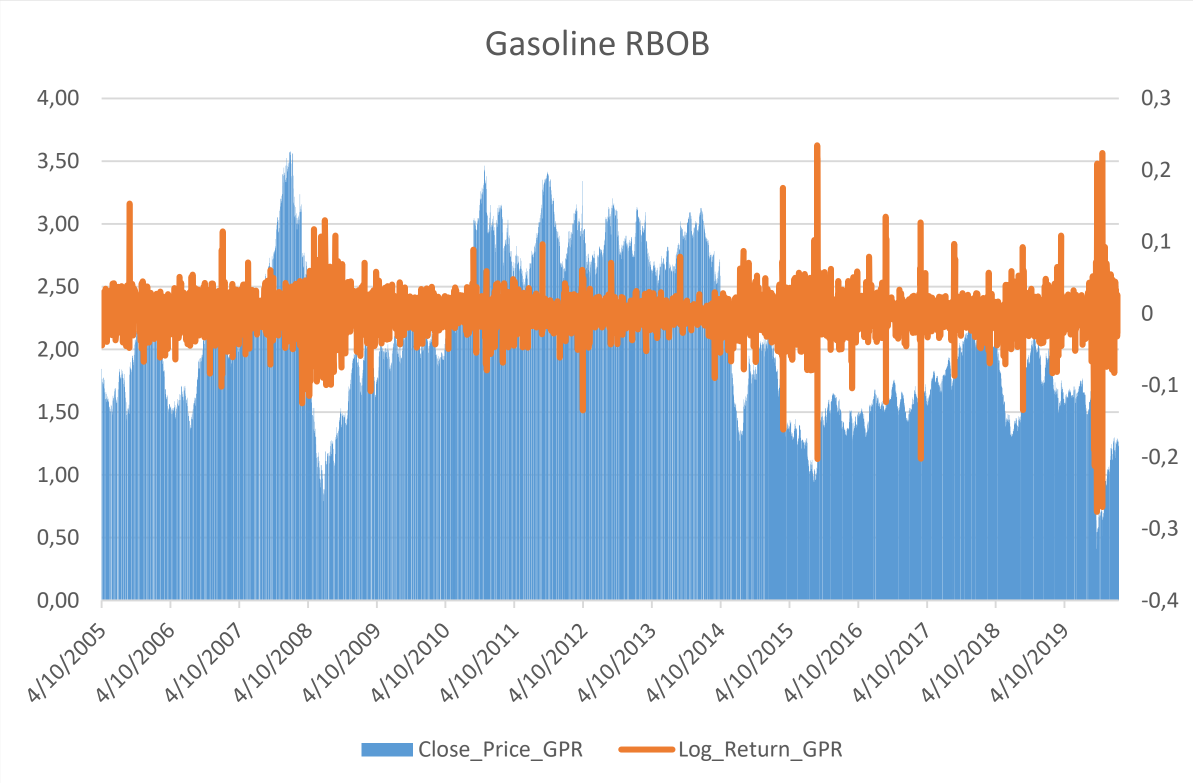


Figure 33: Gasoline daily closing prices and log returns graph

Close_Price_GPR	
Mean	2,049371901
Standard Error	0,009628333
Median	1,96635
Mode	2,3063
Standard Deviation	0,610317866
Sample Variance	0,372487898
Kurtosis	-0,688793157
Skewness	0,318126454
Range	3,1659
Minimum	0,4118
Maximum	3,5777
Sum	8234,3763
Count	4018

Table 29: Gasoline daily close prices descriptive statistics

Log_Return_GPR	
Mean	-0,000102093
Standard Error	0,00043031
Median	0,000558573
Mode	0
Standard Deviation	0,02727298
Sample Variance	0,000743815
Kurtosis	15,66209742
Skewness	-0,4266839
Range	0,511255547
Minimum	-0,276571525
Maximum	0,234684022
Sum	-0,410109268
Count	4017

Table 30: Gasoline daily log returns descriptive statistics

Heating Oil

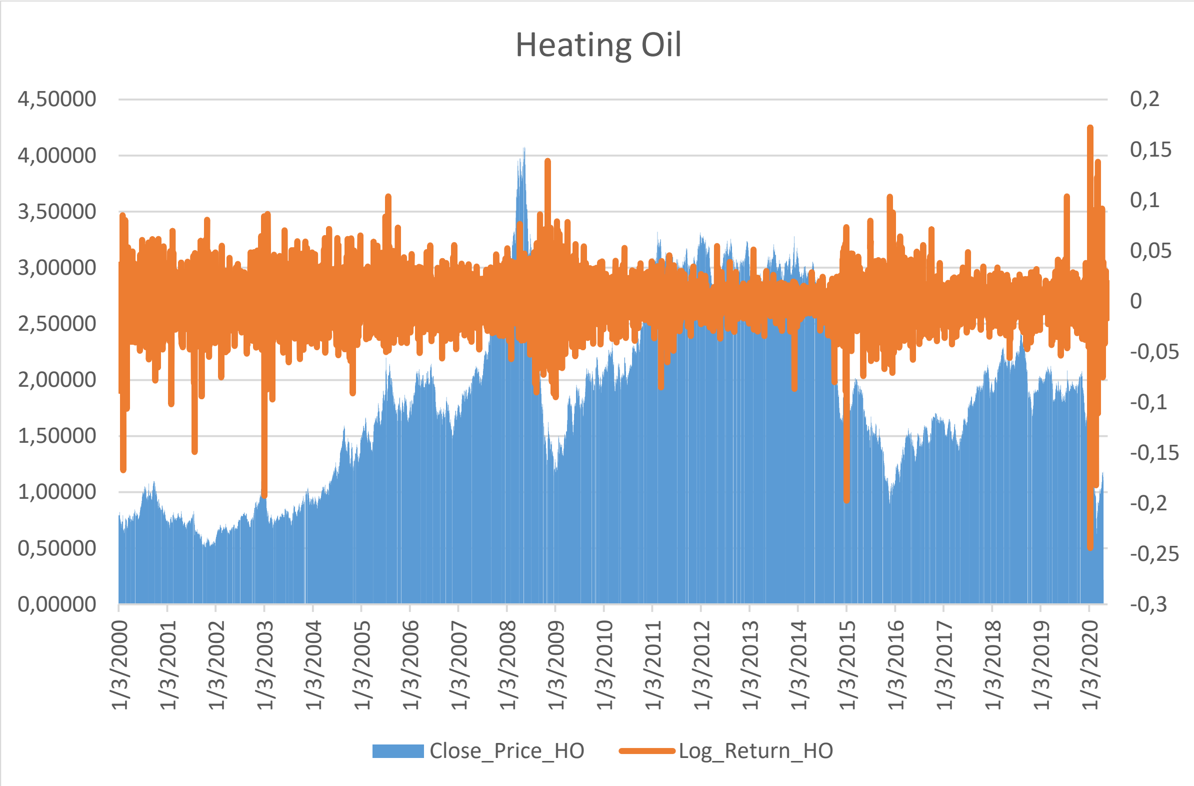


Figure 34: Heating oil daily closing prices and log returns graph

Close_Price_HO	
Mean	1,833069476
Standard Error	0,011090515
Median	1,8064
Mode	0,665
Standard Deviation	0,793107557
Sample Variance	0,629019596
Kurtosis	-0,807850975
Skewness	0,284740022
Range	3,5767
Minimum	0,4999
Maximum	4,0766
Sum	9374,3173
Count	5114

Table 31: Heating oil daily close prices descriptive statistics

Log_Return_HO	
Mean	0,000083444
Standard Error	0,000329393
Median	0,000249333
Mode	0
Standard Deviation	0,023553343
Sample Variance	0,00055476
Kurtosis	8,526598699
Skewness	-0,555001514
Range	0,416455259
Minimum	-0,244189814
Maximum	0,172265446
Sum	0,426649701
Count	5113

Table 32: Heating oil daily log returns descriptive statistics

Natural Gas

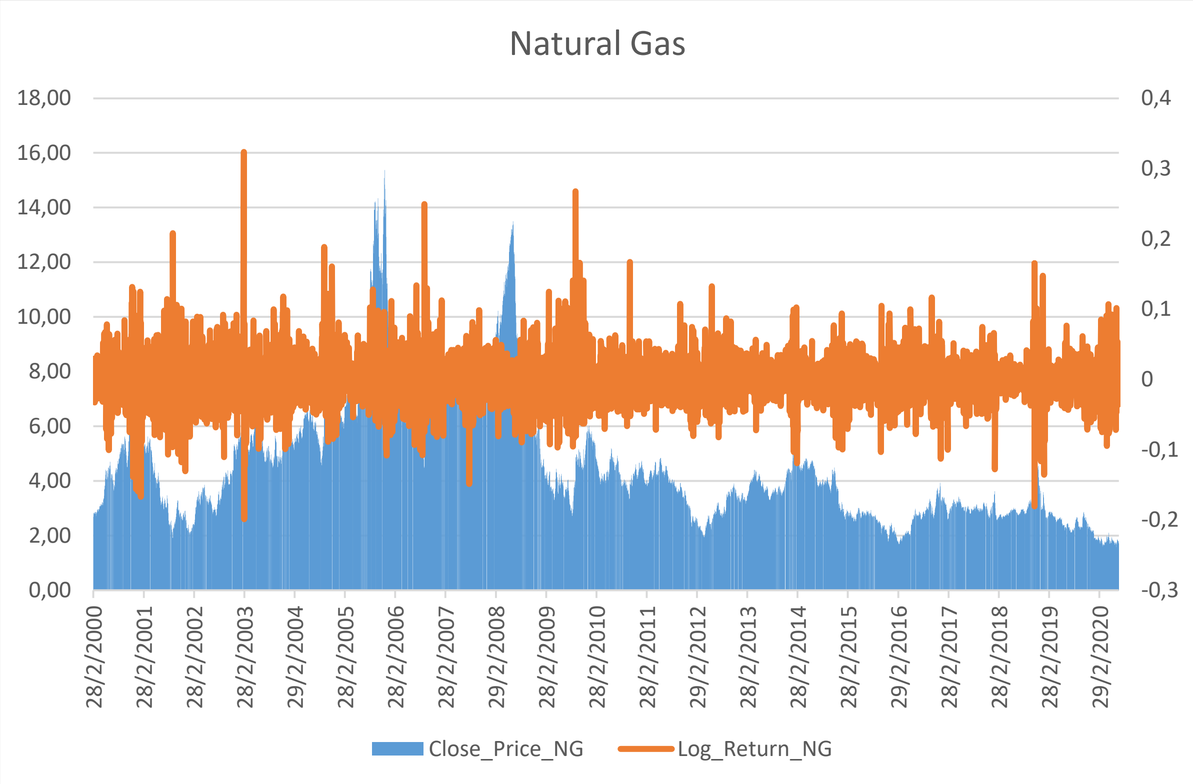


Figure 35: Natural gas daily closing prices and log returns graph

Close_Price_NG	
Mean	4,556685703
Standard Error	0,031692561
Median	3,932
Mode	3,617
Standard Deviation	2,266184354
Sample Variance	5,135591527
Kurtosis	2,678831448
Skewness	1,494685543
Range	13,841
Minimum	1,537
Maximum	15,378
Sum	23298,334
Count	5113

Table 33: Natural gas daily close prices descriptive statistics

Log_Return_NG	
Mean	-0,000088906
Standard Error	0,000472942
Median	-0,000582873
Mode	0
Standard Deviation	0,033814553
Sample Variance	0,001143424
Kurtosis	5,450355855
Skewness	0,505760641
Range	0,52274166
Minimum	-0,19899321
Maximum	0,32374845
Sum	-0,454487987
Count	5112

Table 34: Natural gas daily log returns descriptive statistics

6.3 Agriculture

Corn

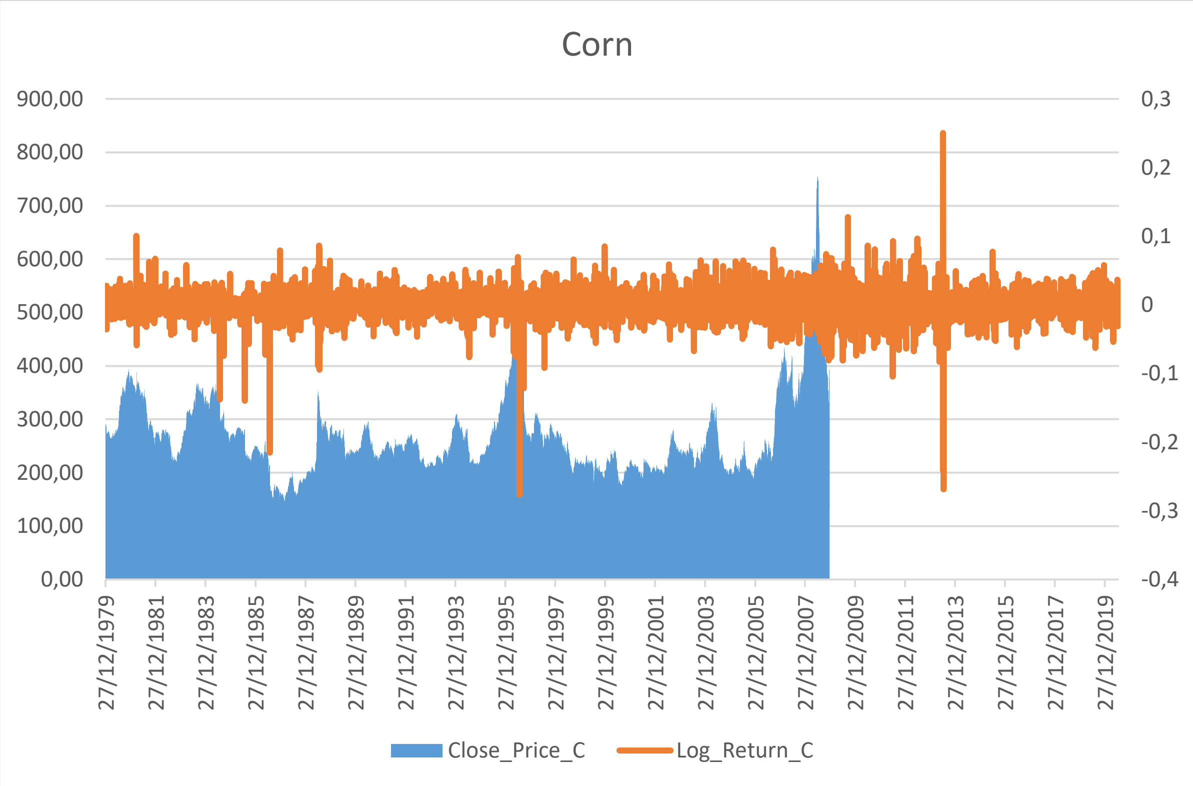


Figure 36: Corn daily closing prices and log returns graph

Close_Price_C	
Mean	323,8759826
Standard Error	1,2939229
Median	279,75
Mode	238,75
Standard Deviation	132,2525933
Sample Variance	17490,74843
Kurtosis	2,438267365
Skewness	1,622992105
Range	688,5
Minimum	142,75
Maximum	831,25
Sum	3383532,39
Count	10447

Table 35: Corn daily close prices descriptive statistics

Log_Return_C	
Mean	0,000013484
Standard Error	0,000165557
Median	0
Mode	0
Standard Deviation	0,016920862
Sample Variance	0,000286316
Kurtosis	27,4340072
Skewness	-0,98131582
Range	0,526494193
Minimum	-0,276205681
Maximum	0,250288511
Sum	0,140851124
Count	10446

Table 36: Corn daily log returns descriptive statistics

Rice

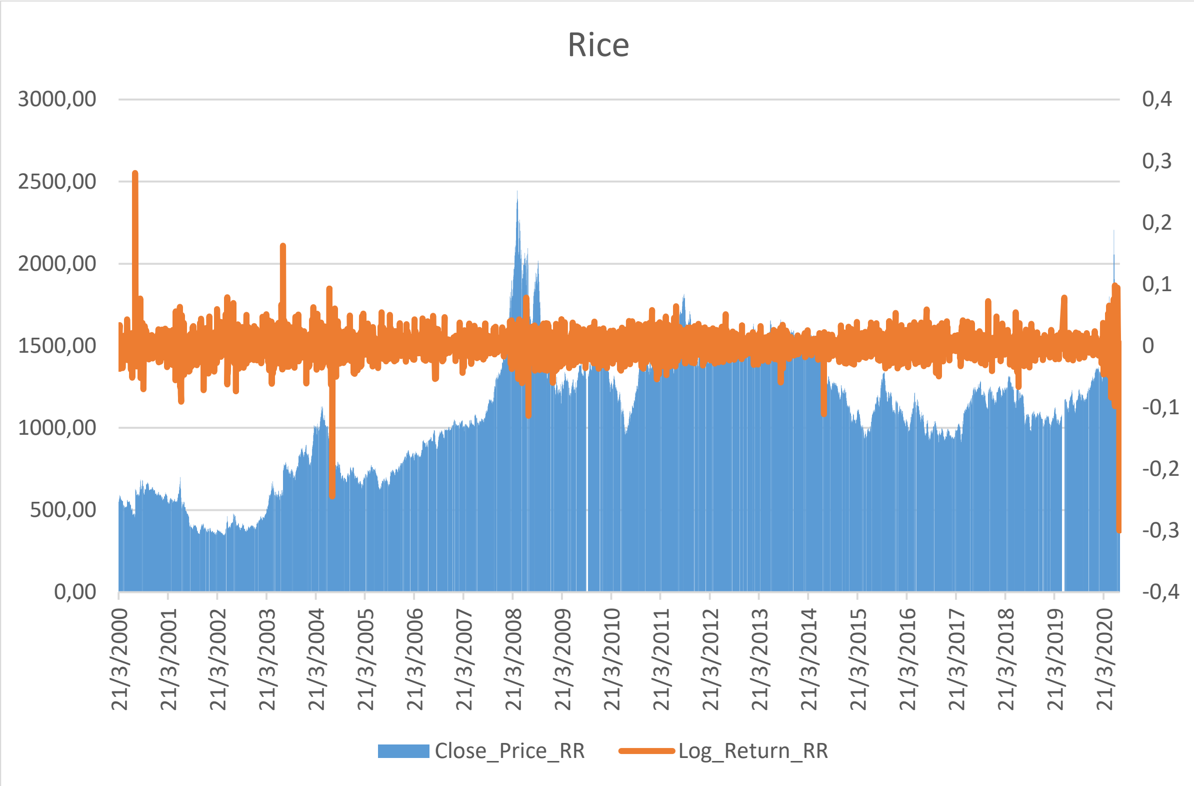


Figure 37: Rice daily closing prices and log returns graph

Close_Price_RR	
Mean	1087,556248
Standard Error	5,433194249
Median	1099
Mode	395
Standard Deviation	386,406697
Sample Variance	149310,1355
Kurtosis	-0,432010479
Skewness	-0,015123069
Range	2103
Minimum	343
Maximum	2446
Sum	5500859,5
Count	5058

Table 37: Rice daily close prices descriptive statistics

Log_Return_RR	
Mean	0,000151368
Standard Error	0,000255356
Median	0
Mode	0
Standard Deviation	0,018159007
Sample Variance	0,00032975
Kurtosis	35,73899979
Skewness	-0,535910422
Range	0,580519395
Minimum	-0,299702943
Maximum	0,280816453
Sum	0,765467842
Count	5057

Table 38: Rice daily log returns descriptive statistics

Soybeans

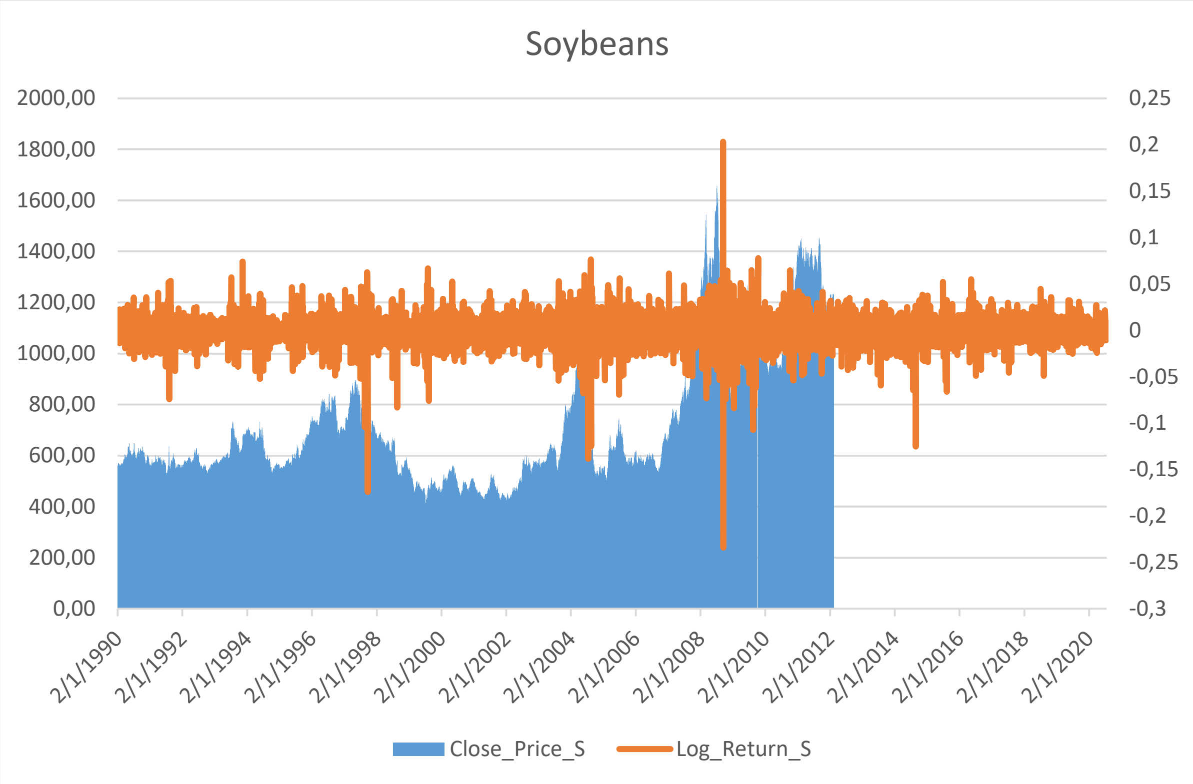


Figure 38: Soybeans daily closing prices and log returns graph

Close_Price_S	
Mean	828,7688969
Standard Error	3,387708206
Median	759,625
Mode	574
Standard Deviation	301,3727764
Sample Variance	90825,55037
Kurtosis	-0,263483
Skewness	0,800866727
Range	1354,75
Minimum	410
Maximum	1764,75
Sum	6558877,05
Count	7914

Table 39: Soybeans daily close prices descriptive statistics

Log_Return_S	
Mean	0,000059467
Standard Error	0,000168094
Median	0,000244776
Mode	0
Standard Deviation	0,014952817
Sample Variance	0,000223587
Kurtosis	19,20799009
Skewness	-0,946794841
Range	0,437318835
Minimum	-0,234109498
Maximum	0,203209336
Sum	0,470560267
Count	7913

Table 40: Soybeans daily log returns descriptive statistics

Soybean oil

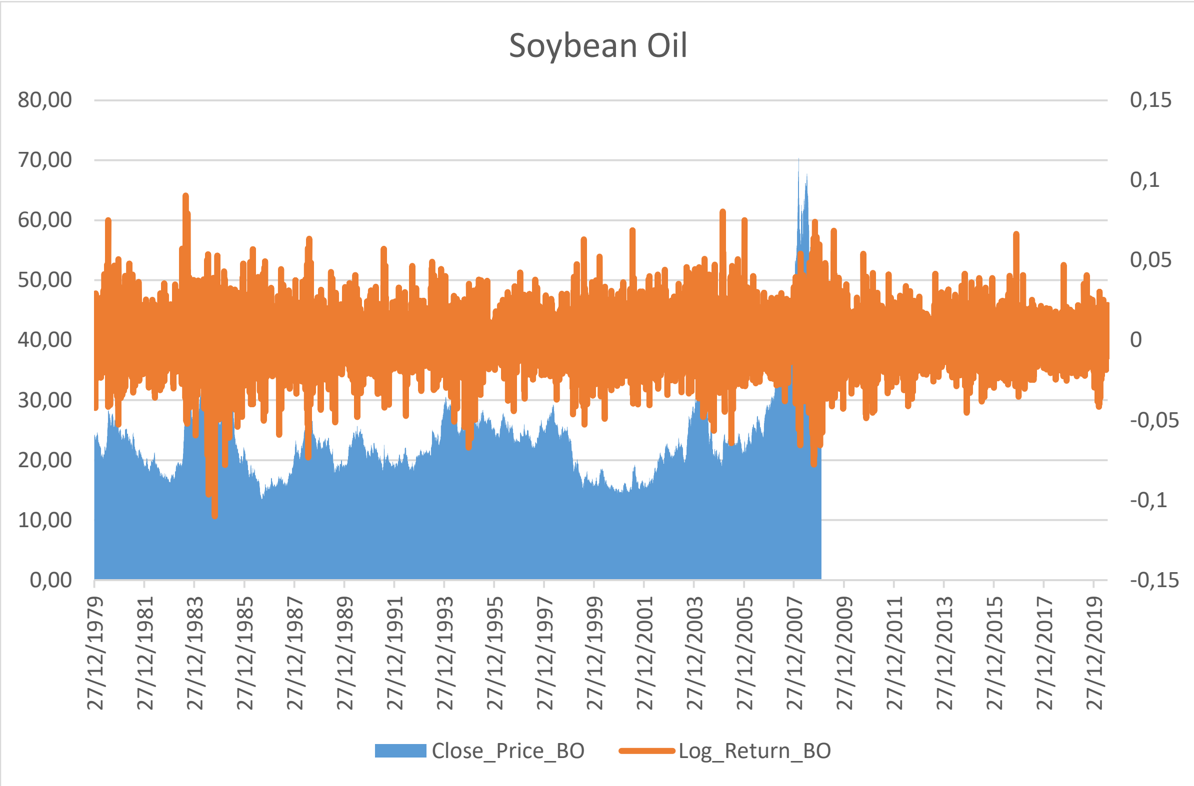


Figure 39: Soybean oil daily closing prices and log returns graph

Close_Price_BO	
Mean	28,08091474
Standard Error	0,103674348
Median	25,43
Mode	23,55
Standard Deviation	10,60421855
Sample Variance	112,4494511
Kurtosis	1,254887431
Skewness	1,28383576
Range	57,33
Minimum	13,07
Maximum	70,4
Sum	293782,53
Count	10462

Table 41: Soybean oil daily close prices descriptive statistics

Log_Return_BO	
Mean	0,000020480
Standard Error	0,000144047
Median	0
Mode	0
Standard Deviation	0,014732973
Sample Variance	0,000217060
Kurtosis	2,628145118
Skewness	0,014458892
Range	0,200571021
Minimum	-0,110186959
Maximum	0,090384061
Sum	0,214242773
Count	10461

Table 42: Soybean oil daily log returns descriptive statistics

Soybean meal

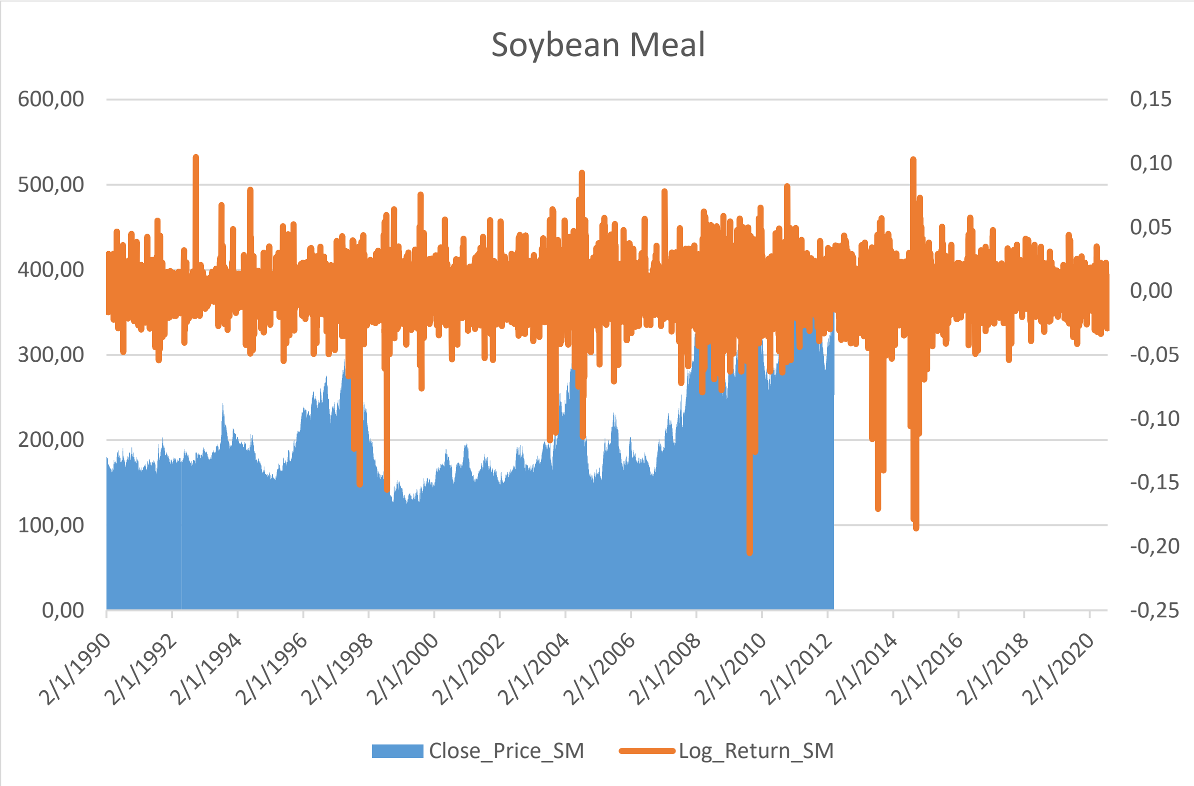


Figure 40: Soybean meal daily closing prices and log returns graph

Close_Price_SM	
Mean	255,3368584
Standard Error	1,0250126
Median	235,7
Mode	173,9
Standard Deviation	90,96084482
Sample Variance	8273,87529
Kurtosis	-0,36502628
Skewness	0,680724917
Range	427,6
Minimum	120,5
Maximum	548,1
Sum	2010777,76
Count	7875

Table 43: Soybean meal daily close prices descriptive statistics

Log_Return_SM	
Mean	0,00005924
Standard Error	0,00019642
Median	0
Mode	0
Standard Deviation	0,017429434
Sample Variance	0,000303785
Kurtosis	12,38679961
Skewness	-1,150068954
Range	0,31027423
Minimum	-0,205213161
Maximum	0,10506107
Sum	0,466449742
Count	7874

Table 44: Soybean meal daily log returns descriptive statistics

Oats

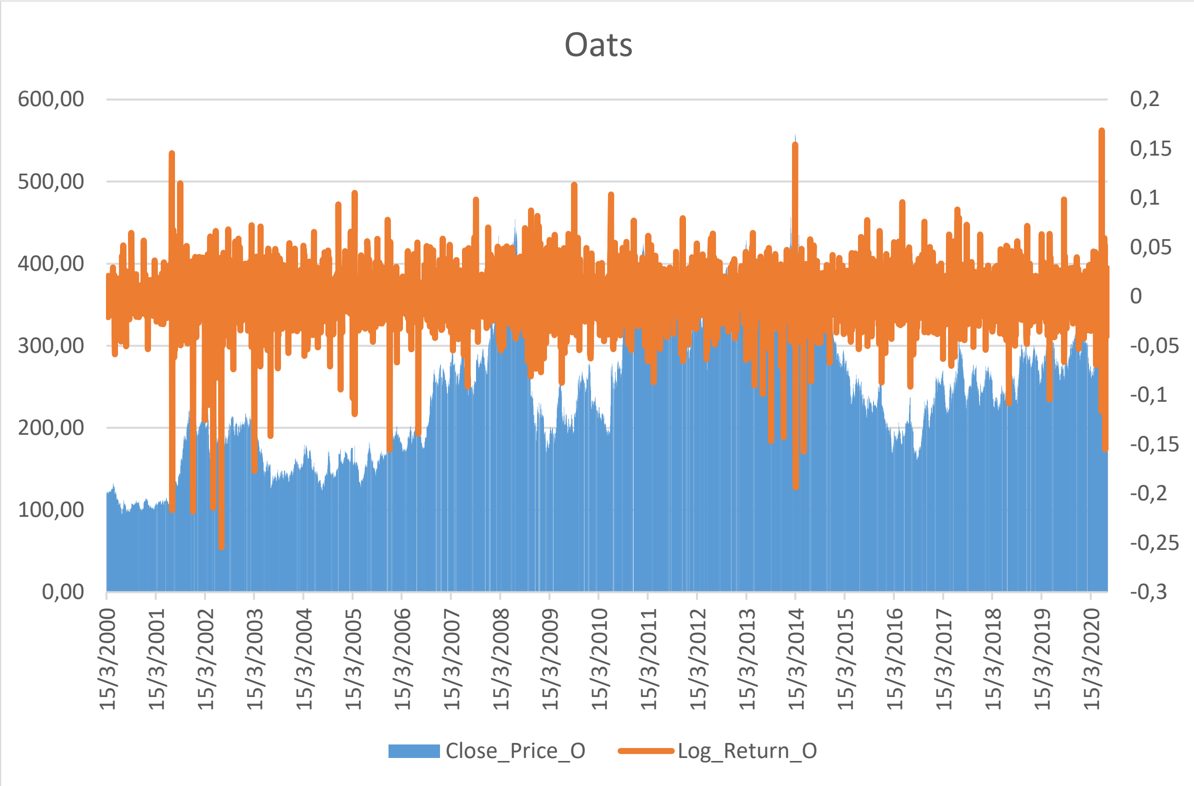


Figure 41: Oats daily closing prices and log returns graph

Close_Price_O	
Mean	247,8990555
Standard Error	1,18227023
Median	243,125
Mode	188
Standard Deviation	84,28185472
Sample Variance	7103,431035
Kurtosis	-0,638879424
Skewness	0,28137672
Range	464
Minimum	93,75
Maximum	557,75
Sum	1259823
Count	5082

Table 45: Oats daily close prices descriptive statistics

Log_Return_O	
Mean	0,000167344
Standard Error	0,000335088
Median	0
Mode	0
Standard Deviation	0,023885459
Sample Variance	0,000570515
Kurtosis	12,27668135
Skewness	-1,060630359
Range	0,423067178
Minimum	-0,254562766
Maximum	0,168504411
Sum	0,850275826
Count	5081

Table 46: Oats daily log returns descriptive statistics

Wheat

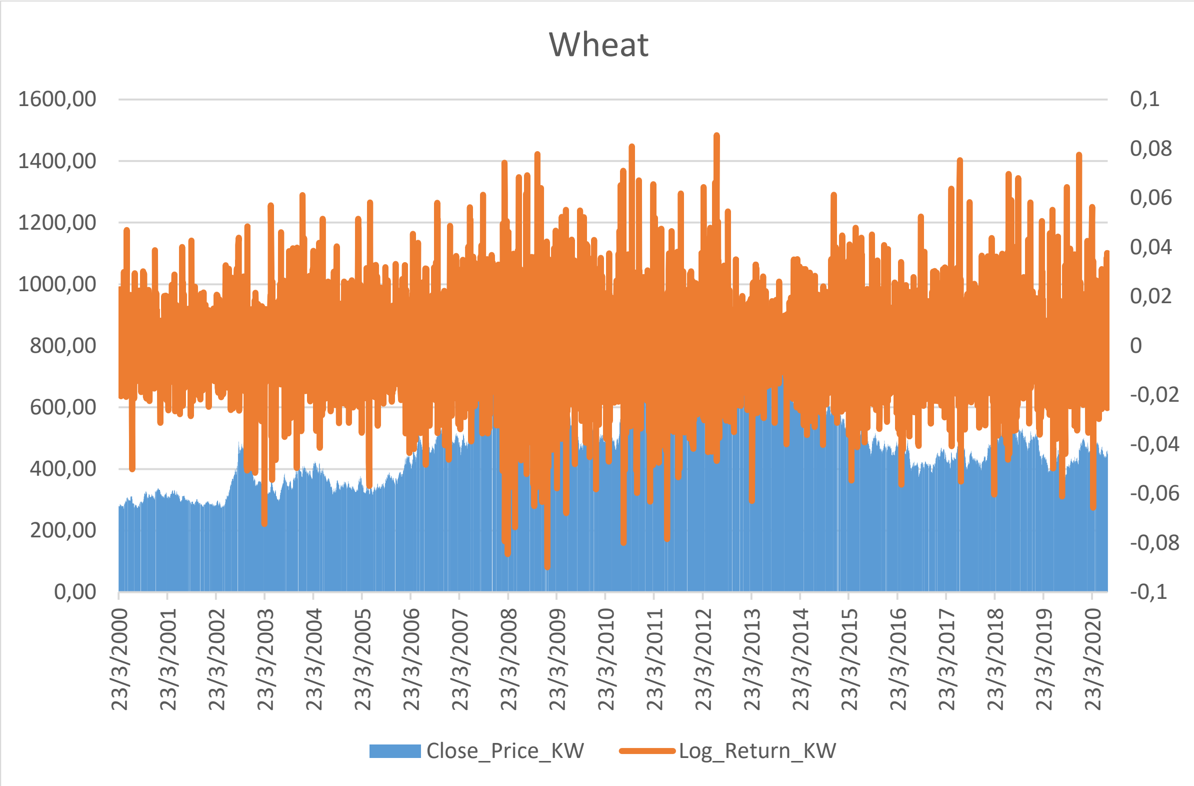


Figure 42: Wheat daily closing prices and log returns graph

Close_Price_KW	
Mean	522,782185
Standard Error	2,589531045
Median	478,25
Mode	282
Standard Deviation	184,5665431
Sample Variance	34064,80884
Kurtosis	0,214675218
Skewness	0,888613308
Range	1066,25
Minimum	270,75
Maximum	1337
Sum	2655733,5
Count	5080

Table 47: Wheat daily close prices descriptive statistics

Log_Return_KW	
Mean	0,000092692
Standard Error	0,000255259
Median	0
Mode	0
Standard Deviation	0,018191539
Sample Variance	0,000330932
Kurtosis	1,702148737
Skewness	0,104088753
Range	0,175394861
Minimum	-0,089948237
Maximum	0,085446625
Sum	0,470783878
Count	5079

Table 48: Wheat daily log returns descriptive statistics

Coffee

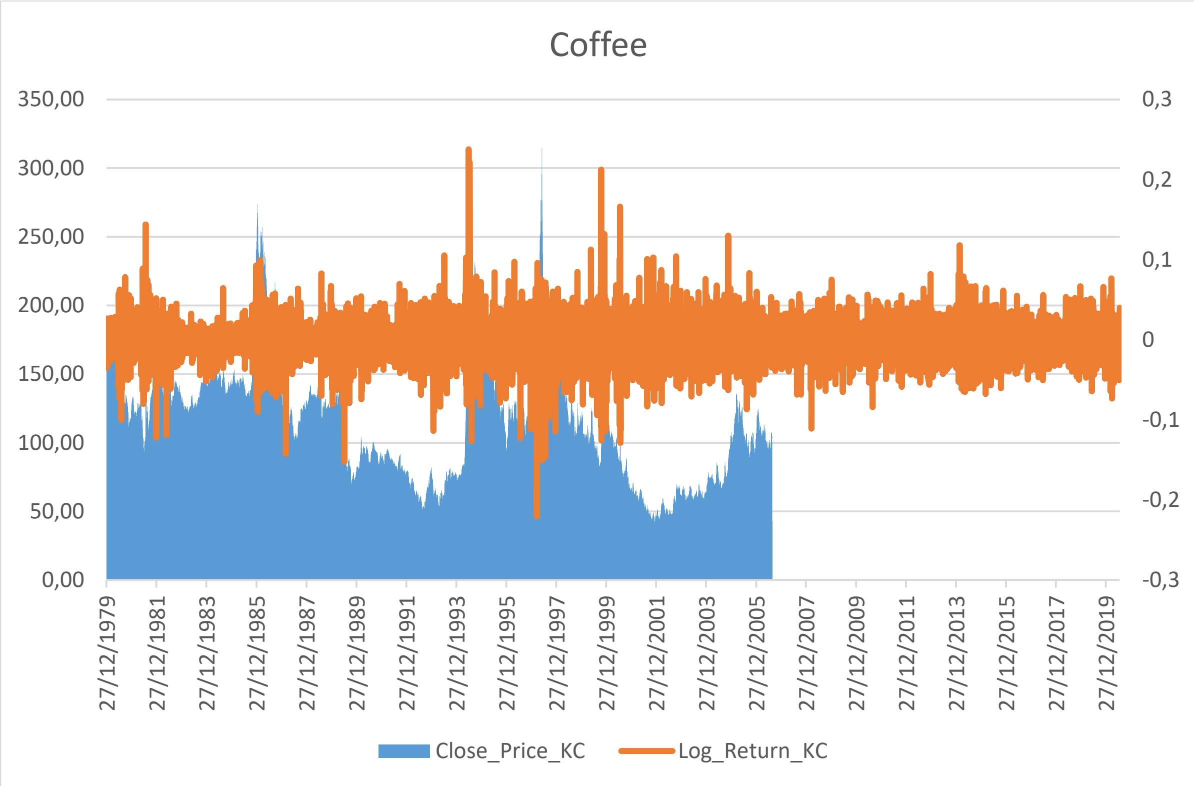


Figure 43: Coffee daily closing prices and log returns graph

Close_Price_KC	
Mean	124,2987496
Standard Error	0,437840007
Median	122,4
Mode	113
Standard Deviation	44,28248978
Sample Variance	1960,938901
Kurtosis	1,193462027
Skewness	0,820697832
Range	273,3
Minimum	41,5
Maximum	314,8
Sum	1271451,91
Count	10229

Table 49: Coffee daily close prices descriptive statistics

Log_Return_KC	
Mean	-0,000058159
Standard Error	0,000226122
Median	0
Mode	0
Standard Deviation	0,022868521
Sample Variance	0,000522969
Kurtosis	7,131080791
Skewness	0,067570762
Range	0,458367002
Minimum	-0,220641912
Maximum	0,23772509
Sum	-0,594853832
Count	10228

Table 50: Coffee daily log returns descriptive statistics

Cocoa

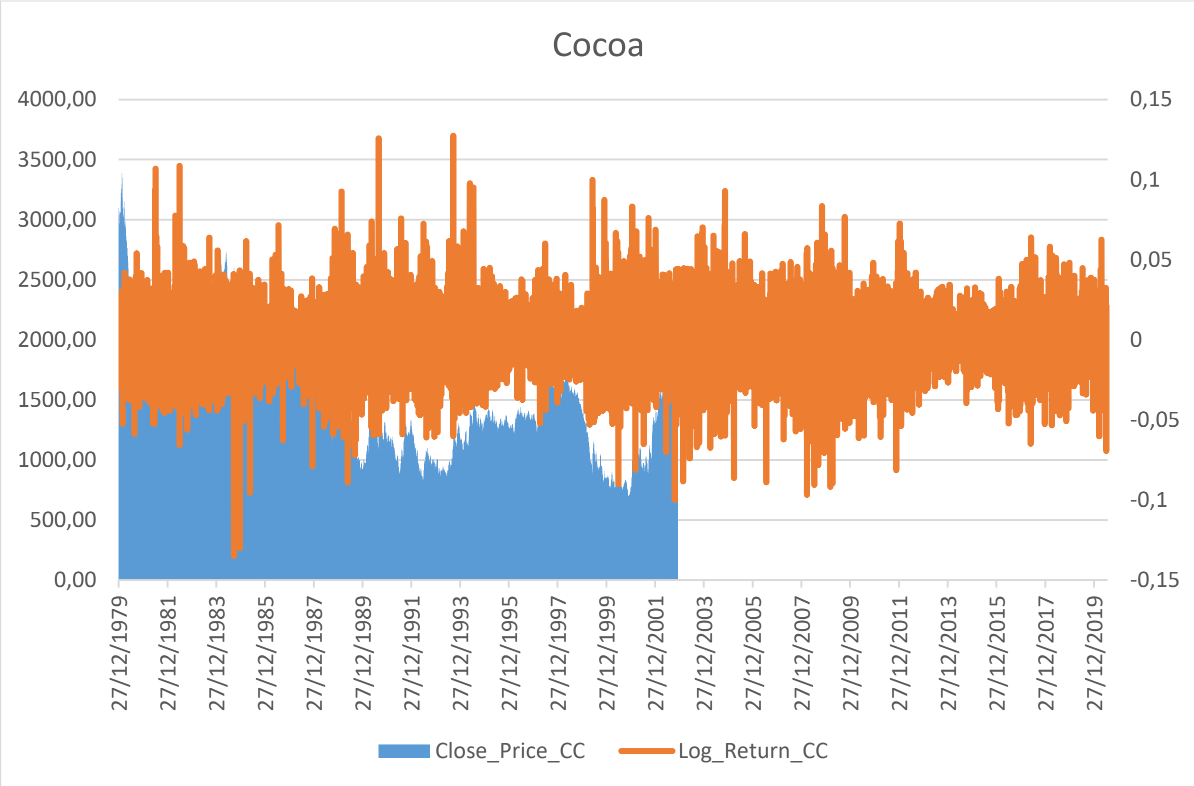


Figure 44: Cocoa daily closing prices and log returns graph

Close_Price_CC	
Mean	1877,725403
Standard Error	6,657888049
Median	1827
Mode	1327
Standard Deviation	671,886142
Sample Variance	451430,9878
Kurtosis	-0,815736743
Skewness	0,366443704
Range	3100
Minimum	674
Maximum	3774
Sum	19122755,5
Count	10184

Table 51: Cocoa daily close prices descriptive statistics

Log_Return_CC	
Mean	-0,000035322
Standard Error	0,000191531
Median	0
Mode	0
Standard Deviation	0,019327541
Sample Variance	0,000373554
Kurtosis	2,647558163
Skewness	0,022824142
Range	0,262439509
Minimum	-0,135068672
Maximum	0,127370837
Sum	-0,359679684
Count	10183

Table 52: Cocoa daily log returns descriptive statistics

Sugar

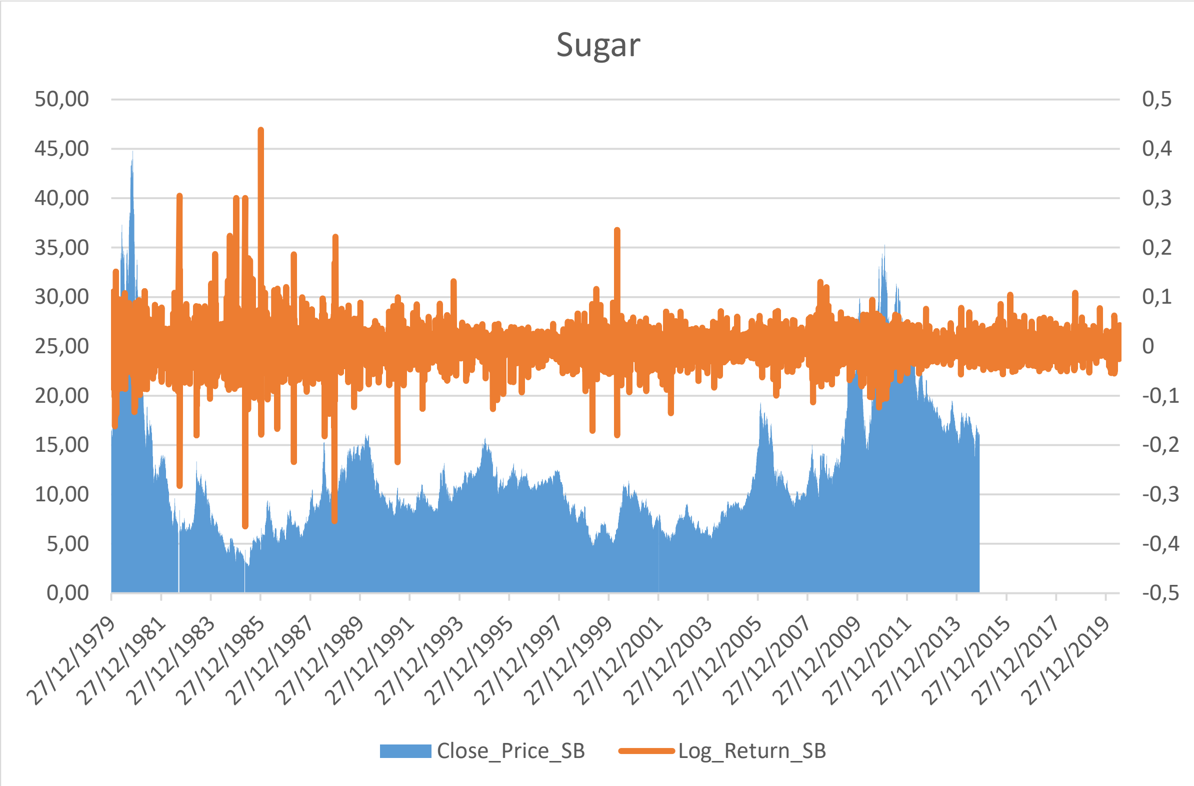


Figure 45: Sugar daily closing prices and log returns graph

Close_Price_SB	
Mean	12,35835895
Standard Error	0,060618001
Median	11,11
Mode	10,97
Standard Deviation	6,126018135
Sample Variance	37,52809819
Kurtosis	3,119591304
Skewness	1,553434081
Range	42,45
Minimum	2,35
Maximum	44,8
Sum	126215,92
Count	10213

Table 53: Sugar daily close prices descriptive statistics

Log_Return_SB	
Mean	-0,000033235
Standard Error	0,000275005
Median	0
Mode	0
Standard Deviation	0,027790484
Sample Variance	0,000772311
Kurtosis	22,51060804
Skewness	0,215930468
Range	0,802822002
Minimum	-0,364187636
Maximum	0,438634366
Sum	-0,339390882
Count	10212

Table 54: Sugar daily log returns descriptive statistics

Cotton

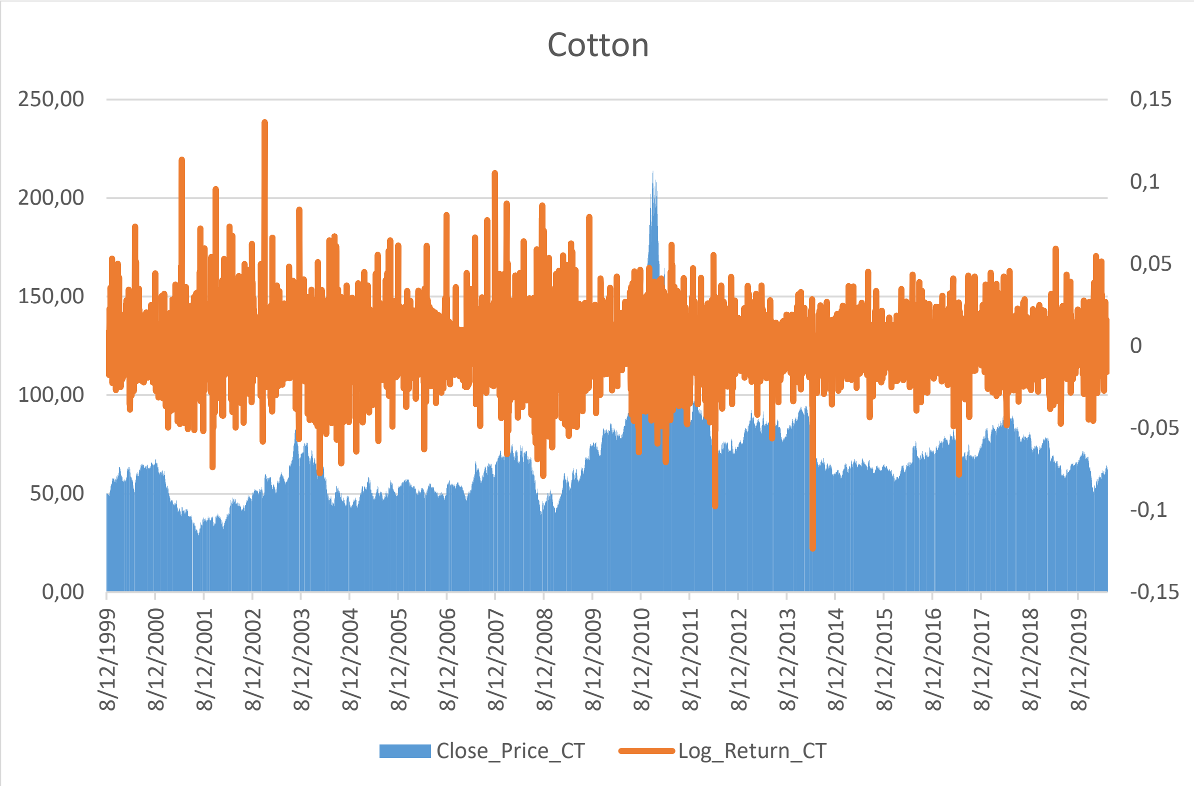


Figure 46: Cotton daily closing prices and log returns graph

Close_Price_CT	
Mean	67,98632726
Standard Error	0,322347521
Median	64,32
Mode	49
Standard Deviation	23,30062027
Sample Variance	542,9189051
Kurtosis	9,677858462
Skewness	2,445798123
Range	185,32
Minimum	28,52
Maximum	213,84
Sum	355228,56
Count	5225

Table 55: Cotton daily close prices descriptive statistics

Log_Return_CT	
Mean	0,000040748
Standard Error	0,000249544
Median	0
Mode	0
Standard Deviation	0,018036369
Sample Variance	0,000325311
Kurtosis	3,563228603
Skewness	0,186082933
Range	0,259700699
Minimum	-0,123482356
Maximum	0,136218343
Sum	0,212867249
Count	5224

Table 56: Cotton daily log returns descriptive statistics

Lumber

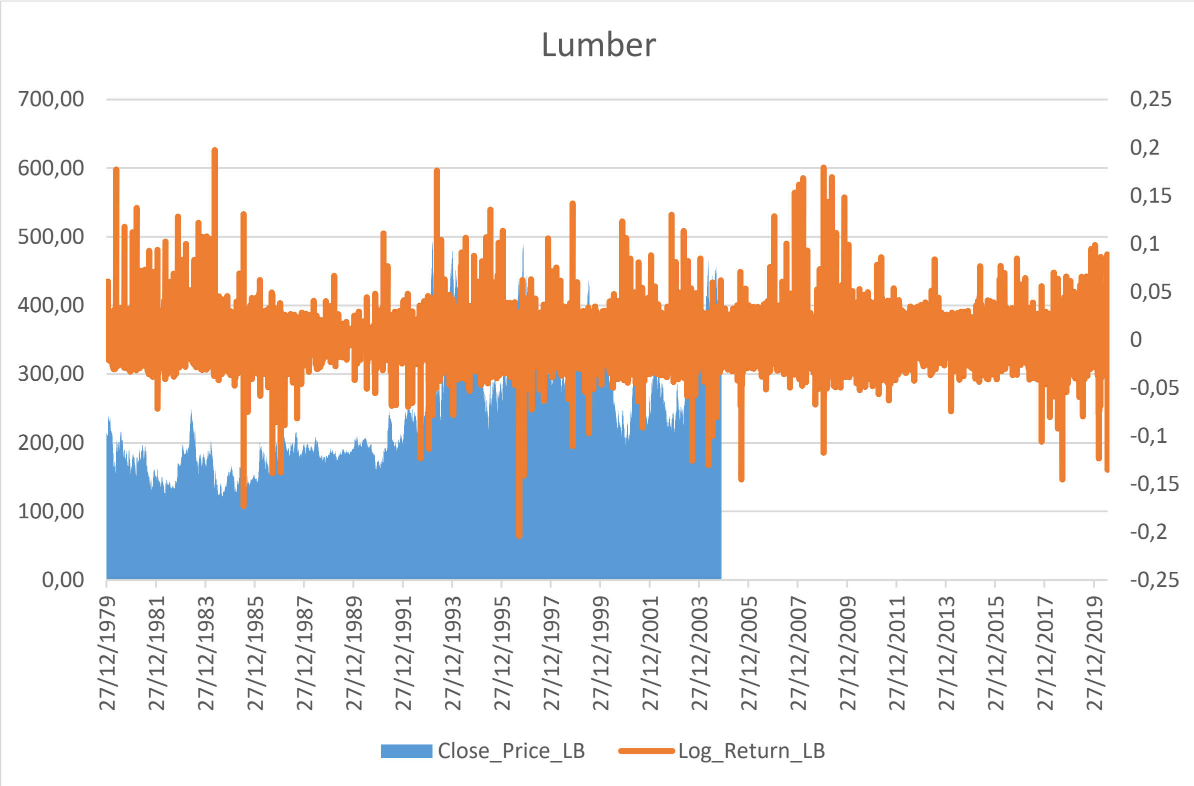


Figure 47: Lumber daily closing prices and log returns graph

Close_Price_LB	
Mean	267,3009875
Standard Error	0,856197007
Median	260,85
Mode	185,3
Standard Deviation	86,59026429
Sample Variance	7497,873869
Kurtosis	0,128602187
Skewness	0,563709664
Range	537
Minimum	114
Maximum	651
Sum	2733954,5
Count	10228

Table 57: Lumber daily close prices descriptive statistics

Log_Return_LB	
Mean	0,000092304
Standard Error	0,000215381
Median	-0,000307172
Mode	0
Standard Deviation	0,021781181
Sample Variance	0,00047442
Kurtosis	8,610894459
Skewness	0,575137116
Range	0,401513139
Minimum	-0,204393361
Maximum	0,197119778
Sum	0,943994864
Count	10227

Table 58: Lumber daily log returns descriptive statistics

Lean hogs

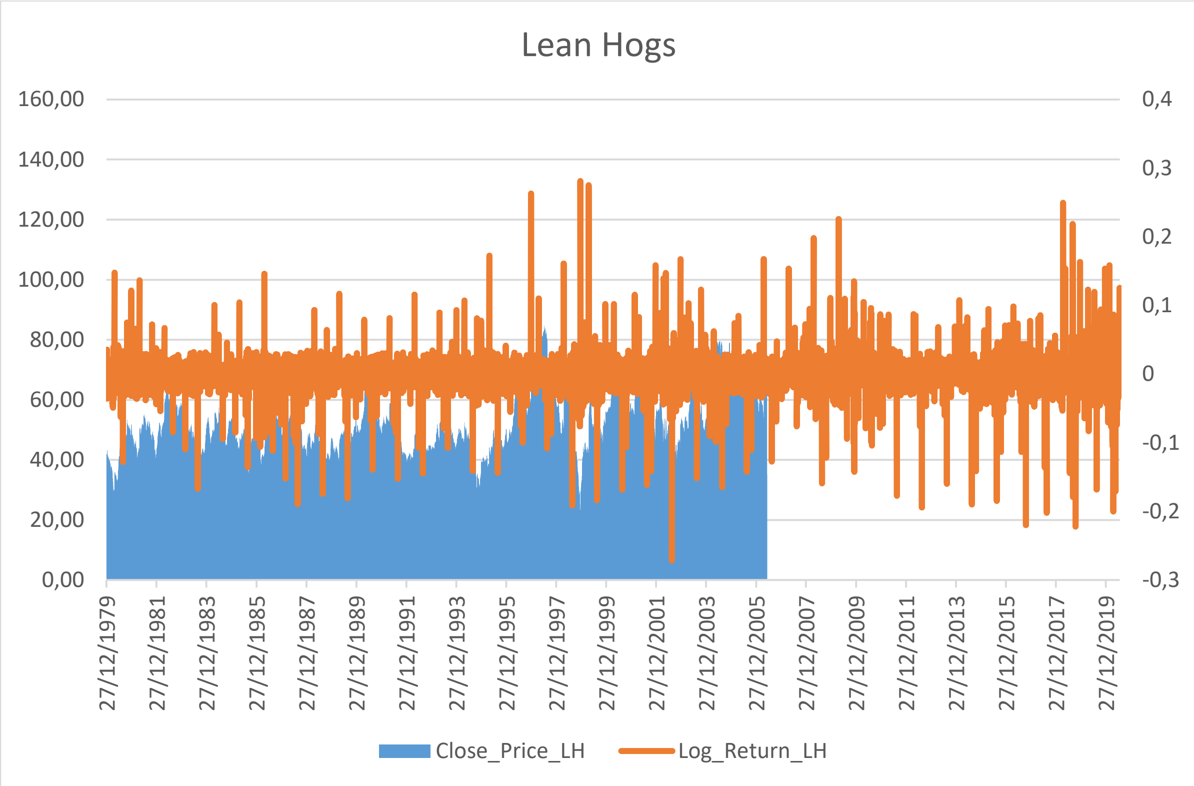


Figure 48: Lean hogs daily closing prices and log returns graph

Close_Price_LH	
Mean	59,97120905
Standard Error	0,160362583
Median	56,7
Mode	47,12
Standard Deviation	16,24022525
Sample Variance	263,7449161
Kurtosis	1,428950533
Skewness	1,048579167
Range	112,28
Minimum	21,1
Maximum	133,38
Sum	615064,72
Count	10256

Table 59: Lean hogs daily close prices descriptive statistics

Log_Return_LH	
Mean	0,000022548
Standard Error	0,000225299
Median	0,000387522
Mode	0
Standard Deviation	0,022815312
Sample Variance	0,000520538
Kurtosis	28,28862786
Skewness	-0,230199851
Range	0,552857692
Minimum	-0,271713532
Maximum	0,281144159
Sum	0,231225364
Count	10255

Table 60: Lean hogs daily log returns descriptive statistics

Feeder Cattle

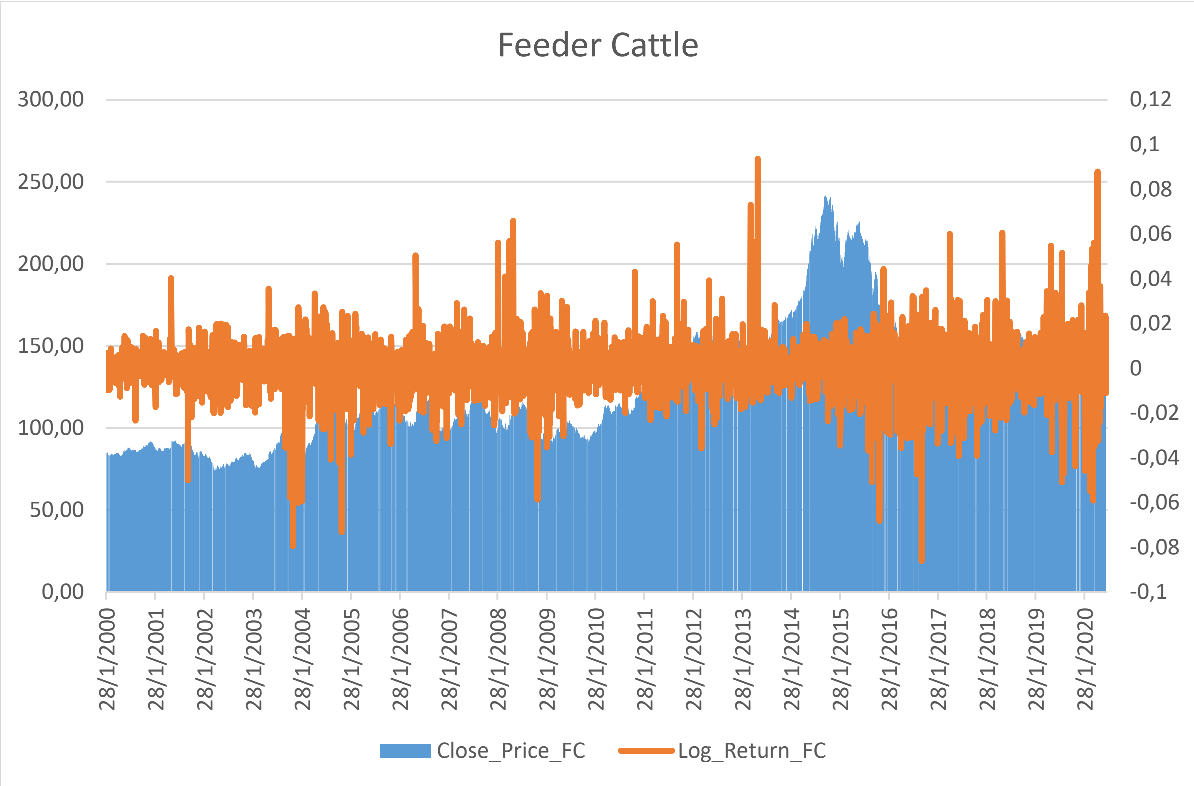


Figure 49: Feeder cattle daily closing prices and log returns graph

Close_Price_FC	
Mean	125,0341583
Standard Error	0,499254164
Median	115,324997
Mode	145,425003
Standard Deviation	35,68532421
Sample Variance	1273,442364
Kurtosis	0,891472172
Skewness	1,022354309
Range	168,824997
Minimum	73,5
Maximum	242,324997
Sum	638799,5147
Count	5109

Table 61: Feeder cattle daily close prices descriptive statistics

Log_Return_FC	
Mean	0,000102198
Standard Error	0,000144497
Median	0,000250827
Mode	0
Standard Deviation	0,010327261
Sample Variance	0,000106652
Kurtosis	11,11200826
Skewness	0,013461268
Range	0,179782919
Minimum	-0,0861144
Maximum	0,093668519
Sum	0,522028451
Count	5108

Table 62: Feeder cattle daily log returns descriptive statistics

Live Cattle

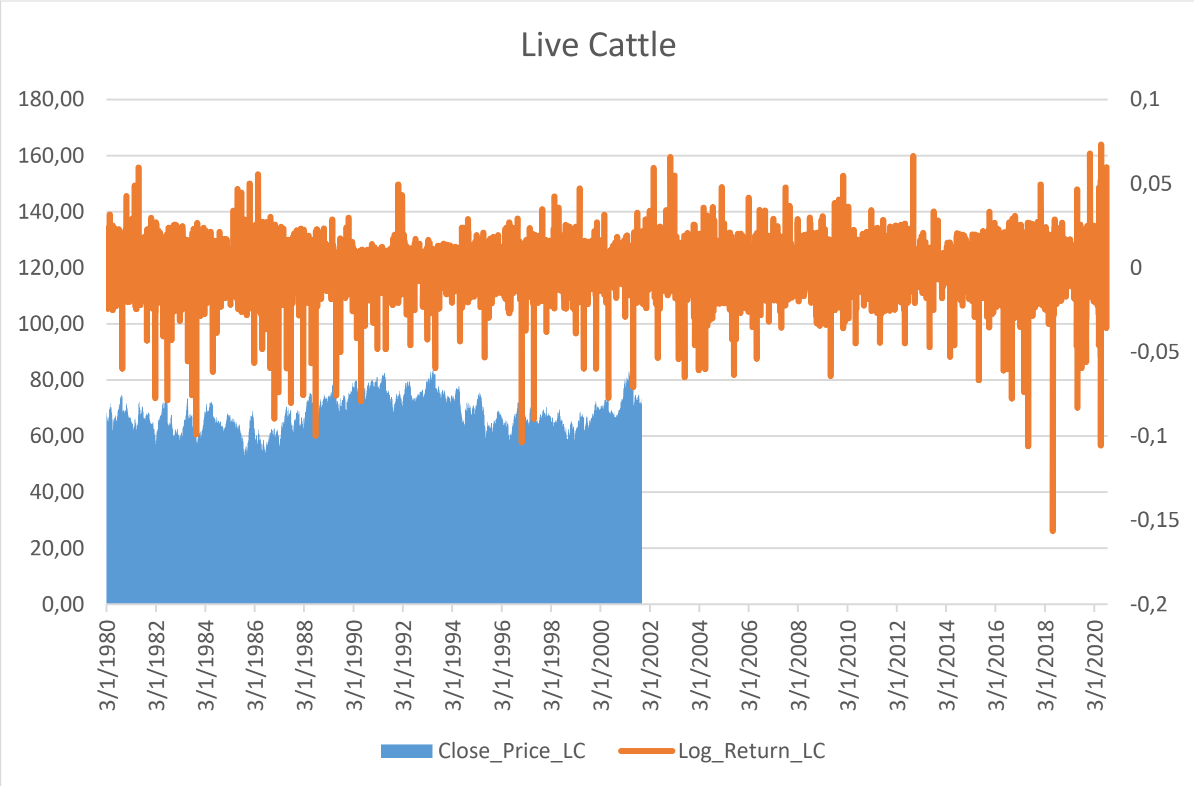


Figure 50: Live cattle daily closing prices and log returns graph

Close_Price_LC	
Mean	85,49260855
Standard Error	0,244847822
Median	75,45
Mode	90
Standard Deviation	24,78169633
Sample Variance	614,1324729
Kurtosis	0,578101804
Skewness	1,174452204
Range	120,03
Minimum	50,97
Maximum	171
Sum	875786,282
Count	10244

Table 63: Live cattle daily close prices descriptive statistics

Log_Return_LC	
Mean	0,000040439
Standard Error	0,000113887
Median	0,000220531
Mode	0
Standard Deviation	0,011526259
Sample Variance	0,000132855
Kurtosis	12,68945903
Skewness	-1,29671308
Range	0,229697407
Minimum	-0,156476615
Maximum	0,073220792
Sum	0,414217899
Count	10243

Table 64: Live cattle daily log returns descriptive statistics

7. EMPIRICAL RESULTS

7.1 ARIMA Models

As we discussed in Methodology chapter we have created two sets of ARIMA models the Custom ARIMA models and the Eviews add in ARIMA models. At the following table, we present all these models.

	Custom Models	Eviews Add in Models
Aluminum	ARIMA(5,1,5)	ARIMA(6,1,6)
Corn	ARIMA(3,1,3)	ARIMA(4,1,5)
Brent Oil	ARIMA(2,1,2)	ARIMA(8,1,8)
Coffee	ARIMA(1,1,1)	ARIMA(6,1,9)
Copper	ARIMA(5,1,5)	ARIMA(8,1,6)
Crude Oil	ARIMA(1,1,6)	ARIMA(5,1,5)
Feeder Cattle	ARIMA(6,1,6)	ARIMA(1,1,0)
Cocoa	ARIMA(3,1,3)	ARIMA(8,1,5)
Gasoline	ARIMA(6,1,1)	ARIMA(6,1,5)
Gold	ARIMA(2,1,2)	ARIMA(7,1,7)
Heating Oil	ARIMA(4,1,4)	ARIMA(8,1,8)
Lead	ARIMA(4,1,4)	ARIMA(5,1,5)
Lean Hogs	ARIMA(3,1,3)	ARIMA(5,1,5)
Live Cattle	ARIMA(4,1,4)	ARIMA(6,1,7)
Lumber	ARIMA(2,1,9)	ARIMA(10,1,10)
Natural Gas	ARIMA(1,1,1)	ARIMA(4,1,4)
Nickel	ARIMA(1,1,1)	ARIMA(2,1,2)
Oats	ARIMA(1,1,5)	ARIMA(5,1,5)
Palladium	ARIMA(6,1,6)	ARIMA(8,1,6)
Platinum	ARIMA(3,1,3)	ARIMA(4,1,0)
Rice	ARIMA(6,1,5)	ARIMA(0,1,1)
Silver	ARIMA(3,1,3)	ARIMA(6,1,4)
Soybean Meal	ARIMA(1,1,5)	ARIMA(7,1,7)
Soybean Oil	ARIMA(2,1,2)	ARIMA(5,1,7)
Soybeans	ARIMA(6,1,6)	ARIMA(10,1,8)
Sugar	ARIMA(3,1,2)	ARIMA(7,1,4)
Tin	ARIMA(5,1,5)	ARIMA(7,1,7)
Wheat	ARIMA(2,1,2)	ARIMA(6,1,6)
Zinc	ARIMA(3,1,3)	ARIMA(6,1,4)
Cotton	ARIMA(2,1,2)	ARIMA(7,1,7)

Table 65: ARIMA models for the commodities

Using these ARIMA models for each commodity, we performed an out of sample forecast. We observe that most of the created models captured the trends and the turns of the daily closing prices. Below you can see the results of each out of sample forecast, as well as the graphical comparison of the two set of models with the actual prices.

Aluminum

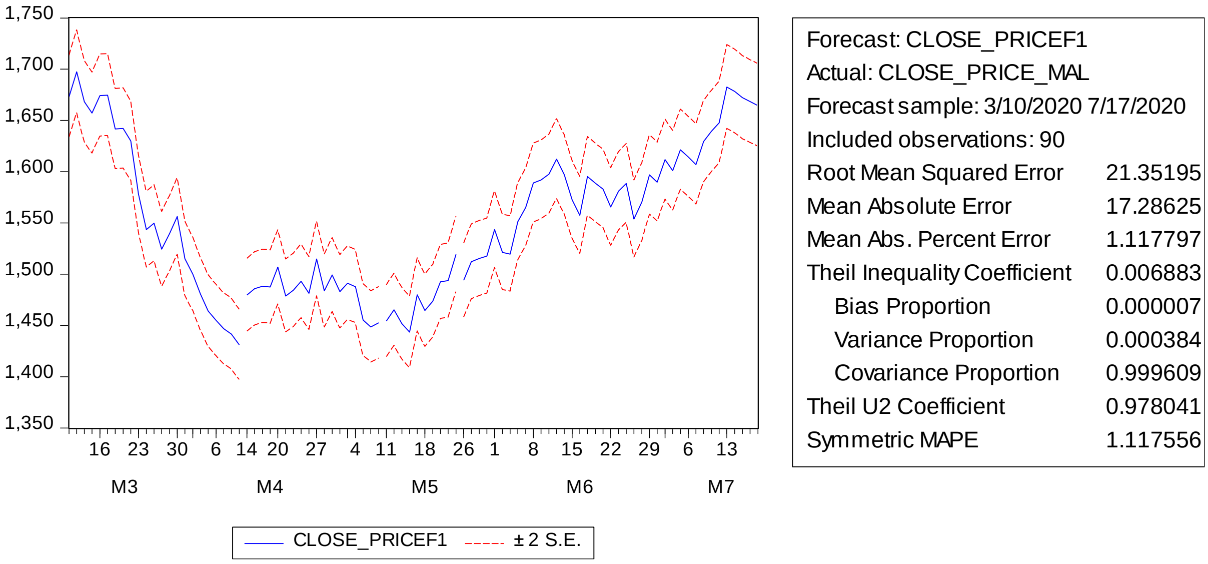


Figure 51: Custom ARIMA Model forecast output for Aluminum

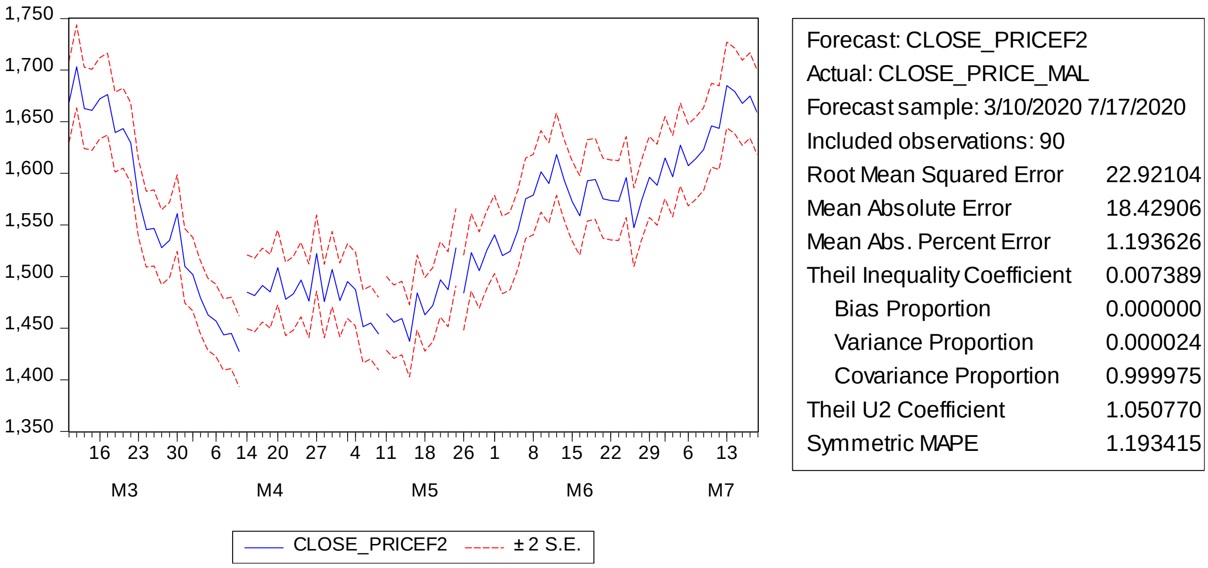


Figure 52: Eviews add in ARIMA Model forecast output for Aluminum

Figure 53: Comparison of the out of sample forecast of two ARIMA models for aluminum

Brent oil

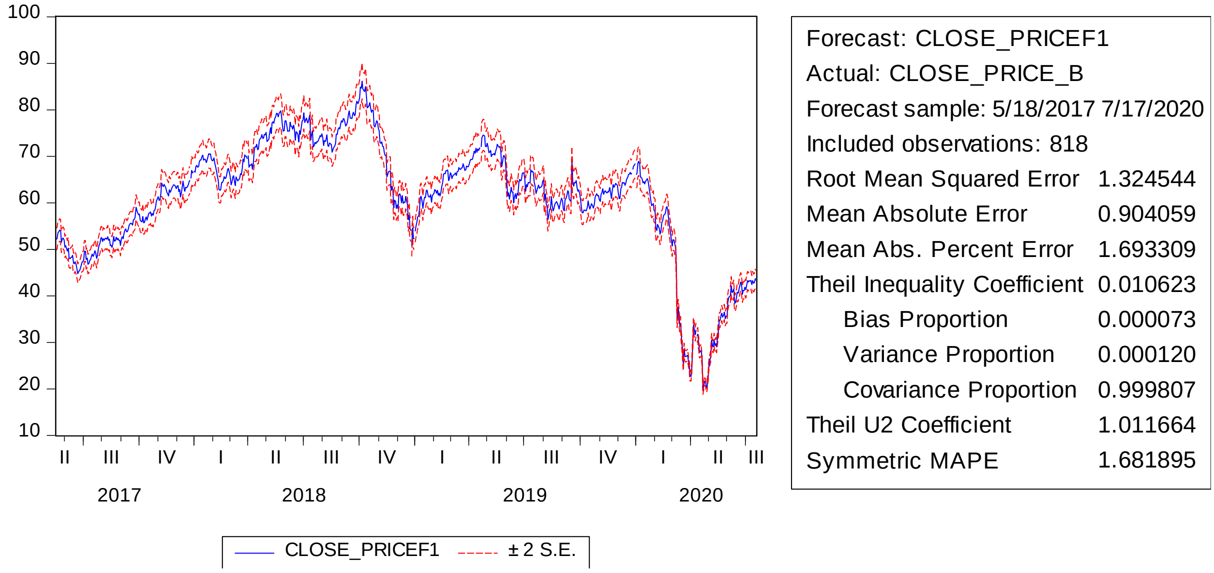


Figure 54: Custom ARIMA Models forecast output for Brent Oil

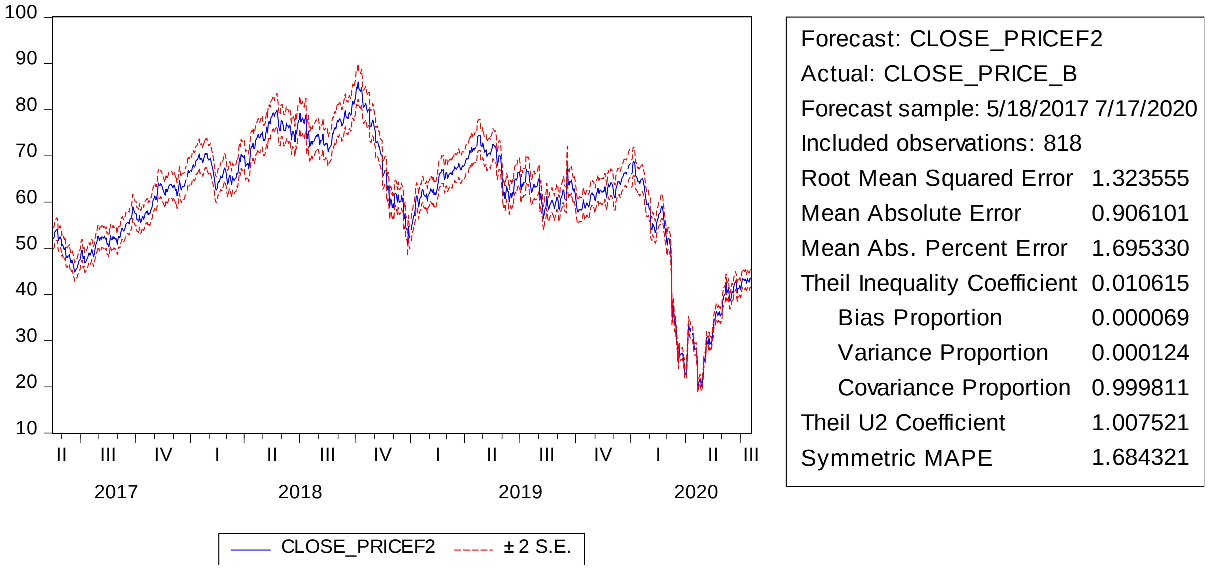


Figure 55: Eviews add in ARIMA Model forecast output for Brent Oil

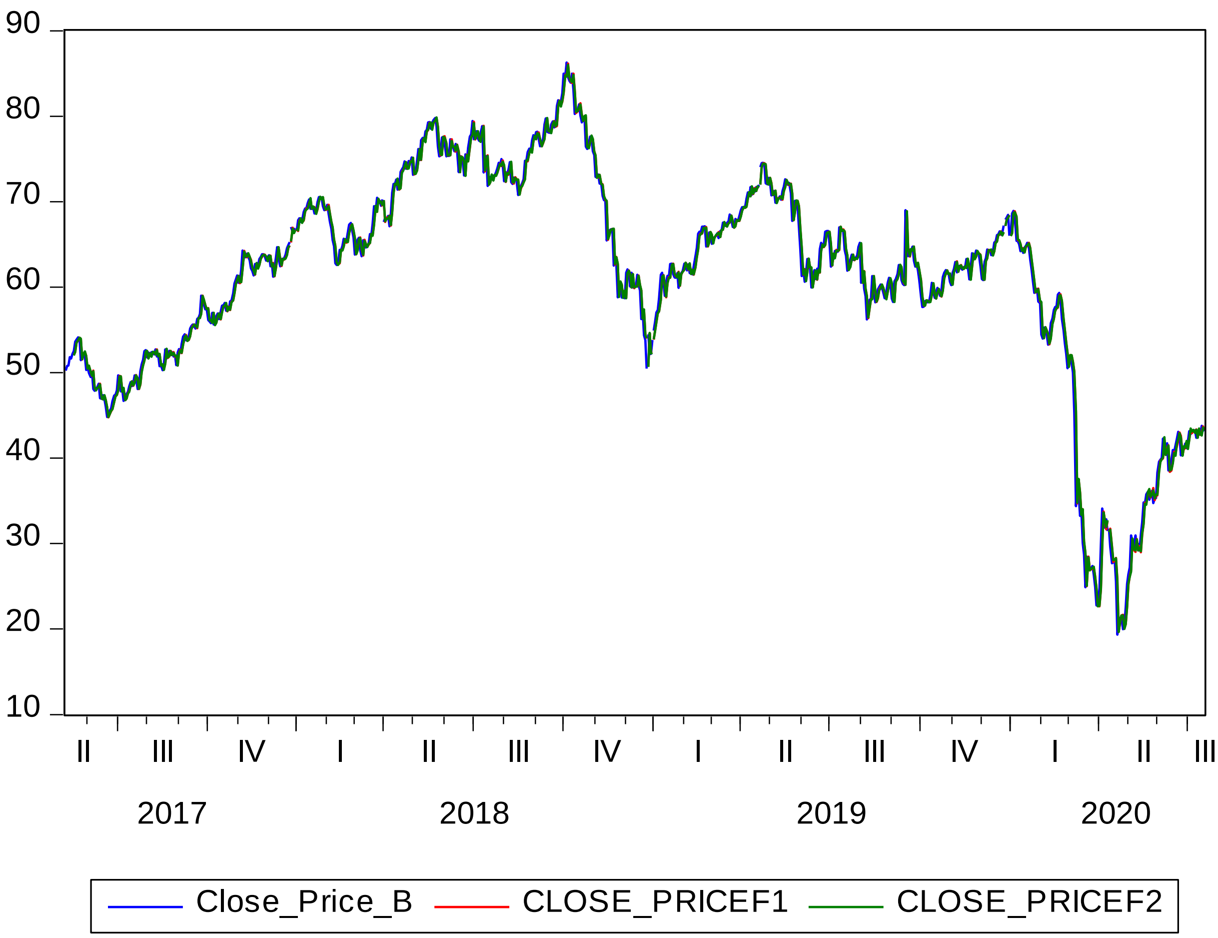
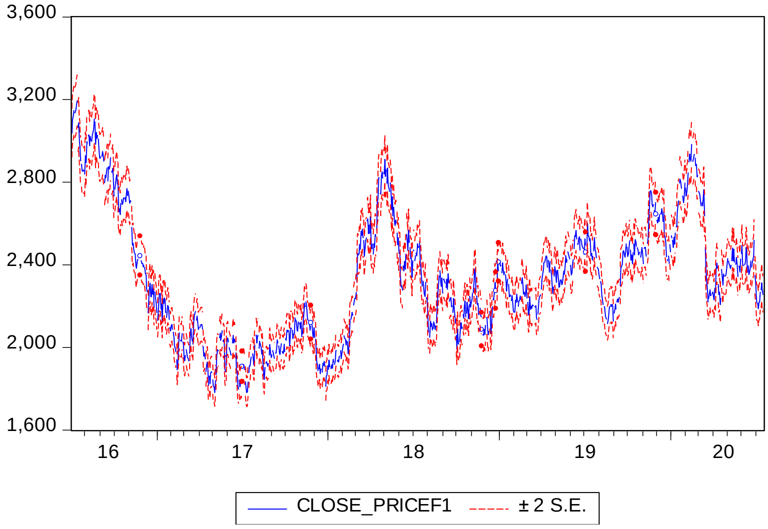


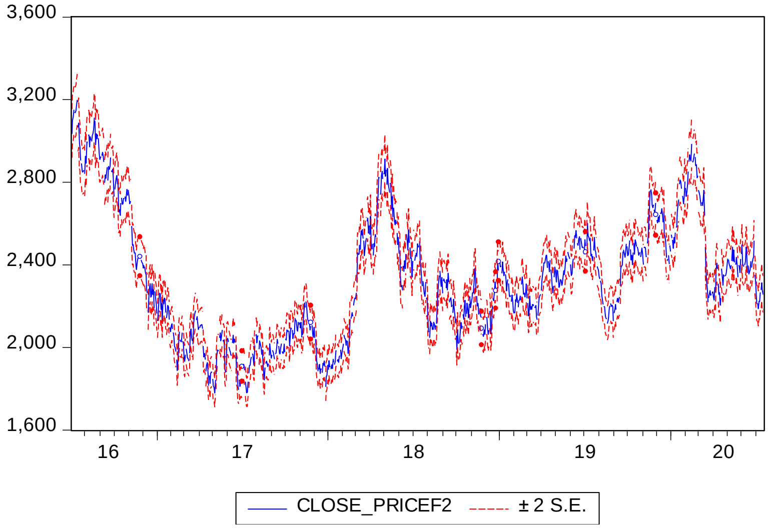
Figure 56: Comparison of the out of sample forecast of two ARIMA models for Brent oil

Cocoa



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_CC	
Forecast sample: 7/05/2016 7/17/2020	
Included observations: 1018	
Root Mean Squared Error	43.80042
Mean Absolute Error	34.14629
Mean Abs. Percent Error	1.476814
Theil Inequality Coefficient	0.009324
Bias Proportion	0.000502
Variance Proportion	0.000009
Covariance Proportion	0.999415
Theil U2 Coefficient	1.000476
Symmetric MAPE	1.475864

Figure 57: Custom ARIMA Model forecast output for Cocoa



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_CC	
Forecast sample: 7/05/2016 7/17/2020	
Included observations: 1018	
Root Mean Squared Error	43.83716
Mean Absolute Error	34.22070
Mean Abs. Percent Error	1.479847
Theil Inequality Coefficient	0.009332
Bias Proportion	0.000498
Variance Proportion	0.000009
Covariance Proportion	0.999414
Theil U2 Coefficient	1.001021
Symmetric MAPE	1.478909

Figure 58: Eviews add in ARIMA Models forecast output for Cocoa

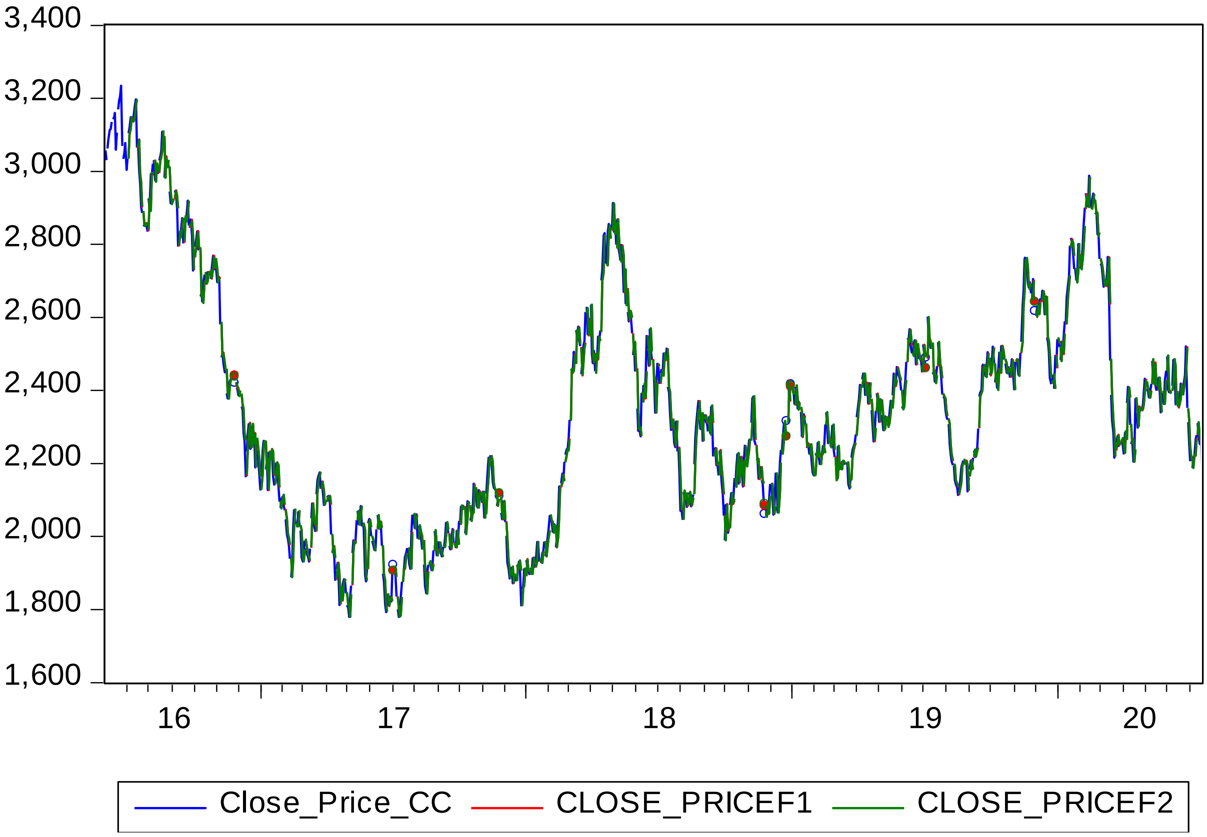
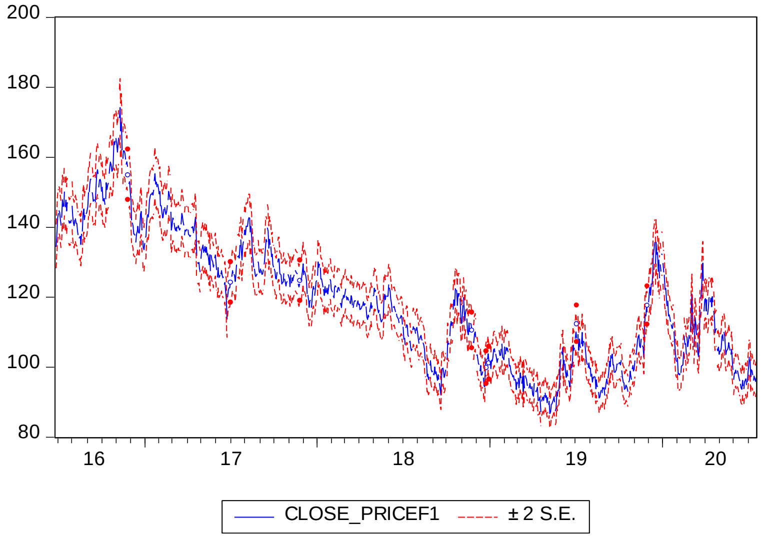


Figure 59: Comparison of the out of sample forecast of two ARIMA models for cocoa

Coffee



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_KC	
Forecast sample: 6/27/2016 7/17/2020	
Included observations: 1023	
Root Mean Squared Error	2.231823
Mean Absolute Error	1.714896
Mean Abs. Percent Error	1.465119
Theil Inequality Coefficient	0.009287
Bias Proportion	0.000227
Variance Proportion	0.000014
Covariance Proportion	0.999765
Theil U2 Coefficient	0.999494
Symmetric MAPE	1.465020

Figure 60: Custom ARIMA Model forecast output for Coffee

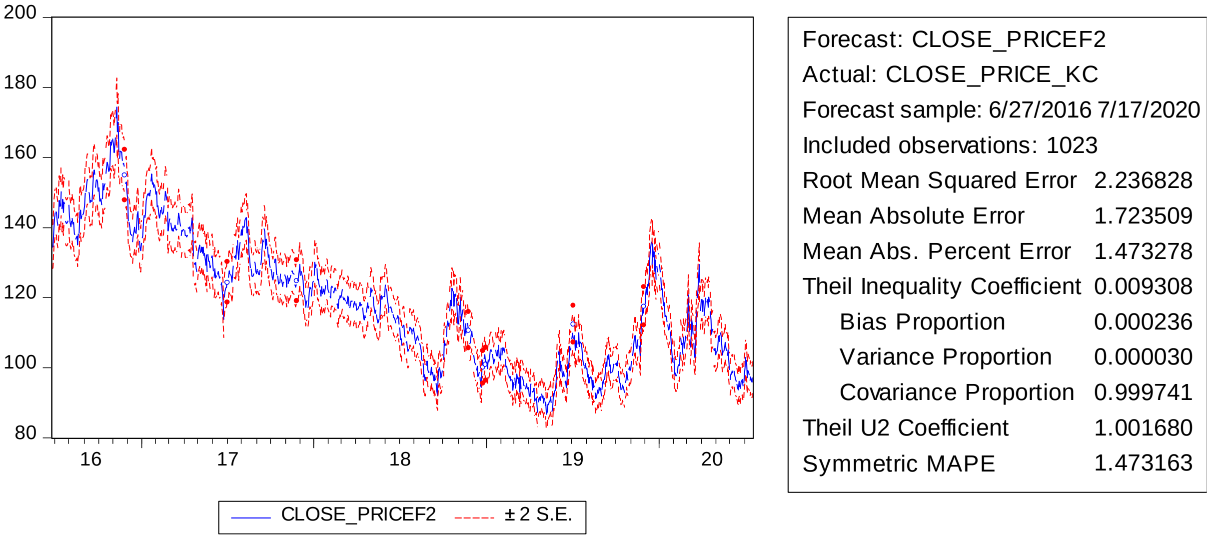


Figure 61: Eviews add in ARIMA Models forecast output for Coffee

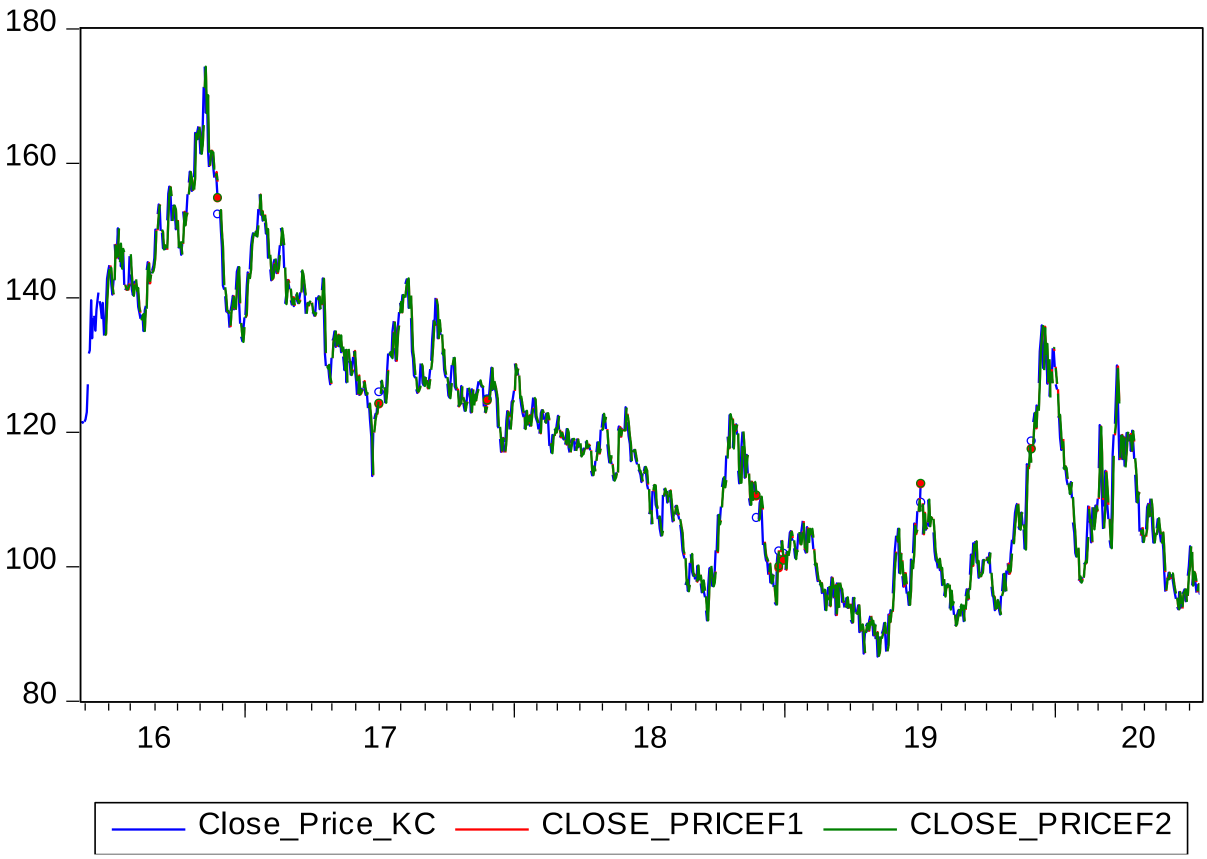
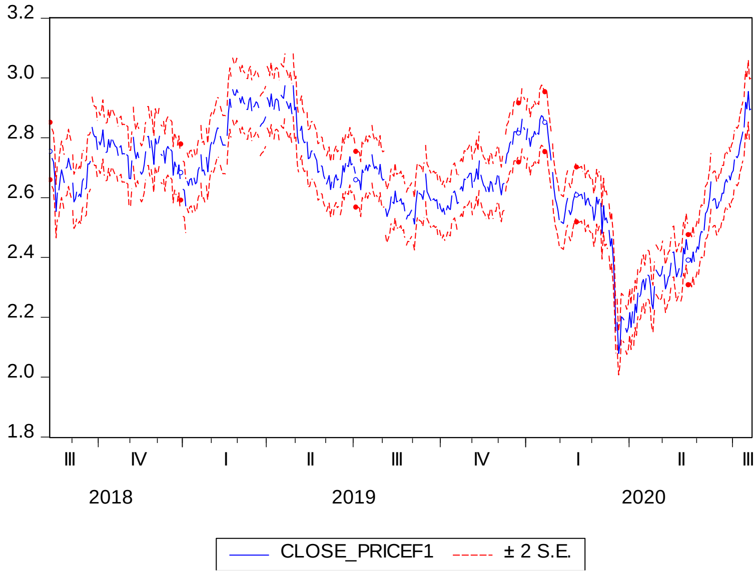


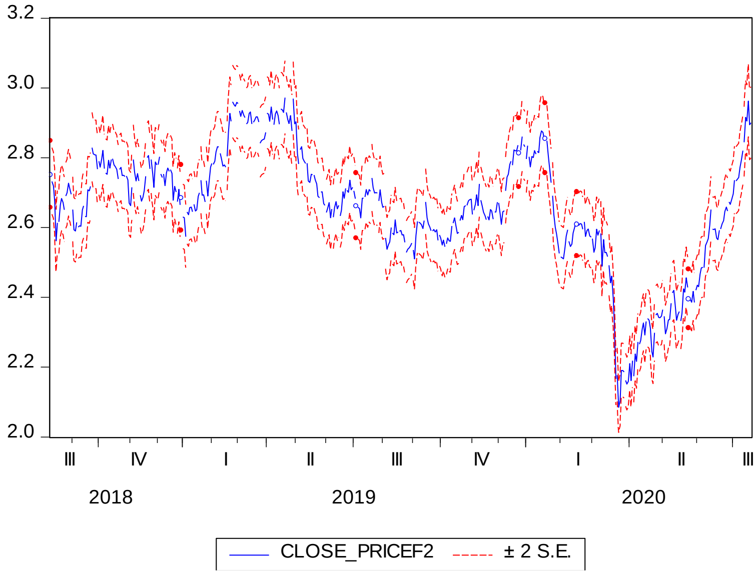
Figure 62: Comparison of the out of sample forecast of two ARIMA models for coffee

Copper



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_HG	
Forecast sample: 8/10/2018 7/17/2020	
Included observations: 509	
Root Mean Squared Error	0.033643
Mean Absolute Error	0.025276
Mean Abs. Percent Error	0.963388
Theil Inequality Coefficient	0.006318
Bias Proportion	0.000079
Variance Proportion	0.000086
Covariance Proportion	0.999837
Theil U2 Coefficient	1.001884
Symmetric MAPE	0.963054

Figure 63: Custom ARIMA Model forecast output for Copper

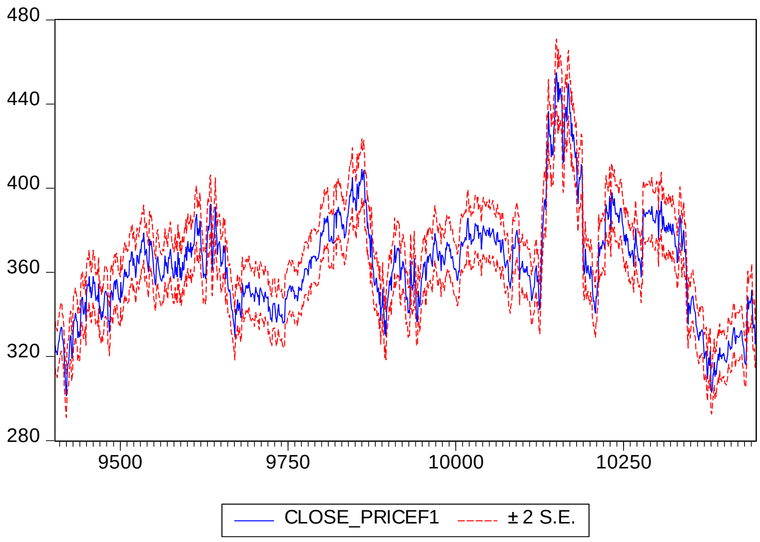


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_HG	
Forecast sample: 8/10/2018 7/17/2020	
Included observations: 509	
Root Mean Squared Error	0.033581
Mean Absolute Error	0.025097
Mean Abs. Percent Error	0.956123
Theil Inequality Coefficient	0.006306
Bias Proportion	0.000164
Variance Proportion	0.000050
Covariance Proportion	0.999788
Theil U2 Coefficient	1.000886
Symmetric MAPE	0.955886

Figure 64: Eviews add in ARIMA Models forecast output for Copper

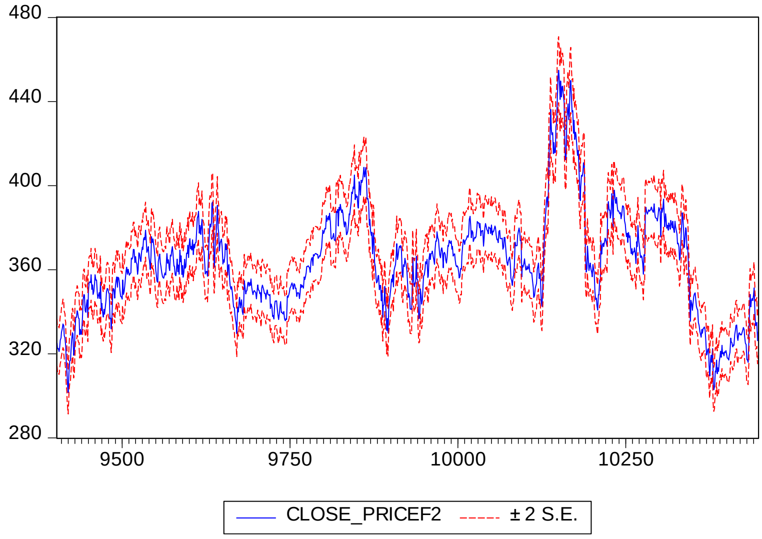
Figure 65: Comparison of the out of sample forecast of two ARIMA models for copper

Corn



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_C	
Forecast sample: 9403 10447	
Included observations: 1045	
Root Mean Squared Error	4.964874
Mean Absolute Error	3.561707
Mean Abs. Percent Error	0.976718
Theil Inequality Coefficient	0.006810
Bias Proportion	0.000002
Variance Proportion	0.000041
Covariance Proportion	0.999931
Theil U2 Coefficient	1.003363
Symmetric MAPE	0.976782

Figure 66: Custom ARIMA Model forecast output for Corn

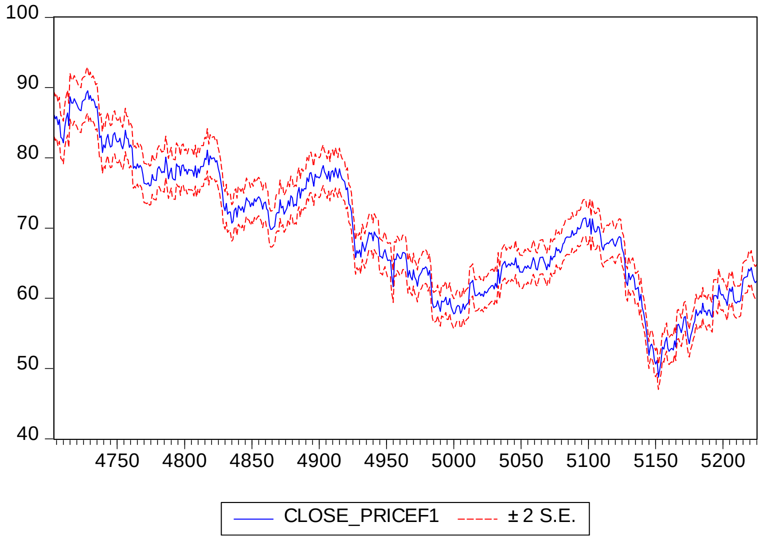


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_C	
Forecast sample: 9403 10447	
Included observations: 1045	
Root Mean Squared Error	4.958549
Mean Absolute Error	3.557583
Mean Abs. Percent Error	0.975414
Theil Inequality Coefficient	0.006801
Bias Proportion	0.000003
Variance Proportion	0.000001
Covariance Proportion	0.999999
Theil U2 Coefficient	1.001591
Symmetric MAPE	0.975466

Figure 67: Eviews add in ARIMA Models forecast output for Corn

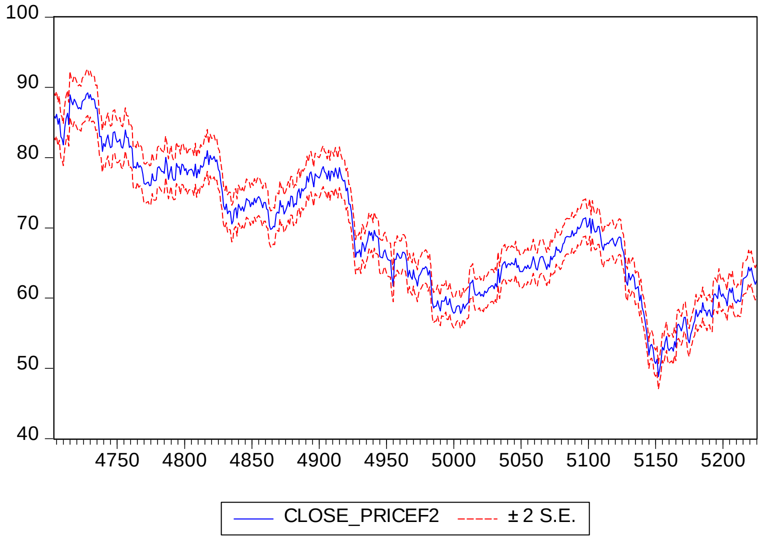
Figure 68: Comparison of the out of sample forecast of two ARIMA models for corn

Cotton



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_CT	
Forecast sample: 4703 5225	
Included observations: 523	
Root Mean Squared Error	0.969273
Mean Absolute Error	0.733092
Mean Abs. Percent Error	1.079159
Theil Inequality Coefficient	0.006936
Bias Proportion	0.002185
Variance Proportion	0.000650
Covariance Proportion	0.997168
Theil U2 Coefficient	1.002314
Symmetric MAPE	1.078650

Figure 69: Custom ARIMA Model forecast output for Cotton

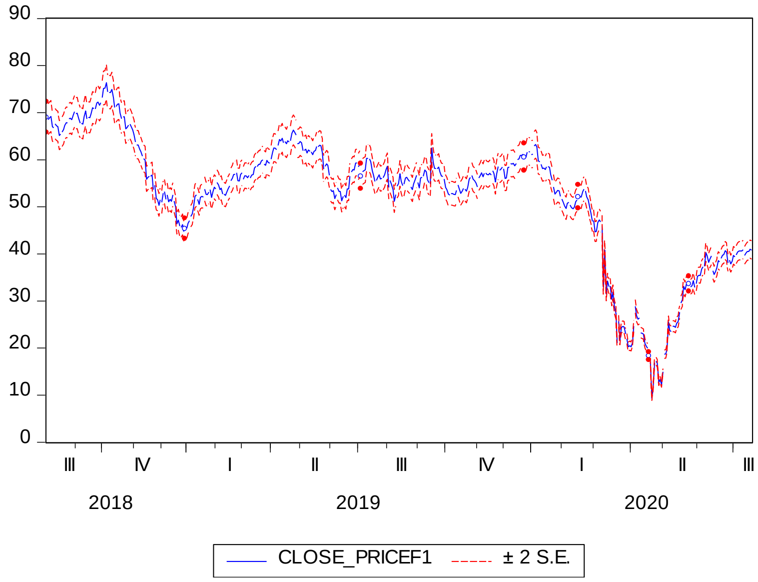


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_CT	
Forecast sample: 4703 5225	
Included observations: 523	
Root Mean Squared Error	0.970197
Mean Absolute Error	0.735544
Mean Abs. Percent Error	1.082665
Theil Inequality Coefficient	0.006943
Bias Proportion	0.002169
Variance Proportion	0.000703
Covariance Proportion	0.997130
Theil U2 Coefficient	1.003844
Symmetric MAPE	1.082151

Figure 70: Eviews add in ARIMA Models forecast output for Cotton

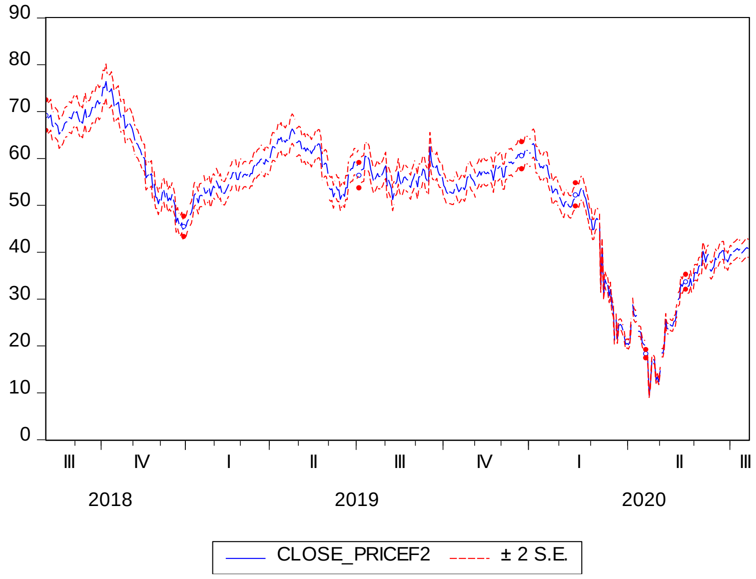
Figure 71: Comparison of the out of sample forecast of two ARIMA models for cotton

Crude oil



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_CL	
Forecast sample: 8/03/2018 7/17/2020	
Included observations: 510	
Root Mean Squared Error	1.631382
Mean Absolute Error	1.018604
Mean Abs. Percent Error	2.636934
Theil Inequality Coefficient	0.015136
Bias Proportion	0.001219
Variance Proportion	0.000027
Covariance Proportion	0.998753
Theil U2 Coefficient	0.995248
Symmetric MAPE	2.576662

Figure 72: Custom ARIMA Model forecast output for Crude oil

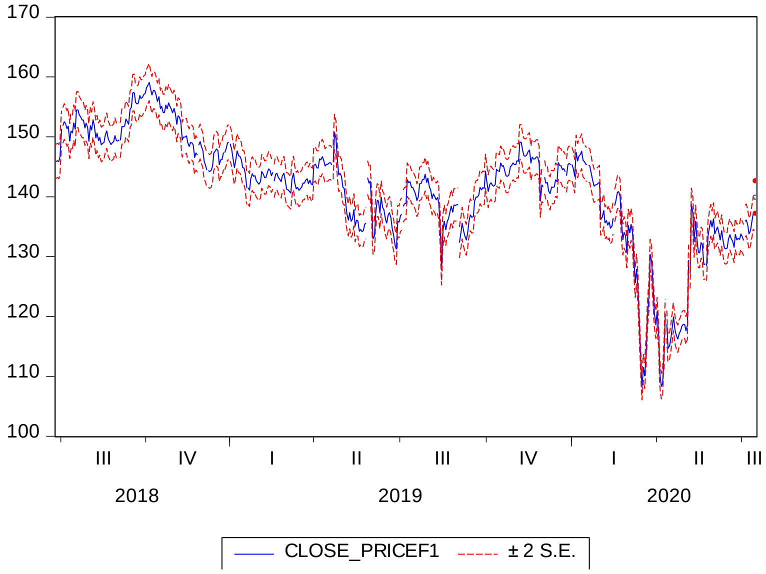


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_CL	
Forecast sample: 8/03/2018 7/17/2020	
Included observations: 510	
Root Mean Squared Error	1.640039
Mean Absolute Error	1.021265
Mean Abs. Percent Error	2.650478
Theil Inequality Coefficient	0.015217
Bias Proportion	0.001258
Variance Proportion	0.000026
Covariance Proportion	0.998716
Theil U2 Coefficient	1.000211
Symmetric MAPE	2.587466

Figure 73: Eviews add in ARIMA Models forecast output for Crude oil

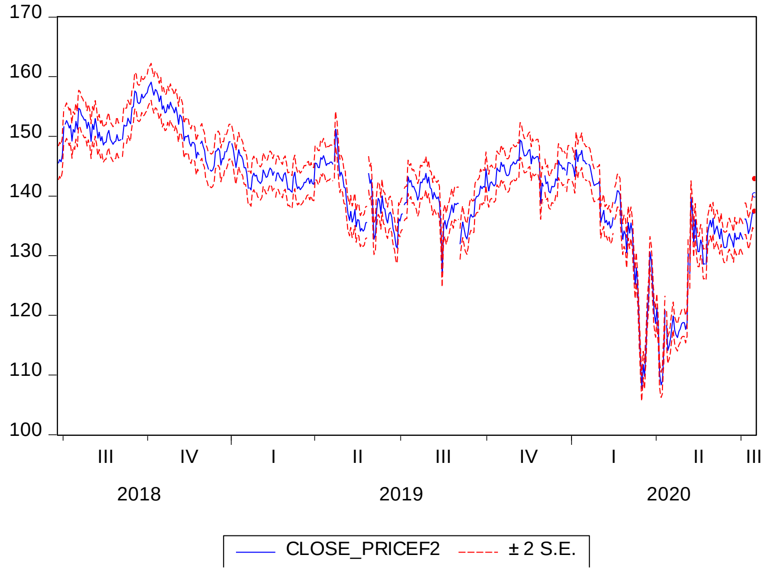
Figure 74: Comparison of the out of sample forecast of two ARIMA models for crude oil

Feeder Cattle



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_FC	
Forecast sample: 6/26/2018 7/17/2020	
Included observations: 511	
Root Mean Squared Error	1.909737
Mean Absolute Error	1.226178
Mean Abs. Percent Error	0.899308
Theil Inequality Coefficient	0.006746
Bias Proportion	0.000010
Variance Proportion	0.000000
Covariance Proportion	0.999991
Theil U2 Coefficient	1.001393
Symmetric MAPE	0.900170

Figure 75: Custom ARIMA Model forecast output for feeder cattle

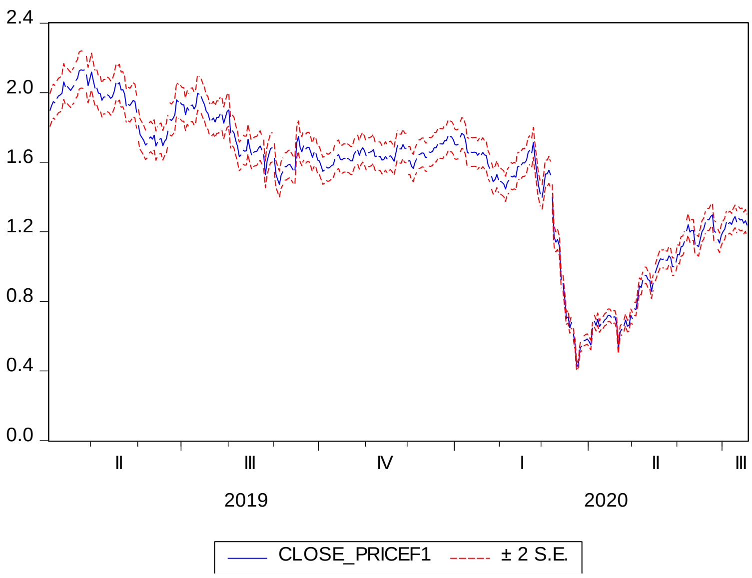


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_FC	
Forecast sample: 6/26/2018 7/17/2020	
Included observations: 511	
Root Mean Squared Error	1.904482
Mean Absolute Error	1.239356
Mean Abs. Percent Error	0.907931
Theil Inequality Coefficient	0.006727
Bias Proportion	0.000008
Variance Proportion	0.000078
Covariance Proportion	0.999917
Theil U2 Coefficient	0.996853
Symmetric MAPE	0.908967

Figure 76: Eviews add in ARIMA Models forecast output for feeder cattle

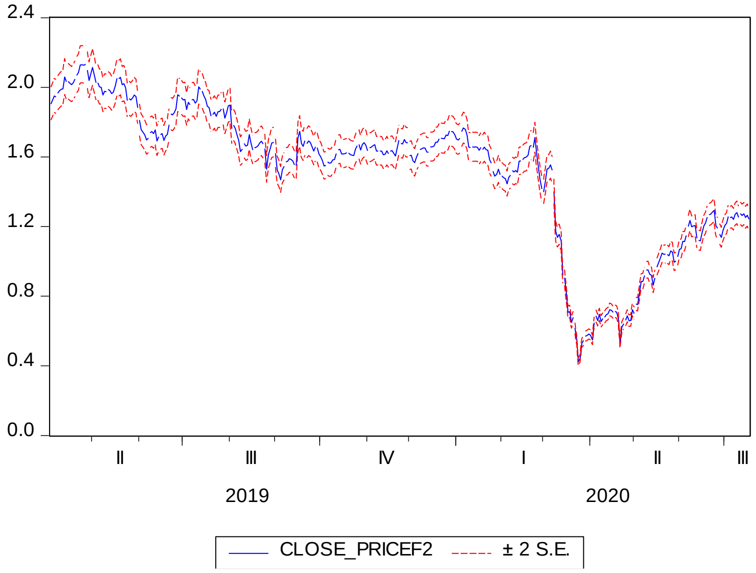
Figure 77: Comparison of the out of sample forecast of two ARIMA models for feeder cattle

Gasoline



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_GPR	
Forecast sample: 4/02/2019 7/17/2020	
Included observations: 402	
Root Mean Squared Error	0.043635
Mean Absolute Error	0.029729
Mean Abs. Percent Error	2.433975
Theil Inequality Coefficient	0.013942
Bias Proportion	0.001706
Variance Proportion	0.000001
Covariance Proportion	0.998294
Theil U2 Coefficient	1.006297
Symmetric MAPE	2.402396

Figure 78: Custom ARIMA Model forecast output for gasoline

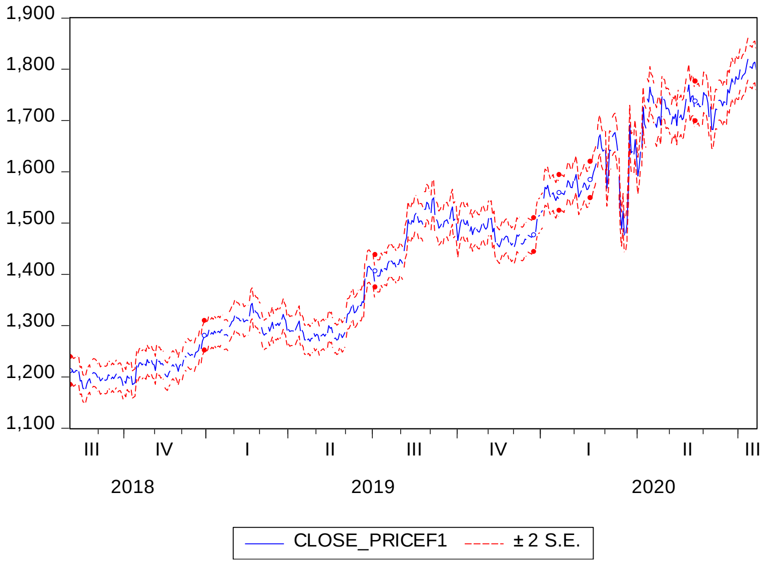


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_GPR	
Forecast sample: 4/02/2019 7/17/2020	
Included observations: 402	
Root Mean Squared Error	0.043391
Mean Absolute Error	0.029541
Mean Abs. Percent Error	2.420009
Theil Inequality Coefficient	0.013864
Bias Proportion	0.001747
Variance Proportion	0.000002
Covariance Proportion	0.998251
Theil U2 Coefficient	1.000006
Symmetric MAPE	2.388800

Figure 79: Eviews add in ARIMA Models forecast output for gasoline

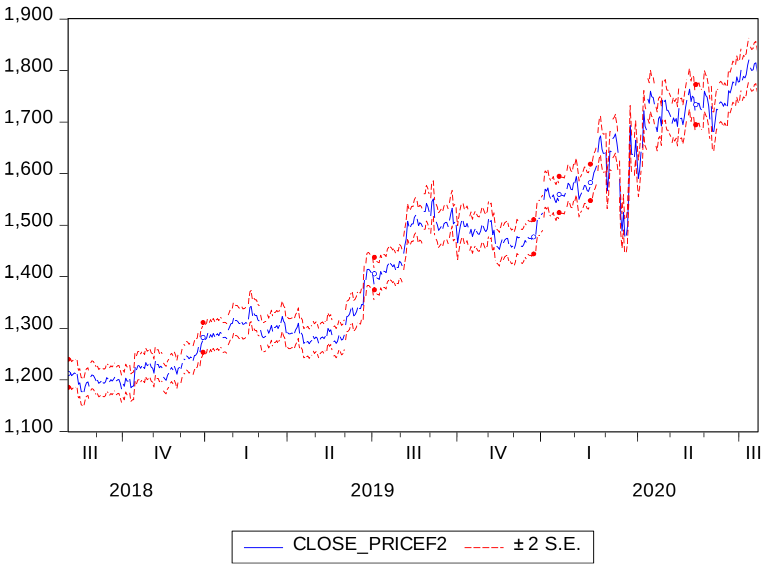
Figure 80: Comparison of the out of sample forecast of two ARIMA models for gasoline

Gold



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_GC	
Forecast sample: 8/03/2018 7/17/2020	
Included observations: 511	
Root Mean Squared Error	15.64058
Mean Absolute Error	9.724018
Mean Abs. Percent Error	0.651738
Theil Inequality Coefficient	0.005371
Bias Proportion	0.005832
Variance Proportion	0.000818
Covariance Proportion	0.993350
Theil U2 Coefficient	0.994487
Symmetric MAPE	0.652636

Figure 81: Custom ARIMA Model forecast output for gold

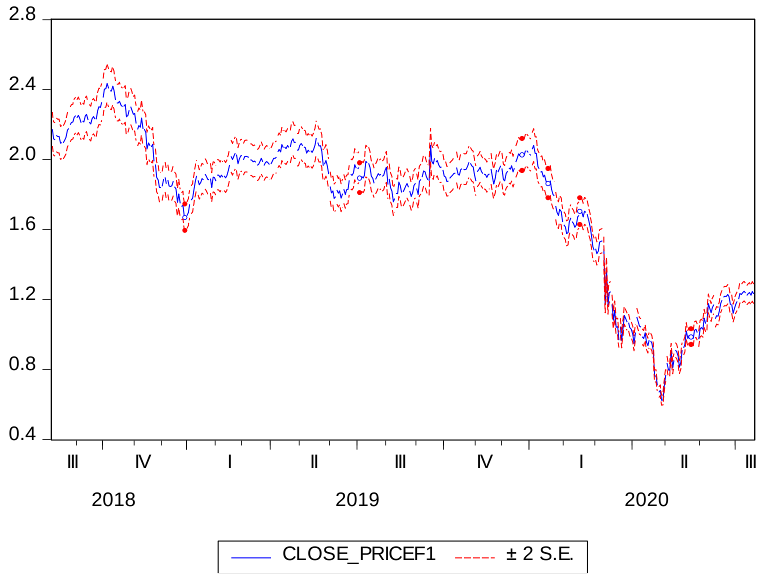


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_GC	
Forecast sample: 8/03/2018 7/17/2020	
Included observations: 511	
Root Mean Squared Error	15.57065
Mean Absolute Error	9.716080
Mean Abs. Percent Error	0.651266
Theil Inequality Coefficient	0.005347
Bias Proportion	0.007661
Variance Proportion	0.001323
Covariance Proportion	0.991015
Theil U2 Coefficient	0.990462
Symmetric MAPE	0.652198

Figure 82: Eviews add in ARIMA Models forecast output for gold

Figure 83: Comparison of the out of sample forecast of two ARIMA models for gold

Heating Oil



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_HO	
Forecast sample: 8/08/2018 7/17/2020	
Included observations: 511	
Root Mean Squared Error	0.040503
Mean Absolute Error	0.027391
Mean Abs. Percent Error	1.848373
Theil Inequality Coefficient	0.011193
Bias Proportion	0.002215
Variance Proportion	0.000067
Covariance Proportion	0.997720
Theil U2 Coefficient	1.002296
Symmetric MAPE	1.838676

Figure 84: Custom ARIMA Model forecast output for heating oil

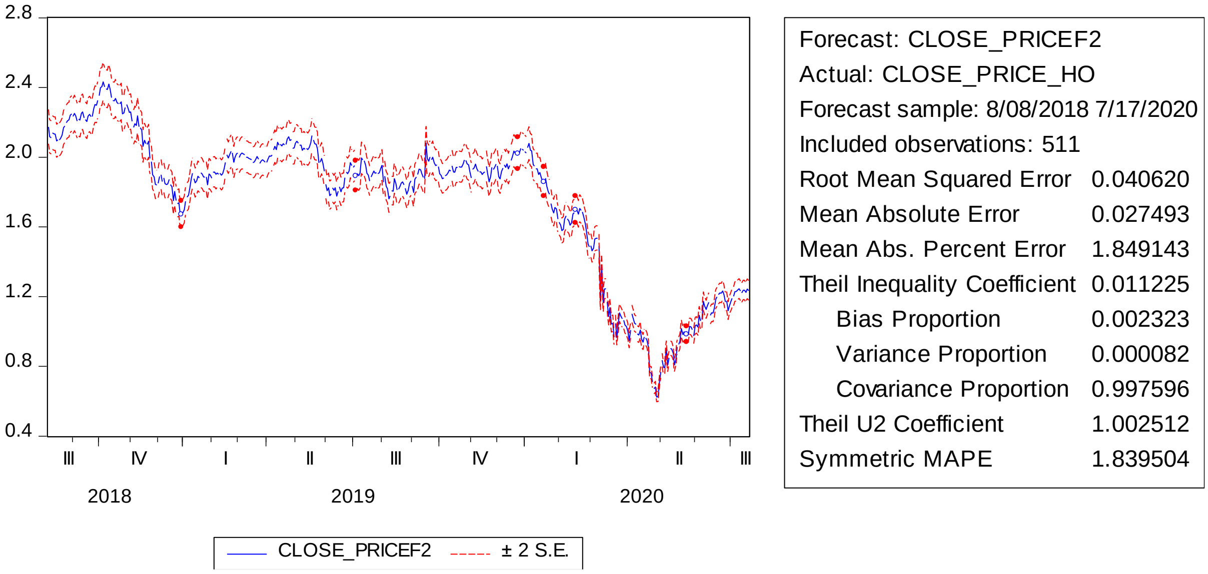
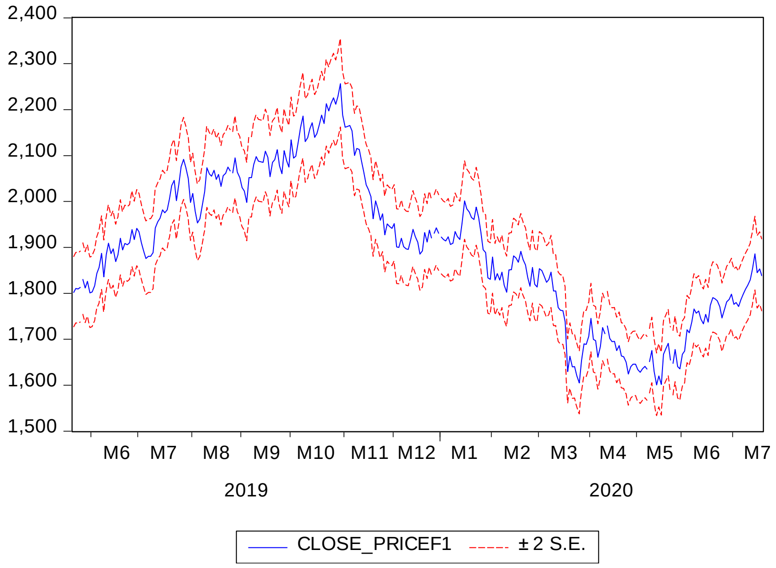


Figure 85: Eviews add in ARIMA Models forecast output for heating oil

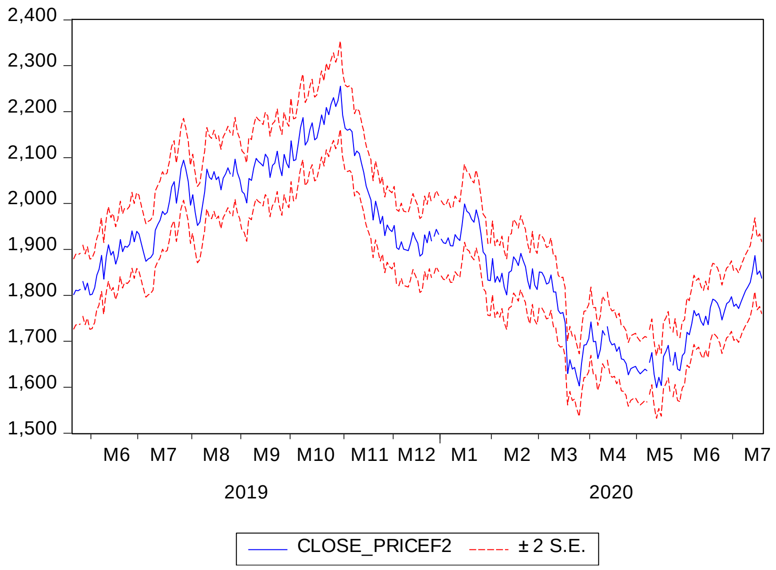
Figure 86: Comparison of the out of sample forecast of two ARIMA models for heating oil

Lead



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_L	
Forecast sample: 5/21/2019 7/17/2020	
Included observations: 295	
Root Mean Squared Error	24.20341
Mean Absolute Error	19.32289
Mean Abs. Percent Error	1.022173
Theil Inequality Coefficient	0.006354
Bias Proportion	0.000001
Variance Proportion	0.000162
Covariance Proportion	0.999839
Theil U2 Coefficient	1.014097
Symmetric MAPE	1.021632

Figure 87: Custom ARIMA Model forecast output for lead



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_L	
Forecast sample: 5/21/2019 7/17/2020	
Included observations: 295	
Root Mean Squared Error	24.47429
Mean Absolute Error	19.57791
Mean Abs. Percent Error	1.034576
Theil Inequality Coefficient	0.006425
Bias Proportion	0.000000
Variance Proportion	0.000145
Covariance Proportion	0.999854
Theil U2 Coefficient	1.024047
Symmetric MAPE	1.033962

Figure 88: Eviews add in ARIMA Models forecast output for lead

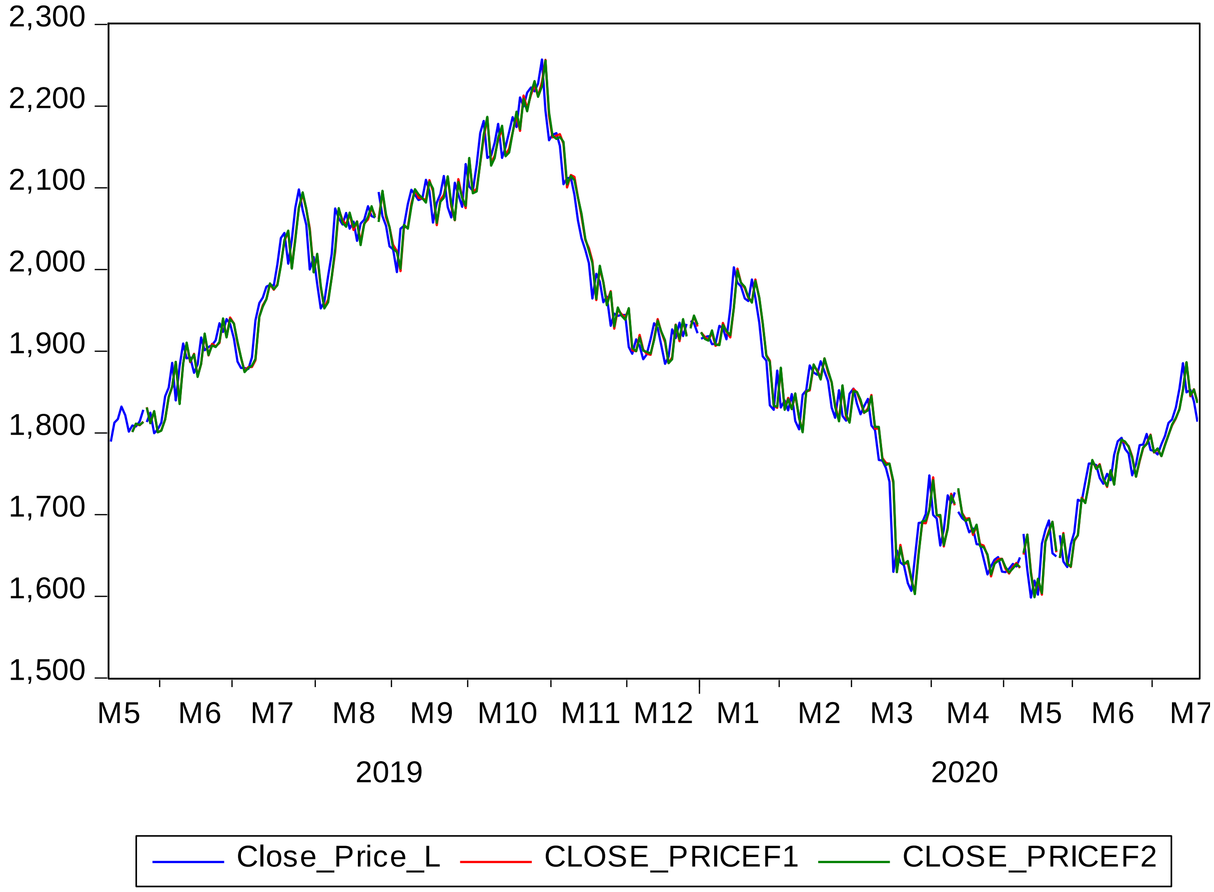
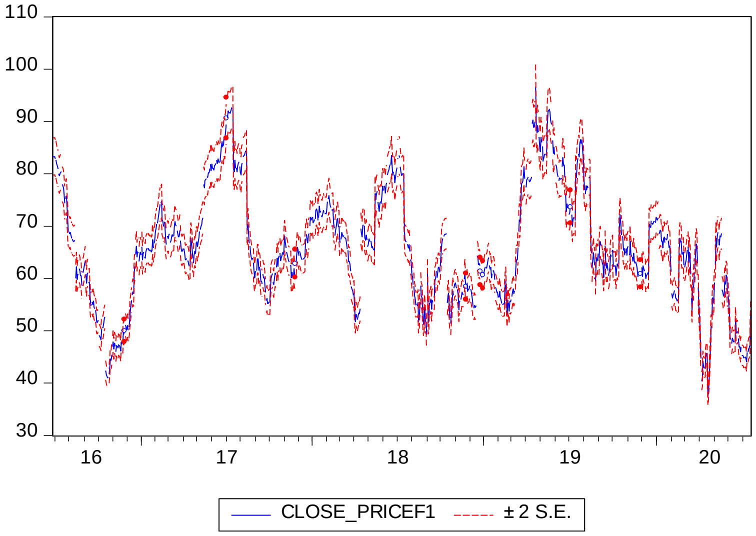


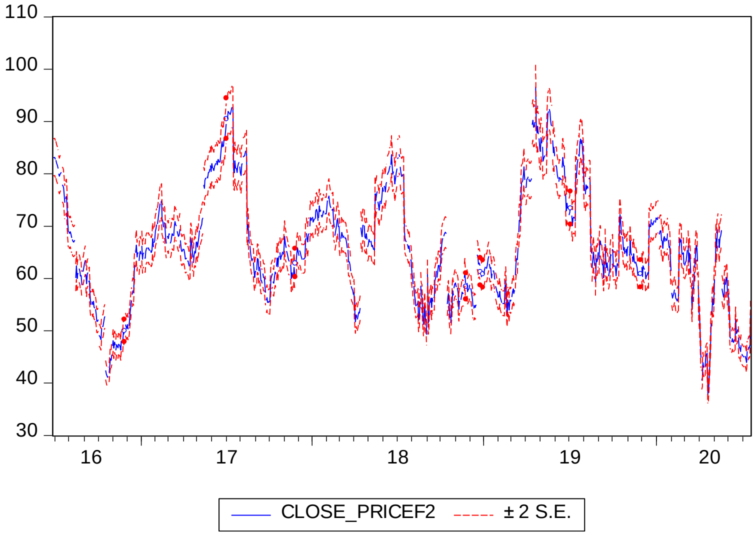
Figure 89: Comparison of the out of sample forecast of two ARIMA models for lead

Lean Hogs



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_LH	
Forecast sample: 6/28/2016 7/17/2020	
Included observations: 1026	
Root Mean Squared Error	2.071871
Mean Absolute Error	1.220104
Mean Abs. Percent Error	1.927946
Theil Inequality Coefficient	0.015549
Bias Proportion	0.000207
Variance Proportion	0.000017
Covariance Proportion	0.999772
Theil U2 Coefficient	1.001496
Symmetric MAPE	1.922205

Figure 90: Custom ARIMA Model forecast output for lean hogs



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_LH	
Forecast sample: 6/28/2016 7/17/2020	
Included observations: 1026	
Root Mean Squared Error	2.071262
Mean Absolute Error	1.220683
Mean Abs. Percent Error	1.929112
Theil Inequality Coefficient	0.015542
Bias Proportion	0.001028
Variance Proportion	0.000440
Covariance Proportion	0.998530
Theil U2 Coefficient	0.999750
Symmetric MAPE	1.921455

Figure 91: Eviews add in ARIMA Models forecast output for lean hogs

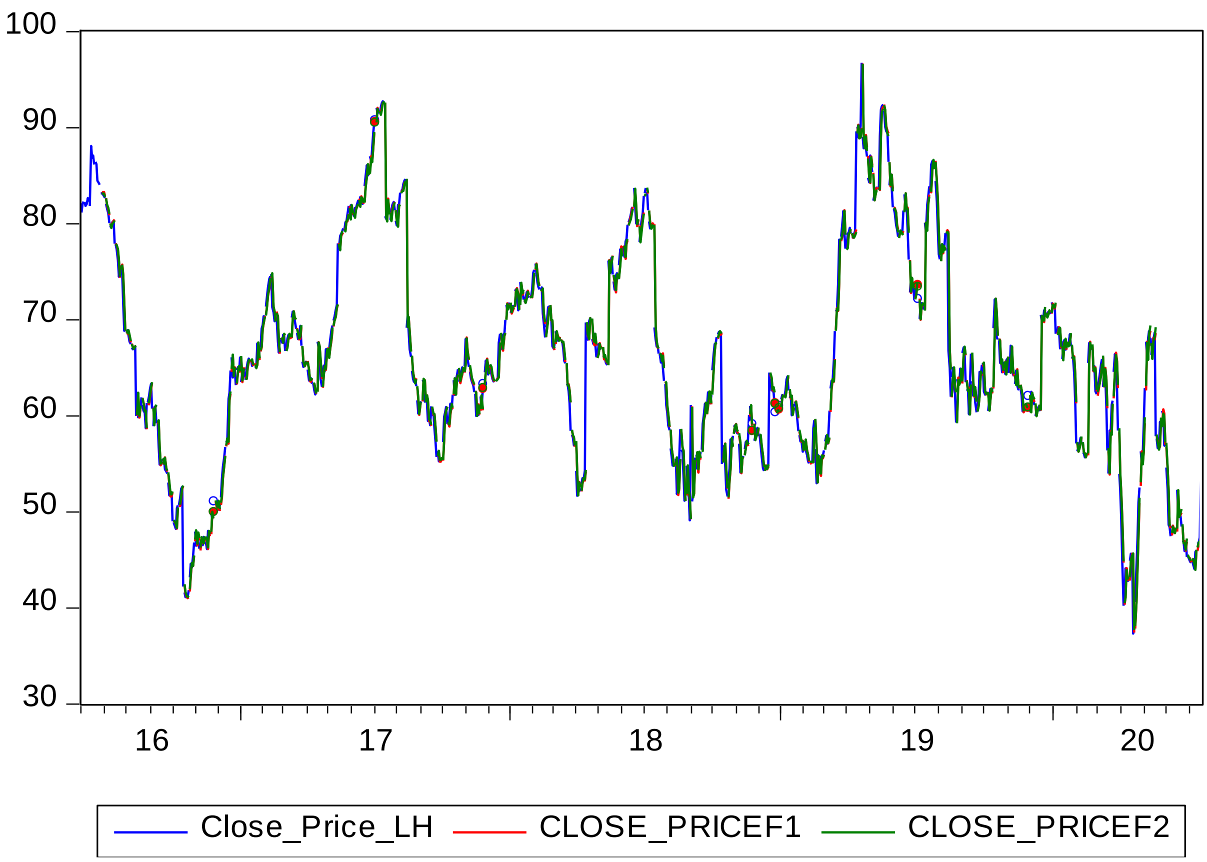
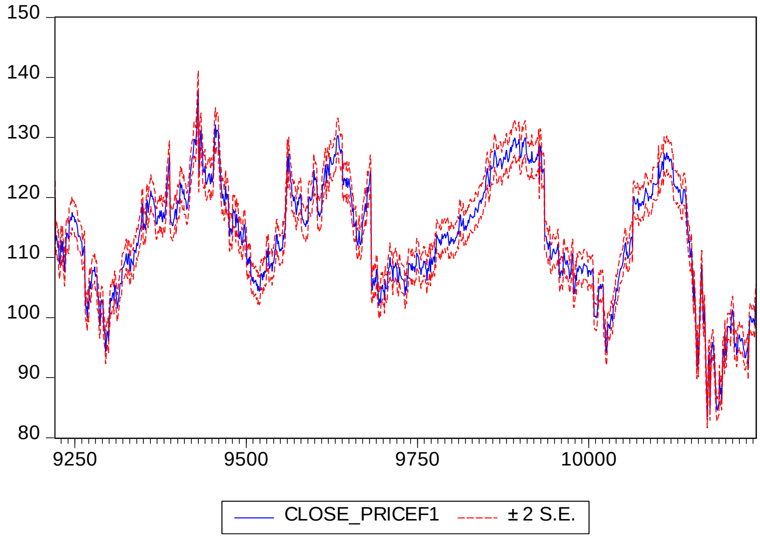


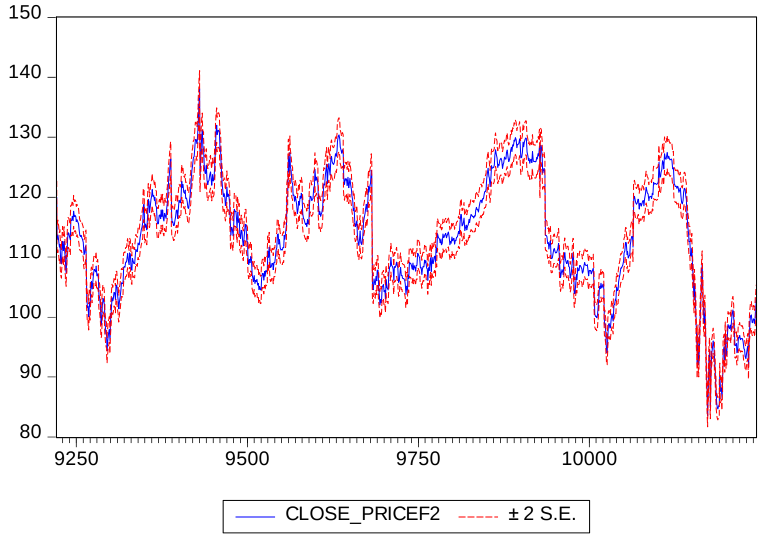
Figure 92: Comparison of the out of sample forecast of two ARIMA models for lean hogs

Live cattle



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_LC	
Forecast sample: 9221 10244	
Included observations: 1024	
Root Mean Squared Error	1.733049
Mean Absolute Error	1.101625
Mean Abs. Percent Error	0.997698
Theil Inequality Coefficient	0.007612
Bias Proportion	0.000093
Variance Proportion	0.000028
Covariance Proportion	0.999883
Theil U2 Coefficient	0.997932
Symmetric MAPE	0.994573

Figure 93: Custom ARIMA Model forecast output for live cattle

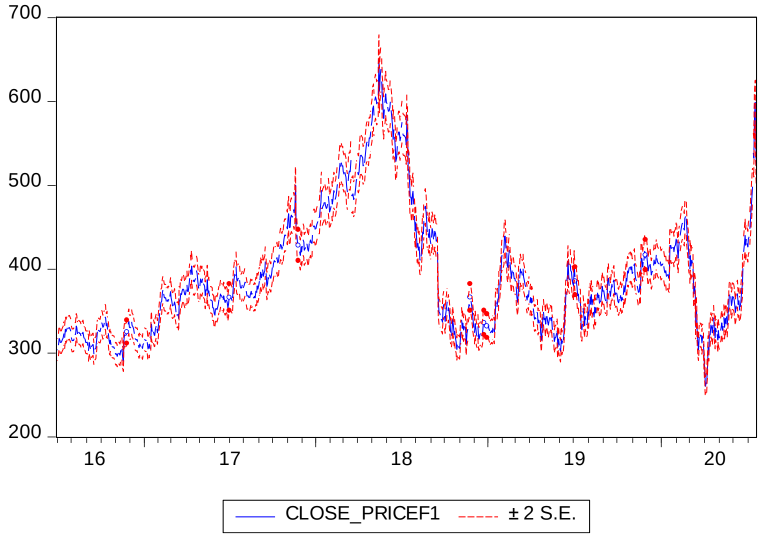


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_LC	
Forecast sample: 9221 10244	
Included observations: 1024	
Root Mean Squared Error	1.735159
Mean Absolute Error	1.106978
Mean Abs. Percent Error	1.002652
Theil Inequality Coefficient	0.007621
Bias Proportion	0.000093
Variance Proportion	0.000029
Covariance Proportion	0.999884
Theil U2 Coefficient	1.000003
Symmetric MAPE	0.999531

Figure 94: Eviews add in ARIMA Models forecast output for live cattle

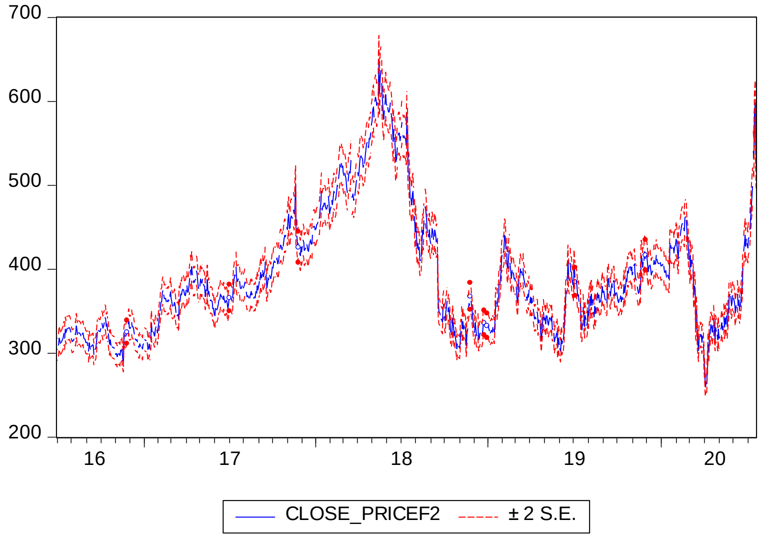
Figure 95: Comparison of the out of sample forecast of two ARIMA models for live cattle

Lumber



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_LB	
Forecast sample: 6/30/2016 7/17/2020	
Included observations: 1024	
Root Mean Squared Error	9.483747
Mean Absolute Error	6.588199
Mean Abs. Percent Error	1.677249
Theil Inequality Coefficient	0.011903
Bias Proportion	0.000676
Variance Proportion	0.000183
Covariance Proportion	0.999146
Theil U2 Coefficient	0.999548
Symmetric MAPE	1.676700

Figure 96: Custom ARIMA Model forecast output for lumber



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_LB	
Forecast sample: 6/30/2016 7/17/2020	
Included observations: 1024	
Root Mean Squared Error	9.503488
Mean Absolute Error	6.636428
Mean Abs. Percent Error	1.689591
Theil Inequality Coefficient	0.011932
Bias Proportion	0.002361
Variance Proportion	0.002616
Covariance Proportion	0.995029
Theil U2 Coefficient	1.001212
Symmetric MAPE	1.689564

Figure 97: Eviews add in ARIMA Models forecast output for lumber

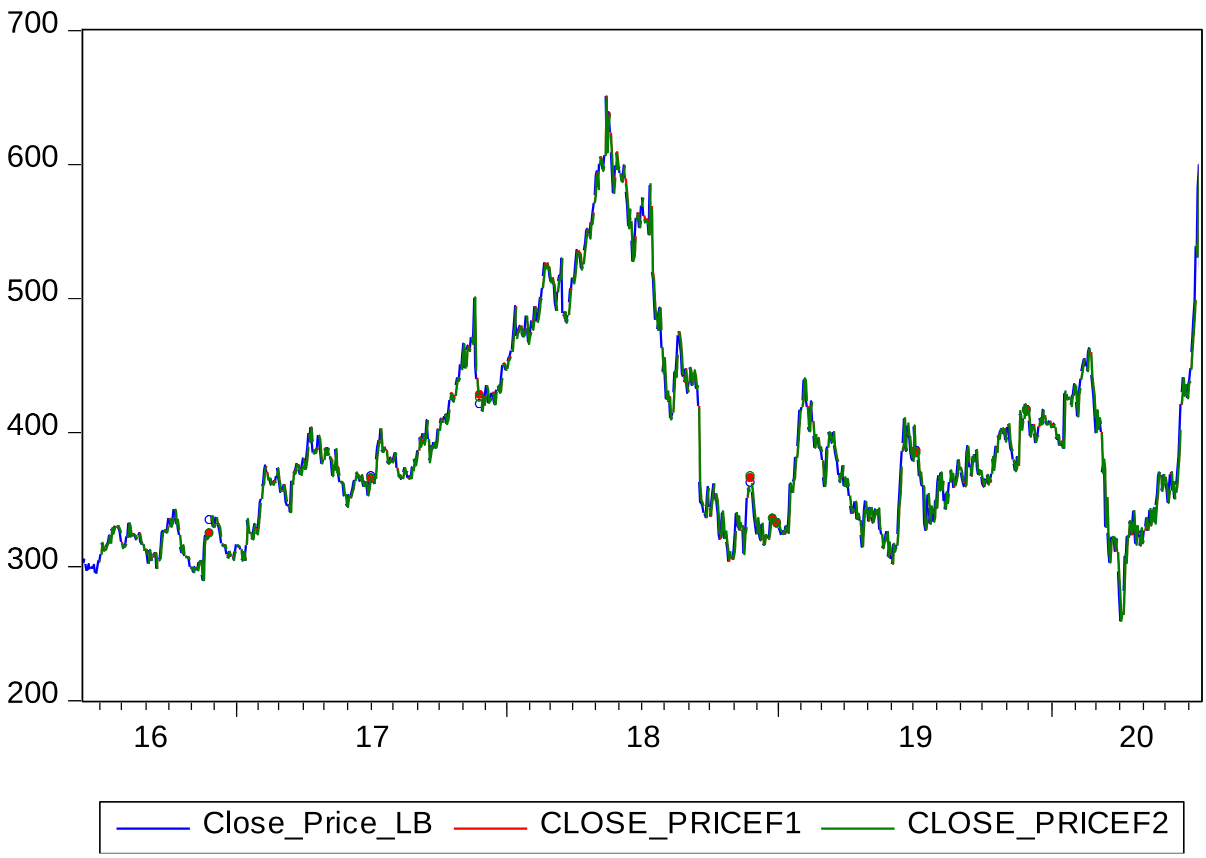
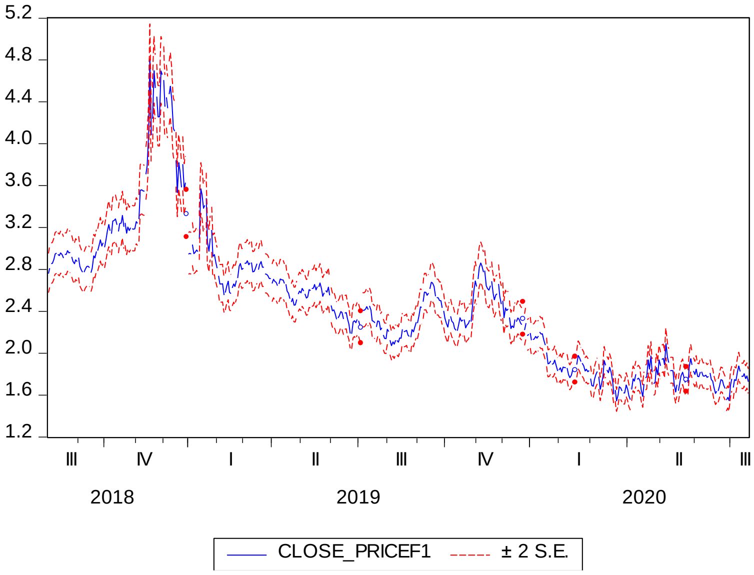


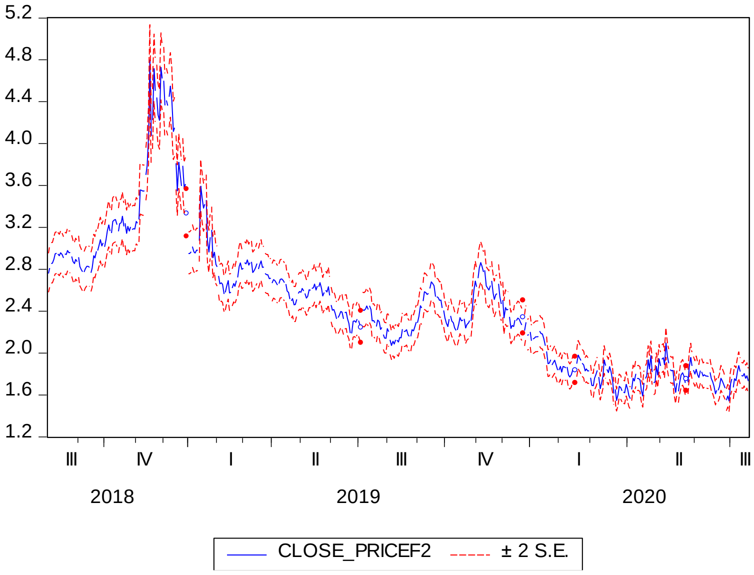
Figure 98: Comparison of the out of sample forecast of two ARIMA models for lumber

Natural Gas



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_NG	
Forecast sample: 8/02/2018 7/17/2020	
Included observations: 511	
Root Mean Squared Error	0.099518
Mean Absolute Error	0.061032
Mean Abs. Percent Error	2.415765
Theil Inequality Coefficient	0.019458
Bias Proportion	0.000437
Variance Proportion	0.000119
Covariance Proportion	0.999444
Theil U2 Coefficient	0.998008
Symmetric MAPE	2.413744

Figure 99: Custom ARIMA Model forecast output for natural gas



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_NG	
Forecast sample: 8/02/2018 7/17/2020	
Included observations: 511	
Root Mean Squared Error	0.099760
Mean Absolute Error	0.061164
Mean Abs. Percent Error	2.429122
Theil Inequality Coefficient	0.019504
Bias Proportion	0.000932
Variance Proportion	0.000771
Covariance Proportion	0.998297
Theil U2 Coefficient	1.003610
Symmetric MAPE	2.426217

Figure 100: Eviews add in ARIMA Models forecast output for natural gas

Figure 101: Comparison of the out of sample forecast of two ARIMA models for natural gas

Nickel

Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_N	
Forecast sample: 5/21/2019 7/17/2020	
Included observations: 295	
Root Mean Squared Error	239.2482
Mean Absolute Error	181.2339
Mean Abs. Percent Error	1.315514
Theil Inequality Coefficient	0.008573
Bias Proportion	0.000337
Variance Proportion	0.000033
Covariance Proportion	0.999630
Theil U2 Coefficient	1.002830
Symmetric MAPE	1.316519

Figure 102: Custom ARIMA Model forecast output for nickel

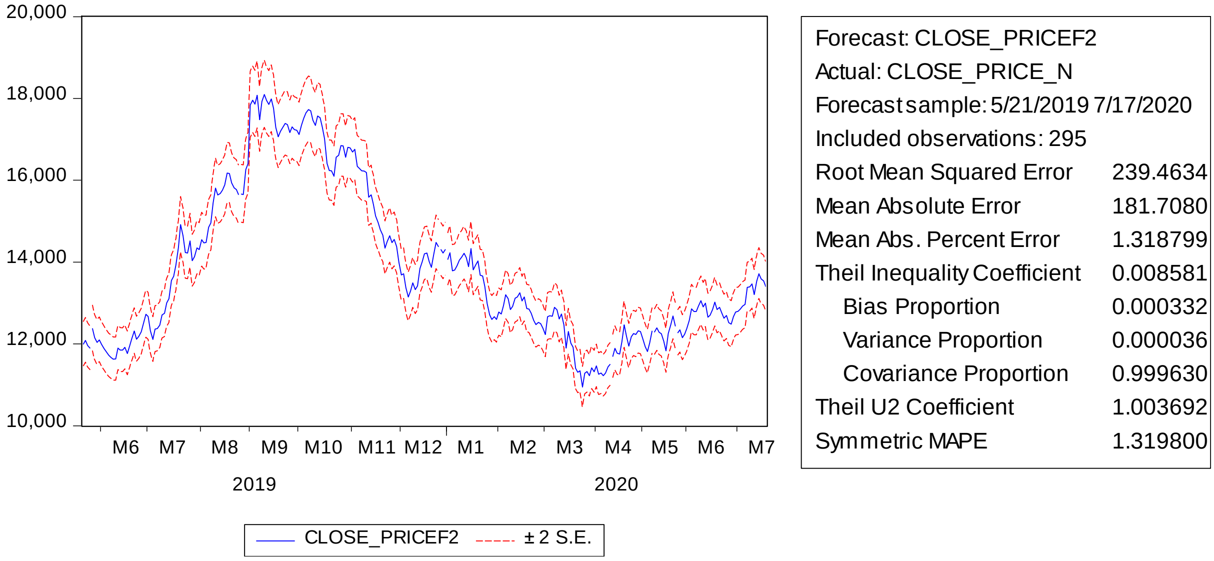


Figure 103: Eviews add in ARIMA Models forecast output for nickel

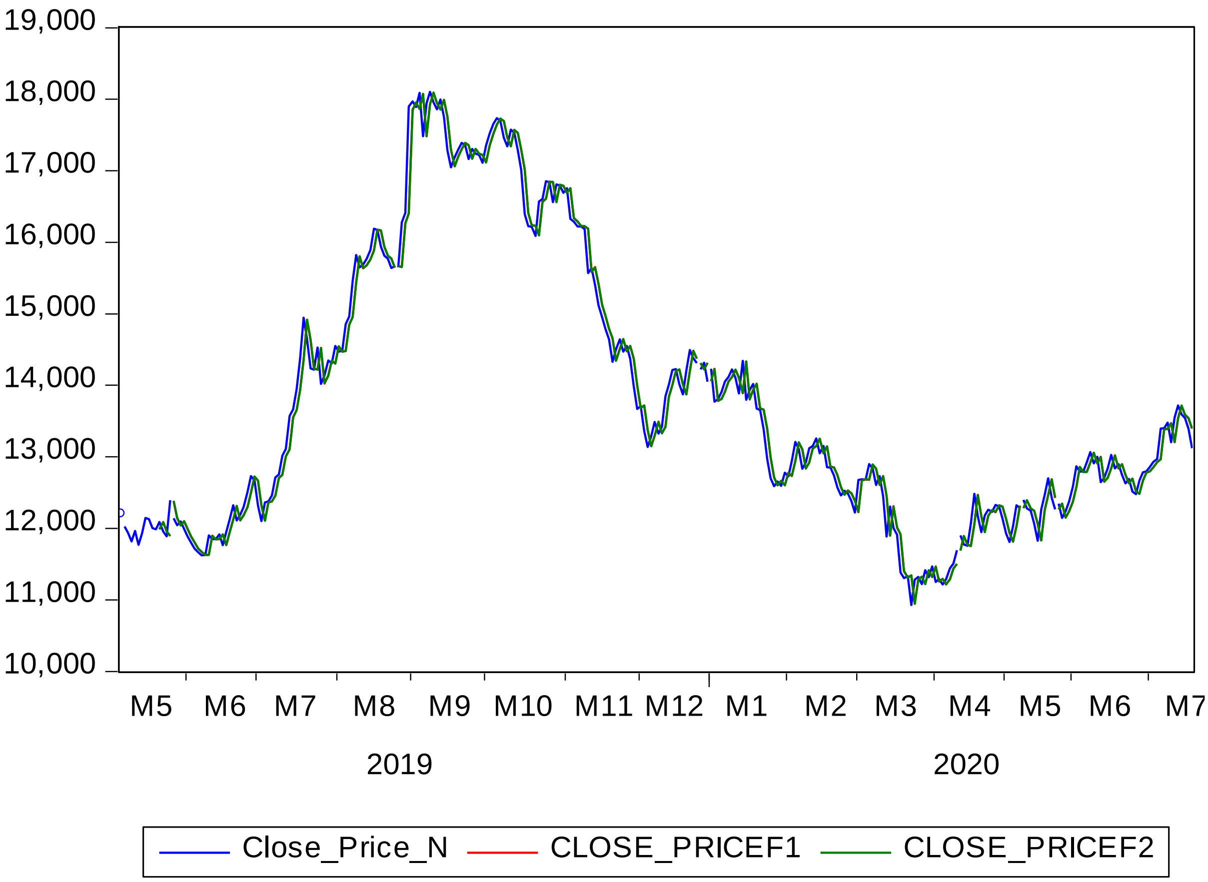
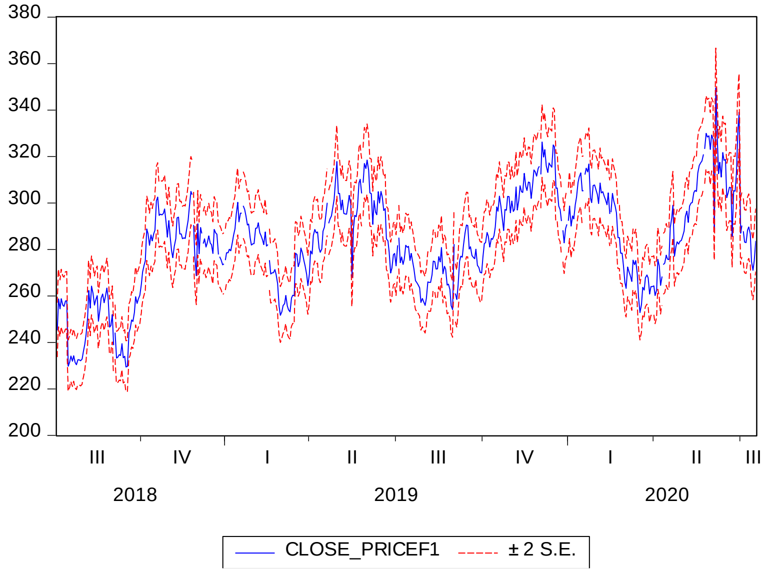


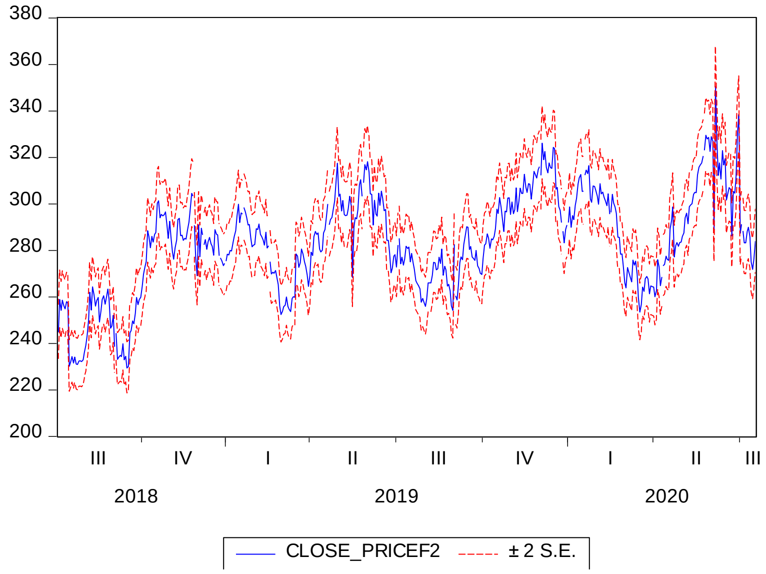
Figure 104: Comparison of the out of sample forecast of two ARIMA models for nickel

Oats



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_O	
Forecast sample: 7/05/2018 7/17/2020	
Included observations: 508	
Root Mean Squared Error	6.946793
Mean Absolute Error	4.474783
Mean Abs. Percent Error	1.572562
Theil Inequality Coefficient	0.012214
Bias Proportion	0.000080
Variance Proportion	0.000363
Covariance Proportion	0.999556
Theil U2 Coefficient	1.011897
Symmetric MAPE	1.569930

Figure 105: Custom ARIMA Model forecast output for oats



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_O	
Forecast sample: 7/05/2018 7/17/2020	
Included observations: 508	
Root Mean Squared Error	6.939288
Mean Absolute Error	4.494601
Mean Abs. Percent Error	1.578778
Theil Inequality Coefficient	0.012202
Bias Proportion	0.000215
Variance Proportion	0.000021
Covariance Proportion	0.999765
Theil U2 Coefficient	1.010506
Symmetric MAPE	1.576475

Figure 106: Eviews add in ARIMA Models forecast output for oats

Figure 107: Comparison of the out of sample forecast of two ARIMA models for oats

Palladium

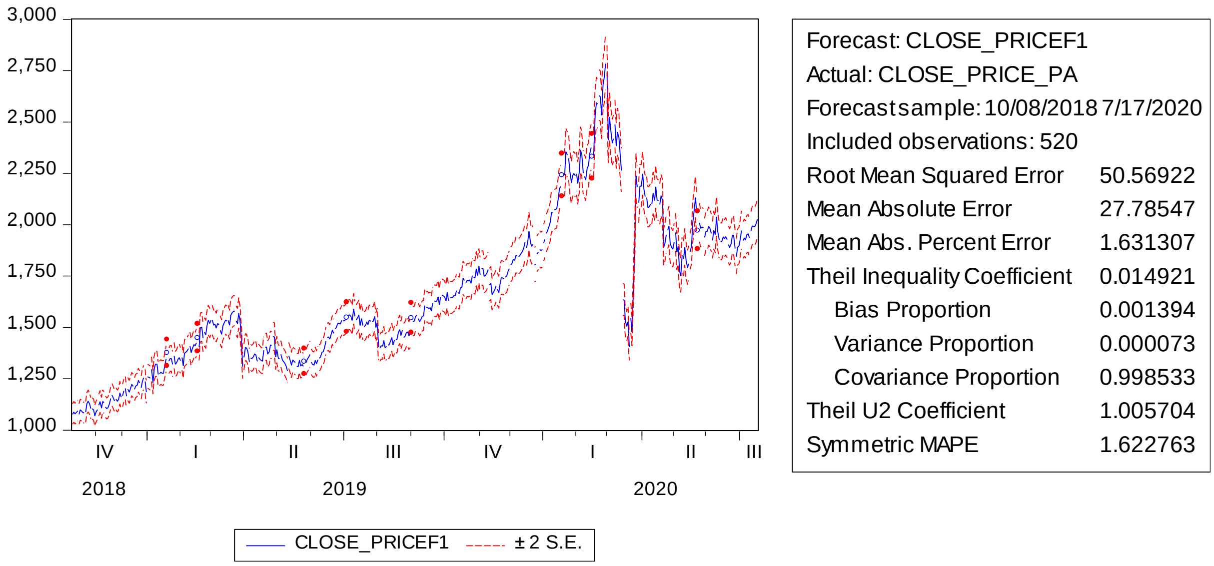
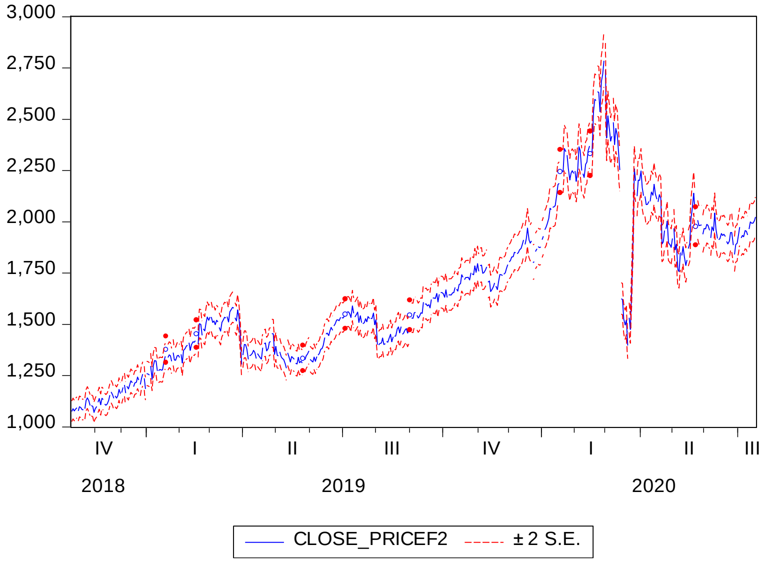


Figure 108: Custom ARIMA Model forecast output for palladium



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_PA	
Forecast sample: 10/08/2018 7/17/2020	
Included observations: 520	
Root Mean Squared Error	50.07625
Mean Absolute Error	27.61719
Mean Abs. Percent Error	1.623455
Theil Inequality Coefficient	0.014775
Bias Proportion	0.001125
Variance Proportion	0.000259
Covariance Proportion	0.998615
Theil U2 Coefficient	0.998311
Symmetric MAPE	1.615186

Figure 109: Eviews add in ARIMA Models forecast output for palladium

Figure 110: Comparison of the out of sample forecast of two ARIMA models for palladium

Platinum

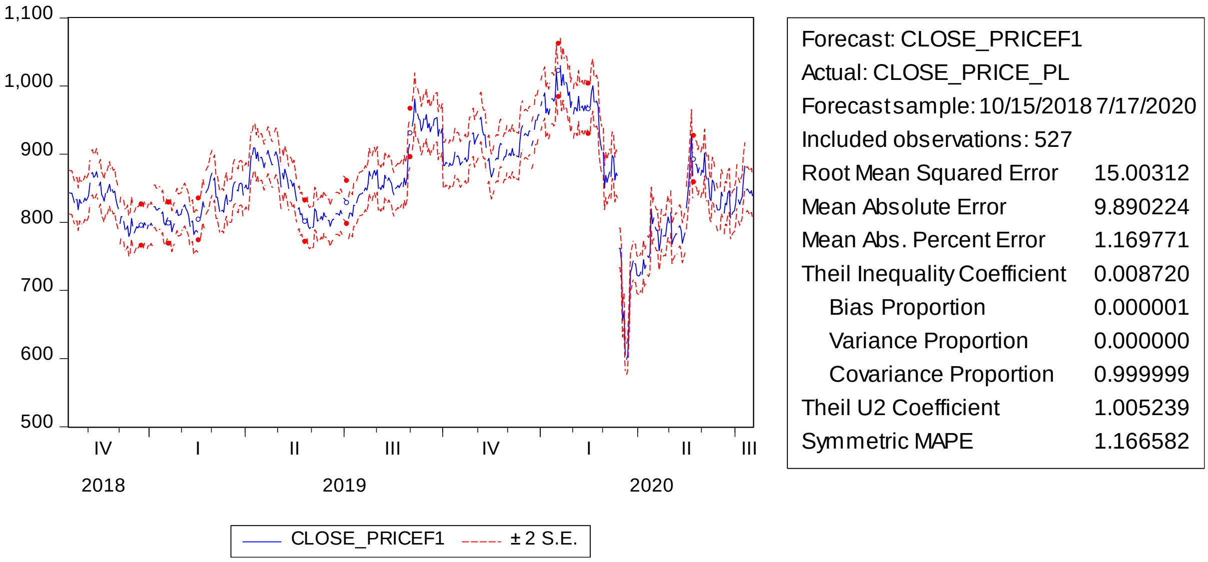


Figure 111: Custom ARIMA Model forecast output for platinum

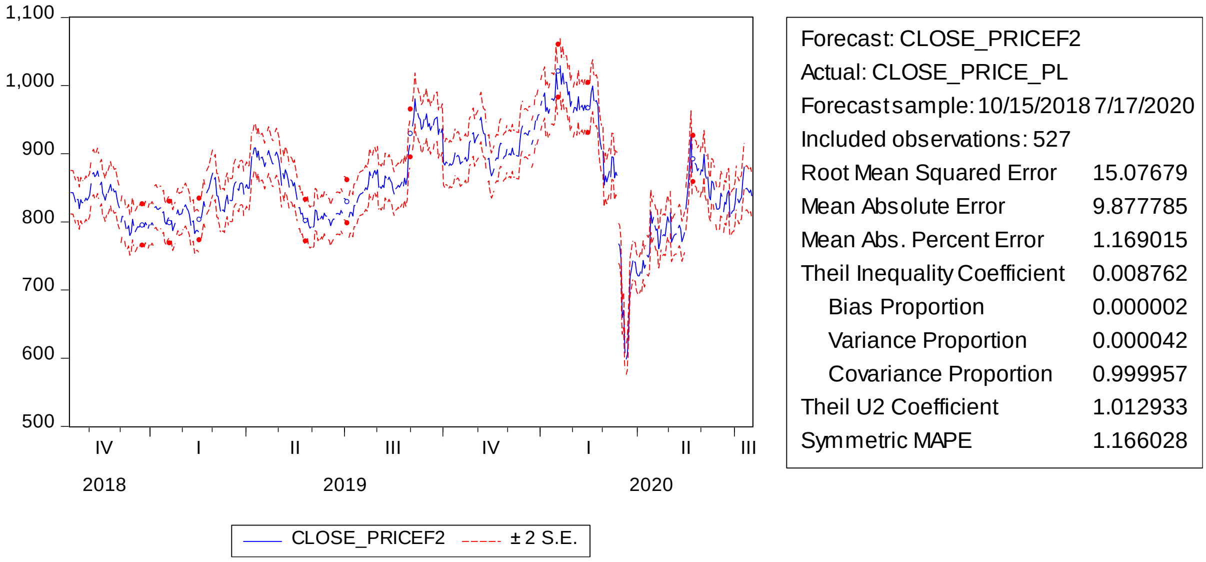
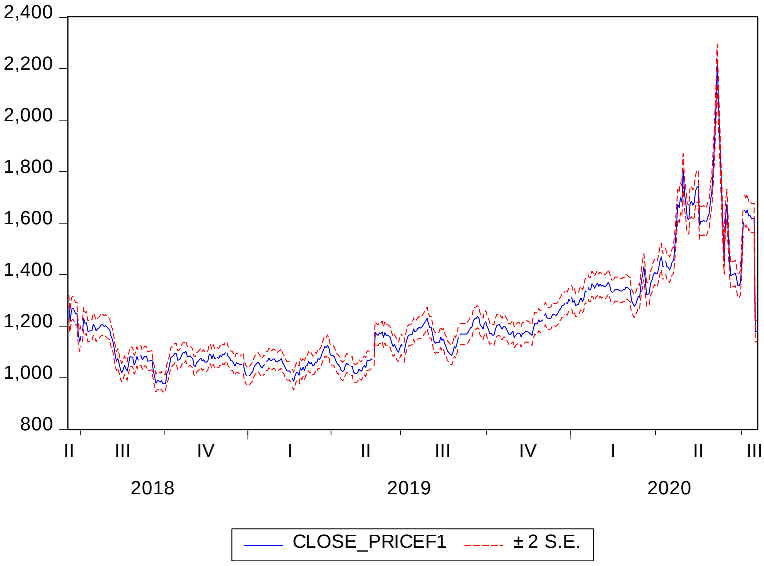


Figure 112: Eviews add in ARIMA Models forecast output for platinum

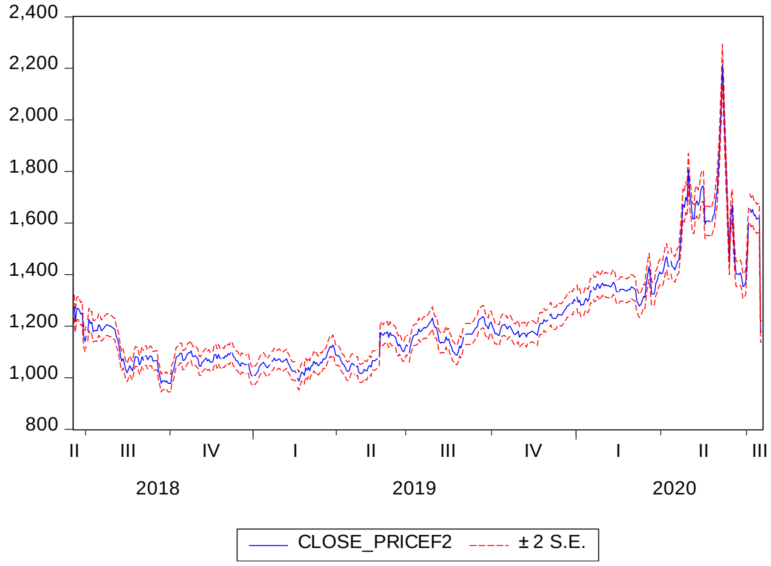
Figure 113: Comparison of the out of sample forecast of two ARIMA models for platinum

Rice



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_RR	
Forecast sample: 6/19/2018 7/17/2020	
Included observations: 506	
Root Mean Squared Error	34.10716
Mean Absolute Error	15.99936
Mean Abs. Percent Error	1.215564
Theil Inequality Coefficient	0.013855
Bias Proportion	0.000034
Variance Proportion	0.000031
Covariance Proportion	0.999935
Theil U2 Coefficient	0.987781
Symmetric MAPE	1.204574

Figure 114: Custom ARIMA Model forecast output for rice

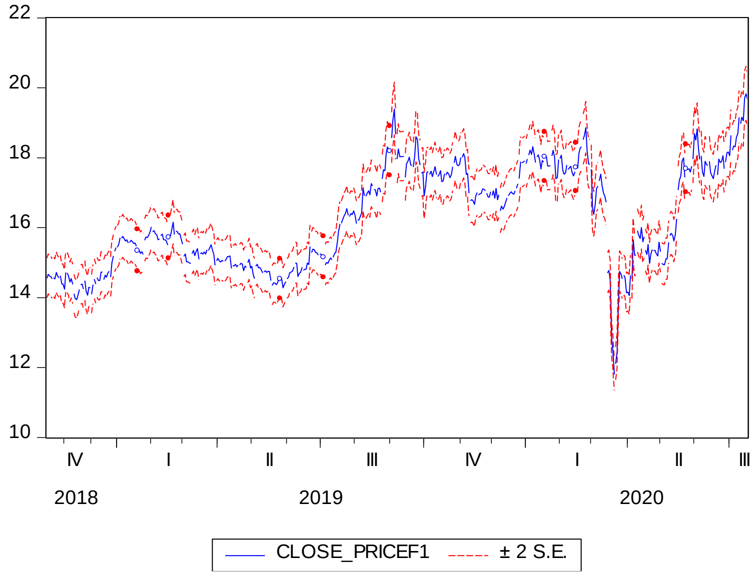


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_RR	
Forecast sample: 6/19/2018 7/17/2020	
Included observations: 506	
Root Mean Squared Error	34.06548
Mean Absolute Error	15.95425
Mean Abs. Percent Error	1.211843
Theil Inequality Coefficient	0.013838
Bias Proportion	0.000034
Variance Proportion	0.000037
Covariance Proportion	0.999929
Theil U2 Coefficient	0.986795
Symmetric MAPE	1.200926

Figure 115: Eviews add in ARIMA Models forecast output for rice

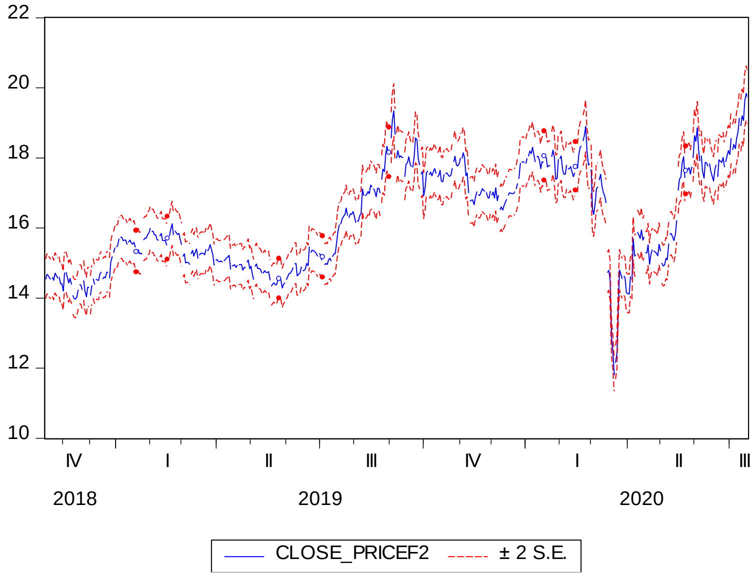
Figure 116: Comparison of the out of sample forecast of two ARIMA models for rice

Silver



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_SI	
Forecast sample: 10/15/2018 7/17/2020	
Included observations: 517	
Root Mean Squared Error	0.267257
Mean Absolute Error	0.171243
Mean Abs. Percent Error	1.057837
Theil Inequality Coefficient	0.008191
Bias Proportion	0.001410
Variance Proportion	0.000536
Covariance Proportion	0.998054
Theil U2 Coefficient	1.002742
Symmetric MAPE	1.056325

Figure 117: Custom ARIMA Model forecast output for silver

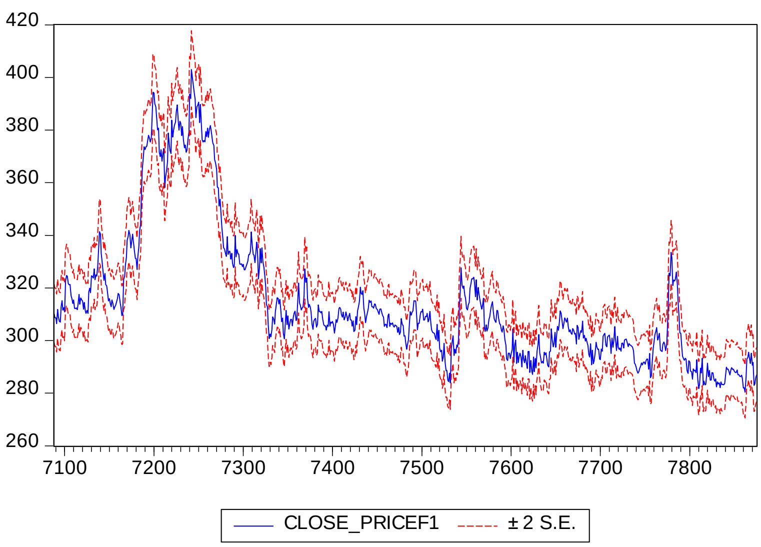


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_SI	
Forecast sample: 10/15/2018 7/17/2020	
Included observations: 517	
Root Mean Squared Error	0.267791
Mean Absolute Error	0.171990
Mean Abs. Percent Error	1.062313
Theil Inequality Coefficient	0.008208
Bias Proportion	0.001685
Variance Proportion	0.000992
Covariance Proportion	0.997325
Theil U2 Coefficient	1.005045
Symmetric MAPE	1.060883

Figure 118: Eviews add in ARIMA Models forecast output for silver

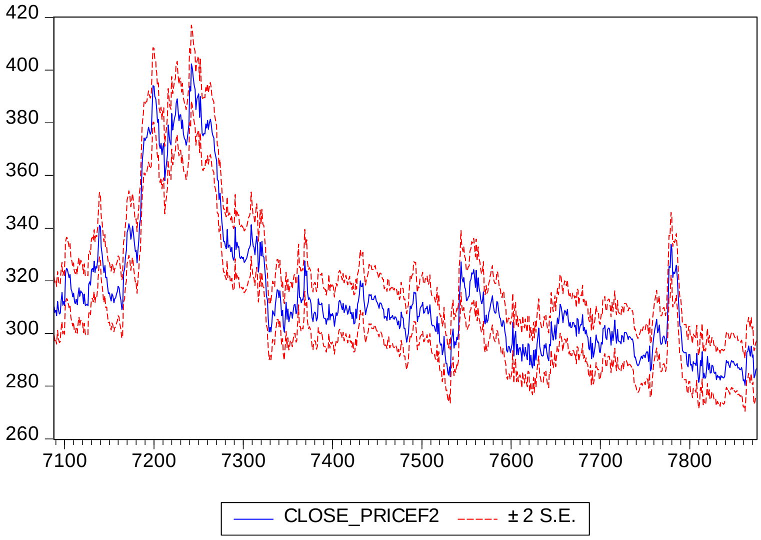
Figure 119: Comparison of the out of sample forecast of two ARIMA models for silver

Soybean meal



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_SM	
Forecast sample: 7088 7875	
Included observations: 788	
Root Mean Squared Error	3.661694
Mean Absolute Error	2.715030
Mean Abs. Percent Error	0.857273
Theil Inequality Coefficient	0.005796
Bias Proportion	0.000066
Variance Proportion	0.000052
Covariance Proportion	0.999885
Theil U2 Coefficient	0.999943
Symmetric MAPE	0.857512

Figure 120: Custom ARIMA Model forecast output for soybean meal

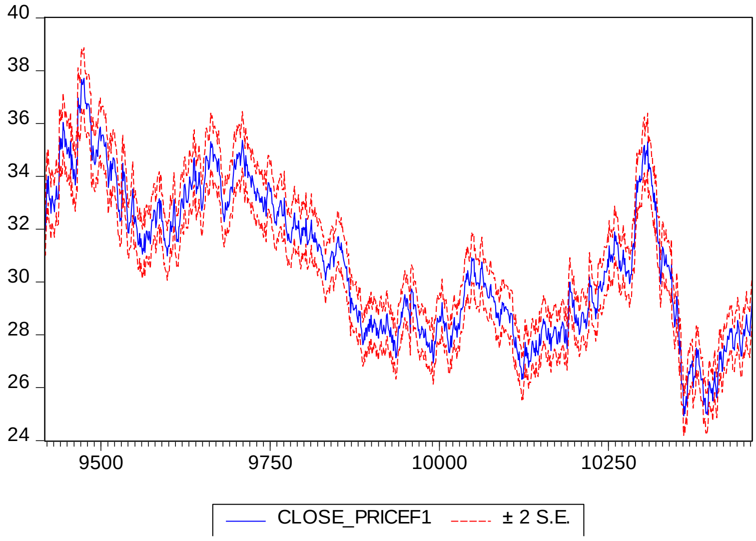


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_SM	
Forecast sample: 7088 7875	
Included observations: 788	
Root Mean Squared Error	3.677214
Mean Absolute Error	2.727728
Mean Abs. Percent Error	0.861674
Theil Inequality Coefficient	0.005821
Bias Proportion	0.000069
Variance Proportion	0.000008
Covariance Proportion	0.999928
Theil U2 Coefficient	1.004820
Symmetric MAPE	0.861879

Figure 121: Eviews add in ARIMA Models forecast output for soybean meal

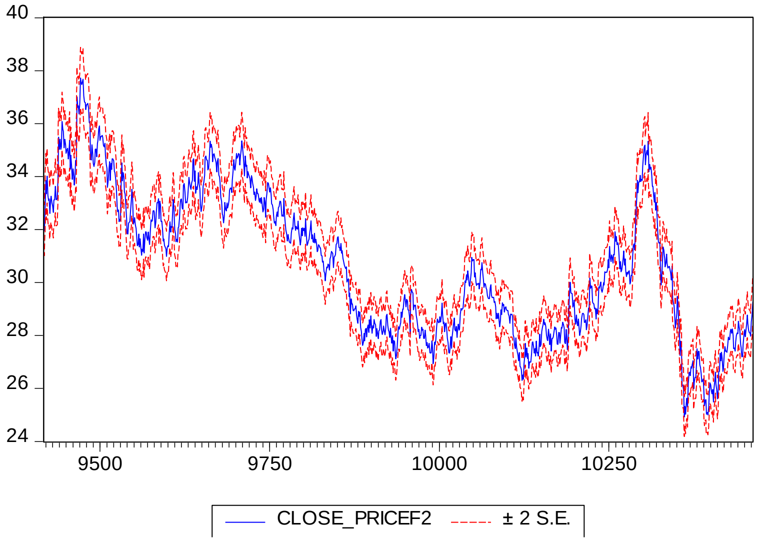
Figure 122: Comparison of the out of sample forecast of two ARIMA models for soybean meal

Soybean oil



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_BO	
Forecast sample: 9417 10462	
Included observations: 1046	
Root Mean Squared Error	0.345137
Mean Absolute Error	0.264604
Mean Abs. Percent Error	0.864490
Theil Inequality Coefficient	0.005601
Bias Proportion	0.000035
Variance Proportion	0.000005
Covariance Proportion	0.999964
Theil U2 Coefficient	1.003707
Symmetric MAPE	0.864672

Figure 123: Custom ARIMA Model forecast output for soybean oil

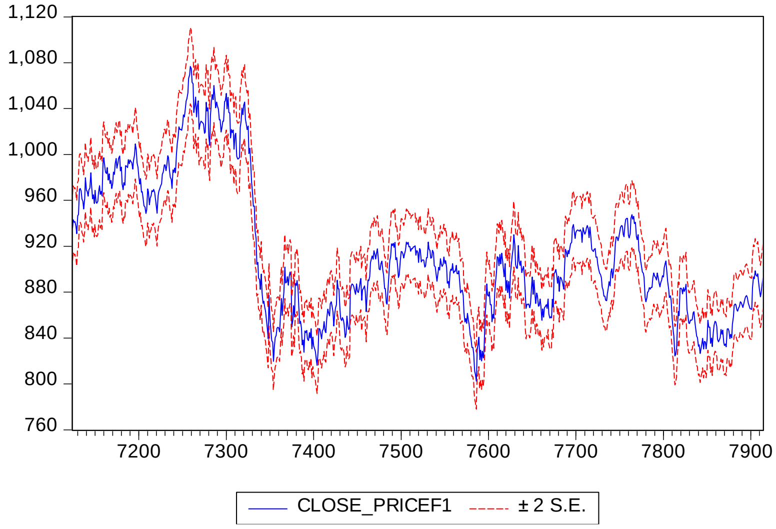


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_BO	
Forecast sample: 9417 10462	
Included observations: 1046	
Root Mean Squared Error	0.345847
Mean Absolute Error	0.265746
Mean Abs. Percent Error	0.868067
Theil Inequality Coefficient	0.005613
Bias Proportion	0.000028
Variance Proportion	0.000041
Covariance Proportion	0.999933
Theil U2 Coefficient	1.005747
Symmetric MAPE	0.868255

Figure 124: Eviews add in ARIMA Models forecast output for soybean oil

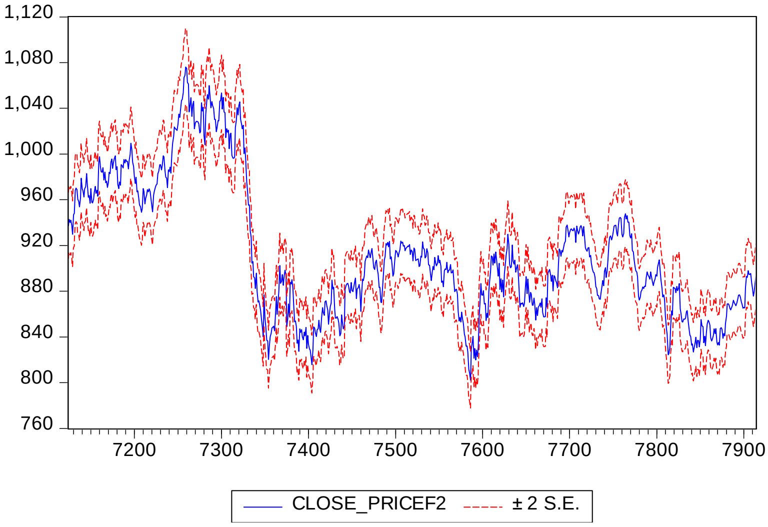
Figure 125: Comparison of the out of sample forecast of two ARIMA models for soybean oil

Soybeans



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_S	
Forecast sample: 7124 7914	
Included observations: 791	
Root Mean Squared Error	8.735596
Mean Absolute Error	6.533941
Mean Abs. Percent Error	0.718273
Theil Inequality Coefficient	0.004774
Bias Proportion	0.000033
Variance Proportion	0.000001
Covariance Proportion	0.999975
Theil U2 Coefficient	1.005313
Symmetric MAPE	0.718425

Figure 126: Custom ARIMA Model forecast output for soybeans

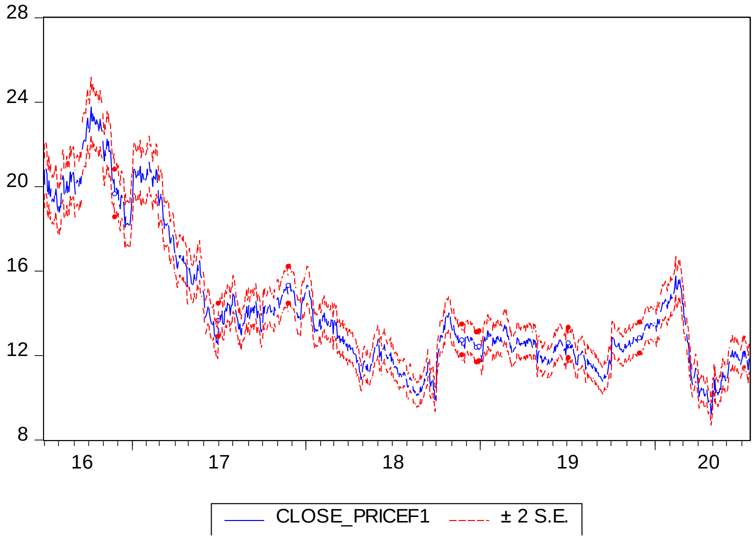


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_S	
Forecast sample: 7124 7914	
Included observations: 791	
Root Mean Squared Error	8.748102
Mean Absolute Error	6.534545
Mean Abs. Percent Error	0.718523
Theil Inequality Coefficient	0.004781
Bias Proportion	0.000034
Variance Proportion	0.000000
Covariance Proportion	0.999959
Theil U2 Coefficient	1.007236
Symmetric MAPE	0.718670

Figure 127: Eviews add in ARIMA Models forecast output for soybeans

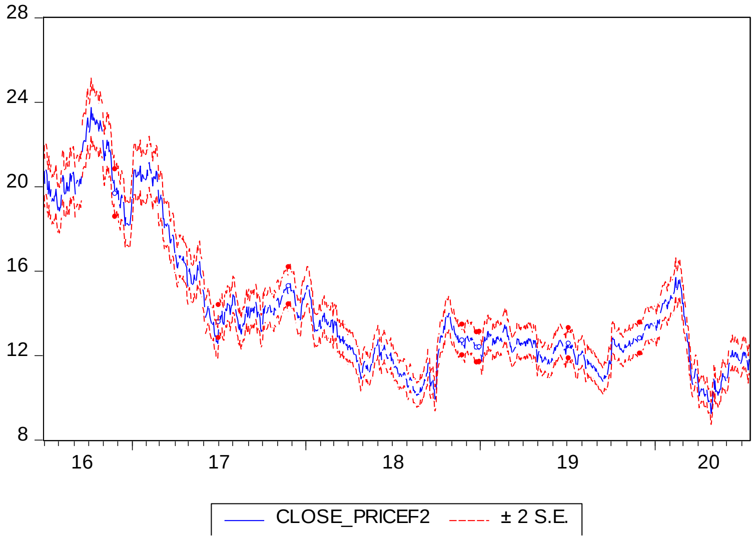
Figure 128: Comparison of the out of sample forecast of two ARIMA models for soybeans

Sugar



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_SB	
Forecast sample: 6/30/2016 7/17/2020	
Included observations: 1021	
Root Mean Squared Error	0.262587
Mean Absolute Error	0.195396
Mean Abs. Percent Error	1.383983
Theil Inequality Coefficient	0.009020
Bias Proportion	0.001214
Variance Proportion	0.000412
Covariance Proportion	0.998369
Theil U2 Coefficient	1.002123
Symmetric MAPE	1.383294

Figure 129: Custom ARIMA Model forecast output for sugar



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_SB	
Forecast sample: 6/30/2016 7/17/2020	
Included observations: 1021	
Root Mean Squared Error	0.265435
Mean Absolute Error	0.197523
Mean Abs. Percent Error	1.398715
Theil Inequality Coefficient	0.009118
Bias Proportion	0.001340
Variance Proportion	0.000327
Covariance Proportion	0.998338
Theil U2 Coefficient	1.014218
Symmetric MAPE	1.397969

Figure 130: Eviews add in ARIMA Models forecast output for sugar

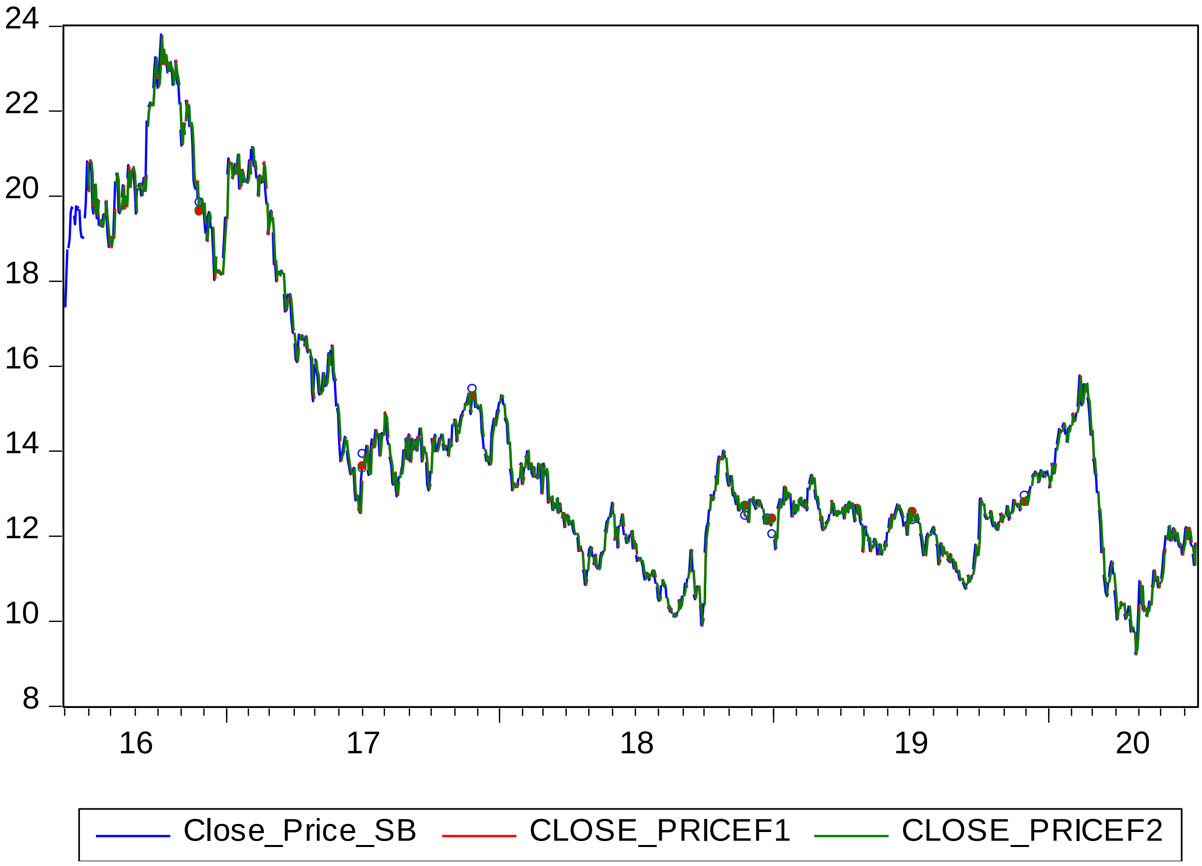


Figure 131: Comparison of the out of sample forecast of two ARIMA models for sugar

Tin

Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_T	
Forecast sample: 5/21/2019 7/17/2020	
Included observations: 295	
Root Mean Squared Error	227.7830
Mean Absolute Error	162.0454
Mean Abs. Percent Error	0.987893
Theil Inequality Coefficient	0.006787
Bias Proportion	0.001125
Variance Proportion	0.001627
Covariance Proportion	0.997245
Theil U2 Coefficient	1.011797
Symmetric MAPE	0.986090

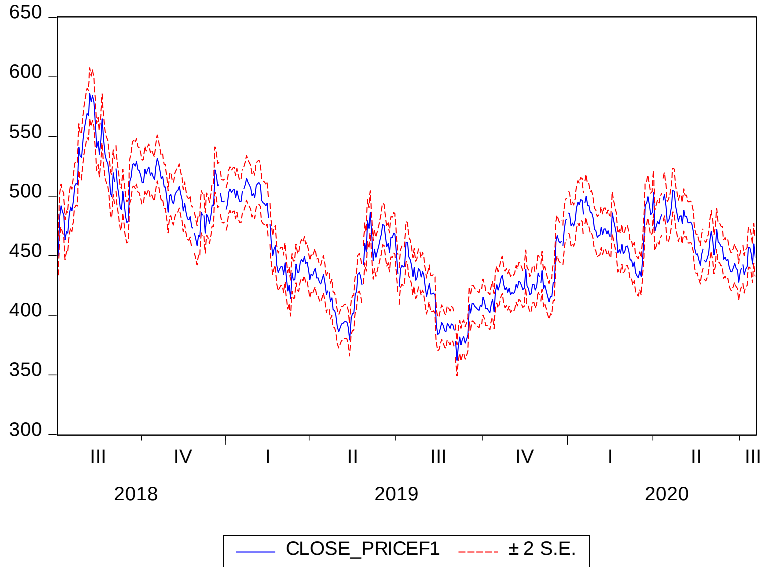
Figure 132: Custom ARIMA Model forecast output for tin

Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_T	
Forecast sample: 5/21/2019 7/17/2020	
Included observations: 295	
Root Mean Squared Error	227.9445
Mean Absolute Error	161.7846
Mean Abs. Percent Error	0.986340
Theil Inequality Coefficient	0.006792
Bias Proportion	0.000815
Variance Proportion	0.001616
Covariance Proportion	0.997566
Theil U2 Coefficient	1.012551
Symmetric MAPE	0.984612

Figure 133: Eviews add in ARIMA Models forecast output for tin

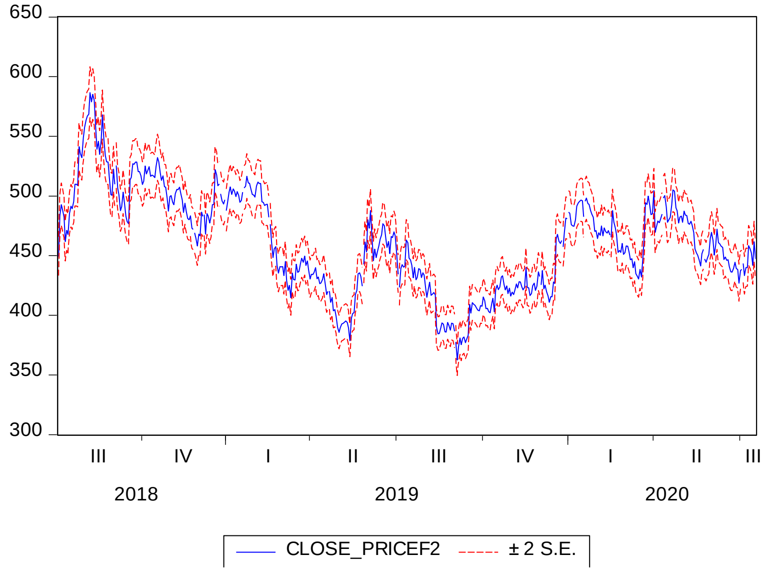
Figure 134: Comparison of the out of sample forecast of two ARIMA models for tin

Wheat



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_KW	
Forecast sample: 7/05/2018 7/17/2020	
Included observations: 508	
Root Mean Squared Error	8.627134
Mean Absolute Error	6.384692
Mean Abs. Percent Error	1.380413
Theil Inequality Coefficient	0.009308
Bias Proportion	0.000000
Variance Proportion	0.000000
Covariance Proportion	0.999998
Theil U2 Coefficient	1.000216
Symmetric MAPE	1.382513

Figure 135: Custom ARIMA Model forecast output for wheat

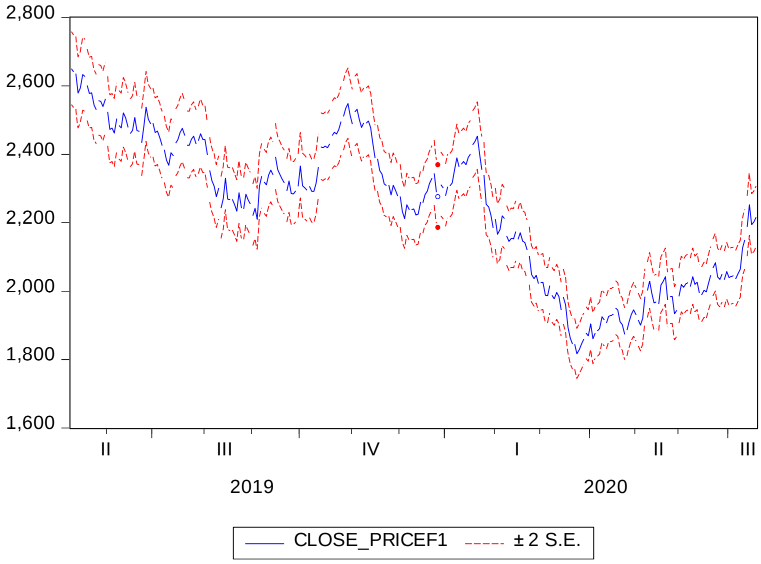


Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_KW	
Forecast sample: 7/05/2018 7/17/2020	
Included observations: 508	
Root Mean Squared Error	8.686749
Mean Absolute Error	6.427517
Mean Abs. Percent Error	1.390108
Theil Inequality Coefficient	0.009372
Bias Proportion	0.000000
Variance Proportion	0.000029
Covariance Proportion	0.999971
Theil U2 Coefficient	1.006956
Symmetric MAPE	1.392320

Figure 136: Eviews add in ARIMA Models forecast output for wheat

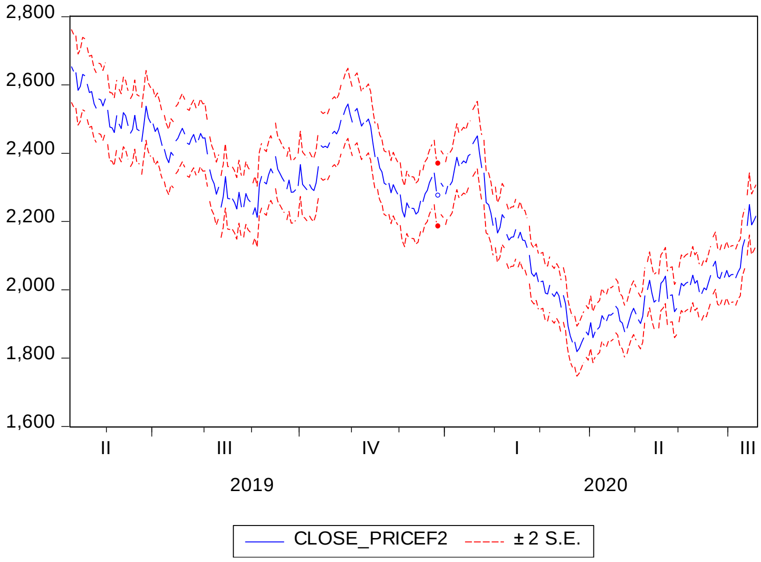
Figure 137: Comparison of the out of sample forecast of two ARIMA models for wheat

Zinc



Forecast: CLOSE_PRICEF1	
Actual: CLOSE_PRICE_Z	
Forecast sample: 5/09/2019 7/17/2020	
Included observations: 303	
Root Mean Squared Error	28.77727
Mean Absolute Error	22.89475
Mean Abs. Percent Error	1.027033
Theil Inequality Coefficient	0.006388
Bias Proportion	0.003121
Variance Proportion	0.001920
Covariance Proportion	0.994958
Theil U2 Coefficient	1.005606
Symmetric MAPE	1.026292

Figure 138: Custom ARIMA Model forecast output for zinc



Forecast: CLOSE_PRICEF2	
Actual: CLOSE_PRICE_Z	
Forecast sample: 5/09/2019 7/17/2020	
Included observations: 303	
Root Mean Squared Error	28.79871
Mean Absolute Error	22.98811
Mean Abs. Percent Error	1.030518
Theil Inequality Coefficient	0.006393
Bias Proportion	0.003537
Variance Proportion	0.001924
Covariance Proportion	0.994539
Theil U2 Coefficient	1.004868
Symmetric MAPE	1.029685

Figure 139: Eviews add in ARIMA Models forecast output for zinc

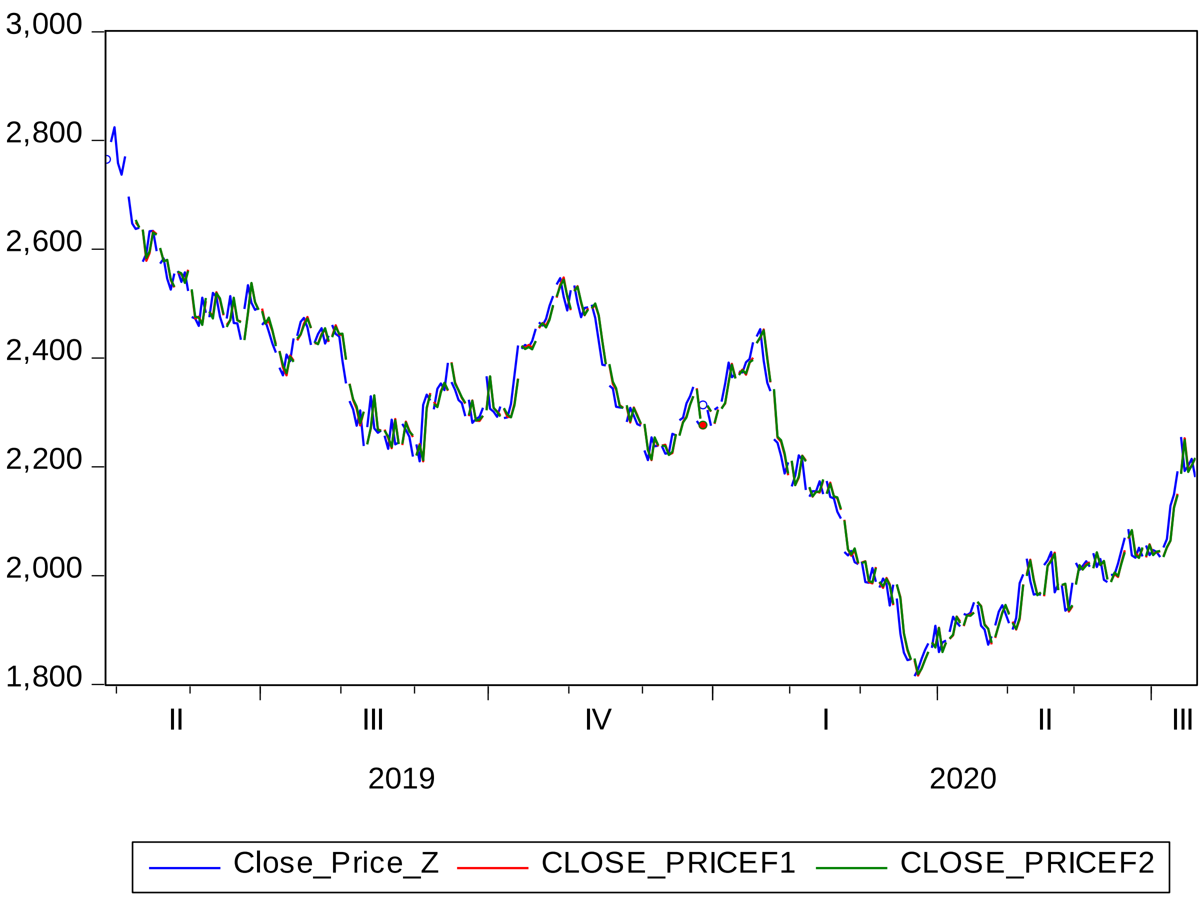


Figure 140: Comparison of the out of sample forecast of two ARIMA models for zinc

After we have conducted the forecast, we performed Diebold-Mariano test to see if the predictive ability of each model differ, so it worth using the one ARIMA model over the other. All of the models passed the test successfully, as |DM statistic|> ± 1.96, indicating that forecast accuracy of two forecast methods differ significantly. The results of this test are presented below.

DM Test Statistic	**DM SQR**	**DM ABS**
Aluminum	17,08052	17,07233
Corn	-239,1550	-238,9285
Brent Oil	122,2663	122,1592
Coffee	275,3240	275,3020
Copper	129,1084	128,7022
Crude Oil	-55,60704	-55,63019
Feeder Cattle	197,7561	197,9185
Cocoa	27,67356	27,66916
Gasoline	-82,51257	-82,87890
Gold	-153,3745	-153,4925
Heating Oil	-66,58352	-66,49447
Lead	15,05732	15,03294
Lean Hogs	150,0289	148,6948
Live Cattle	25,50501	25,50709
Lumber	142,2237	141,3380
Natural Gas	-57,87276	-58,29523
Nickel	275,1852	275,1148
Oats	167,1640	166,9870
Palladium	157,3889	157,3685
Platinum	191,3361	191,3237
Rice	172,5420	172,5841
Silver	-34,11769	-34,11243
Soybean Meal	-69,50640	-69,53258
Soybean Oil	206,6237	206,5803
Soybeans	-98,94952	-99,01308
Sugar	148,9387	148,6837
Tin	34,03102	33,88944
Wheat	33,95192	33,94961
Zinc	-199,0555	-199,1783
Cotton	-42,83575	-42,85928

Table 66: Diebold-Mariano test statistic for each commodity

Due to the fact that the predictability of the two models differ, we should examine which one performs better, resulting to more accurate results on this out of sample forecast. That's why we gathered the 4 accuracy indicators we discussed in the Methodology section and perform comparison between the two sets of ARIMA models, presented at the table 67.

	Custom Model				Eviews Add in Model			
	RMSE	MAE	MAPE	Theil	RMSE	MAE	MAPE	Theil
Aluminum	**21,35**	**17,28**	**1,12**	**0,0069**	22,92	18,43	1,19	0,0074
Corn	4,96	3,56	0,98	0,0068	4,96	3,56	0,98	0,0068
Brent Oil	1,32	**0,90**	1,69	0,0106	1,32	0,91	1,70	0,0106
Coffee	**2,23**	**1,71**	1,47	0,0093	2,24	1,72	1,47	0,0093
Copper	0,03	0,03	0,96	0,0063	0,03	0,03	0,96	0,0063
Crude Oil	**1,63**	1,02	**2,64**	**0,0151**	1,64	1,02	2,65	0,0152
Feeder Cattle	1,91	**1,23**	**0,90**	0,0067	**1,90**	1,24	0,91	0,0067
Cocoa	**43,80**	**34,15**	1,48	0,0093	43,84	34,22	1,48	0,0093
Gasoline	0,044	0,03	2,43	0,0139	**0,043**	0,03	**2,42**	0,0139
Gold	15,64	9,72	0,65	0,0054	**15,57**	9,72	0,65	**0,0053**
Heating Oil	0,04	0,027	1,85	0,0112	0,04	0,027	1,85	0,0112
Lead	**24,20**	**19,32**	**1,02**	0,0064	24,47	19,58	1,03	0,0064
Lean Hogs	2,07	1,22	1,93	0,0155	2,07	1,22	1,93	0,0155
Live Cattle	**1,73**	**1,10**	**0,998**	0,0076	1,74	1,11	1,00	0,0076
Lumber	**9,48**	**6,59**	**1,68**	0,0119	9,5	6,64	1,69	0,0119
Natural Gas	0,1	0,06	**2,42**	0,0195	0,1	0,06	2,43	0,0195
Nickel	**239,24**	**181,23**	1,32	0,0086	239,46	181,71	1,32	0,0086
Oats	6,95	**4,47**	**1,57**	0,0122	**6,94**	4,49	1,58	0,0122
Palladium	50,57	27,79	1,63	0,0149	**50,08**	**27,62**	**1,62**	**0,0148**
Platinum	**15,00**	9,89	1,17	**0,0087**	15,08	**9,88**	1,17	0,0088
Rice	34,11	**15,00**	1,22	0,0139	**34,07**	15,95	**1,21**	**0,0138**
Silver	0,27	0,17	1,06	0,0082	0,27	0,17	1,06	0,0082
Soybean Meal	**3,66**	**2,72**	0,86	0,0058	3,68	2,73	0,86	0,0058
Soybean Oil	0,35	0,26	0,86	0,0056	0,35	**0,27**	**0,87**	0,0056
Soybeans	8,74	6,53	0,72	0,0048	8,75	6,53	0,72	0,0048
Sugar	**0,26**	0,20	**1,38**	**0,0090**	0,27	0,20	1,40	0,0091
Tin	**227,78**	162,05	0,99	0,0068	227,94	**161,78**	0,99	0,0068
Wheat	**8,63**	**6,38**	**1,38**	**0,0093**	8,69	6,43	1,39	0,0094
Zinc	**28,78**	**22,89**	1,03	0,0064	28,80	22,99	1,03	0,0064
Cotton	0,97	**0,73**	1,08	0,0069	0,97	0,74	1,08	0,0069

Table 67: Forecasting accuracy indicators comparison between models for each commodity

Overall, we observe that most of the times the Custom models perform better than the Eviews add in models. Forecasting with custom models is more accurate for aluminum, coffee, crude oil, feeder cattle, cocoa, lead, live cattle, lumber, nickel, oats, platinum, soybean meal, sugar, wheat and zinc, while forecasting with Eviews add in models is more accurate for gasoline, gold, palladium, rice and soybean oil. Prediction accuracy for corn, brent oil, copper, heating oil, lean hogs, natural gas, silver, soybeans, tin and cotton is indifferent for whoever model from both we use, according to the corresponding indicators.

7.2 Jumps in Commodities Returns

Jumps are considered to be discontinuous variations in assets' prices and generate returns that lie outside their usual scale of value. Those jumps can either be significant investing opportunities or massive threats to profit and losses. Hence, the higher the jump activity, the higher the uncertainty for market participants. Identifying jumps in commodity returns represents indeed an essential step to understanding the dynamics of these markets. They usually occur as extreme, discontinued events that happen rarely in financial markets (Chevallier & Ielpo, 2014).

To analyze the daily returns of the selected commodities we calculate these jumps in an effort to explain volatility and risk. Then we calculate the percentage of positive and negative jumps for every commodity, as well as the percentage of jumps to whole sample. The jumps are indicating abnormal returns or losses that happen unexpectedly and cannot be predicted very easily, occurring usually during short or long crisis periods of the markets. The results are shown at the table 68.

We see that the commodities with the highest percentage of jumps relating to the sample size are lean hogs, feeder cattle, live cattle, oats, gasoline, tin, silver, platinum and lumber. Also, metals and energy commodities present a higher percentage of negative jumps. On the contrary, agricultural commodities, and more specifically grains and softs, present higher percentage of positive jumps something that Chevallier & Ielpo (2014) observed as well. The highest number of jumps occurs between livestock commodities, while the lowest number of jumps is observed in energy cluster of commodities (except gasoline).

The existence of these jumps is indication of risk in commodities markets. This implies that commodities are not necessary providing investors with as much diversification as one could expect. Commodities should not be overlooked when it comes to systemic risk (Chevallier & Ielpo, 2014). So, the notion that commodities are doing well during crisis is generally correct but there can be times during these crisis that jumps will occur, affecting the hedging role of commodities. With this analysis we can have an idea regarding the risk involved in daily returns of commodities.

Commodities	Total daily log returns observations	Total Jumps	% of total daily returns	Positive Jumps	% of total jumps	Negative Jumps	% of total jumps
METALS							
Precious							
gold	5.107	42	0,8224	16	38%	26	62%
silver	5.165	57	1,1036	16	28%	41	72%
platinum	5.266	53	1,0065	23	43%	30	57%
palladium	5.201	48	0,9229	19	40%	29	60%
Industrial/Base							
aluminum	901	6	0,6659	4	67%	2	33%
copper	6.233	34	0,5458	11	32%	23	68%
lead	2.945	21	0,7131	10	48%	11	52%
nickel	2.945	16	0,7131	8	50%	8	50%
tin	2.945	37	1,2564	7	19%	30	81%
zinc	3.032	15	0,4947	5	33%	10	67%
ENERGY							
crude oil	5.094	28	0,0055	7	25%	21	75%
brent oil	8.181	45	0,5501	15	33%	30	67%
gasoline rbob	4.017	49	1,2198	18	37%	31	63%
heating oil	5.113	28	0,5476	9	32%	19	68%
natural gas	5.112	25	0,489	18	72%	7	28%
AGRICULTURE							
Grains							
corn	10.446	95	0,9077	59	62%	36	38%
rice	5.057	37	0,7317	25	68%	12	32%
soybeans	7.913	52	0,6571	19	37%	33	63%
soybean oil	10.461	29	0,2772	17	59%	12	41%
soybean meal	7.874	63	0,8001	28	44%	35	56%
oats	5.081	66	1,299	26	39%	40	61%
wheat	5.079	19	0,3741	15	79%	4	21%
Softs							
coffee	10.228	70	0,6844	34	49%	36	51%
cocoa	10.183	50	0,491	24	48%	26	52%
sugar	10.212	101	0,989	44	44%	57	56%
cotton	5.224	43	0,8231	29	67%	14	33%
lumber	10.227	120	1,1734	80	67%	40	33%
Livestock							
lean logs	10.255	206	2,0088	95	46%	111	54%
feeder cattle	5.108	91	1,8135	38	42%	53	58%
live cattle	10.243	123	1,2008	41	33%	82	67%

Table 68: Jumps results for commodities

9. CONCLUSION

Commodities is a very special market with its own characteristics. We can separate them into three categories, agriculture, metals and energy, to understand and study them better, drawing interesting conclusions. They have their own pricing dynamics that needs special analysis to be understood extensively. From the analysis of commodity fundamentals we conclude that most of the times over the counter deals regarding commodities are affected by the commodities that trade freely at the open market, based on supply and demand dynamics. Also, we observe that most of the commodities are used for industrial purposes as raw materials for the creation of other products. Generally, they are doing good during high inflation periods, used as a safe for investments. Precious metals are usually used combined with industrial metals as alloys to improve their properties. However, many metals are energy intensive to be produced, with industries and governments seeking for alternative solutions. The commodities that correlate more with each other are those which belong to the energy complex, as they are distillates of the same base commodity, oil. Furthermore, there is a strong substitution effect between of the same group, especially when the prices are high for one commodity; consumers tend to substitute it with another. Most of the commodities are affected by weather either directly, like agricultural commodities, or indirectly. Brazil is the biggest producer of agricultural commodities with high rank to many others, with huge future potential. Finally, China seems to be the biggest end user of almost all commodities due to their rapid growth and the shift of production from advanced economies to the East.

The interesting part from investment perspective is to create models that can predict commodities prices. We have created such ARIMA models and most of the times the “custom ARIMA models”, were better in an out of sample forecast. These models differ from the other set, because we create them more conservatively, trying to have all the ARMA terms statistically significant and have a very stable structure. However, both sets of ARIMA models seem to capture the trends and turns of the closing prices during forecasting. Moreover, we conclude that livestock commodities are those with the highest risk involved in their volatility, as they present the highest number of jumps to their daily returns. Metals and energy present a high number of negative jumps, while agriculture commodities present a high number of positive jumps. A very important aspect of commodities for future research would be the analysis of risk of daily returns and the creation of even more accurate forecasting models for daily prices and daily returns.

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11. APPENDIX

11.1 APPENDIX I: Unit root tests results for stationarity

Aluminum

- **Correlogram**

Sample: 11/21/2016 3/09/2020
Included observations: 811

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.009	-0.009	0.0633	0.801
		2	0.096	0.095	7.5026	0.023
		3	-0.038	-0.036	8.6565	0.034
		4	-0.028	-0.038	9.2894	0.054
		5	-0.034	-0.028	10.239	0.069
		6	-0.050	-0.046	12.276	0.056
		7	-0.040	-0.037	13.565	0.059
		8	-0.019	-0.013	13.847	0.086
		9	-0.110	-0.110	23.745	0.005
		10	-0.023	-0.030	24.165	0.007
		11	-0.108	-0.098	33.783	0.000
		12	0.059	0.047	36.620	0.000
		13	-0.009	-0.004	36.691	0.000
		14	-0.023	-0.054	37.115	0.001
		15	0.052	0.037	39.371	0.001
		16	-0.033	-0.042	40.280	0.001
		17	0.059	0.036	43.129	0.000
		18	0.013	0.007	43.271	0.001
		19	0.055	0.040	45.827	0.001
		20	-0.013	-0.035	45.967	0.001
		21	0.028	0.029	46.605	0.001
		23	-0.028	-0.025	47.259	0.002
		24	0.004	0.014	47.270	0.003
		25	0.025	0.026	47.801	0.004
		27	-0.015	-0.028	48.163	0.007
		29	-0.047	-0.049	53.930	0.003
		30	-0.063	-0.049	57.229	0.002
		31	0.021	0.023	57.611	0.003
		32	-0.031	-0.032	58.414	0.003
		33	0.039	0.024	59.701	0.003
		35	0.014	0.007	60.322	0.005
		36	0.034	0.023	61.299	0.005

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.33860	0.0000
Test critical values:	1% level	-3.438208	
	5% level	-2.864898	
	10% level	-2.568613	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 11/24/2016 3/09/2020
Included observations: 809 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.913495	0.049813	-18.33860	0.0000
D(R(-1))	-0.096203	0.035103	-2.740597	0.0063
C	-7.70E-05	0.000416	-0.185026	0.8533

R-squared	0.509953	Mean dependent var	-7.54E-06
Adjusted R-squared	0.508737	S.D. dependent var	0.016878
S.E. of regression	0.011830	Akaike info criterion	-6.032728
Sum squared resid	0.112791	Schwarz criterion	-6.015315
Log likelihood	2443.239	Hannan-Quinn criter.	-6.026042
F-statistic	419.3700	Durbin-Watson stat	1.991909
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.246736
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000141
HAC corrected variance (Bartlett kernel)	0.000118

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 11/22/2016 3/09/2020
Included observations: 811 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.83E-05	0.000417	-0.091787	0.9269

R-squared	0.000000	Mean dependent var	-3.83E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.011887
S.E. of regression	0.011887	Akaike info criterion	-6.025556
Sum squared resid	0.114448	Schwarz criterion	-6.019763
Log likelihood	2444.363	Hannan-Quinn criter.	-6.023332
Durbin-Watson stat	2.012998		

- **Phillips – Perron test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-28.86268	0.0000
Test critical values:	1% level	-3.438198	
	5% level	-2.864894	
	10% level	-2.568610	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000141
HAC corrected variance (Bartlett kernel)	0.000120

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 11/23/2016 3/09/2020
Included observations: 810 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.008822	0.035098	-28.74317	0.0000
C	-6.70E-05	0.000417	-0.160673	0.8724

R-squared	0.505559	Mean dependent var	-2.59E-05
Adjusted R-squared	0.504947	S.D. dependent var	0.016875
S.E. of regression	0.011873	Akaike info criterion	-6.026556
Sum squared resid	0.113911	Schwarz criterion	-6.014958
Log likelihood	2442.755	Hannan-Quinn criter.	-6.022103
F-statistic	826.1699	Durbin-Watson stat	2.001031
Prob(F-statistic)	0.000000		

Brent Oil

- **Correlogram**

Sample: 6/27/1988 5/17/2017
Included observations: 7363

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.022	-0.022	3.5672	0.059
		2	-0.023	-0.023	7.3283	0.026
		3	-0.020	-0.021	10.371	0.016
		4	-0.004	-0.006	10.506	0.033
		5	-0.010	-0.011	11.238	0.047
		6	-0.022	-0.023	14.651	0.023
		7	0.008	0.006	15.087	0.035
		8	-0.011	-0.012	15.987	0.043
		9	-0.005	-0.007	16.198	0.063
		10	0.038	0.037	26.821	0.003
		11	-0.004	-0.003	26.930	0.005
		12	-0.002	-0.001	26.969	0.008
		13	0.011	0.012	27.798	0.010
		14	0.039	0.039	38.946	0.000
		15	0.013	0.016	40.113	0.000
		16	0.022	0.027	43.838	0.000
		17	-0.018	-0.015	46.218	0.000
		18	0.000	0.003	46.219	0.000
		19	-0.004	-0.002	46.329	0.000
		20	0.020	0.020	49.148	0.000
		21	0.018	0.019	51.435	0.000
		23	0.010	0.010	52.333	0.000
		24	0.011	0.010	53.179	0.001
		26	0.008	0.009	53.914	0.001
		27	-0.011	-0.009	54.824	0.001
		28	-0.005	-0.007	55.026	0.002
		29	-0.004	-0.004	55.122	0.002
		31	-0.006	-0.007	57.080	0.003
		32	0.012	0.013	58.182	0.003
		33	-0.004	-0.004	58.302	0.004
		34	-0.024	-0.027	62.591	0.002
		35	0.012	0.009	63.653	0.002
		36	0.001	-0.001	63.664	0.003

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-87.69979	0.0001
Test critical values:	1% level	-3.431061	
	5% level	-2.861739	
	10% level	-2.566918	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 6/29/1988 5/17/2017
Included observations: 7362 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.022007	0.011653	-87.69979	0.0000
C	0.000171	0.000261	0.655150	0.5124

R-squared	0.511004	Mean dependent var	-5.59E-08
Adjusted R-squared	0.510938	S.D. dependent var	0.031960
S.E. of regression	0.022351	Akaike info criterion	-4.763635
Sum squared resid	3.676760	Schwarz criterion	-4.761759
Log likelihood	17536.94	Hannan-Quinn criter.	-4.762990
F-statistic	7691.254	Durbin-Watson stat	2.001018
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.079377
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000500
HAC corrected variance (Bartlett kernel)	0.000467

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 6/28/1988 5/17/2017
Included observations: 7363 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000168	0.000261	0.646770	0.5178

R-squared	0.000000	Mean dependent var	0.000168
Adjusted R-squared	0.000000	S.D. dependent var	0.022354
S.E. of regression	0.022354	Akaike info criterion	-4.763525
Sum squared resid	3.678663	Schwarz criterion	-4.762587
Log likelihood	17537.92	Hannan-Quinn criter.	-4.763202
Durbin-Watson stat	2.043949		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-87.71858	0.0001
Test critical values:	1% level	-3.431061	
	5% level	-2.861739	
	10% level	-2.566918	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000499
HAC corrected variance (Bartlett kernel)	0.000491

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 6/29/1988 5/17/2017
Included observations: 7362 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.022007	0.011653	-87.69979	0.0000
C	0.000171	0.000261	0.655150	0.5124

R-squared	0.511004	Mean dependent var	-5.59E-08
Adjusted R-squared	0.510938	S.D. dependent var	0.031960
S.E. of regression	0.022351	Akaike info criterion	-4.763635
Sum squared resid	3.676760	Schwarz criterion	-4.761759
Log likelihood	17536.94	Hannan-Quinn criter.	-4.762990
F-statistic	7691.254	Durbin-Watson stat	2.001018
Prob(F-statistic)	0.000000		

Cocoa

- **Correlogram**

Sample: 12/27/1979 7/01/2016
Included observations: 9165

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0057	0.940
		2	-0.020	-0.020	3.6503	0.161
		3	0.015	0.015	5.6472	0.130
		4	-0.015	-0.015	7.6026	0.107
		5	0.001	0.002	7.6148	0.179
		6	-0.003	-0.004	7.6910	0.262
		7	-0.009	-0.008	8.3552	0.302
		8	0.005	0.005	8.6277	0.375
		9	-0.001	-0.001	8.6387	0.471
		10	-0.014	-0.014	10.414	0.405
		11	-0.003	-0.004	10.512	0.485
		12	-0.010	-0.010	11.363	0.498
		13	-0.024	-0.024	16.603	0.218
		14	-0.013	-0.014	18.148	0.200
		15	-0.010	-0.011	19.154	0.207
		16	-0.024	-0.024	24.467	0.080
		17	-0.002	-0.003	24.496	0.107
		18	-0.004	-0.005	24.616	0.136
		19	0.009	0.009	25.434	0.147
		20	-0.001	-0.003	25.450	0.185
		21	-0.017	-0.016	27.978	0.141
		22	-0.023	-0.024	32.995	0.062
		23	-0.002	-0.003	33.029	0.081
		25	-0.001	-0.002	33.628	0.116
		26	-0.005	-0.007	33.850	0.139
		28	-0.011	-0.013	37.668	0.105
		29	-0.001	-0.003	37.673	0.130
		30	-0.003	-0.004	37.777	0.156
		32	0.003	0.001	37.967	0.216
		33	-0.007	-0.008	38.477	0.235
		34	-0.004	-0.006	38.650	0.268
		35	-0.031	-0.033	47.538	0.077
		36	0.013	0.012	49.053	0.072

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-95.64579	0.0001
Test critical values:	1% level	-3.430888	
	5% level	-2.861662	
	10% level	-2.566877	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 7/01/2016
Included observations: 9164 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.999213	0.010447	-95.64579	0.0000
C	-2.85E-07	0.000202	-0.001407	0.9989

R-squared	0.499621	Mean dependent var	2.97E-06
Adjusted R-squared	0.499566	S.D. dependent var	0.027397
S.E. of regression	0.019381	Akaike info criterion	-5.048808
Sum squared resid	3.441532	Schwarz criterion	-5.047253
Log likelihood	23135.64	Hannan-Quinn criter.	-5.048279
F-statistic	9148.117	Durbin-Watson stat	1.999984
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.153121
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000376
HAC corrected variance (Bartlett kernel)	0.000350

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 12/28/1979 7/01/2016
Included observations: 9165 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.17E-06	0.000202	-0.010729	0.9914

R-squared	0.000000	Mean dependent var	-2.17E-06
Adjusted R-squared	-0.000000	S.D. dependent var	0.019380
S.E. of regression	0.019380	Akaike info criterion	-5.049048
Sum squared resid	3.441833	Schwarz criterion	-5.048271
Log likelihood	23138.26	Hannan-Quinn criter.	-5.048783
Durbin-Watson stat	1.998310		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-95.70716	0.0001
Test critical values:	1% level	-3.430888	
	5% level	-2.861662	
	10% level	-2.566877	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000376
HAC corrected variance (Bartlett kernel)	0.000349

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 7/01/2016
Included observations: 9164 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.999213	0.010447	-95.64579	0.0000
C	-2.85E-07	0.000202	-0.001407	0.9989

R-squared	0.499621	Mean dependent var	2.97E-06
Adjusted R-squared	0.499566	S.D. dependent var	0.027397
S.E. of regression	0.019381	Akaike info criterion	-5.048808
Sum squared resid	3.441532	Schwarz criterion	-5.047253
Log likelihood	23135.64	Hannan-Quinn criter.	-5.048279
F-statistic	9148.117	Durbin-Watson stat	1.999984
Prob(F-statistic)	0.000000		

Coffee

- **Correlogram**

Sample: 12/27/1979 6/24/2016
Included observations: 9205

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.014	-0.014	1.7252	0.189
		2	-0.021	-0.021	5.7312	0.057
		3	0.015	0.014	7.8034	0.050
		4	-0.005	-0.005	7.9977	0.092
		5	-0.028	-0.027	15.184	0.010
		6	0.001	0.000	15.205	0.019
		7	-0.016	-0.017	17.625	0.014
		8	0.017	0.017	20.146	0.010
		9	-0.002	-0.003	20.193	0.017
		10	0.016	0.016	22.588	0.012
		11	0.007	0.007	23.026	0.018
		12	0.002	0.002	23.052	0.027
		13	0.003	0.003	23.111	0.040
		14	0.001	0.000	23.115	0.058
		15	0.013	0.014	24.572	0.056
		16	-0.009	-0.009	25.369	0.064
		17	-0.020	-0.019	28.901	0.035
		18	-0.021	-0.022	32.809	0.018
		19	0.011	0.010	33.839	0.019
		20	-0.010	-0.010	34.794	0.021
		21	-0.012	-0.013	36.229	0.021
		24	-0.003	-0.004	47.624	0.003
		25	-0.010	-0.011	48.458	0.003
		27	-0.003	-0.006	48.569	0.007
		28	0.009	0.009	49.247	0.008
		29	-0.034	-0.035	59.663	0.001
		30	-0.012	-0.012	60.888	0.001
		32	-0.002	-0.000	61.464	0.001
		33	0.012	0.014	62.801	0.001
		34	0.011	0.008	63.823	0.001
		35	0.015	0.016	65.790	0.001
		36	-0.002	-0.003	65.833	0.002

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-97.23782	0.0001
Test critical values:	1% level	-3.430885	
	5% level	-2.861661	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 6/24/2016
Included observations: 9204 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.013691	0.010425	-97.23782	0.0000
C	-3.31E-05	0.000242	-0.136605	0.8913

R-squared	0.506785	Mean dependent var	-2.91E-06
Adjusted R-squared	0.506732	S.D. dependent var	0.033107
S.E. of regression	0.023252	Akaike info criterion	-4.684656
Sum squared resid	4.975004	Schwarz criterion	-4.683107
Log likelihood	21560.79	Hannan-Quinn criter.	-4.684129
F-statistic	9455.193	Durbin-Watson stat	2.000318
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.049188
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000541
HAC corrected variance (Bartlett kernel)	0.000541

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 12/28/1979 6/24/2016
Included observations: 9205 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.37E-05	0.000242	-0.138972	0.8895

R-squared	0.000000	Mean dependent var	-3.37E-05
Adjusted R-squared	-0.000000	S.D. dependent var	0.023252
S.E. of regression	0.023252	Akaike info criterion	-4.684778
Sum squared resid	4.976018	Schwarz criterion	-4.684004
Log likelihood	21562.69	Hannan-Quinn criter.	-4.684515
Durbin-Watson stat	2.027102		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-97.24969	0.0001
Test critical values:	1% level	-3.430885	
	5% level	-2.861661	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000541
HAC corrected variance (Bartlett kernel)	0.000533

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 6/24/2016
Included observations: 9204 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.013691	0.010425	-97.23782	0.0000
C	-3.31E-05	0.000242	-0.136605	0.8913

R-squared	0.506785	Mean dependent var	-2.91E-06
Adjusted R-squared	0.506732	S.D. dependent var	0.033107
S.E. of regression	0.023252	Akaike info criterion	-4.684656
Sum squared resid	4.975004	Schwarz criterion	-4.683107
Log likelihood	21560.79	Hannan-Quinn criter.	-4.684129
F-statistic	9455.193	Durbin-Watson stat	2.000318
Prob(F-statistic)	0.000000		

Copper

- **Correlogram**

Sample: 3/30/2000 8/09/2018
Included observations: 4583

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.078	-0.078	28.235	0.000
		2	0.001	-0.005	28.244	0.000
		3	0.008	0.008	28.553	0.000
		4	0.014	0.015	29.468	0.000
		5	-0.024	-0.022	32.187	0.000
		6	0.008	0.004	32.451	0.000
		7	0.018	0.018	33.897	0.000
		8	0.027	0.030	37.130	0.000
		9	-0.024	-0.019	39.811	0.000
		10	0.066	0.062	59.603	0.000
		11	-0.022	-0.013	61.779	0.000
		12	0.033	0.031	66.678	0.000
		13	0.012	0.017	67.344	0.000
		14	-0.014	-0.014	68.201	0.000
		15	0.004	0.004	68.293	0.000
		16	0.024	0.022	70.913	0.000
		17	0.005	0.009	71.036	0.000
		18	0.006	0.004	71.178	0.000
		19	-0.006	-0.005	71.361	0.000
		20	0.051	0.043	83.143	0.000
		21	-0.033	-0.022	88.024	0.000
		22	0.014	0.007	88.925	0.000
		24	0.005	0.002	90.046	0.000
		25	0.004	0.005	90.111	0.000
		26	-0.007	-0.010	90.318	0.000
		27	0.006	0.005	90.500	0.000
		28	0.031	0.027	94.797	0.000
		29	-0.003	0.004	94.835	0.000
		32	0.013	0.009	100.34	0.000
		33	-0.029	-0.025	104.19	0.000
		34	-0.006	-0.011	104.37	0.000
		35	0.009	0.006	104.74	0.000
		36	0.014	0.015	105.67	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-73.21129	0.0001
Test critical values:	1% level	-3.431594	
	5% level	-2.861975	
	10% level	-2.567044	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 4/03/2000 8/09/2018
Included observations: 4582 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.078466	0.014731	-73.21129	0.0000
C	0.000291	0.000258	1.126720	0.2599

R-squared	0.539230	Mean dependent var	1.87E-06
Adjusted R-squared	0.539130	S.D. dependent var	0.025744
S.E. of regression	0.017477	Akaike info criterion	-5.255400
Sum squared resid	1.398976	Schwarz criterion	-5.252594
Log likelihood	12042.12	Hannan-Quinn criter.	-5.254412
F-statistic	5359.893	Durbin-Watson stat	2.000733
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.230671
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000307
HAC corrected variance (Bartlett kernel)	0.000273

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 3/31/2000 8/09/2018
Included observations: 4583 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000269	0.000259	1.039649	0.2986

R-squared	0.000000	Mean dependent var	0.000269
Adjusted R-squared	0.000000	S.D. dependent var	0.017528
S.E. of regression	0.017528	Akaike info criterion	-5.249871
Sum squared resid	1.407654	Schwarz criterion	-5.248468
Log likelihood	12031.08	Hannan-Quinn criter.	-5.249377
Durbin-Watson stat	2.156902		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-73.14867	0.0001
Test critical values:	1% level	-3.431594	
	5% level	-2.861975	
	10% level	-2.567044	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000305
HAC corrected variance (Bartlett kernel)	0.000313

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 4/03/2000 8/09/2018
Included observations: 4582 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.078466	0.014731	-73.21129	0.0000
C	0.000291	0.000258	1.126720	0.2599

R-squared	0.539230	Mean dependent var	1.87E-06
Adjusted R-squared	0.539130	S.D. dependent var	0.025744
S.E. of regression	0.017477	Akaike info criterion	-5.255400
Sum squared resid	1.398976	Schwarz criterion	-5.252594
Log likelihood	12042.12	Hannan-Quinn criter.	-5.254412
F-statistic	5359.893	Durbin-Watson stat	2.000733
Prob(F-statistic)	0.000000		

Corn

- **Correlogram**

Sample: 1 9402
Included observations: 9401

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.005	-0.005	0.2531	0.615
		2	-0.006	-0.006	0.5798	0.748
		3	0.006	0.006	0.8974	0.826
		4	-0.007	-0.007	1.3778	0.848
		5	-0.011	-0.011	2.4552	0.783
		6	-0.010	-0.010	3.3714	0.761
		7	0.031	0.030	12.183	0.095
		8	-0.002	-0.001	12.211	0.142
		9	0.007	0.008	12.720	0.176
		10	-0.005	-0.005	12.928	0.228
		11	-0.001	-0.000	12.931	0.298
		12	0.001	0.001	12.936	0.374
		13	0.007	0.008	13.432	0.415
		14	0.006	0.005	13.742	0.469
		15	0.023	0.024	18.870	0.220
		16	-0.008	-0.009	19.539	0.242
		17	0.006	0.007	19.894	0.280
		18	-0.008	-0.008	20.475	0.307
		19	0.023	0.023	25.325	0.150
		20	0.002	0.002	25.367	0.188
		21	0.004	0.004	25.500	0.226
		22	-0.015	-0.017	27.581	0.190
		23	-0.016	-0.015	30.037	0.148
		24	-0.008	-0.009	30.621	0.165
		26	0.001	-0.001	32.074	0.191
		27	-0.016	-0.017	34.473	0.153
		28	0.002	0.000	34.515	0.184
		29	-0.012	-0.012	35.844	0.178
		29	-0.012	-0.012	35.844	0.178
		30	-0.002	-0.002	35.892	0.212
		31	0.009	0.009	36.574	0.226
		33	0.019	0.019	40.041	0.186
		34	0.001	0.000	40.047	0.220
		35	0.011	0.012	41.262	0.216
		36	-0.003	-0.002	41.330	0.249

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-97.44820	0.0001
Test critical values:	1% level	-3.430870	
	5% level	-2.861654	
	10% level	-2.566872	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 9402
Included observations: 9400 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.005188	0.010315	-97.44820	0.0000
C	1.18E-05	0.000178	0.066325	0.9471

R-squared	0.502597	Mean dependent var	-4.05E-07
Adjusted R-squared	0.502544	S.D. dependent var	0.024475
S.E. of regression	0.017262	Akaike info criterion	-5.280365
Sum squared resid	2.800499	Schwarz criterion	-5.278844
Log likelihood	24819.71	Hannan-Quinn criter.	-5.279848
F-statistic	9496.152	Durbin-Watson stat	2.000006
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.044938
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000298
HAC corrected variance (Bartlett kernel)	0.000291

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2 9402
Included observations: 9401 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.25E-05	0.000178	0.070090	0.9441

R-squared	0.000000	Mean dependent var	1.25E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.017261
S.E. of regression	0.017261	Akaike info criterion	-5.280640
Sum squared resid	2.800622	Schwarz criterion	-5.279880
Log likelihood	24822.65	Hannan-Quinn criter.	-5.280382
Durbin-Watson stat	2.010356		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-97.45415	0.0001
Test critical values:	1% level	-3.430870	
	5% level	-2.861654	
	10% level	-2.566872	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000298
HAC corrected variance (Bartlett kernel)	0.000294

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 9402
Included observations: 9400 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.005188	0.010315	-97.44820	0.0000
C	1.18E-05	0.000178	0.066325	0.9471

R-squared	0.502597	Mean dependent var	-4.05E-07
Adjusted R-squared	0.502544	S.D. dependent var	0.024475
S.E. of regression	0.017262	Akaike info criterion	-5.280365
Sum squared resid	2.800499	Schwarz criterion	-5.278844
Log likelihood	24819.71	Hannan-Quinn criter.	-5.279848
F-statistic	9496.152	Durbin-Watson stat	2.000006
Prob(F-statistic)	0.000000		

Cotton

- **Correlogram**

Sample: 1 4702
Included observations: 4701

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.032	0.032	4.9565	0.026
		2	-0.012	-0.013	5.6496	0.059
		3	-0.004	-0.003	5.7142	0.126
		4	0.023	0.023	8.1817	0.085
		5	-0.002	-0.004	8.2045	0.145
		6	0.018	0.019	9.7060	0.138
		7	-0.008	-0.009	9.9883	0.189
		8	0.004	0.004	10.055	0.261
		9	0.002	0.002	10.073	0.345
		10	-0.014	-0.015	10.957	0.361
		11	-0.007	-0.005	11.175	0.429
		12	0.013	0.013	11.994	0.446
		13	-0.004	-0.005	12.078	0.521
		14	-0.001	0.000	12.079	0.600
		15	-0.001	-0.001	12.084	0.673
		16	0.004	0.004	12.156	0.733
		17	-0.001	-0.001	12.161	0.790
		18	-0.020	-0.020	13.984	0.730
		19	-0.001	0.000	13.995	0.784
		20	-0.007	-0.008	14.242	0.818
		21	0.002	0.002	14.255	0.858
		23	0.055	0.054	28.385	0.202
		24	-0.011	-0.014	28.955	0.222
		25	0.003	0.005	28.999	0.264
		26	-0.007	-0.007	29.237	0.300
		28	-0.007	-0.006	29.458	0.390
		28	-0.007	-0.006	29.458	0.390
		29	0.011	0.009	30.083	0.410
		30	-0.018	-0.017	31.613	0.386
		32	0.004	0.006	34.688	0.341
		33	0.005	0.005	34.817	0.382
		34	-0.009	-0.008	35.176	0.412
		35	0.006	0.006	35.360	0.451
		36	-0.016	-0.016	36.542	0.444

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-66.35207	0.0001
Test critical values:	1% level	-3.431559	
	5% level	-2.861959	
	10% level	-2.567036	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 4702
Included observations: 4700 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.967539	0.014582	-66.35207	0.0000
C	0.000112	0.000268	0.418758	0.6754

R-squared	0.483770	Mean dependent var	1.48E-06
Adjusted R-squared	0.483660	S.D. dependent var	0.025595
S.E. of regression	0.018392	Akaike info criterion	-5.153420
Sum squared resid	1.589103	Schwarz criterion	-5.150673
Log likelihood	12112.54	Hannan-Quinn criter.	-5.152454
F-statistic	4402.598	Durbin-Watson stat	1.999134
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.038441
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000338
HAC corrected variance (Bartlett kernel)	0.000362

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2 4702
Included observations: 4701 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000115	0.000268	0.429592	0.6675

R-squared	0.000000	Mean dependent var	0.000115
Adjusted R-squared	0.000000	S.D. dependent var	0.018397
S.E. of regression	0.018397	Akaike info criterion	-5.152996
Sum squared resid	1.590793	Schwarz criterion	-5.151622
Log likelihood	12113.12	Hannan-Quinn criter.	-5.152513
Durbin-Watson stat	1.935064		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-66.35594	0.0001
Test critical values:	1% level	-3.431559	
	5% level	-2.861959	
	10% level	-2.567036	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000338
HAC corrected variance (Bartlett kernel)	0.000339

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 4702
Included observations: 4700 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.967539	0.014582	-66.35207	0.0000
C	0.000112	0.000268	0.418758	0.6754

R-squared	0.483770	Mean dependent var	1.48E-06
Adjusted R-squared	0.483660	S.D. dependent var	0.025595
S.E. of regression	0.018392	Akaike info criterion	-5.153420
Sum squared resid	1.589103	Schwarz criterion	-5.150673
Log likelihood	12112.54	Hannan-Quinn criter.	-5.152454
F-statistic	4402.598	Durbin-Watson stat	1.999134
Prob(F-statistic)	0.000000		

Crude oil

- **Correlogram**

Sample: 3/22/2000 7/17/2020
Included observations: 5094

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.089	-0.089	40.370	0.000
		2	0.003	-0.005	40.419	0.000
		3	-0.040	-0.041	48.763	0.000
		4	-0.005	-0.012	48.880	0.000
		5	0.009	0.008	49.327	0.000
		6	0.019	0.019	51.081	0.000
		7	-0.001	0.002	51.085	0.000
		8	0.034	0.035	56.826	0.000
		9	-0.061	-0.053	75.572	0.000
		10	0.085	0.076	112.28	0.000
		11	-0.025	-0.010	115.48	0.000
		12	-0.021	-0.028	117.83	0.000
		13	-0.013	-0.013	118.68	0.000
		14	0.018	0.016	120.34	0.000
		15	0.028	0.029	124.41	0.000
		16	0.003	0.003	124.45	0.000
		17	-0.010	-0.004	124.95	0.000
		18	0.013	0.008	125.75	0.000
		19	-0.011	0.001	126.39	0.000
		20	-0.020	-0.030	128.42	0.000
		21	0.004	0.000	128.52	0.000
		22	-0.002	-0.001	128.54	0.000
		23	0.024	0.023	131.47	0.000
		24	0.009	0.011	131.85	0.000
		25	0.064	0.064	152.66	0.000
		26	-0.005	0.009	152.80	0.000
		27	-0.024	-0.017	155.63	0.000
		28	0.007	0.008	155.88	0.000
		29	-0.036	-0.039	162.40	0.000
		30	0.038	0.033	169.87	0.000
		30	0.038	0.033	169.87	0.000
		31	-0.009	-0.009	170.28	0.000
		32	-0.027	-0.031	174.10	0.000
		33	0.043	0.036	183.75	0.000
		34	-0.038	-0.025	191.13	0.000
		36	0.031	0.041	205.87	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=32)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-78.01086	0.0001
Test critical values:	1% level	-3.431453	
	5% level	-2.861912	
	10% level	-2.567011	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/24/2000 7/17/2020
Included observations: 5093 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.088996	0.013960	-78.01086	0.0000
C	8.46E-05	0.000405	0.208977	0.8345

R-squared	0.544499	Mean dependent var	1.58E-07
Adjusted R-squared	0.544409	S.D. dependent var	0.042809
S.E. of regression	0.028895	Akaike info criterion	-4.249927
Sum squared resid	4.250483	Schwarz criterion	-4.247361
Log likelihood	10824.44	Hannan-Quinn criter.	-4.249028
F-statistic	6085.695	Durbin-Watson stat	2.000662
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.124825
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000841
HAC corrected variance (Bartlett kernel)	0.000699

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 3/23/2000 7/17/2020
Included observations: 5094 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.66E-05	0.000406	0.188541	0.8505

R-squared	0.000000	Mean dependent var	7.66E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.029004
S.E. of regression	0.029004	Akaike info criterion	-4.242557
Sum squared resid	4.284448	Schwarz criterion	-4.241274
Log likelihood	10806.79	Hannan-Quinn criter.	-4.242108
Durbin-Watson stat	2.177979		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-78.14775	0.0001
Test critical values:	1% level	-3.431453	
	5% level	-2.861912	
	10% level	-2.567011	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000835
HAC corrected variance (Bartlett kernel)	0.000805

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/24/2000 7/17/2020
Included observations: 5093 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.088996	0.013960	-78.01086	0.0000
C	8.46E-05	0.000405	0.208977	0.8345

R-squared	0.544499	Mean dependent var	1.58E-07
Adjusted R-squared	0.544409	S.D. dependent var	0.042809
S.E. of regression	0.028895	Akaike info criterion	-4.249927
Sum squared resid	4.250483	Schwarz criterion	-4.247361
Log likelihood	10824.44	Hannan-Quinn criter.	-4.249028
F-statistic	6085.695	Durbin-Watson stat	2.000662
Prob(F-statistic)	0.000000		

Feeder Cattle

- **Correlogram**

Sample: 1/28/2000 6/25/2018
Included observations: 4597

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.079	0.079	28.623	0.000
		2	0.015	0.008	29.612	0.000
		3	-0.009	-0.010	29.953	0.000
		4	0.002	0.004	29.981	0.000
		5	-0.024	-0.024	32.577	0.000
		6	-0.022	-0.019	34.873	0.000
		7	0.001	0.005	34.875	0.000
		8	0.007	0.007	35.113	0.000
		9	-0.012	-0.014	35.796	0.000
		10	-0.019	-0.017	37.392	0.000
		11	-0.006	-0.004	37.550	0.000
		12	0.006	0.007	37.718	0.000
		13	0.007	0.007	37.959	0.000
		14	-0.007	-0.008	38.159	0.000
		15	0.021	0.021	40.231	0.000
		16	-0.000	-0.004	40.231	0.001
		17	0.001	0.001	40.234	0.001
		18	0.011	0.012	40.805	0.002
		19	0.031	0.029	45.255	0.001
		20	0.002	-0.003	45.269	0.001
		21	0.007	0.007	45.485	0.001
		23	0.007	0.004	46.564	0.003
		24	0.032	0.034	51.402	0.001
		26	0.001	-0.002	52.369	0.002
		27	0.016	0.017	53.579	0.002
		28	-0.020	-0.022	55.502	0.001
		29	-0.029	-0.023	59.335	0.001
		30	0.001	0.007	59.337	0.001
		32	-0.003	-0.002	59.625	0.002
		34	0.039	0.039	67.266	0.001
		35	-0.006	-0.013	67.460	0.001
		36	0.018	0.018	68.931	0.001

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-62.58539	0.0001
Test critical values:	1% level	-3.431590	
	5% level	-2.861973	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 2/01/2000 6/25/2018
Included observations: 4596 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.921019	0.014716	-62.58539	0.0000
C	0.000107	0.000144	0.743923	0.4570

R-squared	0.460224	Mean dependent var	-6.54E-06
Adjusted R-squared	0.460106	S.D. dependent var	0.013239
S.E. of regression	0.009728	Akaike info criterion	-6.427194
Sum squared resid	0.434743	Schwarz criterion	-6.424395
Log likelihood	14771.69	Hannan-Quinn criter.	-6.426209
F-statistic	3916.931	Durbin-Watson stat	2.000102
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 10 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.068231
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	9.52E-05
HAC corrected variance (Bartlett kernel)	0.000105

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 1/31/2000 6/25/2018
Included observations: 4597 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000118	0.000144	0.819510	0.4125

R-squared	0.000000	Mean dependent var	0.000118
Adjusted R-squared	0.000000	S.D. dependent var	0.009757
S.E. of regression	0.009757	Akaike info criterion	-6.421494
Sum squared resid	0.437514	Schwarz criterion	-6.420094
Log likelihood	14760.80	Hannan-Quinn criter.	-6.421001
Durbin-Watson stat	1.840887		

- **Phillips - Perron**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-62.47438	0.0001
Test critical values:	1% level	-3.431590	
	5% level	-2.861973	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	9.46E-05
HAC corrected variance (Bartlett kernel)	8.97E-05

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 2/01/2000 6/25/2018
Included observations: 4596 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.921019	0.014716	-62.58539	0.0000
C	0.000107	0.000144	0.743923	0.4570

R-squared	0.460224	Mean dependent var	-6.54E-06
Adjusted R-squared	0.460106	S.D. dependent var	0.013239
S.E. of regression	0.009728	Akaike info criterion	-6.427194
Sum squared resid	0.434743	Schwarz criterion	-6.424395
Log likelihood	14771.69	Hannan-Quinn criter.	-6.426209
F-statistic	3916.931	Durbin-Watson stat	2.000102
Prob(F-statistic)	0.000000		

Gasoline

- **Correlogram**

Sample: 10/04/2005 4/01/2019
Included observations: 3615

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.111	-0.111	44.627	0.000
		2	0.015	0.002	45.393	0.000
		3	0.002	0.003	45.401	0.000
		4	-0.005	-0.005	45.497	0.000
		5	0.024	0.023	47.582	0.000
		6	-0.032	-0.027	51.259	0.000
		7	0.021	0.014	52.858	0.000
		8	-0.016	-0.012	53.745	0.000
		9	0.020	0.017	55.128	0.000
		10	0.019	0.023	56.437	0.000
		11	0.025	0.031	58.713	0.000
		12	0.002	0.006	58.727	0.000
		13	0.038	0.041	64.015	0.000
		14	0.002	0.009	64.033	0.000
		15	0.032	0.034	67.655	0.000
		16	0.008	0.014	67.882	0.000
		17	-0.021	-0.018	69.523	0.000
		18	0.023	0.017	71.529	0.000
		19	0.017	0.024	72.543	0.000
		20	-0.001	-0.001	72.551	0.000
		21	0.004	0.005	72.623	0.000
		23	0.032	0.026	76.581	0.000
		24	-0.007	-0.003	76.755	0.000
		25	0.032	0.029	80.555	0.000
		26	0.005	0.008	80.636	0.000
		27	0.008	0.009	80.842	0.000
		27	0.008	0.009	80.842	0.000
		28	0.002	-0.001	80.863	0.000
		29	-0.003	-0.003	80.894	0.000
		31	-0.011	-0.006	83.335	0.000
		32	0.023	0.019	85.263	0.000
		33	-0.029	-0.026	88.318	0.000
		34	0.008	-0.003	88.535	0.000
		35	0.007	0.006	88.709	0.000
		36	0.014	0.014	89.458	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=29)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-67.21971	0.0001
Test critical values:	1% level	-3.431973	
	5% level	-2.862142	
	10% level	-2.567134	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 10/06/2005 4/01/2019
Included observations: 3614 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.111064	0.016529	-67.21971	0.0000
C	2.09E-05	0.000413	0.050594	0.9597

R-squared	0.555746	Mean dependent var	1.41E-05
Adjusted R-squared	0.555623	S.D. dependent var	0.037275
S.E. of regression	0.024848	Akaike info criterion	-4.551518
Sum squared resid	2.230151	Schwarz criterion	-4.548091
Log likelihood	8226.592	Hannan-Quinn criter.	-4.550296
F-statistic	4518.489	Durbin-Watson stat	2.000289
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.048978
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000625
HAC corrected variance (Bartlett kernel)	0.000518

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 10/05/2005 4/01/2019
Included observations: 3615 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.92E-06	0.000416	0.019044	0.9848

R-squared	0.000000	Mean dependent var	7.92E-06
Adjusted R-squared	0.000000	S.D. dependent var	0.025007
S.E. of regression	0.025007	Akaike info criterion	-4.539048
Sum squared resid	2.260008	Schwarz criterion	-4.537335
Log likelihood	8205.330	Hannan-Quinn criter.	-4.538438
Durbin-Watson stat	2.221228		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-67.20678	0.0001
Test critical values:	1% level	-3.431973	
	5% level	-2.862142	
	10% level	-2.567134	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000617
HAC corrected variance (Bartlett kernel)	0.000619

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 10/06/2005 4/01/2019
Included observations: 3614 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.111064	0.016529	-67.21971	0.0000
C	2.09E-05	0.000413	0.050594	0.9597

R-squared	0.555746	Mean dependent var	1.41E-05
Adjusted R-squared	0.555623	S.D. dependent var	0.037275
S.E. of regression	0.024848	Akaike info criterion	-4.551518
Sum squared resid	2.230151	Schwarz criterion	-4.548091
Log likelihood	8226.592	Hannan-Quinn criter.	-4.550296
F-statistic	4518.489	Durbin-Watson stat	2.000289
Prob(F-statistic)	0.000000		

Gold

- **Correlogram**

Sample: 2/28/2000 8/02/2018
Included observations: 4596

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.007	-0.007	0.2515	0.616
		2	-0.008	-0.008	0.5739	0.751
		3	0.005	0.005	0.6989	0.873
		4	0.007	0.007	0.9423	0.918
		5	0.015	0.015	1.9278	0.859
		6	-0.032	-0.032	6.6994	0.350
		7	-0.022	-0.022	8.9336	0.257
		8	-0.008	-0.009	9.2139	0.325
		9	0.019	0.019	10.945	0.280
		10	0.007	0.007	11.144	0.346
		11	-0.055	-0.053	24.956	0.009
		12	-0.007	-0.008	25.172	0.014
		13	-0.005	-0.008	25.293	0.021
		14	0.002	0.001	25.316	0.032
		15	0.027	0.028	28.639	0.018
		16	0.004	0.007	28.709	0.026
		17	-0.006	-0.008	28.851	0.036
		18	-0.017	-0.020	30.179	0.036
		19	0.011	0.008	30.711	0.043
		20	0.022	0.023	32.939	0.034
		21	-0.031	-0.028	37.462	0.015
		23	-0.025	-0.027	41.456	0.010
		24	-0.008	-0.012	41.737	0.014
		26	-0.027	-0.022	45.343	0.011
		27	-0.011	-0.010	45.909	0.013
		28	0.006	0.004	46.090	0.017
		29	0.021	0.016	48.077	0.014
		31	-0.031	-0.029	53.420	0.007
		32	-0.018	-0.023	54.987	0.007
		33	0.005	0.002	55.088	0.009
		34	0.001	-0.003	55.090	0.013
		35	-0.013	-0.013	55.911	0.014
		36	-0.027	-0.026	59.186	0.009

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-68.27242	0.0001
Test critical values:	1% level	-3.431590	
	5% level	-2.861973	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/01/2000 8/02/2018
Included observations: 4595 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.007396	0.014756	-68.27242	0.0000
C	0.000311	0.000165	1.883047	0.0598

R-squared	0.503681	Mean dependent var	-1.23E-06
Adjusted R-squared	0.503573	S.D. dependent var	0.015909
S.E. of regression	0.011209	Akaike info criterion	-6.143798
Sum squared resid	0.577053	Schwarz criterion	-6.140998
Log likelihood	14117.38	Hannan-Quinn criter.	-6.142812
F-statistic	4661.123	Durbin-Watson stat	2.000042
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.279570
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000126
HAC corrected variance (Bartlett kernel)	0.000122

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2/29/2000 8/02/2018
Included observations: 4596 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000309	0.000165	1.869587	0.0616

R-squared	0.000000	Mean dependent var	0.000309
Adjusted R-squared	0.000000	S.D. dependent var	0.011207
S.E. of regression	0.011207	Akaike info criterion	-6.144395
Sum squared resid	0.577085	Schwarz criterion	-6.142996
Log likelihood	14120.82	Hannan-Quinn criter.	-6.143903
Durbin-Watson stat	2.014720		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-68.27982	0.0001
Test critical values:	1% level	-3.431590	
	5% level	-2.861973	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000126
HAC corrected variance (Bartlett kernel)	0.000123

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/01/2000 8/02/2018
Included observations: 4595 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.007396	0.014756	-68.27242	0.0000
C	0.000311	0.000165	1.883047	0.0598

R-squared	0.503681	Mean dependent var	-1.23E-06
Adjusted R-squared	0.503573	S.D. dependent var	0.015909
S.E. of regression	0.011209	Akaike info criterion	-6.143798
Sum squared resid	0.577053	Schwarz criterion	-6.140998
Log likelihood	14117.38	Hannan-Quinn criter.	-6.142812
F-statistic	4661.123	Durbin-Watson stat	2.000042
Prob(F-statistic)	0.000000		

Heating oil

- **Correlogram**

Sample: 3/01/2000 8/07/2018
Included observations: 4602

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.049	-0.049	10.918	0.001
		2	-0.009	-0.011	11.258	0.004
		3	-0.005	-0.006	11.368	0.010
		4	0.020	0.019	13.224	0.010
		5	-0.005	-0.003	13.354	0.020
		6	-0.018	-0.019	14.927	0.021
		7	-0.007	-0.009	15.169	0.034
		8	-0.014	-0.016	16.056	0.042
		9	-0.018	-0.019	17.471	0.042
		10	0.007	0.006	17.713	0.060
		11	-0.026	-0.026	20.918	0.034
		12	-0.009	-0.011	21.256	0.047
		13	0.016	0.015	22.447	0.049
		14	0.060	0.061	39.350	0.000
		15	-0.011	-0.005	39.938	0.000
		16	-0.006	-0.006	40.106	0.001
		17	-0.000	-0.003	40.106	0.001
		18	-0.014	-0.018	41.032	0.002
		19	0.033	0.033	46.143	0.000
		20	-0.009	-0.005	46.530	0.001
		21	-0.007	-0.006	46.757	0.001
		22	-0.012	-0.011	47.428	0.001
		24	-0.006	-0.005	47.970	0.003
		26	0.008	0.009	48.332	0.005
		27	-0.020	-0.023	50.202	0.004
		28	0.008	0.003	50.475	0.006
		29	0.005	0.005	50.586	0.008
		31	-0.016	-0.012	54.084	0.006
		32	-0.041	-0.042	61.992	0.001
		33	0.026	0.016	65.190	0.001
		34	-0.000	0.002	65.190	0.001
		35	-0.005	-0.003	65.300	0.001
		36	-0.007	-0.005	65.538	0.002

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-71.19989	0.0001
Test critical values:	1% level	-3.431588	
	5% level	-2.861972	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/03/2000 8/07/2018
Included observations: 4601 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.048695	0.014729	-71.19989	0.0000
C	0.000229	0.000332	0.689682	0.4904

R-squared	0.524328	Mean dependent var	3.14E-06
Adjusted R-squared	0.524224	S.D. dependent var	0.032658
S.E. of regression	0.022527	Akaike info criterion	-4.747805
Sum squared resid	2.333753	Schwarz criterion	-4.745008
Log likelihood	10924.32	Hannan-Quinn criter.	-4.746820
F-statistic	5069.425	Durbin-Watson stat	2.000987
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 20 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.100960
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000508
HAC corrected variance (Bartlett kernel)	0.000434

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 3/02/2000 8/07/2018
Included observations: 4602 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000218	0.000332	0.657005	0.5112

R-squared	0.000000	Mean dependent var	0.000218
Adjusted R-squared	0.000000	S.D. dependent var	0.022548
S.E. of regression	0.022548	Akaike info criterion	-4.746083
Sum squared resid	2.339301	Schwarz criterion	-4.744684
Log likelihood	10921.74	Hannan-Quinn criter.	-4.745590
Durbin-Watson stat	2.097303		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 19 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-71.35389	0.0001
Test critical values:	1% level	-3.431588	
	5% level	-2.861972	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000507
HAC corrected variance (Bartlett kernel)	0.000475

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/03/2000 8/07/2018
Included observations: 4601 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.048695	0.014729	-71.19989	0.0000
C	0.000229	0.000332	0.689682	0.4904

R-squared	0.524328	Mean dependent var	3.14E-06
Adjusted R-squared	0.524224	S.D. dependent var	0.032658
S.E. of regression	0.022527	Akaike info criterion	-4.747805
Sum squared resid	2.333753	Schwarz criterion	-4.745008
Log likelihood	10924.32	Hannan-Quinn criter.	-4.746820
F-statistic	5069.425	Durbin-Watson stat	2.000987
Prob(F-statistic)	0.000000		

Lead

- **Correlogram**

Sample: 7/07/2008 5/20/2019
Included observations: 2650

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.035	0.035	3.2003	0.074
		2	-0.022	-0.023	4.4869	0.106
		3	-0.032	-0.030	7.1707	0.067
		4	0.021	0.023	8.3750	0.079
		5	-0.024	-0.027	9.9531	0.077
		6	0.006	0.008	10.040	0.123
		7	-0.019	-0.019	10.985	0.139
		8	-0.022	-0.023	12.280	0.139
		9	-0.005	-0.003	12.345	0.195
		10	-0.020	-0.023	13.437	0.200
		11	0.026	0.027	15.238	0.172
		12	0.009	0.006	15.449	0.218
		13	-0.055	-0.057	23.598	0.035
		14	-0.007	0.000	23.724	0.049
		15	-0.021	-0.027	24.934	0.051
		16	-0.008	-0.009	25.100	0.068
		17	-0.019	-0.018	26.029	0.074
		18	-0.015	-0.019	26.638	0.086
		19	-0.003	-0.000	26.667	0.113
		20	-0.019	-0.025	27.681	0.117
		21	-0.021	-0.021	28.817	0.118
		22	-0.011	-0.012	29.116	0.142
		23	0.008	0.001	29.269	0.172
		24	-0.001	-0.001	29.274	0.210
		25	0.009	0.006	29.472	0.245
		26	-0.014	-0.018	29.981	0.268
		27	-0.008	-0.009	30.171	0.307
		28	0.055	0.053	38.424	0.091
		29	0.070	0.064	51.713	0.006
		30	0.020	0.015	52.742	0.006
		31	-0.087	-0.086	73.039	0.000
		32	-0.015	-0.008	73.663	0.000
		33	-0.014	-0.019	74.198	0.000
		34	0.050	0.045	80.978	0.000
		35	-0.006	-0.007	81.068	0.000
		36	-0.010	-0.011	81.312	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-49.68977	0.0001
Test critical values:	1% level	-3.432626	
	5% level	-2.862431	
	10% level	-2.567289	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 7/09/2008 5/20/2019
Included observations: 2649 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.965264	0.019426	-49.68977	0.0000
C	3.87E-05	0.000414	0.093609	0.9254

R-squared	0.482611	Mean dependent var	-5.92E-06
Adjusted R-squared	0.482416	S.D. dependent var	0.029588
S.E. of regression	0.021286	Akaike info criterion	-4.860748
Sum squared resid	1.199378	Schwarz criterion	-4.856307
Log likelihood	6440.060	Hannan-Quinn criter.	-4.859140
F-statistic	2469.074	Durbin-Watson stat	1.990860
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.054165
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000453
HAC corrected variance (Bartlett kernel)	0.000414

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 7/08/2008 5/20/2019
Included observations: 2650 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.21E-05	0.000414	0.101688	0.9190

R-squared	0.000000	Mean dependent var	4.21E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.021291
S.E. of regression	0.021291	Akaike info criterion	-4.860655
Sum squared resid	1.200848	Schwarz criterion	-4.858436
Log likelihood	6441.368	Hannan-Quinn criter.	-4.859852
Durbin-Watson stat	1.930416		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-49.72014	0.0001
Test critical values:	1% level	-3.432626	
	5% level	-2.862431	
	10% level	-2.567289	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000453
HAC corrected variance (Bartlett kernel)	0.000382

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 7/09/2008 5/20/2019
Included observations: 2649 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.965264	0.019426	-49.68977	0.0000
C	3.87E-05	0.000414	0.093609	0.9254

R-squared	0.482611	Mean dependent var	-5.92E-06
Adjusted R-squared	0.482416	S.D. dependent var	0.029588
S.E. of regression	0.021286	Akaike info criterion	-4.860748
Sum squared resid	1.199378	Schwarz criterion	-4.856307
Log likelihood	6440.060	Hannan-Quinn criter.	-4.859140
F-statistic	2469.074	Durbin-Watson stat	1.990860
Prob(F-statistic)	0.000000		

Lean hogs

- **Correlogram**

Sample: 12/27/1979 6/27/2016
Included observations: 9229

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.010	-0.010	0.8631	0.353
		2	0.009	0.009	1.6399	0.440
		3	0.002	0.002	1.6739	0.643
		4	0.023	0.023	6.7300	0.151
		5	-0.008	-0.008	7.3879	0.193
		6	0.005	0.005	7.6602	0.264
		7	-0.018	-0.018	10.586	0.158
		8	0.005	0.004	10.832	0.211
		9	0.004	0.005	11.015	0.275
		10	0.009	0.009	11.828	0.297
		11	-0.026	-0.025	18.224	0.077
		12	0.012	0.010	19.467	0.078
		13	-0.014	-0.014	21.325	0.067
		14	0.013	0.012	22.988	0.060
		15	0.001	0.003	22.994	0.084
		16	-0.005	-0.006	23.246	0.107
		17	-0.019	-0.017	26.436	0.067
		18	-0.001	-0.003	26.442	0.090
		19	-0.001	-0.000	26.453	0.118
		20	-0.000	-0.000	26.454	0.151
		21	-0.005	-0.003	26.687	0.181
		23	-0.015	-0.014	31.151	0.119
		24	-0.002	-0.004	31.173	0.149
		25	-0.011	-0.009	32.240	0.151
		26	-0.023	-0.024	37.034	0.074
		27	-0.023	-0.022	41.810	0.034
		28	-0.006	-0.007	42.141	0.042
		29	-0.023	-0.022	47.106	0.018
		30	-0.011	-0.011	48.145	0.019
		32	-0.011	-0.011	51.467	0.016
		33	0.002	0.003	51.490	0.021
		34	0.011	0.010	52.663	0.022
		35	0.008	0.010	53.227	0.025
		36	0.001	0.000	53.244	0.032

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-96.98403	0.0001
Test critical values:	1% level	-3.430883	
	5% level	-2.861660	
	10% level	-2.566875	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 6/27/2016
Included observations: 9228 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.009669	0.010411	-96.98403	0.0000
C	7.52E-05	0.000223	0.337698	0.7356

R-squared	0.504828	Mean dependent var	-9.60E-07
Adjusted R-squared	0.504774	S.D. dependent var	0.030400
S.E. of regression	0.021393	Akaike info criterion	-4.851271
Sum squared resid	4.222451	Schwarz criterion	-4.849726
Log likelihood	22385.77	Hannan-Quinn criter.	-4.850746
F-statistic	9405.902	Durbin-Watson stat	1.999797
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 10 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.008238
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000458
HAC corrected variance (Bartlett kernel)	0.000466

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 12/28/1979 6/27/2016
Included observations: 9229 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.43E-05	0.000223	0.333498	0.7388

R-squared	0.000000	Mean dependent var	7.43E-05
Adjusted R-squared	-0.000000	S.D. dependent var	0.021392
S.E. of regression	0.021392	Akaike info criterion	-4.851502
Sum squared resid	4.222850	Schwarz criterion	-4.850729
Log likelihood	22388.26	Hannan-Quinn criter.	-4.851239
Durbin-Watson stat	2.019309		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 10 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-96.98324	0.0001
Test critical values:	1% level	-3.430883	
	5% level	-2.861660	
	10% level	-2.566875	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000458
HAC corrected variance (Bartlett kernel)	0.000475

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 6/27/2016
Included observations: 9228 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.009669	0.010411	-96.98403	0.0000
C	7.52E-05	0.000223	0.337698	0.7356

R-squared	0.504828	Mean dependent var	-9.60E-07
Adjusted R-squared	0.504774	S.D. dependent var	0.030400
S.E. of regression	0.021393	Akaike info criterion	-4.851271
Sum squared resid	4.222451	Schwarz criterion	-4.849726
Log likelihood	22385.77	Hannan-Quinn criter.	-4.850746
F-statistic	9405.902	Durbin-Watson stat	1.999797
Prob(F-statistic)	0.000000		

Live cattle

- **Correlogram**

Sample: 1 9220
Included observations: 9219

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.029	0.029	7.8570	0.005
		2	0.010	0.009	8.8336	0.012
		3	0.006	0.006	9.1769	0.027
		4	0.015	0.014	11.189	0.025
		5	-0.021	-0.022	15.121	0.010
		6	-0.034	-0.033	25.665	0.000
		7	-0.018	-0.016	28.778	0.000
		8	-0.019	-0.017	32.102	0.000
		9	-0.017	-0.014	34.647	0.000
		10	-0.026	-0.024	40.770	0.000
		11	-0.027	-0.026	47.411	0.000
		12	-0.019	-0.018	50.733	0.000
		13	0.007	0.007	51.205	0.000
		14	-0.011	-0.012	52.232	0.000
		15	0.001	0.000	52.250	0.000
		16	0.014	0.011	54.085	0.000
		17	-0.012	-0.017	55.524	0.000
		18	0.007	0.005	55.983	0.000
		19	0.033	0.030	65.747	0.000
		20	0.030	0.026	74.075	0.000
		21	-0.005	-0.008	74.337	0.000
		22	-0.008	-0.010	74.961	0.000
		23	-0.003	-0.005	75.030	0.000
		25	0.001	0.004	75.042	0.000
		27	-0.008	-0.007	76.812	0.000
		28	0.002	0.003	76.846	0.000
		29	-0.005	-0.004	77.040	0.000
		30	0.000	0.003	77.041	0.000
		31	-0.016	-0.014	79.487	0.000
		32	-0.009	-0.008	80.201	0.000
		33	0.003	0.004	80.302	0.000
		34	-0.001	-0.001	80.311	0.000
		35	-0.003	-0.003	80.395	0.000
		36	-0.007	-0.007	80.903	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-93.24279	0.0001
Test critical values:	1% level	-3.430884	
	5% level	-2.861660	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 9220
Included observations: 9218 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.970809	0.010412	-93.24279	0.0000
C	6.10E-05	0.000114	0.535947	0.5920

R-squared	0.485433	Mean dependent var	2.57E-06
Adjusted R-squared	0.485378	S.D. dependent var	0.015240
S.E. of regression	0.010933	Akaike info criterion	-6.193877
Sum squared resid	1.101558	Schwarz criterion	-6.192330
Log likelihood	28549.58	Hannan-Quinn criter.	-6.193351
F-statistic	8694.218	Durbin-Watson stat	2.000621
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 38 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.041310
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000120
HAC corrected variance (Bartlett kernel)	0.000105

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2 9220
Included observations: 9219 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.12E-05	0.000114	0.537362	0.5910

R-squared	0.000000	Mean dependent var	6.12E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.010937
S.E. of regression	0.010937	Akaike info criterion	-6.193158
Sum squared resid	1.102709	Schwarz criterion	-6.192385
Log likelihood	28548.36	Hannan-Quinn criter.	-6.192896
Durbin-Watson stat	1.941355		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 39 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-93.39006	0.0001
Test critical values:	1% level	-3.430884	
	5% level	-2.861660	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000120
HAC corrected variance (Bartlett kernel)	9.93E-05

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 9220
Included observations: 9218 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.970809	0.010412	-93.24279	0.0000
C	6.10E-05	0.000114	0.535947	0.5920

R-squared	0.485433	Mean dependent var	2.57E-06
Adjusted R-squared	0.485378	S.D. dependent var	0.015240
S.E. of regression	0.010933	Akaike info criterion	-6.193877
Sum squared resid	1.101558	Schwarz criterion	-6.192330
Log likelihood	28549.58	Hannan-Quinn criter.	-6.193351
F-statistic	8694.218	Durbin-Watson stat	2.000621
Prob(F-statistic)	0.000000		

Lumber

- **Correlogram**

Sample: 12/27/1979 6/30/2016
Included observations: 9204

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.045	0.045	18.790	0.000
		2	-0.027	-0.029	25.316	0.000
		3	-0.011	-0.009	26.473	0.000
		4	0.002	0.002	26.515	0.000
		5	0.001	0.000	26.525	0.000
		6	0.003	0.003	26.601	0.000
		7	-0.001	-0.001	26.609	0.000
		8	-0.003	-0.003	26.679	0.001
		9	0.019	0.019	29.990	0.000
		10	-0.002	-0.004	30.019	0.001
		11	-0.012	-0.011	31.334	0.001
		12	-0.005	-0.004	31.569	0.002
		13	-0.014	-0.014	33.332	0.002
		14	-0.008	-0.007	33.852	0.002
		15	-0.007	-0.007	34.332	0.003
		16	-0.013	-0.013	35.976	0.003
		17	-0.002	-0.001	36.023	0.005
		18	-0.009	-0.010	36.746	0.006
		19	-0.021	-0.021	40.936	0.002
		20	-0.007	-0.005	41.401	0.003
		21	-0.015	-0.016	43.479	0.003
		22	-0.013	-0.012	45.085	0.003
		23	-0.012	-0.012	46.380	0.003
		24	0.005	0.005	46.636	0.004
		25	0.008	0.007	47.232	0.005
		27	-0.002	-0.001	48.674	0.006
		28	-0.034	-0.035	59.608	0.000
		29	0.002	0.004	59.654	0.001
		30	0.006	0.003	59.961	0.001
		32	-0.003	-0.003	60.027	0.002
		34	0.004	0.002	60.205	0.004
		35	-0.001	-0.002	60.213	0.005
		36	-0.008	-0.009	60.855	0.006

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-91.68247	0.0001
Test critical values:	1% level	-3.430885	
	5% level	-2.861661	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 6/30/2016
Included observations: 9203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.954824	0.010414	-91.68247	0.0000
C	3.69E-05	0.000225	0.164062	0.8697

R-squared	0.477414	Mean dependent var	5.90E-07
Adjusted R-squared	0.477357	S.D. dependent var	0.029846
S.E. of regression	0.021577	Akaike info criterion	-4.834169
Sum squared resid	4.283642	Schwarz criterion	-4.832621
Log likelihood	22246.43	Hannan-Quinn criter.	-4.833643
F-statistic	8405.675	Durbin-Watson stat	1.997413
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.016126
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000466
HAC corrected variance (Bartlett kernel)	0.000479

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 12/28/1979 6/30/2016
Included observations: 9204 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.80E-05	0.000225	0.168597	0.8661

R-squared	0.000000	Mean dependent var	3.80E-05
Adjusted R-squared	-0.000000	S.D. dependent var	0.021597
S.E. of regression	0.021597	Akaike info criterion	-4.832444
Sum squared resid	4.292440	Schwarz criterion	-4.831669
Log likelihood	22239.91	Hannan-Quinn criter.	-4.832180
Durbin-Watson stat	1.909639		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-91.60982	0.0001
Test critical values:	1% level	-3.430885	
	5% level	-2.861661	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000465
HAC corrected variance (Bartlett kernel)	0.000444

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 6/30/2016
Included observations: 9203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.954824	0.010414	-91.68247	0.0000
C	3.69E-05	0.000225	0.164062	0.8697

R-squared	0.477414	Mean dependent var	5.90E-07
Adjusted R-squared	0.477357	S.D. dependent var	0.029846
S.E. of regression	0.021577	Akaike info criterion	-4.834169
Sum squared resid	4.283642	Schwarz criterion	-4.832621
Log likelihood	22246.43	Hannan-Quinn criter.	-4.833643
F-statistic	8405.675	Durbin-Watson stat	1.997413
Prob(F-statistic)	0.000000		

Natural gas

- **Correlogram**

Sample: 2/28/2000 8/01/2018
Included observations: 4601

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.050	-0.050	11.370	0.001
		2	0.018	0.016	12.877	0.002
		3	-0.023	-0.022	15.384	0.002
		4	0.008	0.006	15.684	0.003
		5	-0.026	-0.024	18.709	0.002
		6	-0.016	-0.020	19.949	0.003
		7	0.031	0.030	24.346	0.001
		8	-0.022	-0.020	26.570	0.001
		9	-0.003	-0.007	26.615	0.002
		10	0.016	0.017	27.730	0.002
		11	-0.007	-0.007	27.937	0.003
		12	0.024	0.024	30.641	0.002
		13	0.006	0.010	30.817	0.004
		14	0.031	0.029	35.319	0.001
		15	-0.024	-0.018	37.943	0.001
		16	0.004	0.001	38.006	0.002
		17	-0.011	-0.009	38.554	0.002
		18	-0.008	-0.008	38.828	0.003
		19	0.044	0.045	47.918	0.000
		20	-0.029	-0.026	51.924	0.000
		21	0.001	-0.005	51.926	0.000
		22	0.002	0.006	51.949	0.000
		23	-0.030	-0.033	55.988	0.000
		24	-0.012	-0.014	56.692	0.000
		25	-0.008	-0.008	57.000	0.000
		26	0.001	-0.006	57.009	0.000
		27	-0.030	-0.027	61.306	0.000
		28	-0.021	-0.026	63.253	0.000
		29	0.010	0.006	63.690	0.000
		30	0.001	0.004	63.697	0.000
		31	-0.015	-0.019	64.797	0.000
		33	-0.010	-0.015	66.293	0.001
		34	0.008	0.011	66.556	0.001
		35	-0.004	-0.003	66.629	0.001
		36	0.040	0.039	74.045	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-71.27159	0.0001
Test critical values:	1% level	-3.431589	
	5% level	-2.861972	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/01/2000 8/01/2018
Included observations: 4600 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.049695	0.014728	-71.27159	0.0000
C	-1.72E-07	0.000498	-0.000345	0.9997

R-squared	0.524884	Mean dependent var	-8.19E-06
Adjusted R-squared	0.524781	S.D. dependent var	0.048949
S.E. of regression	0.033743	Akaike info criterion	-3.939627
Sum squared resid	5.235372	Schwarz criterion	-3.936830
Log likelihood	9063.142	Hannan-Quinn criter.	-3.938643
F-statistic	5079.640	Durbin-Watson stat	1.998571
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 14 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.086797
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.001141
HAC corrected variance (Bartlett kernel)	0.001017

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2/29/2000 8/01/2018
Included observations: 4601 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.75E-06	0.000498	0.011545	0.9908

R-squared	0.000000	Mean dependent var	5.75E-06
Adjusted R-squared	0.000000	S.D. dependent var	0.033781
S.E. of regression	0.033781	Akaike info criterion	-3.937646
Sum squared resid	5.249175	Schwarz criterion	-3.936248
Log likelihood	9059.555	Hannan-Quinn criter.	-3.937154
Durbin-Watson stat	2.099215		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-71.33831	0.0001
Test critical values:	1% level	-3.431589	
	5% level	-2.861972	
	10% level	-2.567043	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001138
HAC corrected variance (Bartlett kernel)	0.001102

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/01/2000 8/01/2018
Included observations: 4600 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.049695	0.014728	-71.27159	0.0000
C	-1.72E-07	0.000498	-0.000345	0.9997

R-squared	0.524884	Mean dependent var	-8.19E-06
Adjusted R-squared	0.524781	S.D. dependent var	0.048949
S.E. of regression	0.033743	Akaike info criterion	-3.939627
Sum squared resid	5.235372	Schwarz criterion	-3.936830
Log likelihood	9063.142	Hannan-Quinn criter.	-3.938643
F-statistic	5079.640	Durbin-Watson stat	1.998571
Prob(F-statistic)	0.000000		

Nickel

- **Correlogram**

Sample: 7/07/2008 5/20/2019
Included observations: 2650

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.014	-0.014	0.5373	0.464
		2	-0.005	-0.005	0.6081	0.738
		3	-0.049	-0.049	7.0549	0.070
		4	0.007	0.006	7.1958	0.126
		5	0.004	0.004	7.2452	0.203
		6	0.002	-0.001	7.2529	0.298
		7	-0.038	-0.037	11.066	0.136
		8	-0.016	-0.017	11.733	0.164
		9	0.038	0.038	15.639	0.075
		10	-0.029	-0.032	17.931	0.056
		11	0.045	0.044	23.290	0.016
		12	0.058	0.063	32.118	0.001
		13	0.016	0.015	32.801	0.002
		14	-0.001	0.003	32.805	0.003
		15	-0.037	-0.033	36.453	0.002
		16	-0.032	-0.030	39.179	0.001
		17	-0.007	-0.011	39.321	0.002
		18	0.039	0.036	43.377	0.001
		19	0.003	0.010	43.400	0.001
		20	-0.009	-0.010	43.627	0.002
		21	-0.021	-0.019	44.786	0.002
		22	0.007	0.005	44.933	0.003
		23	0.030	0.021	47.342	0.002
		24	-0.018	-0.023	48.196	0.002
		25	-0.024	-0.022	49.691	0.002
		26	-0.015	-0.010	50.276	0.003
		27	-0.014	-0.014	50.817	0.004
		29	0.049	0.050	58.361	0.001
		30	-0.002	-0.004	58.376	0.001
		31	-0.005	-0.009	58.455	0.002
		32	-0.051	-0.051	65.336	0.000
		33	-0.032	-0.031	68.126	0.000
		34	0.084	0.083	87.202	0.000
		35	-0.016	-0.018	87.920	0.000
		36	0.029	0.034	90.257	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-52.19110	0.0001
Test critical values:	1% level	-3.432626	
	5% level	-2.862431	
	10% level	-2.567289	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 7/09/2008 5/20/2019
Included observations: 2649 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.014231	0.019433	-52.19110	0.0000
C	-0.000205	0.000439	-0.466503	0.6409

R-squared	0.507160	Mean dependent var	5.40E-06
Adjusted R-squared	0.506974	S.D. dependent var	0.032173
S.E. of regression	0.022590	Akaike info criterion	-4.741841
Sum squared resid	1.350817	Schwarz criterion	-4.737400
Log likelihood	6282.568	Hannan-Quinn criter.	-4.740233
F-statistic	2723.910	Durbin-Watson stat	1.997993
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.053726
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000510
HAC corrected variance (Bartlett kernel)	0.000466

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 7/08/2008 5/20/2019
Included observations: 2650 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000208	0.000439	-0.473358	0.6360

R-squared	0.000000	Mean dependent var	-0.000208
Adjusted R-squared	0.000000	S.D. dependent var	0.022586
S.E. of regression	0.022586	Akaike info criterion	-4.742592
Sum squared resid	1.351332	Schwarz criterion	-4.740372
Log likelihood	6284.934	Hannan-Quinn criter.	-4.741789
Durbin-Watson stat	2.028282		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-52.24170	0.0001
Test critical values:	1% level	-3.432626	
	5% level	-2.862431	
	10% level	-2.567289	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000510
HAC corrected variance (Bartlett kernel)	0.000478

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 7/09/2008 5/20/2019
Included observations: 2649 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.014231	0.019433	-52.19110	0.0000
C	-0.000205	0.000439	-0.466503	0.6409

R-squared	0.507160	Mean dependent var	5.40E-06
Adjusted R-squared	0.506974	S.D. dependent var	0.032173
S.E. of regression	0.022590	Akaike info criterion	-4.741841
Sum squared resid	1.350817	Schwarz criterion	-4.737400
Log likelihood	6282.568	Hannan-Quinn criter.	-4.740233
F-statistic	2723.910	Durbin-Watson stat	1.997993
Prob(F-statistic)	0.000000		

Oats

- **Correlogram**

Sample: 3/15/2000 7/02/2018
Included observations: 4573

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.073	0.073	24.353	0.000
		2	-0.021	-0.026	26.351	0.000
		3	-0.013	-0.009	27.094	0.000
		4	-0.008	-0.007	27.365	0.000
		5	-0.033	-0.033	32.437	0.000
		6	-0.000	0.004	32.438	0.000
		7	-0.013	-0.015	33.234	0.000
		8	0.021	0.022	35.237	0.000
		9	-0.029	-0.034	39.191	0.000
		10	-0.041	-0.037	46.891	0.000
		11	-0.013	-0.008	47.682	0.000
		12	-0.021	-0.023	49.645	0.000
		13	-0.014	-0.011	50.561	0.000
		14	0.008	0.005	50.828	0.000
		15	0.010	0.006	51.316	0.000
		16	0.003	-0.001	51.352	0.000
		17	-0.008	-0.009	51.614	0.000
		18	0.018	0.020	53.158	0.000
		19	0.003	-0.002	53.206	0.000
		20	-0.029	-0.030	57.122	0.000
		21	-0.012	-0.008	57.749	0.000
		22	-0.008	-0.011	58.020	0.000
		23	-0.018	-0.018	59.446	0.000
		24	0.029	0.031	63.221	0.000
		25	0.016	0.010	64.421	0.000
		26	-0.015	-0.018	65.486	0.000
		27	-0.019	-0.016	67.105	0.000
		28	-0.021	-0.018	69.210	0.000
		29	-0.014	-0.012	70.141	0.000
		31	-0.005	-0.008	70.426	0.000
		32	-0.028	-0.033	74.150	0.000
		34	0.001	0.003	74.709	0.000
		35	0.013	0.013	75.518	0.000
		36	-0.003	-0.007	75.552	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-62.83225	0.0001
Test critical values:	1% level	-3.431597	
	5% level	-2.861976	
	10% level	-2.567045	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/17/2000 7/02/2018
Included observations: 4572 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.927036	0.014754	-62.83225	0.0000
C	0.000144	0.000353	0.407881	0.6834

R-squared	0.463482	Mean dependent var	-5.78E-06
Adjusted R-squared	0.463365	S.D. dependent var	0.032558
S.E. of regression	0.023850	Akaike info criterion	-4.633599
Sum squared resid	2.599594	Schwarz criterion	-4.630787
Log likelihood	10594.41	Hannan-Quinn criter.	-4.632609
F-statistic	3947.892	Durbin-Watson stat	1.995958
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.067355
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000572
HAC corrected variance (Bartlett kernel)	0.000539

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 3/16/2000 7/02/2018
Included observations: 4573 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000157	0.000354	0.444013	0.6571

R-squared	0.000000	Mean dependent var	0.000157
Adjusted R-squared	0.000000	S.D. dependent var	0.023909
S.E. of regression	0.023909	Akaike info criterion	-4.628904
Sum squared resid	2.613543	Schwarz criterion	-4.627498
Log likelihood	10584.99	Hannan-Quinn criter.	-4.628409
Durbin-Watson stat	1.853924		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-62.69367	0.0001
Test critical values:	1% level	-3.431597	
	5% level	-2.861976	
	10% level	-2.567045	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000569
HAC corrected variance (Bartlett kernel)	0.000461

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/17/2000 7/02/2018
Included observations: 4572 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.927036	0.014754	-62.83225	0.0000
C	0.000144	0.000353	0.407881	0.6834

R-squared	0.463482	Mean dependent var	-5.78E-06
Adjusted R-squared	0.463365	S.D. dependent var	0.032558
S.E. of regression	0.023850	Akaike info criterion	-4.633599
Sum squared resid	2.599594	Schwarz criterion	-4.630787
Log likelihood	10594.41	Hannan-Quinn criter.	-4.632609
F-statistic	3947.892	Durbin-Watson stat	1.995958
Prob(F-statistic)	0.000000		

Palladium

- **Correlogram**

Sample: 3/27/1998 10/05/2018
Included observations: 4681

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.075	0.075	26.212	0.000
		2	-0.005	-0.011	26.335	0.000
		3	-0.046	-0.045	36.420	0.000
		4	0.013	0.021	37.274	0.000
		5	-0.005	-0.008	37.401	0.000
		6	0.018	0.017	38.865	0.000
		7	0.015	0.014	39.935	0.000
		8	0.011	0.008	40.463	0.000
		9	0.016	0.017	41.736	0.000
		10	-0.041	-0.043	49.443	0.000
		11	0.000	0.007	49.443	0.000
		12	-0.021	-0.022	51.608	0.000
		13	0.028	0.027	55.267	0.000
		14	-0.023	-0.026	57.664	0.000
		15	0.010	0.010	58.094	0.000
		16	0.008	0.011	58.396	0.000
		17	0.030	0.026	62.557	0.000
		18	0.006	0.005	62.715	0.000
		19	-0.014	-0.013	63.618	0.000
		20	-0.010	-0.007	64.059	0.000
		21	0.012	0.014	64.782	0.000
		22	0.018	0.012	66.357	0.000
		23	-0.026	-0.027	69.569	0.000
		22	0.018	0.012	66.357	0.000
		23	-0.026	-0.027	69.569	0.000
		24	-0.005	-0.004	69.696	0.000
		25	-0.000	0.003	69.696	0.000
		26	0.007	0.002	69.905	0.000
		27	0.026	0.030	73.069	0.000
		28	0.009	0.004	73.468	0.000
		29	0.013	0.014	74.321	0.000
		30	0.007	0.006	74.533	0.000
		32	0.002	0.006	74.581	0.000
		33	-0.003	-0.007	74.624	0.000
		34	-0.009	-0.011	75.034	0.000
		36	-0.021	-0.022	77.535	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-63.46048	0.0001
Test critical values:	1% level	-3.431565	
	5% level	-2.861962	
	10% level	-2.567037	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/31/1998 10/05/2018
Included observations: 4680 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.925190	0.014579	-63.46048	0.0000
C	0.000286	0.000340	0.841483	0.4001

R-squared	0.462622	Mean dependent var	6.45E-06
Adjusted R-squared	0.462507	S.D. dependent var	0.031702
S.E. of regression	0.023242	Akaike info criterion	-4.685291
Sum squared resid	2.526995	Schwarz criterion	-4.682534
Log likelihood	10965.58	Hannan-Quinn criter.	-4.684321
F-statistic	4027.232	Durbin-Watson stat	1.997914
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 14 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.073108
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000543
HAC corrected variance (Bartlett kernel)	0.000597

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 3/30/1998 10/05/2018
Included observations: 4681 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000304	0.000341	0.893433	0.3717

R-squared	0.000000	Mean dependent var	0.000304
Adjusted R-squared	0.000000	S.D. dependent var	0.023304
S.E. of regression	0.023304	Akaike info criterion	-4.680167
Sum squared resid	2.541604	Schwarz criterion	-4.678789
Log likelihood	10954.93	Hannan-Quinn criter.	-4.679683
Durbin-Watson stat	1.850192		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 13 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-63.37541	0.0001
Test critical values:	1% level	-3.431565	
	5% level	-2.861962	
	10% level	-2.567037	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000540
HAC corrected variance (Bartlett kernel)	0.000518

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/31/1998 10/05/2018
Included observations: 4680 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.925190	0.014579	-63.46048	0.0000
C	0.000286	0.000340	0.841483	0.4001

R-squared	0.462622	Mean dependent var	6.45E-06
Adjusted R-squared	0.462507	S.D. dependent var	0.031702
S.E. of regression	0.023242	Akaike info criterion	-4.685291
Sum squared resid	2.526995	Schwarz criterion	-4.682534
Log likelihood	10965.58	Hannan-Quinn criter.	-4.684321
F-statistic	4027.232	Durbin-Watson stat	1.997914
Prob(F-statistic)	0.000000		

Platinum

Correlogram

Sample: 4/28/1997 10/14/2018
Included observations: 4739

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.058	-0.058	15.693	0.000
		2	-0.071	-0.075	39.705	0.000
		3	0.011	0.002	40.268	0.000
		4	0.049	0.044	51.472	0.000
		5	-0.018	-0.011	52.955	0.000
		6	0.002	0.007	52.981	0.000
		7	0.007	0.005	53.221	0.000
		8	0.004	0.004	53.311	0.000
		9	0.026	0.029	56.505	0.000
		10	-0.015	-0.012	57.612	0.000
		11	-0.025	-0.024	60.562	0.000
		12	0.032	0.027	65.390	0.000
		13	0.013	0.011	66.165	0.000
		14	0.000	0.008	66.166	0.000
		15	-0.008	-0.005	66.489	0.000
		16	0.007	0.003	66.736	0.000
		17	0.031	0.031	71.356	0.000
		18	0.037	0.041	77.797	0.000
		19	-0.004	0.007	77.859	0.000
		20	-0.021	-0.016	79.940	0.000
		21	-0.003	-0.011	79.984	0.000
		22	-0.036	-0.043	86.071	0.000
		23	-0.032	-0.036	90.853	0.000
		24	0.011	0.002	91.385	0.000
		26	-0.013	-0.013	92.992	0.000
		27	0.011	0.010	93.619	0.000
		28	-0.004	-0.003	93.682	0.000
		30	-0.010	-0.014	94.964	0.000
		31	0.008	0.004	95.256	0.000
		32	0.011	0.013	95.837	0.000
		33	-0.006	-0.005	96.022	0.000
		34	0.006	0.008	96.203	0.000
		35	-0.005	-0.005	96.333	0.000
		36	0.024	0.022	99.121	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-53.92020	0.0001
Test critical values:	1% level	-3.431548	
	5% level	-2.861954	
	10% level	-2.567033	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 5/01/1997 10/14/2018
Included observations: 4737 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.136523	0.021078	-53.92020	0.0000
D(R(-1))	0.074712	0.014494	5.154825	0.0000
C	0.000197	0.000275	0.715104	0.4746

R-squared	0.531388	Mean dependent var	3.46E-06
Adjusted R-squared	0.531190	S.D. dependent var	0.027680
S.E. of regression	0.018953	Akaike info criterion	-5.093118
Sum squared resid	1.700458	Schwarz criterion	-5.089025
Log likelihood	12066.05	Hannan-Quinn criter.	-5.091679
F-statistic	2684.091	Durbin-Watson stat	1.999485
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 13 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.235727
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000362
HAC corrected variance (Bartlett kernel)	0.000311

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 4/29/1997 10/14/2018
Included observations: 4739 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000172	0.000276	0.623636	0.5329

R-squared	0.000000	Mean dependent var	0.000172
Adjusted R-squared	0.000000	S.D. dependent var	0.019030
S.E. of regression	0.019030	Akaike info criterion	-5.085430
Sum squared resid	1.715754	Schwarz criterion	-5.084066
Log likelihood	12050.93	Hannan-Quinn criter.	-5.084950
Durbin-Watson stat	2.115010		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 14 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-72.99816	0.0001
Test critical values:	1% level	-3.431548	
	5% level	-2.861954	
	10% level	-2.567033	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000361
HAC corrected variance (Bartlett kernel)	0.000346

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 4/30/1997 10/14/2018
Included observations: 4738 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.057529	0.014507	-72.89713	0.0000
C	0.000182	0.000276	0.657891	0.5106

R-squared	0.528756	Mean dependent var	1.14E-06
Adjusted R-squared	0.528656	S.D. dependent var	0.027678
S.E. of regression	0.019002	Akaike info criterion	-5.088116
Sum squared resid	1.710068	Schwarz criterion	-5.085387
Log likelihood	12055.75	Hannan-Quinn criter.	-5.087157
F-statistic	5313.991	Durbin-Watson stat	2.008497
Prob(F-statistic)	0.000000		

Rice

- **Correlogram**

Sample: 3/21/2000 7/17/2020
Included observations: 5057

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.086	0.086	37.190	0.000
		2	-0.001	-0.009	37.196	0.000
		3	-0.002	-0.001	37.209	0.000
		4	-0.013	-0.013	38.048	0.000
		5	-0.018	-0.016	39.722	0.000
		6	0.010	0.012	40.186	0.000
		7	-0.003	-0.005	40.223	0.000
		8	-0.000	0.000	40.224	0.000
		9	-0.036	-0.037	46.791	0.000
		10	-0.015	-0.009	47.909	0.000
		11	-0.012	-0.010	48.679	0.000
		12	-0.015	-0.013	49.800	0.000
		13	0.006	0.008	49.999	0.000
		14	-0.010	-0.013	50.494	0.000
		15	-0.045	-0.043	60.826	0.000
		16	-0.014	-0.007	61.810	0.000
		17	-0.025	-0.024	64.965	0.000
		18	-0.008	-0.005	65.274	0.000
		19	0.007	0.006	65.557	0.000
		20	0.011	0.008	66.197	0.000
		21	-0.022	-0.025	68.563	0.000
		22	-0.022	-0.019	70.984	0.000
		23	0.001	0.004	70.995	0.000
		24	0.035	0.031	77.138	0.000
		26	0.034	0.026	86.689	0.000
		27	0.029	0.022	90.965	0.000
		28	-0.012	-0.015	91.669	0.000
		29	-0.031	-0.028	96.578	0.000
		30	0.002	0.005	96.603	0.000
		31	0.000	-0.002	96.603	0.000
		32	0.001	-0.002	96.605	0.000
		33	-0.019	-0.021	98.499	0.000
		35	-0.005	0.000	99.494	0.000
		36	-0.001	0.001	99.497	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=32)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-65.23733	0.0001
Test critical values:	1% level	-3.431462	
	5% level	-2.861916	
	10% level	-2.567013	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/23/2000 7/17/2020
Included observations: 5056 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.914269	0.014015	-65.23733	0.0000
C	0.000137	0.000254	0.539859	0.5893

R-squared	0.457138	Mean dependent var	-4.90E-07
Adjusted R-squared	0.457030	S.D. dependent var	0.024558
S.E. of regression	0.018096	Akaike info criterion	-5.185903
Sum squared resid	1.654932	Schwarz criterion	-5.183320
Log likelihood	13111.96	Hannan-Quinn criter.	-5.184998
F-statistic	4255.909	Durbin-Watson stat	1.998391
Prob(F-statistic)	0.000000		

KPSS Test

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.084071
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000330
HAC corrected variance (Bartlett kernel)	0.000348

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 3/22/2000 7/17/2020
Included observations: 5057 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000151	0.000255	0.592773	0.5534

R-squared	0.000000	Mean dependent var	0.000151
Adjusted R-squared	0.000000	S.D. dependent var	0.018159
S.E. of regression	0.018159	Akaike info criterion	-5.179102
Sum squared resid	1.667214	Schwarz criterion	-5.177811
Log likelihood	13096.36	Hannan-Quinn criter.	-5.178650
Durbin-Watson stat	1.828517		

Phillips – Perron Test

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-65.00166	0.0001
Test critical values:	1% level	-3.431462	
	5% level	-2.861916	
	10% level	-2.567013	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000327
HAC corrected variance (Bartlett kernel)	0.000283

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/23/2000 7/17/2020
Included observations: 5056 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.914269	0.014015	-65.23733	0.0000
C	0.000137	0.000254	0.539859	0.5893

R-squared	0.457138	Mean dependent var	-4.90E-07
Adjusted R-squared	0.457030	S.D. dependent var	0.024558
S.E. of regression	0.018096	Akaike info criterion	-5.185903
Sum squared resid	1.654932	Schwarz criterion	-5.183320
Log likelihood	13111.96	Hannan-Quinn criter.	-5.184998
F-statistic	4255.909	Durbin-Watson stat	1.998391
Prob(F-statistic)	0.000000		

Silver

- **Correlogram**

Sample: 2/28/2000 10/12/2018
Included observations: 4648

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.022	-0.022	2.1698	0.141
		2	0.010	0.010	2.6652	0.264
		3	0.000	0.001	2.6659	0.446
		4	-0.011	-0.011	3.2447	0.518
		5	0.017	0.017	4.6648	0.458
		6	-0.008	-0.007	4.9547	0.550
		7	-0.001	-0.002	4.9585	0.665
		8	-0.017	-0.017	6.2453	0.620
		9	0.021	0.021	8.3415	0.500
		10	-0.004	-0.003	8.4114	0.589
		11	-0.034	-0.034	13.814	0.243
		12	0.025	0.024	16.837	0.156
		13	-0.032	-0.029	21.492	0.064
		14	-0.011	-0.014	22.034	0.078
		15	0.010	0.010	22.525	0.095
		16	-0.001	0.001	22.527	0.127
		17	-0.016	-0.018	23.762	0.126
		18	0.028	0.028	27.363	0.072
		19	-0.006	-0.006	27.552	0.092
		20	0.014	0.015	28.442	0.099
		21	-0.015	-0.016	29.433	0.104
		23	-0.035	-0.034	36.236	0.039
		25	-0.007	-0.007	36.481	0.065
		26	0.005	0.008	36.620	0.081
		28	0.007	0.007	37.950	0.099
		29	0.013	0.015	38.735	0.107
		30	-0.012	-0.014	39.372	0.118
		31	-0.030	-0.029	43.514	0.067
		32	0.019	0.019	45.253	0.060
		33	0.022	0.022	47.435	0.050
		34	0.017	0.015	48.742	0.049
		35	0.002	0.002	48.768	0.061
		36	-0.016	-0.018	50.009	0.060

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-69.64250	0.0001
Test critical values:	1% level	-3.431575	
	5% level	-2.861966	
	10% level	-2.567040	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/01/2000 10/12/2018
Included observations: 4647 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.021599	0.014669	-69.64250	0.0000
C	0.000233	0.000285	0.816095	0.4145

R-squared	0.510799	Mean dependent var	4.29E-07
Adjusted R-squared	0.510694	S.D. dependent var	0.027813
S.E. of regression	0.019455	Akaike info criterion	-5.040989
Sum squared resid	1.758129	Schwarz criterion	-5.038216
Log likelihood	11714.74	Hannan-Quinn criter.	-5.040013
F-statistic	4850.077	Durbin-Watson stat	1.999558
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.192053
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000378
HAC corrected variance (Bartlett kernel)	0.000368

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2/29/2000 10/12/2018
Included observations: 4648 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000228	0.000285	0.798826	0.4244

R-squared	0.000000	Mean dependent var	0.000228
Adjusted R-squared	0.000000	S.D. dependent var	0.019455
S.E. of regression	0.019455	Akaike info criterion	-5.041168
Sum squared resid	1.758950	Schwarz criterion	-5.039782
Log likelihood	11716.67	Hannan-Quinn criter.	-5.040680
Durbin-Watson stat	2.043196		

Phillips – Perron Test

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-69.63701	0.0001
Test critical values:	1% level	-3.431575	
	5% level	-2.861966	
	10% level	-2.567040	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000378
HAC corrected variance (Bartlett kernel)	0.000381

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/01/2000 10/12/2018
Included observations: 4647 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.021599	0.014669	-69.64250	0.0000
C	0.000233	0.000285	0.816095	0.4145

R-squared	0.510799	Mean dependent var	4.29E-07
Adjusted R-squared	0.510694	S.D. dependent var	0.027813
S.E. of regression	0.019455	Akaike info criterion	-5.040989
Sum squared resid	1.758129	Schwarz criterion	-5.038216
Log likelihood	11714.74	Hannan-Quinn criter.	-5.040013
F-statistic	4850.077	Durbin-Watson stat	1.999558
Prob(F-statistic)	0.000000		

Soybean meal

- **Correlogram**

Sample: 1 7875
Included observations: 7874

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.019	0.019	2.8029	0.094
		2	0.007	0.007	3.2126	0.201
		3	0.002	0.002	3.2506	0.355
		4	-0.021	-0.021	6.6539	0.155
		5	-0.050	-0.049	25.969	0.000
		6	0.021	0.024	29.589	0.000
		7	-0.002	-0.002	29.613	0.000
		8	0.017	0.016	31.810	0.000
		9	0.033	0.030	40.335	0.000
		10	-0.000	-0.003	40.335	0.000
		11	-0.011	-0.009	41.273	0.000
		12	-0.007	-0.007	41.684	0.000
		13	-0.015	-0.012	43.511	0.000
		14	-0.022	-0.019	47.348	0.000
		15	-0.005	-0.006	47.536	0.000
		16	-0.024	-0.024	51.915	0.000
		17	-0.012	-0.013	53.088	0.000
		18	0.005	0.003	53.249	0.000
		19	0.022	0.021	56.918	0.000
		20	0.012	0.011	57.970	0.000
		21	0.011	0.008	58.883	0.000
		22	0.020	0.021	62.035	0.000
		23	-0.022	-0.020	65.711	0.000
		24	-0.010	-0.006	66.462	0.000
		25	-0.019	-0.017	69.456	0.000
		26	-0.022	-0.020	73.352	0.000
		27	-0.014	-0.014	74.841	0.000
		28	-0.006	-0.011	75.148	0.000
		29	-0.008	-0.010	75.677	0.000
		30	-0.003	-0.007	75.751	0.000
		31	0.002	0.000	75.780	0.000
		32	-0.030	-0.029	82.916	0.000
		33	0.019	0.022	85.860	0.000
		34	0.014	0.015	87.331	0.000
		35	-0.002	0.001	87.361	0.000
		36	0.012	0.013	88.441	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-87.06057	0.0001
Test critical values:	1% level	-3.431004	
	5% level	-2.861713	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 7875
Included observations: 7873 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.981136	0.011270	-87.06057	0.0000
C	5.79E-05	0.000196	0.294838	0.7681

R-squared	0.490568	Mean dependent var	-4.33E-07
Adjusted R-squared	0.490503	S.D. dependent var	0.024417
S.E. of regression	0.017429	Akaike info criterion	-5.261162
Sum squared resid	2.390847	Schwarz criterion	-5.259391
Log likelihood	20712.56	Hannan-Quinn criter.	-5.260555
F-statistic	7579.543	Durbin-Watson stat	2.000242
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 13 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.030090
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000304
HAC corrected variance (Bartlett kernel)	0.000306

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2 7875
Included observations: 7874 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.92E-05	0.000196	0.301595	0.7630

R-squared	0.000000	Mean dependent var	5.92E-05
Adjusted R-squared	-0.000000	S.D. dependent var	0.017429
S.E. of regression	0.017429	Akaike info criterion	-5.261186
Sum squared resid	2.391701	Schwarz criterion	-5.260300
Log likelihood	20714.29	Hannan-Quinn criter.	-5.260882
Durbin-Watson stat	1.962270		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 13 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-87.04645	0.0001
Test critical values:	1% level	-3.431004	
	5% level	-2.861713	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000304
HAC corrected variance (Bartlett kernel)	0.000296

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 7875
Included observations: 7873 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.981136	0.011270	-87.06057	0.0000
C	5.79E-05	0.000196	0.294838	0.7681

R-squared	0.490568	Mean dependent var	-4.33E-07
Adjusted R-squared	0.490503	S.D. dependent var	0.024417
S.E. of regression	0.017429	Akaike info criterion	-5.261162
Sum squared resid	2.390847	Schwarz criterion	-5.259391
Log likelihood	20712.56	Hannan-Quinn criter.	-5.260555
F-statistic	7579.543	Durbin-Watson stat	2.000242
Prob(F-statistic)	0.000000		

Soybean oil

- **Correlogram**

Sample: 1 9416
Included observations: 9415

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.038	0.038	13.933	0.000
		2	-0.019	-0.020	17.268	0.000
		3	-0.010	-0.008	18.129	0.000
		4	0.009	0.010	18.973	0.001
		5	-0.021	-0.022	22.974	0.000
		6	0.012	0.014	24.407	0.000
		7	0.015	0.013	26.481	0.000
		8	0.002	0.001	26.515	0.001
		9	-0.003	-0.001	26.578	0.002
		10	0.003	0.003	26.680	0.003
		11	0.003	0.003	26.742	0.005
		12	0.020	0.020	30.481	0.002
		13	0.012	0.011	31.876	0.003
		14	-0.005	-0.006	32.149	0.004
		15	0.002	0.003	32.184	0.006
		16	-0.001	-0.001	32.188	0.009
		17	0.012	0.012	33.462	0.010
		18	0.006	0.005	33.764	0.013
		19	0.027	0.026	40.528	0.003
		20	-0.005	-0.007	40.768	0.004
		21	-0.000	0.001	40.769	0.006
		22	-0.007	-0.006	41.219	0.008
		24	-0.014	-0.012	45.546	0.005
		25	-0.022	-0.023	49.995	0.002
		26	-0.009	-0.009	50.795	0.003
		27	0.009	0.009	51.534	0.003
		28	0.014	0.012	53.401	0.003
		29	0.001	-0.000	53.407	0.004
		30	0.020	0.020	57.086	0.002
		31	0.004	0.002	57.218	0.003
		32	-0.004	-0.003	57.348	0.004
		33	0.005	0.007	57.615	0.005
		34	0.005	0.003	57.834	0.007
		35	0.017	0.018	60.555	0.005
		36	0.007	0.006	60.990	0.006

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-93.34685	0.0001
Test critical values:	1% level	-3.430869	
	5% level	-2.861654	
	10% level	-2.566872	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 9416
Included observations: 9414 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.961531	0.010301	-93.34685	0.0000
C	2.84E-05	0.000155	0.182708	0.8550

R-squared	0.480735	Mean dependent var	1.24E-06
Adjusted R-squared	0.480680	S.D. dependent var	0.020909
S.E. of regression	0.015068	Akaike info criterion	-5.552316
Sum squared resid	2.136855	Schwarz criterion	-5.550797
Log likelihood	26136.75	Hannan-Quinn criter.	-5.551800
F-statistic	8713.635	Durbin-Watson stat	1.997988
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.046660
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000227
HAC corrected variance (Bartlett kernel)	0.000235

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2 9416
Included observations: 9415 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.00E-05	0.000155	0.193238	0.8468

R-squared	0.000000	Mean dependent var	3.00E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.015077
S.E. of regression	0.015077	Akaike info criterion	-5.551141
Sum squared resid	2.140050	Schwarz criterion	-5.550381
Log likelihood	26133.00	Hannan-Quinn criter.	-5.550883
Durbin-Watson stat	1.922925		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-93.29514	0.0001
Test critical values:	1% level	-3.430869	
	5% level	-2.861654	
	10% level	-2.566872	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000227
HAC corrected variance (Bartlett kernel)	0.000219

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 9416
Included observations: 9414 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.961531	0.010301	-93.34685	0.0000
C	2.84E-05	0.000155	0.182708	0.8550

R-squared	0.480735	Mean dependent var	1.24E-06
Adjusted R-squared	0.480680	S.D. dependent var	0.020909
S.E. of regression	0.015068	Akaike info criterion	-5.552316
Sum squared resid	2.136855	Schwarz criterion	-5.550797
Log likelihood	26136.75	Hannan-Quinn criter.	-5.551800
F-statistic	8713.635	Durbin-Watson stat	1.997988
Prob(F-statistic)	0.000000		

Soybeans

- **Correlogram**

Sample: 1 7123
Included observations: 7122

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.000	0.000	0.0002	0.989
		2	-0.009	-0.009	0.6133	0.736
		3	0.013	0.013	1.7305	0.630
		4	-0.011	-0.011	2.5549	0.635
		5	-0.032	-0.032	9.9346	0.077
		6	0.004	0.004	10.065	0.122
		7	-0.014	-0.015	11.528	0.117
		8	0.028	0.029	17.177	0.028
		9	0.019	0.018	19.717	0.020
		10	0.005	0.005	19.866	0.031
		11	-0.013	-0.013	20.984	0.034
		12	-0.004	-0.005	21.096	0.049
		13	0.006	0.008	21.319	0.067
		14	-0.023	-0.022	25.236	0.032
		15	0.022	0.023	28.648	0.018
		16	-0.013	-0.015	29.887	0.019
		17	-0.008	-0.008	30.395	0.024
		18	-0.006	-0.008	30.677	0.031
		19	0.016	0.015	32.442	0.028
		20	-0.014	-0.011	33.783	0.028
		21	0.038	0.037	44.131	0.002
		22	0.026	0.027	48.968	0.001
		23	-0.025	-0.025	53.411	0.000
		24	-0.034	-0.034	61.600	0.000
		25	-0.004	-0.005	61.708	0.000
		26	0.002	0.007	61.750	0.000
		27	0.010	0.011	62.456	0.000
		29	-0.004	-0.006	62.602	0.000
		30	-0.012	-0.016	63.568	0.000
		31	-0.008	-0.009	64.081	0.000
		33	0.016	0.021	80.581	0.000
		34	0.016	0.013	82.538	0.000
		35	0.008	0.009	82.952	0.000
		36	0.008	0.005	83.396	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=34)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-84.36294	0.0001
Test critical values:	1% level	-3.431091	
	5% level	-2.861752	
	10% level	-2.566925	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 7123
Included observations: 7121 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.999835	0.011852	-84.36294	0.0000
C	7.02E-05	0.000183	0.383899	0.7011

R-squared	0.499933	Mean dependent var	-1.23E-06
Adjusted R-squared	0.499863	S.D. dependent var	0.021827
S.E. of regression	0.015436	Akaike info criterion	-5.503937
Sum squared resid	1.696263	Schwarz criterion	-5.502007
Log likelihood	19598.77	Hannan-Quinn criter.	-5.503273
F-statistic	7117.105	Durbin-Watson stat	1.999876
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.048004
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000238
HAC corrected variance (Bartlett kernel)	0.000231

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2 7123
Included observations: 7122 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.17E-05	0.000183	0.392146	0.6950

R-squared	0.000000	Mean dependent var	7.17E-05
Adjusted R-squared	-0.000000	S.D. dependent var	0.015434
S.E. of regression	0.015434	Akaike info criterion	-5.504293
Sum squared resid	1.696375	Schwarz criterion	-5.503328
Log likelihood	19601.79	Hannan-Quinn criter.	-5.503960
Durbin-Watson stat	1.999602		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-84.37146	0.0001
Test critical values:	1% level	-3.431091	
	5% level	-2.861752	
	10% level	-2.566925	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000238
HAC corrected variance (Bartlett kernel)	0.000231

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3 7123
Included observations: 7121 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.999835	0.011852	-84.36294	0.0000
C	7.02E-05	0.000183	0.383899	0.7011

R-squared	0.499933	Mean dependent var	-1.23E-06
Adjusted R-squared	0.499863	S.D. dependent var	0.021827
S.E. of regression	0.015436	Akaike info criterion	-5.503937
Sum squared resid	1.696263	Schwarz criterion	-5.502007
Log likelihood	19598.77	Hannan-Quinn criter.	-5.503273
F-statistic	7117.105	Durbin-Watson stat	1.999876
Prob(F-statistic)	0.000000		

Sugar

- **Correlogram**

Sample: 12/27/1979 6/29/2016
Included observations: 9191

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.085	-0.085	65.694	0.000
		2	-0.064	-0.071	103.17	0.000
		3	0.023	0.012	108.24	0.000
		4	-0.004	-0.005	108.36	0.000
		5	-0.011	-0.009	109.43	0.000
		6	0.017	0.014	112.02	0.000
		7	0.002	0.004	112.05	0.000
		8	0.002	0.005	112.09	0.000
		9	-0.021	-0.021	116.04	0.000
		10	-0.014	-0.018	117.88	0.000
		11	0.010	0.005	118.86	0.000
		12	-0.009	-0.010	119.65	0.000
		13	0.014	0.014	121.36	0.000
		14	0.001	0.001	121.36	0.000
		15	0.011	0.014	122.42	0.000
		16	-0.001	0.002	122.43	0.000
		17	-0.013	-0.012	124.00	0.000
		18	0.010	0.007	124.88	0.000
		19	0.001	-0.000	124.89	0.000
		20	-0.011	-0.009	126.00	0.000
		21	0.010	0.008	126.98	0.000
		22	-0.001	-0.001	127.00	0.000
		23	-0.006	-0.004	127.36	0.000
		24	0.022	0.020	131.64	0.000
		25	-0.015	-0.012	133.82	0.000
		27	0.009	0.010	138.85	0.000
		28	0.006	0.011	139.13	0.000
		29	-0.020	-0.019	142.86	0.000
		30	0.024	0.021	148.17	0.000
		31	0.012	0.015	149.54	0.000
		32	-0.011	-0.006	150.63	0.000
		33	0.004	0.004	150.75	0.000
		34	-0.004	-0.005	150.87	0.000
		35	0.007	0.009	151.35	0.000
		36	-0.005	-0.003	151.56	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=37)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-75.80450	0.0001
Test critical values:	1% level	-3.430886	
	5% level	-2.861661	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 1/02/1980 6/29/2016
Included observations: 9189 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.162132	0.015331	-75.80450	0.0000
D(R(-1))	0.071531	0.010409	6.872212	0.0000
C	2.94E-05	0.000297	0.098819	0.9213

R-squared	0.544539	Mean dependent var	7.00E-06
Adjusted R-squared	0.544440	S.D. dependent var	0.042192
S.E. of regression	0.028478	Akaike info criterion	-4.279051
Sum squared resid	7.449753	Schwarz criterion	-4.276725
Log likelihood	19663.10	Hannan-Quinn criter.	-4.278261
F-statistic	5491.287	Durbin-Watson stat	1.997832
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 26 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.086919
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000821
HAC corrected variance (Bartlett kernel)	0.000613

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 12/28/1979 6/29/2016
Included observations: 9191 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.55E-05	0.000299	0.085337	0.9320

R-squared	0.000000	Mean dependent var	2.55E-05
Adjusted R-squared	-0.000000	S.D. dependent var	0.028648
S.E. of regression	0.028648	Akaike info criterion	-4.267370
Sum squared resid	7.542211	Schwarz criterion	-4.266595
Log likelihood	19611.70	Hannan-Quinn criter.	-4.267106
Durbin-Watson stat	2.168726		

Phillips – Perron Test

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 22 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-105.1161	0.0001
Test critical values:	1% level	-3.430886	
	5% level	-2.861661	
	10% level	-2.566876	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000815
HAC corrected variance (Bartlett kernel)	0.000715

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 12/31/1979 6/29/2016
Included observations: 9190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.084558	0.010397	-104.3161	0.0000
C	2.64E-05	0.000298	0.088691	0.9293

R-squared	0.542199	Mean dependent var	4.62E-06
Adjusted R-squared	0.542149	S.D. dependent var	0.042191
S.E. of regression	0.028548	Akaike info criterion	-4.274224
Sum squared resid	7.488250	Schwarz criterion	-4.272673
Log likelihood	19642.06	Hannan-Quinn criter.	-4.273697
F-statistic	10881.84	Durbin-Watson stat	2.011691
Prob(F-statistic)	0.000000		

Tin

- **Correlogram**

Sample: 7/07/2008 5/20/2019
Included observations: 2650

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.040	0.040	4.2428	0.039
		2	0.010	0.009	4.5191	0.104
		3	-0.048	-0.049	10.647	0.014
		4	-0.009	-0.006	10.877	0.028
		5	-0.017	-0.015	11.638	0.040
		6	-0.027	-0.028	13.629	0.034
		7	-0.007	-0.005	13.770	0.055
		8	0.034	0.033	16.801	0.032
		9	-0.026	-0.032	18.594	0.029
		10	-0.049	-0.049	24.945	0.005
		11	0.038	0.045	28.737	0.002
		12	0.023	0.018	30.174	0.003
		13	0.015	0.008	30.799	0.004
		14	-0.011	-0.008	31.119	0.005
		15	0.004	0.005	31.169	0.008
		16	-0.056	-0.059	39.608	0.001
		17	-0.006	0.002	39.700	0.001
		18	-0.008	-0.001	39.891	0.002
		19	0.018	0.008	40.717	0.003
		20	-0.026	-0.031	42.541	0.002
		21	0.004	0.008	42.575	0.004
		22	0.046	0.047	48.333	0.001
		24	0.018	0.015	60.309	0.000
		25	-0.022	-0.023	61.619	0.000
		26	-0.029	-0.028	63.802	0.000
		27	0.001	0.010	63.805	0.000
		27	0.001	0.010	63.805	0.000
		29	0.054	0.055	76.362	0.000
		30	-0.030	-0.044	78.811	0.000
		31	-0.050	-0.048	85.571	0.000
		32	-0.033	-0.021	88.459	0.000
		33	0.015	0.025	89.090	0.000
		34	0.011	0.006	89.399	0.000
		35	0.006	-0.002	89.510	0.000
		36	0.023	0.011	90.892	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-49.43626	0.0001
Test critical values:	1% level	-3.432626	
	5% level	-2.862431	
	10% level	-2.567289	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 7/09/2008 5/20/2019
Included observations: 2649 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.960009	0.019419	-49.43626	0.0000
C	-5.26E-05	0.000349	-0.150828	0.8801

R-squared	0.480057	Mean dependent var	4.79E-06
Adjusted R-squared	0.479861	S.D. dependent var	0.024893
S.E. of regression	0.017953	Akaike info criterion	-5.201355
Sum squared resid	0.853163	Schwarz criterion	-5.196915
Log likelihood	6891.195	Hannan-Quinn criter.	-5.199748
F-statistic	2443.944	Durbin-Watson stat	1.999645
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.062320
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000323
HAC corrected variance (Bartlett kernel)	0.000319

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 7/08/2008 5/20/2019
Included observations: 2650 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6.01E-05	0.000349	-0.172136	0.8633

R-squared	0.000000	Mean dependent var	-6.01E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.017963
S.E. of regression	0.017963	Akaike info criterion	-5.200677
Sum squared resid	0.854709	Schwarz criterion	-5.198457
Log likelihood	6891.897	Hannan-Quinn criter.	-5.199873
Durbin-Watson stat	1.919808		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-49.39637	0.0001
Test critical values:	1% level	-3.432626	
	5% level	-2.862431	
	10% level	-2.567289	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000322
HAC corrected variance (Bartlett kernel)	0.000297

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 7/09/2008 5/20/2019
Included observations: 2649 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.960009	0.019419	-49.43626	0.0000
C	-5.26E-05	0.000349	-0.150828	0.8801

R-squared	0.480057	Mean dependent var	4.79E-06
Adjusted R-squared	0.479861	S.D. dependent var	0.024893
S.E. of regression	0.017953	Akaike info criterion	-5.201355
Sum squared resid	0.853163	Schwarz criterion	-5.196915
Log likelihood	6891.195	Hannan-Quinn criter.	-5.199748
F-statistic	2443.944	Durbin-Watson stat	1.999645
Prob(F-statistic)	0.000000		

Wheat

- **Correlogram**

Sample: 3/23/2000 7/02/2018
Included observations: 4571

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.034	0.034	5.3919	0.020
		2	-0.004	-0.005	5.4533	0.065
		3	0.012	0.013	6.1659	0.104
		4	0.002	0.001	6.1796	0.186
		5	0.008	0.008	6.4589	0.264
		6	-0.020	-0.021	8.2546	0.220
		7	-0.022	-0.021	10.486	0.163
		8	0.009	0.010	10.847	0.211
		9	-0.006	-0.006	10.994	0.276
		10	-0.005	-0.004	11.095	0.350
		11	0.016	0.016	12.207	0.348
		12	0.020	0.019	13.973	0.302
		13	-0.028	-0.030	17.548	0.175
		14	0.007	0.009	17.778	0.217
		15	0.009	0.008	18.167	0.254
		16	-0.004	-0.005	18.251	0.309
		17	-0.046	-0.046	27.921	0.046
		18	0.037	0.042	34.204	0.012
		19	-0.019	-0.023	35.824	0.011
		20	0.010	0.012	36.299	0.014
		21	-0.003	-0.004	36.350	0.020
		22	-0.034	-0.033	41.684	0.007
		23	-0.018	-0.020	43.140	0.007
		24	0.019	0.021	44.825	0.006
		25	-0.013	-0.012	45.656	0.007
		26	0.034	0.033	50.922	0.002
		27	-0.009	-0.010	51.275	0.003
		28	-0.006	-0.004	51.419	0.004
		29	-0.042	-0.046	59.603	0.001
		30	0.021	0.023	61.721	0.001
		31	0.008	0.009	61.987	0.001
		32	0.016	0.016	63.240	0.001
		34	0.006	0.007	63.854	0.001
		35	0.007	0.005	64.083	0.002
		36	0.012	0.007	64.697	0.002

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-65.25662	0.0001
Test critical values:	1% level	-3.431598	
	5% level	-2.861976	
	10% level	-2.567045	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/27/2000 7/02/2018
Included observations: 4570 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.965617	0.014797	-65.25662	0.0000
C	0.000101	0.000268	0.377374	0.7059

R-squared	0.482463	Mean dependent var	-8.34E-06
Adjusted R-squared	0.482350	S.D. dependent var	0.025207
S.E. of regression	0.018136	Akaike info criterion	-5.181387
Sum squared resid	1.502498	Schwarz criterion	-5.178575
Log likelihood	11841.47	Hannan-Quinn criter.	-5.180397
F-statistic	4258.426	Durbin-Watson stat	1.998075
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.129017
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000329
HAC corrected variance (Bartlett kernel)	0.000349

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 3/24/2000 7/02/2018
Included observations: 4571 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000103	0.000268	0.385158	0.7001

R-squared	0.000000	Mean dependent var	0.000103
Adjusted R-squared	0.000000	S.D. dependent var	0.018143
S.E. of regression	0.018143	Akaike info criterion	-5.180818
Sum squared resid	1.504340	Schwarz criterion	-5.179412
Log likelihood	11841.76	Hannan-Quinn criter.	-5.180323
Durbin-Watson stat	1.929863		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-65.24927	0.0001
Test critical values:	1% level	-3.431598	
	5% level	-2.861976	
	10% level	-2.567045	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000329
HAC corrected variance (Bartlett kernel)	0.000327

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 3/27/2000 7/02/2018
Included observations: 4570 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.965617	0.014797	-65.25662	0.0000
C	0.000101	0.000268	0.377374	0.7059

R-squared	0.482463	Mean dependent var	-8.34E-06
Adjusted R-squared	0.482350	S.D. dependent var	0.025207
S.E. of regression	0.018136	Akaike info criterion	-5.181387
Sum squared resid	1.502498	Schwarz criterion	-5.178575
Log likelihood	11841.47	Hannan-Quinn criter.	-5.180397
F-statistic	4258.426	Durbin-Watson stat	1.998075
Prob(F-statistic)	0.000000		

Zinc

- **Correlogram**

Sample: 2/18/2008 5/08/2019
Included observations: 2729

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.056	-0.056	8.4220	0.004
		2	-0.012	-0.015	8.7942	0.012
		3	-0.029	-0.030	11.048	0.011
		4	0.028	0.025	13.233	0.010
		5	-0.058	-0.056	22.423	0.000
		6	0.019	0.013	23.414	0.001
		7	0.016	0.017	24.093	0.001
		8	0.024	0.023	25.712	0.001
		9	-0.021	-0.014	26.942	0.001
		10	-0.006	-0.010	27.038	0.003
		11	0.005	0.006	27.116	0.004
		12	0.034	0.035	30.379	0.002
		13	-0.069	-0.064	43.608	0.000
		14	0.009	0.001	43.844	0.000
		15	0.026	0.025	45.655	0.000
		16	-0.035	-0.037	48.974	0.000
		17	0.004	0.009	49.011	0.000
		18	-0.009	-0.017	49.218	0.000
		19	0.005	0.002	49.297	0.000
		20	-0.014	-0.008	49.820	0.000
		21	-0.005	-0.008	49.890	0.000
		23	0.016	0.012	51.091	0.001
		24	-0.020	-0.016	52.164	0.001
		26	-0.039	-0.042	57.426	0.000
		27	0.023	0.016	58.855	0.000
		28	0.009	0.020	59.065	0.001
		29	0.025	0.016	60.723	0.001
		30	0.013	0.023	61.182	0.001
		31	-0.041	-0.045	65.782	0.000
		32	-0.004	-0.003	65.822	0.000
		33	0.024	0.025	67.462	0.000
		34	0.055	0.057	75.731	0.000
		35	-0.040	-0.036	80.186	0.000
		36	0.025	0.021	81.950	0.000

- **ADF Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-55.32406	0.0001
Test critical values:	1% level	-3.432555	
	5% level	-2.862400	
	10% level	-2.567273	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 2/22/2008 5/08/2019
Included observations: 2728 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.055539	0.019079	-55.32406	0.0000
C	2.03E-05	0.000384	0.052832	0.9579

R-squared	0.528924	Mean dependent var	-3.38E-05
Adjusted R-squared	0.528751	S.D. dependent var	0.029215
S.E. of regression	0.020055	Akaike info criterion	-4.979938
Sum squared resid	1.096412	Schwarz criterion	-4.975604
Log likelihood	6794.635	Hannan-Quinn criter.	-4.978371
F-statistic	3060.752	Durbin-Watson stat	1.999684
Prob(F-statistic)	0.000000		

- **KPSS Test**

Null Hypothesis: R is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.069375
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000405
HAC corrected variance (Bartlett kernel)	0.000349

KPSS Test Equation
Dependent Variable: R
Method: Least Squares
Sample (adjusted): 2/21/2008 5/08/2019
Included observations: 2729 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.45E-05	0.000385	0.115387	0.9081

R-squared	0.000000	Mean dependent var	4.45E-05
Adjusted R-squared	0.000000	S.D. dependent var	0.020128
S.E. of regression	0.020128	Akaike info criterion	-4.973004
Sum squared resid	1.105256	Schwarz criterion	-4.970838
Log likelihood	6786.664	Hannan-Quinn criter.	-4.972221
Durbin-Watson stat	2.105817		

- **Phillips – Perron Test**

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-55.44480	0.0001
Test critical values:	1% level	-3.432555	
	5% level	-2.862400	
	10% level	-2.567273	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000402
HAC corrected variance (Bartlett kernel)	0.000379

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Sample (adjusted): 2/22/2008 5/08/2019
Included observations: 2728 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-1.055539	0.019079	-55.32406	0.0000
C	2.03E-05	0.000384	0.052832	0.9579

R-squared	0.528924	Mean dependent var	-3.38E-05
Adjusted R-squared	0.528751	S.D. dependent var	0.029215
S.E. of regression	0.020055	Akaike info criterion	-4.979938
Sum squared resid	1.096412	Schwarz criterion	-4.975604
Log likelihood	6794.635	Hannan-Quinn criter.	-4.978371
F-statistic	3060.752	Durbin-Watson stat	1.999684
Prob(F-statistic)	0.000000		

11.2 APPENDIX II: ARIMA Models output

Aluminum

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 11/22/2016 3/09/2020
Included observations: 811
Convergence achieved after 93 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.526802	0.168561	-3.125298	0.0018
AR(2)	1.236533	0.084584	14.61898	0.0000
AR(3)	1.045899	0.179082	5.840325	0.0000
AR(4)	-0.682084	0.061774	-11.04155	0.0000
AR(5)	-0.770937	0.139288	-5.534850	0.0000
MA(1)	0.486195	0.176741	2.750892	0.0061
MA(2)	-1.184044	0.096575	-12.26038	0.0000
MA(3)	-0.995479	0.175228	-5.681048	0.0000
MA(4)	0.617488	0.079455	7.771587	0.0000
MA(5)	0.700074	0.143970	4.862630	0.0000
SIGMASQ	0.000136	4.72E-06	28.83770	0.0000

R-squared	0.036491	Mean dependent var	-3.83E-05
Adjusted R-squared	0.024447	S.D. dependent var	0.011887
S.E. of regression	0.011741	Akaike info criterion	-6.037496
Sum squared resid	0.110272	Schwarz criterion	-5.973771
Log likelihood	2459.205	Hannan-Quinn criter.	-6.013031
Durbin-Watson stat	1.951423		

Inverted AR Roots	.93+.32i	.93-.32i	-.76-.58i	-.76+.58i
	-.87			
Inverted MA Roots	.92+.31i	.92-.31i	-.74-.59i	-.74+.59i
	-.84			

Eviews add in ARIMA Model

Dependent Variable: D(MAL)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 11/22/2016 3/09/2020
Included observations: 811
Convergence achieved after 70 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.411214	0.145088	-9.726593	0.0000
AR(2)	0.748318	0.117958	6.343928	0.0000
AR(3)	2.159202	0.216810	9.958975	0.0000
AR(4)	0.252144	0.173813	1.450661	0.1473
AR(5)	-1.344325	0.138497	-9.706531	0.0000
AR(6)	-0.727092	0.112471	-6.464684	0.0000
MA(1)	1.397152	0.140953	9.912185	0.0000
MA(2)	-0.707845	0.120846	-5.857434	0.0000
MA(3)	-2.098884	0.210194	-9.985436	0.0000
MA(4)	-0.316228	0.164194	-1.925943	0.0545
MA(5)	1.228951	0.139872	8.786263	0.0000
MA(6)	0.708532	0.100444	7.053962	0.0000
SIGMASQ	0.000134	4.84E-06	27.72125	0.0000

R-squared	0.048517	Mean dependent var	-3.83E-05
Adjusted R-squared	0.034209	S.D. dependent var	0.011887
S.E. of regression	0.011682	Akaike info criterion	-6.044609
Sum squared resid	0.108896	Schwarz criterion	-5.969298
Log likelihood	2464.089	Hannan-Quinn criter.	-6.015697
Durbin-Watson stat	1.982389		

Inverted AR Roots	.93-.32i	.93+.32i	-.73-.54i	-.73+.54i
	-.91-.29i	-.91+.29i		
Inverted MA Roots	.92-.31i	.92+.31i	-.69-.56i	-.69+.56i
	-.93+.31i	-.93-.31i		

Brent oil

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 6/28/1988 5/17/2017
Included observations: 7363
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.864076	0.020678	90.14820	0.0000
AR(2)	-0.920885	0.019989	-46.06909	0.0000
MA(1)	-1.885968	0.019039	-99.05785	0.0000
MA(2)	0.940394	0.018251	51.52431	0.0000
SIGMASQ	0.000498	2.57E-06	194.0870	0.0000

R-squared	0.003421	Mean dependent var	0.000168
Adjusted R-squared	0.002879	S.D. dependent var	0.022354
S.E. of regression	0.022321	Akaike info criterion	-4.765858
Sum squared resid	3.666078	Schwarz criterion	-4.761170
Log likelihood	17550.51	Hannan-Quinn criter.	-4.764247
Durbin-Watson stat	2.006392		

Inverted AR Roots	.93+.23i	.93-.23i
Inverted MA Roots	.94-.23i	.94+.23i

Eviews add in ARIMA Model

Dependent Variable: D(B)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 6/28/1988 5/17/2017
Included observations: 7363
Convergence achieved after 240 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.074067	0.026521	2.792790	0.0052
AR(2)	-0.045046	0.025915	-1.738226	0.0822
AR(3)	0.313251	0.025712	12.18285	0.0000
AR(4)	0.262871	0.025728	10.21736	0.0000
AR(5)	0.343837	0.025412	13.53029	0.0000
AR(6)	0.005494	0.025207	0.217942	0.8275
AR(7)	0.183835	0.022113	8.313549	0.0000
AR(8)	-0.900821	0.023690	-38.02532	0.0000
MA(1)	-0.098563	0.026726	-3.687909	0.0002
MA(2)	0.017715	0.026177	0.676747	0.4986
MA(3)	-0.329391	0.025405	-12.96547	0.0000
MA(4)	-0.259943	0.026831	-9.688018	0.0000
MA(5)	-0.335263	0.026003	-12.89340	0.0000
MA(6)	-0.001893	0.024894	-0.076040	0.9394
MA(7)	-0.172592	0.022056	-7.825029	0.0000
MA(8)	0.904945	0.023821	37.98979	0.0000
SIGMASQ	0.000495	3.34E-06	148.4677	0.0000

R-squared	0.008355	Mean dependent var	0.000168
Adjusted R-squared	0.006195	S.D. dependent var	0.022354
S.E. of regression	0.022284	Akaike info criterion	-4.767508
Sum squared resid	3.647927	Schwarz criterion	-4.751567
Log likelihood	17568.58	Hannan-Quinn criter.	-4.762029
Durbin-Watson stat	1.997831		

Inverted AR Roots	.94-.23i	.94+.23i	.34+.93i	.34-.93i
	-.34-.93i	-.34+.93i	-.90-.43i	-.90+.43i
Inverted MA Roots	.95+.23i	.95-.23i	.35+.92i	.35-.92i
	-.35-.93i	-.35+.93i	-.90+.43i	-.90-.43i

Cocoa

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 7/01/2016
Included observations: 9165
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(2)	0.575793	0.141322	4.074337	0.0000
AR(3)	0.344063	0.140037	2.456947	0.0140
MA(2)	-0.604370	0.139584	-4.329784	0.0000
MA(3)	-0.336794	0.138716	-2.427946	0.0152
SIGMASQ	0.000375	3.61E-06	103.7662	0.0000

R-squared	0.002042	Mean dependent var	-2.17E-06
Adjusted R-squared	0.001606	S.D. dependent var	0.019380
S.E. of regression	0.019364	Akaike info criterion	-5.050216
Sum squared resid	3.434806	Schwarz criterion	-5.046330
Log likelihood	23147.61	Hannan-Quinn criter.	-5.048895
Durbin-Watson stat	1.999616		

Inverted AR Roots	.97	-.48+.35i	-.48-.35i
Inverted MA Roots	.97	-.49-.33i	-.49+.33i

Eviews add in ARIMA Model

Dependent Variable: D(CC)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 7/01/2016
Included observations: 9165
Convergence achieved after 66 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.529145	0.059626	8.874394	0.0000
AR(2)	-0.906645	0.075570	-11.99740	0.0000
AR(3)	0.821915	0.085044	9.664577	0.0000
AR(4)	-0.517280	0.070590	-7.327981	0.0000
AR(5)	0.935609	0.050956	18.36099	0.0000
AR(6)	-0.040844	0.015272	-2.674393	0.0075
AR(7)	0.021532	0.011578	1.859669	0.0630
AR(8)	-0.015829	0.010349	-1.529612	0.1261
MA(1)	-0.529394	0.058899	-8.988212	0.0000
MA(2)	0.886760	0.074872	11.84374	0.0000
MA(3)	-0.797270	0.083233	-9.578753	0.0000
MA(4)	0.474963	0.069916	6.793351	0.0000
MA(5)	-0.907592	0.051738	-17.54215	0.0000
SIGMASQ	0.000374	3.65E-06	102.5537	0.0000

R-squared	0.004110	Mean dependent var	-2.17E-06
Adjusted R-squared	0.002695	S.D. dependent var	0.019380
S.E. of regression	0.019354	Akaike info criterion	-5.050230
Sum squared resid	3.427688	Schwarz criterion	-5.039349
Log likelihood	23156.68	Hannan-Quinn criter.	-5.046531
Durbin-Watson stat	1.999918		

Inverted AR Roots	.96	.30+.95i	.30-.95i	.25
	-.11-.24i	-.11+.24i	-.52+.82i	-.52-.82i
Inverted MA Roots	.97	.30+.95i	.30-.95i	-.52+.82i
	-.52-.82i			

Coffee

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 6/24/2016
Included observations: 9205
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.684224	0.183058	3.737754	0.0002
MA(1)	-0.699552	0.179679	-3.893347	0.0001
SIGMASQ	0.000540	3.69E-06	146.2443	0.0000

R-squared	0.000439	Mean dependent var	-3.37E-05
Adjusted R-squared	0.000222	S.D. dependent var	0.023252
S.E. of regression	0.023249	Akaike info criterion	-4.684783
Sum squared resid	4.973831	Schwarz criterion	-4.682460
Log likelihood	21564.71	Hannan-Quinn criter.	-4.683993
Durbin-Watson stat	1.997127		

Inverted AR Roots	.68
Inverted MA Roots	.70

Eviews add in ARIMA Model

Dependent Variable: D(KC)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 6/24/2016
Included observations: 9205
Convergence achieved after 54 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.476962	1.043551	0.457057	0.6476
AR(2)	0.610992	0.078828	7.750934	0.0000
AR(3)	-0.957535	0.602634	-1.588917	0.1121
AR(4)	0.233072	0.718134	0.324552	0.7455
AR(5)	0.866520	0.146278	5.923810	0.0000
AR(6)	-0.370088	0.816715	-0.453142	0.6505
MA(1)	-0.490055	1.044180	-0.469321	0.6389
MA(2)	-0.625800	0.076937	-8.133881	0.0000
MA(3)	0.991590	0.625526	1.585209	0.1130
MA(4)	-0.247171	0.741473	-0.333351	0.7389
MA(5)	-0.911742	0.146238	-6.234646	0.0000
MA(6)	0.413703	0.863746	0.478964	0.6320
MA(7)	0.000295	0.019050	0.015468	0.9877
MA(8)	-0.014654	0.015825	-0.926011	0.3545
MA(9)	0.011891	0.012977	0.916340	0.3595
SIGMASQ	0.000539	3.81E-06	141.5074	0.0000

R-squared	0.003753	Mean dependent var	-3.37E-05
Adjusted R-squared	0.002127	S.D. dependent var	0.023252
S.E. of regression	0.023227	Akaike info criterion	-4.685271
Sum squared resid	4.957344	Schwarz criterion	-4.672882
Log likelihood	21579.96	Hannan-Quinn criter.	-4.681060
Durbin-Watson stat	1.999593		

Inverted AR Roots	.94	.46+.86i	.46-.86i	.44
	-.91+.32i	-.91-.32i		
Inverted MA Roots	.94	.52	.46+.87i	.46-.87i
	.12-.28i	.12+.28i	-.29	-.92-.33i
	-.92+.33i			

Copper

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/31/2000 8/09/2018
Included observations: 4583
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(5)	-0.899291	0.034547	-26.03079	0.0000
MA(5)	0.869741	0.039082	22.25428	0.0000
SIGMASQ	0.000306	3.58E-06	85.43584	0.0000

R-squared	0.004340	Mean dependent var	0.000269
Adjusted R-squared	0.003905	S.D. dependent var	0.017528
S.E. of regression	0.017493	Akaike info criterion	-5.253327
Sum squared resid	1.401546	Schwarz criterion	-5.249118
Log likelihood	12041.00	Hannan-Quinn criter.	-5.251845
Durbin-Watson stat	2.150688		

Inverted AR Roots	.79-.58i	.79+.58i	-.30+.93i	-.30-.93i
	-.98			
Inverted MA Roots	.79-.57i	.79+.57i	-.30+.92i	-.30-.92i
	-.97			

Eviews add in ARIMA Model

Dependent Variable: D(HG)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/31/2000 8/09/2018
Included observations: 4583
Convergence achieved after 127 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.147249	0.024201	-6.084397	0.0000
AR(2)	1.344347	0.023911	56.22410	0.0000
AR(3)	0.141651	0.027471	5.156385	0.0000
AR(4)	-1.332148	0.026403	-50.45406	0.0000
AR(5)	-0.106177	0.028840	-3.681603	0.0002
AR(6)	0.868438	0.027618	31.44448	0.0000
AR(7)	0.078471	0.010834	7.243125	0.0000
AR(8)	0.046204	0.010092	4.578132	0.0000
MA(1)	0.071550	0.021872	3.271274	0.0011
MA(2)	-1.360888	0.020988	-64.84245	0.0000
MA(3)	-0.034405	0.020357	-1.690048	0.0911
MA(4)	1.372325	0.019884	69.01741	0.0000
MA(5)	-0.005338	0.022160	-0.240884	0.8097
MA(6)	-0.905598	0.020616	-43.92685	0.0000
SIGMASQ	0.000302	3.62E-06	83.37754	0.0000

R-squared	0.018244	Mean dependent var	0.000269
Adjusted R-squared	0.015235	S.D. dependent var	0.017528
S.E. of regression	0.017393	Akaike info criterion	-5.261972
Sum squared resid	1.381973	Schwarz criterion	-5.240927
Log likelihood	12072.81	Hannan-Quinn criter.	-5.254563
Durbin-Watson stat	1.999448		

Inverted AR Roots	.97	.77-.63i	.77+.63i	-.04+.22i
	-.04-.22i	-.79-.61i	-.79+.61i	-.99
Inverted MA Roots	.96	.76+.63i	.76-.63i	-.79+.61i
	-.79-.61i	-.97		

Corn

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 9402
Included observations: 9401
Convergence achieved after 59 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.982938	0.065864	-14.92378	0.0000
AR(2)	0.934830	0.128644	7.266797	0.0000
AR(3)	0.941055	0.065908	14.27841	0.0000
MA(1)	0.988316	0.067382	14.66739	0.0000
MA(2)	-0.932700	0.132023	-7.064695	0.0000
MA(3)	-0.942145	0.067945	-13.86638	0.0000
SIGMASQ	0.000297	1.25E-06	237.4122	0.0000

R-squared	0.001742	Mean dependent var	1.25E-05
Adjusted R-squared	0.001105	S.D. dependent var	0.017261
S.E. of regression	0.017251	Akaike info criterion	-5.281101
Sum squared resid	2.795742	Schwarz criterion	-5.275779
Log likelihood	24830.82	Hannan-Quinn criter.	-5.279294
Durbin-Watson stat	2.017840		

Inverted AR Roots	.97	-.98-.11i	-.98+.11i
Inverted MA Roots	.97	-.98+.10i	-.98-.10i

Eviews add in ARIMA Model

Dependent Variable: D(CORN)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 9402
Included observations: 9401
Convergence achieved after 80 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.076443	1.150977	-0.066416	0.9470
AR(2)	-0.332733	0.696112	-0.477988	0.6327
AR(3)	-0.459254	0.806660	-0.569327	0.5691
AR(4)	0.480026	0.969310	0.495225	0.6205
MA(1)	0.071693	1.151027	0.062286	0.9503
MA(2)	0.323800	0.687480	0.470995	0.6377
MA(3)	0.469028	0.794538	0.590315	0.5550
MA(4)	-0.497106	0.975204	-0.509745	0.6102
MA(5)	0.001404	0.019581	0.071708	0.9428
SIGMASQ	0.000298	1.42E-06	209.8699	0.0000

R-squared	0.001021	Mean dependent var	1.25E-05
Adjusted R-squared	0.000064	S.D. dependent var	0.017261
S.E. of regression	0.017260	Akaike info criterion	-5.279746
Sum squared resid	2.797762	Schwarz criterion	-5.272142
Log likelihood	24827.45	Hannan-Quinn criter.	-5.277164
Durbin-Watson stat	1.999994		

Inverted AR Roots	.56	.13-.96i	.13+.96i	-.91
Inverted MA Roots	.57	.14-.96i	.14+.96i	.00
	-.92			

Cotton

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 4702
Included observations: 4701
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.245856	0.191350	-6.510890	0.0000
AR(2)	-0.612264	0.167140	-3.663187	0.0003
MA(1)	1.280113	0.186644	6.858585	0.0000
MA(2)	0.642746	0.160742	3.998625	0.0001
SIGMASQ	0.000338	4.20E-06	80.49391	0.0000

R-squared	0.001900	Mean dependent var	0.000115
Adjusted R-squared	0.001050	S.D. dependent var	0.018397
S.E. of regression	0.018388	Akaike info criterion	-5.153194
Sum squared resid	1.587771	Schwarz criterion	-5.146328
Log likelihood	12117.58	Hannan-Quinn criter.	-5.150780
Durbin-Watson stat	2.001590		

Inverted AR Roots	-.62-.47i	-.62+.47i
Inverted MA Roots	-.64-.48i	-.64+.48i

Eviews add in ARIMA Model

Dependent Variable: D(CT)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 4702
Included observations: 4701
Convergence achieved after 152 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.296215	0.213838	-6.061681	0.0000
AR(2)	-0.689740	0.188408	-3.660882	0.0003
AR(3)	-0.803418	0.060965	-13.17833	0.0000
AR(4)	-0.559136	0.153074	-3.652718	0.0003
AR(5)	-0.996384	0.059441	-16.76265	0.0000
AR(6)	-1.305945	0.189505	-6.891350	0.0000
AR(7)	-0.446957	0.204939	-2.180930	0.0292
MA(1)	1.330169	0.208753	6.371979	0.0000
MA(2)	0.720347	0.183903	3.916988	0.0001
MA(3)	0.797768	0.058082	13.73520	0.0000
MA(4)	0.574071	0.146483	3.919033	0.0001
MA(5)	1.014527	0.056252	18.03534	0.0000
MA(6)	1.349135	0.186331	7.240534	0.0000
MA(7)	0.492669	0.200540	2.456709	0.0141
SIGMASQ	0.000336	4.37E-06	77.00122	0.0000

R-squared	0.006707	Mean dependent var	0.000115
Adjusted R-squared	0.003739	S.D. dependent var	0.018397
S.E. of regression	0.018363	Akaike info criterion	-5.153659
Sum squared resid	1.580124	Schwarz criterion	-5.133061
Log likelihood	12128.68	Hannan-Quinn criter.	-5.146417
Durbin-Watson stat	2.000644		

Inverted AR Roots	.73-.67i	.73+.67i	-.18+.98i	-.18-.98i
	-.54	-.89	-.96	
Inverted MA Roots	.73+.67i	.73-.67i	-.19-.98i	-.19+.98i
	-.63	-.81	-.98	

Crude oil

Custom ARIMA Model

Dependent Variable: D(LOG(CLOSE_PRICE_CL))
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/23/2000 8/02/2018
Included observations: 4584
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.042625	0.009907	-4.302364	0.0000
MA(6)	-0.021905	0.010473	-2.091456	0.0365
SIGMASQ	0.000564	6.77E-06	83.21545	0.0000

R-squared	0.002214	Mean dependent var	0.000201
Adjusted R-squared	0.001778	S.D. dependent var	0.023767
S.E. of regression	0.023746	Akaike info criterion	-4.642127
Sum squared resid	2.583158	Schwarz criterion	-4.637919
Log likelihood	10642.76	Hannan-Quinn criter.	-4.640646
Durbin-Watson stat	2.001009		

Inverted AR Roots	-.04			
Inverted MA Roots	.53	.26+.46i	.26-.46i	-.26-.46i
	-.26+.46i	-.53		

Eviews add in ARIMA Model

Dependent Variable: D(LOG(CLOSE_PRICE_CL))
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/23/2000 8/02/2018
Included observations: 4584
Convergence achieved after 53 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.086315	0.142545	7.620868	0.0000
AR(2)	-0.695018	0.115540	-6.015370	0.0000
AR(3)	0.946607	0.065812	14.38341	0.0000
AR(4)	-1.184631	0.116589	-10.16078	0.0000
AR(5)	0.307017	0.137607	2.231115	0.0257
MA(1)	-1.130758	0.138120	-8.186808	0.0000
MA(2)	0.733009	0.110169	6.653469	0.0000
MA(3)	-0.963715	0.062362	-15.45360	0.0000
MA(4)	1.222901	0.111770	10.94125	0.0000
MA(5)	-0.371465	0.132010	-2.813923	0.0049
SIGMASQ	0.000560	7.13E-06	78.52128	0.0000

R-squared	0.008408	Mean dependent var	0.000201
Adjusted R-squared	0.006240	S.D. dependent var	0.023767
S.E. of regression	0.023693	Akaike info criterion	-4.644795
Sum squared resid	2.567121	Schwarz criterion	-4.629364
Log likelihood	10656.87	Hannan-Quinn criter.	-4.639363
Durbin-Watson stat	1.999700		

Inverted AR Roots	.82+.50i	.82-.50i	.33	-.45-.89i
	-.45+.89i			
Inverted MA Roots	.81+.50i	.81-.50i	.41	-.45+.89i
	-.45-.89i			

Feeder cattle

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 1/31/2000 6/25/2018
Included observations: 4597
Convergence achieved after 35 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(2)	1.095696	0.072548	15.10311	0.0000
AR(3)	-0.170232	0.055266	-3.080225	0.0021
AR(6)	-0.442618	0.068003	-6.508805	0.0000
MA(2)	-1.088647	0.076091	-14.30716	0.0000
MA(3)	0.162028	0.058051	2.791144	0.0053
MA(6)	0.424542	0.072019	5.894901	0.0000
SIGMASQ	9.50E-05	8.06E-07	117.8104	0.0000

R-squared	0.001776	Mean dependent var	0.000118
Adjusted R-squared	0.000471	S.D. dependent var	0.009757
S.E. of regression	0.009754	Akaike info criterion	-6.420655
Sum squared resid	0.436737	Schwarz criterion	-6.410859
Log likelihood	14764.88	Hannan-Quinn criter.	-6.417207
Durbin-Watson stat	1.842217		

Inverted AR Roots	.92-.29i	.92+.29i	.02+.72i	.02-.72i
	-.94-.16i	-.94+.16i		
Inverted MA Roots	.91-.29i	.91+.29i	.02+.72i	.02-.72i
	-.94-.16i	-.94+.16i		

Eviews add in ARIMA Model

Dependent Variable: D(FC)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 1/31/2000 6/25/2018
Included observations: 4597
Convergence achieved after 7 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.079110	0.011365	6.960897	0.0000
SIGMASQ	9.46E-05	7.87E-07	120.2238	0.0000

R-squared	0.006108	Mean dependent var	0.000118
Adjusted R-squared	0.005891	S.D. dependent var	0.009757
S.E. of regression	0.009728	Akaike info criterion	-6.427184
Sum squared resid	0.434842	Schwarz criterion	-6.424385
Log likelihood	14774.88	Hannan-Quinn criter.	-6.426198
Durbin-Watson stat	1.999953		

Inverted AR Roots	.08

Gasoline

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 10/05/2005 4/01/2019
Included observations: 3615
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(6)	-0.027863	0.014178	-1.965278	0.0495
MA(1)	-0.108280	0.008339	-12.98548	0.0000
SIGMASQ	0.000617	6.97E-06	88.50976	0.0000

R-squared	0.012904	Mean dependent var	7.92E-06
Adjusted R-squared	0.012358	S.D. dependent var	0.025007
S.E. of regression	0.024852	Akaike info criterion	-4.550926
Sum squared resid	2.230844	Schwarz criterion	-4.545786
Log likelihood	8228.798	Hannan-Quinn criter.	-4.549095
Durbin-Watson stat	2.002104		

Inverted AR Roots	.48-.28i	.48+.28i	.00+.55i	-.00-.55i
	-.48-.28i	-.48+.28i		
Inverted MA Roots	.11			

Eviews add in ARIMA Model

Dependent Variable: D(GPR)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 10/05/2005 4/01/2019
Included observations: 3615
Convergence achieved after 82 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.460563	0.072245	-6.375010	0.0000
AR(2)	0.658975	0.049789	13.23527	0.0000
AR(3)	0.811127	0.042340	19.15740	0.0000
AR(4)	-0.367191	0.054559	-6.730109	0.0000
AR(5)	-0.893571	0.065888	-13.56199	0.0000
AR(6)	-0.116836	0.011269	-10.36809	0.0000
MA(1)	0.349122	0.074023	4.716409	0.0000
MA(2)	-0.710660	0.050444	-14.08799	0.0000
MA(3)	-0.738243	0.042214	-17.48798	0.0000
MA(4)	0.444094	0.055643	7.981122	0.0000
MA(5)	0.852919	0.067330	12.66780	0.0000
SIGMASQ	0.000615	7.52E-06	81.74082	0.0000

R-squared	0.016916	Mean dependent var	7.92E-06
Adjusted R-squared	0.013915	S.D. dependent var	0.025007
S.E. of regression	0.024832	Akaike info criterion	-4.549983
Sum squared resid	2.221777	Schwarz criterion	-4.529426
Log likelihood	8236.094	Hannan-Quinn criter.	-4.542659
Durbin-Watson stat	1.995257		

Inverted AR Roots	.89+.43i	.89-.43i	-.14	-.60-.77i
	-.60+.77i	-.88		
Inverted MA Roots	.89-.43i	.89+.43i	-.61-.78i	-.61+.78i
	-.91			

Gold

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2/29/2000 8/02/2018
Included observations: 4596
Convergence achieved after 61 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.669256	0.027239	24.56946	0.0000
AR(2)	-0.938323	0.026837	-34.96441	0.0000
MA(1)	-0.688008	0.027175	-25.31805	0.0000
MA(2)	0.940809	0.026959	34.89791	0.0000
SIGMASQ	0.000125	1.37E-06	91.50578	0.0000

R-squared	0.002336	Mean dependent var	0.000309
Adjusted R-squared	0.001467	S.D. dependent var	0.011207
S.E. of regression	0.011198	Akaike info criterion	-6.144983
Sum squared resid	0.575737	Schwarz criterion	-6.137984
Log likelihood	14126.17	Hannan-Quinn criter.	-6.142519
Durbin-Watson stat	1.977878		

Inverted AR Roots	.33-.91i	.33+.91i
Inverted MA Roots	.34-.91i	.34+.91i

Eviews add in ARIMA Model

Dependent Variable: D(GC)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2/29/2000 8/02/2018
Included observations: 4596
Convergence achieved after 122 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.591698	0.077976	7.588159	0.0000
AR(2)	-0.604469	0.061951	-9.757216	0.0000
AR(3)	-0.305567	0.040971	-7.458156	0.0000
AR(4)	0.217256	0.049574	4.382496	0.0000
AR(5)	0.709158	0.041830	16.95323	0.0000
AR(6)	-0.677565	0.064059	-10.57728	0.0000
AR(7)	0.783101	0.076291	10.26467	0.0000
MA(1)	-0.603176	0.073509	-8.205456	0.0000
MA(2)	0.609942	0.059270	10.29098	0.0000
MA(3)	0.306757	0.039033	7.858915	0.0000
MA(4)	-0.226142	0.046434	-4.870168	0.0000
MA(5)	-0.707023	0.039252	-18.01242	0.0000
MA(6)	0.667004	0.059696	11.17341	0.0000
MA(7)	-0.804333	0.070246	-11.45021	0.0000
SIGMASQ	0.000124	1.44E-06	86.68694	0.0000

R-squared	0.008681	Mean dependent var	0.000309
Adjusted R-squared	0.005652	S.D. dependent var	0.011207
S.E. of regression	0.011175	Akaike info criterion	-6.146918
Sum squared resid	0.572075	Schwarz criterion	-6.125923
Log likelihood	14140.62	Hannan-Quinn criter.	-6.139528
Durbin-Watson stat	1.992783		

Inverted AR Roots	.95	.45-.81i	.45+.81i	.23+.96i
	.23-.96i	-.85-.52i	-.85+.52i	
Inverted MA Roots	.96	.45-.82i	.45+.82i	.22+.96i
	.22-.96i	-.85+.52i	-.85-.52i	

Heating oil

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/02/2000 8/07/2018
Included observations: 4602
Convergence achieved after 157 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.102254	0.047819	-23.05074	0.0000
AR(2)	-0.894101	0.052866	-16.91274	0.0000
AR(3)	-1.011323	0.050625	-19.97686	0.0000
AR(4)	-0.880910	0.038134	-23.10009	0.0000
MA(1)	1.067583	0.048697	21.92320	0.0000
MA(2)	0.855140	0.051856	16.49076	0.0000
MA(3)	0.982563	0.049535	19.83564	0.0000
MA(4)	0.875014	0.039755	22.01020	0.0000
SIGMASQ	0.000505	6.18E-06	81.72598	0.0000

R-squared	0.006107	Mean dependent var	0.000218
Adjusted R-squared	0.004376	S.D. dependent var	0.022548
S.E. of regression	0.022499	Akaike info criterion	-4.748713
Sum squared resid	2.325014	Schwarz criterion	-4.736130
Log likelihood	10935.79	Hannan-Quinn criter.	-4.744284
Durbin-Watson stat	2.028210		

Inverted AR Roots	.29+.92i	.29-.92i	-.84-.49i	-.84+.49i
Inverted MA Roots	.30+.91i	.30-.91i	-.84-.49i	-.84+.49i

Eviews add in ARIMA Model

Dependent Variable: D(HO)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/02/2000 8/07/2018
Included observations: 4602
Convergence achieved after 92 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.739590	0.053475	13.83045	0.0000
AR(2)	-0.709251	0.051405	-13.79726	0.0000
AR(3)	0.419862	0.045466	9.234691	0.0000
AR(4)	0.308138	0.045131	6.827650	0.0000
AR(5)	0.431548	0.041344	10.43800	0.0000
AR(6)	-0.751634	0.043888	-17.12630	0.0000
AR(7)	0.687585	0.051995	13.22405	0.0000
AR(8)	-0.830650	0.041493	-20.01904	0.0000
MA(1)	-0.781010	0.053033	-14.72680	0.0000
MA(2)	0.732842	0.052218	14.03433	0.0000
MA(3)	-0.442671	0.045411	-9.748192	0.0000
MA(4)	-0.285736	0.046014	-6.209793	0.0000
MA(5)	-0.440010	0.042068	-10.45953	0.0000
MA(6)	0.769188	0.043929	17.50973	0.0000
MA(7)	-0.727294	0.051919	-14.00827	0.0000
MA(8)	0.840279	0.041043	20.47335	0.0000
SIGMASQ	0.000504	6.28E-06	80.23091	0.0000

R-squared	0.008951	Mean dependent var	0.000218
Adjusted R-squared	0.005493	S.D. dependent var	0.022548
S.E. of regression	0.022486	Akaike info criterion	-4.748074
Sum squared resid	2.318361	Schwarz criterion	-4.724306
Log likelihood	10942.32	Hannan-Quinn criter.	-4.739708
Durbin-Watson stat	2.017231		

Inverted AR Roots	.94-.26i	.94+.26i	.29+.92i	.29-.92i
	-.01-.98i	-.01+.98i	-.85-.51i	-.85+.51i
Inverted MA Roots	.95+.26i	.95-.26i	.30-.91i	.30+.91i
	-.01-.98i	-.01+.98i	-.84+.51i	-.84-.51i

Lead

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 7/08/2008 5/20/2019
Included observations: 2650
Convergence achieved after 131 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.512764	0.032530	-15.76295	0.0000
AR(2)	-0.542169	0.021345	-25.40031	0.0000
AR(3)	-0.590843	0.021651	-27.28922	0.0000
AR(4)	-0.880207	0.032092	-27.42742	0.0000
MA(1)	0.542132	0.029158	18.59288	0.0000
MA(2)	0.529925	0.020372	26.01273	0.0000
MA(3)	0.570005	0.020509	27.79359	0.0000
MA(4)	0.904028	0.027796	32.52350	0.0000
SIGMASQ	0.000448	6.69E-06	66.87955	0.0000

R-squared	0.012246	Mean dependent var	4.21E-05
Adjusted R-squared	0.009254	S.D. dependent var	0.021291
S.E. of regression	0.021193	Akaike info criterion	-4.866792
Sum squared resid	1.186143	Schwarz criterion	-4.846814
Log likelihood	6457.499	Hannan-Quinn criter.	-4.859561
Durbin-Watson stat	1.984834		

Inverted AR Roots	.46+.88i	.46-.88i	-.72-.61i	-.72+.61i
Inverted MA Roots	.47-.87i	.47+.87i	-.74+.62i	-.74-.62i

Eviews add in ARIMA Model

Dependent Variable: D(L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 7/08/2008 5/20/2019
Included observations: 2650
Convergence achieved after 68 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.127904	0.055273	-2.314031	0.0207
AR(2)	-0.365711	0.055748	-6.560099	0.0000
AR(3)	0.136022	0.068648	1.981457	0.0476
AR(4)	0.109095	0.056504	1.930752	0.0536
AR(5)	0.802105	0.052695	15.22155	0.0000
MA(1)	0.154637	0.049503	3.123767	0.0018
MA(2)	0.348239	0.050479	6.898658	0.0000
MA(3)	-0.157546	0.062227	-2.531804	0.0114
MA(4)	-0.117764	0.051398	-2.291214	0.0220
MA(5)	-0.857342	0.046836	-18.30516	0.0000
SIGMASQ	0.000447	6.66E-06	67.07890	0.0000

R-squared	0.013972	Mean dependent var	4.21E-05
Adjusted R-squared	0.010235	S.D. dependent var	0.021291
S.E. of regression	0.021182	Akaike info criterion	-4.866640
Sum squared resid	1.184070	Schwarz criterion	-4.842223
Log likelihood	6459.298	Hannan-Quinn criter.	-4.857801
Durbin-Watson stat	1.980093		

Inverted AR Roots	.92	.19+.98i	.19-.98i	-.72-.61i
	-.72+.61i			
Inverted MA Roots	.93	.19+.98i	.19-.98i	-.73-.62i
	-.73+.62i			

Lean hogs

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 7/08/2008 5/20/2019
Included observations: 2650
Convergence achieved after 45 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.507425	0.055248	-9.184430	0.0000
AR(2)	0.433763	0.069454	6.245340	0.0000
AR(3)	0.809011	0.053163	15.21750	0.0000
MA(1)	0.529919	0.049458	10.71462	0.0000
MA(2)	-0.451480	0.063300	-7.132358	0.0000
MA(3)	-0.859390	0.047110	-18.24230	0.0000
SIGMASQ	0.000449	6.60E-06	68.09752	0.0000

R-squared	0.008303	Mean dependent var	4.21E-05
Adjusted R-squared	0.006052	S.D. dependent var	0.021291
S.E. of regression	0.021227	Akaike info criterion	-4.864426
Sum squared resid	1.190877	Schwarz criterion	-4.848888
Log likelihood	6452.365	Hannan-Quinn criter.	-4.858802
Durbin-Watson stat	1.969411		

Inverted AR Roots	.92	-.71-.61i	-.71+.61i
Inverted MA Roots	.94	-.73-.62i	-.73+.62i

Eviews add in ARIMA Model

Dependent Variable: D(LH)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/03/20 Time: 20:36
Sample: 12/28/1979 6/27/2016
Included observations: 9229
Convergence achieved after 60 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.400647	0.085007	16.47680	0.0000
AR(2)	-0.536026	0.078848	-6.798222	0.0000
AR(3)	-0.437748	0.073479	-5.957458	0.0000
AR(4)	1.332991	0.069664	19.13464	0.0000
AR(5)	-0.764171	0.077036	-9.919614	0.0000
MA(1)	-1.411699	0.088678	-15.91940	0.0000
MA(2)	0.561652	0.085304	6.584130	0.0000
MA(3)	0.413810	0.080328	5.151508	0.0000
MA(4)	-1.309360	0.075192	-17.41364	0.0000
MA(5)	0.746358	0.080846	9.231799	0.0000
SIGMASQ	0.000455	1.93E-06	235.5879	0.0000

R-squared	0.006540	Mean dependent var	7.43E-05
Adjusted R-squared	0.005462	S.D. dependent var	0.021392
S.E. of regression	0.021333	Akaike info criterion	-4.855798
Sum squared resid	4.195233	Schwarz criterion	-4.847300
Log likelihood	22418.08	Hannan-Quinn criter.	-4.852910
Durbin-Watson stat	2.001530		

Inverted AR Roots	.99	.82	.27+.96i	.27-.96i
	-.96			
Inverted MA Roots	1.00	.80	.28+.95i	.28-.95i
	-.94			

Live Cattle

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 9220
Included observations: 9219
Convergence achieved after 52 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.864602	0.045411	19.03955	0.0000
AR(2)	-0.161980	0.045279	-3.577401	0.0003
AR(3)	0.910391	0.042078	21.63596	0.0000
AR(4)	-0.855021	0.041569	-20.56875	0.0000
MA(1)	-0.834946	0.047562	-17.55495	0.0000
MA(2)	0.145748	0.043389	3.359104	0.0008
MA(3)	-0.911890	0.040166	-22.70315	0.0000
MA(4)	0.830050	0.044388	18.70003	0.0000
SIGMASQ	0.000119	7.51E-07	158.4148	0.0000

R-squared	0.005024	Mean dependent var	6.12E-05
Adjusted R-squared	0.004160	S.D. dependent var	0.010937
S.E. of regression	0.010915	Akaike info criterion	-6.196453
Sum squared resid	1.097169	Schwarz criterion	-6.189493
Log likelihood	28571.55	Hannan-Quinn criter.	-6.194088
Durbin-Watson stat	2.007187		

Inverted AR Roots	.90-.27i	.90+.27i	-.47+.86i	-.47-.86i
Inverted MA Roots	.89+.26i	.89-.26i	-.47+.86i	-.47-.86i

Eviews add in ARIMA Model

Dependent Variable: D(LC)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 9220
Included observations: 9219
Convergence achieved after 201 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.447529	0.051580	8.676389	0.0000
AR(2)	0.739823	0.028499	25.95982	0.0000
AR(3)	-1.012584	0.043796	-23.12021	0.0000
AR(4)	0.622827	0.041218	15.11067	0.0000
AR(5)	0.604058	0.024025	25.14246	0.0000
AR(6)	-0.846278	0.045364	-18.65520	0.0000
MA(1)	-0.420336	0.052253	-8.044319	0.0000
MA(2)	-0.743247	0.033472	-22.20513	0.0000
MA(3)	0.996690	0.044341	22.47796	0.0000
MA(4)	-0.599643	0.042134	-14.23196	0.0000
MA(5)	-0.635263	0.025718	-24.70080	0.0000
MA(6)	0.808267	0.048926	16.52018	0.0000
MA(7)	0.014161	0.011681	1.212396	0.2254
SIGMASQ	0.000119	7.62E-07	155.7902	0.0000

R-squared	0.007782	Mean dependent var	6.12E-05
Adjusted R-squared	0.006381	S.D. dependent var	0.010937
S.E. of regression	0.010902	Akaike info criterion	-6.198049
Sum squared resid	1.094127	Schwarz criterion	-6.187223
Log likelihood	28583.91	Hannan-Quinn criter.	-6.194370
Durbin-Watson stat	1.999776		

Inverted AR Roots	.90+.27i	.90-.27i	.30-.93i	.30+.93i
	-.97-.23i	-.97+.23i		
Inverted MA Roots	.89+.25i	.89-.25i	.30-.93i	.30+.93i
	-.02	-.97+.23i	-.97-.23i	

Lumber

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 6/30/2016
Included observations: 9204
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(2)	-0.026396	0.009053	-2.915653	0.0036
MA(9)	0.018995	0.009265	2.050212	0.0404
SIGMASQ	0.000466	2.97E-06	156.7903	0.0000

R-squared	0.001060	Mean dependent var	3.80E-05
Adjusted R-squared	0.000843	S.D. dependent var	0.021597
S.E. of regression	0.021588	Akaike info criterion	-4.833069
Sum squared resid	4.287891	Schwarz criterion	-4.830746
Log likelihood	22244.78	Hannan-Quinn criter.	-4.832279
Durbin-Watson stat	1.907483		

Inverted AR Roots	-.00+.16i	-.00-.16i		
Inverted MA Roots	.60+.22i	.60-.22i	.32-.56i	.32+.56i
	-.11-.63i	-.11+.63i	-.49-.41i	-.49+.41i
	-.64			

Eviews add in ARIMA Model

Dependent Variable: D(LB)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 6/30/2016
Included observations: 9204
Convergence achieved after 95 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.131247	0.406202	0.323109	0.7466
AR(2)	0.398074	0.302437	1.316221	0.1881
AR(3)	-0.036227	0.304669	-0.118905	0.9054
AR(4)	-0.427225	0.278638	-1.533265	0.1252
AR(5)	-0.097815	0.281185	-0.347868	0.7279
AR(6)	0.408671	0.296350	1.379015	0.1679
AR(7)	0.259976	0.264129	0.984276	0.3250
AR(8)	-0.243437	0.326376	-0.745879	0.4558
AR(9)	0.595491	0.270688	2.199922	0.0278
AR(10)	-0.050608	0.208247	-0.243019	0.8080
MA(1)	-0.086040	0.406309	-0.211761	0.8323
MA(2)	-0.431771	0.314542	-1.372698	0.1699
MA(3)	0.008752	0.315129	0.027772	0.9778
MA(4)	0.440837	0.297851	1.480059	0.1389
MA(5)	0.124004	0.288363	0.430029	0.6672
MA(6)	-0.418794	0.309269	-1.354145	0.1757
MA(7)	-0.298584	0.268817	-1.110735	0.2667
MA(8)	0.240471	0.340714	0.705788	0.4803
MA(9)	-0.559797	0.282233	-1.983458	0.0473
MA(10)	0.005279	0.213421	0.024733	0.9803
SIGMASQ	0.000462	3.48E-06	132.9052	0.0000

R-squared	0.008663	Mean dependent var	3.80E-05
Adjusted R-squared	0.006503	S.D. dependent var	0.021597
S.E. of regression	0.021526	Akaike info criterion	-4.836741
Sum squared resid	4.255257	Schwarz criterion	-4.820480
Log likelihood	22279.68	Hannan-Quinn criter.	-4.831214
Durbin-Watson stat	1.999979		

Inverted AR Roots	.99	.74+.66i	.74-.66i	.23-.74i
	.23+.74i	.09	-.51-.86i	-.51+.86i
	-.94+.34i	-.94-.34i		
Inverted MA Roots	1.00	.74+.66i	.74-.66i	.24+.72i
	.24-.72i	.01	-.51-.85i	-.51+.85i
	-.94+.34i	-.94-.34i		

Natural gas

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2/29/2000 8/01/2018
Included observations: 4601
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.536587	0.155579	-3.448980	0.0006
MA(1)	0.489751	0.160891	3.043995	0.0023
SIGMASQ	0.001137	1.22E-05	93.50114	0.0000

R-squared	0.003073	Mean dependent var	5.75E-06
Adjusted R-squared	0.002639	S.D. dependent var	0.033781
S.E. of regression	0.033736	Akaike info criterion	-3.939854
Sum squared resid	5.233045	Schwarz criterion	-3.935658
Log likelihood	9066.633	Hannan-Quinn criter.	-3.938377
Durbin-Watson stat	2.002800		

Inverted AR Roots	-.54
Inverted MA Roots	-.49

Eviews add in ARIMA Model

Dependent Variable: D(NG)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2/29/2000 8/01/2018
Included observations: 4601
Convergence achieved after 66 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.424171	0.392100	-1.081794	0.2794
AR(2)	0.859066	0.262015	3.278689	0.0011
AR(3)	0.777361	0.277241	2.803918	0.0051
AR(4)	-0.226646	0.368219	-0.615520	0.5382
MA(1)	0.378652	0.389636	0.971811	0.3312
MA(2)	-0.865500	0.250699	-3.452351	0.0006
MA(3)	-0.759442	0.273437	-2.777393	0.0055
MA(4)	0.251766	0.363342	0.692919	0.4884
SIGMASQ	0.001131	1.23E-05	92.34086	0.0000

R-squared	0.008454	Mean dependent var	5.75E-06
Adjusted R-squared	0.006726	S.D. dependent var	0.033781
S.E. of regression	0.033667	Akaike info criterion	-3.942592
Sum squared resid	5.204799	Schwarz criterion	-3.930006
Log likelihood	9078.932	Hannan-Quinn criter.	-3.938162
Durbin-Watson stat	2.000299		

Inverted AR Roots	.99	.24	-.83-.51i	-.83+.51i
Inverted MA Roots	1.00	.27	-.82-.52i	-.82+.52i

Nickel

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 7/08/2008 5/20/2019
Included observations: 2650
Convergence achieved after 34 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.704073	0.166654	4.224764	0.0000
MA(1)	-0.725218	0.162819	-4.454134	0.0000
SIGMASQ	0.000510	6.99E-06	72.89820	0.0000

R-squared	0.000803	Mean dependent var	-0.000208
Adjusted R-squared	0.000048	S.D. dependent var	0.022586
S.E. of regression	0.022586	Akaike info criterion	-4.741885
Sum squared resid	1.350248	Schwarz criterion	-4.735226
Log likelihood	6285.997	Hannan-Quinn criter.	-4.739474
Durbin-Watson stat	1.987466		

Inverted AR Roots	.70
Inverted MA Roots	.73

Eviews add in ARIMA Model

Dependent Variable: D(N)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/04/20 Time: 23:18
Sample: 7/08/2008 5/20/2019
Included observations: 2650
Convergence achieved after 36 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.031364	0.409520	-0.076588	0.9390
AR(2)	0.562778	0.222670	2.527411	0.0115
MA(1)	0.003073	0.413834	0.007425	0.9941
MA(2)	-0.566852	0.228034	-2.485817	0.0130
SIGMASQ	0.000509	7.27E-06	70.04814	0.0000

R-squared	0.001093	Mean dependent var	-0.000208
Adjusted R-squared	-0.000418	S.D. dependent var	0.022586
S.E. of regression	0.022591	Akaike info criterion	-4.740666
Sum squared resid	1.349856	Schwarz criterion	-4.729567
Log likelihood	6286.382	Hannan-Quinn criter.	-4.736648
Durbin-Watson stat	1.972120		

Inverted AR Roots	.73	-.77
Inverted MA Roots	.75	-.75

Oats

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/16/2000 7/02/2018
Included observations: 4573
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.072829	0.011032	6.601918	0.0000
MA(5)	-0.035807	0.013855	-2.584520	0.0098
SIGMASQ	0.000568	4.50E-06	126.1583	0.0000

R-squared	0.006463	Mean dependent var	0.000157
Adjusted R-squared	0.006028	S.D. dependent var	0.023909
S.E. of regression	0.023837	Akaike info criterion	-4.634510
Sum squared resid	2.596652	Schwarz criterion	-4.630293
Log likelihood	10599.81	Hannan-Quinn criter.	-4.633026
Durbin-Watson stat	1.995777		

Inverted AR Roots	.07			
Inverted MA Roots	.51	.16-.49i	.16+.49i	-.42+.30i
	-.42-.30i			

Eviews add in ARIMA Model

Dependent Variable: D(O)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/16/2000 7/02/2018
Included observations: 4573
Convergence achieved after 38 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.596651	0.136669	4.365678	0.0000
AR(2)	0.070498	0.190224	0.370606	0.7109
AR(3)	-0.577071	0.181721	-3.175583	0.0015
AR(4)	0.295662	0.163272	1.810852	0.0702
AR(5)	0.443954	0.125429	3.539472	0.0004
MA(1)	-0.527662	0.133208	-3.961175	0.0001
MA(2)	-0.142698	0.180958	-0.788570	0.4304
MA(3)	0.572567	0.167539	3.417520	0.0006
MA(4)	-0.249413	0.152518	-1.635309	0.1021
MA(5)	-0.515227	0.121193	-4.251291	0.0000
SIGMASQ	0.000565	5.60E-06	100.7780	0.0000

R-squared	0.012130	Mean dependent var	0.000157
Adjusted R-squared	0.009965	S.D. dependent var	0.023909
S.E. of regression	0.023790	Akaike info criterion	-4.636683
Sum squared resid	2.581840	Schwarz criterion	-4.621221
Log likelihood	10612.77	Hannan-Quinn criter.	-4.631239
Durbin-Watson stat	1.992585		

Inverted AR Roots	.94	.47+.87i	.47-.87i	-.64+.26i
	-.64-.26i			
Inverted MA Roots	.96	.47+.88i	.47-.88i	-.68+.29i
	-.68-.29i			

Palladium

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/30/1998 10/05/2018
Included observations: 4681
Convergence achieved after 60 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.388613	0.114727	-3.387284	0.0007
AR(3)	-0.821711	0.107554	-7.639954	0.0000
AR(4)	-0.564282	0.084837	-6.651354	0.0000
AR(6)	-0.260702	0.080667	-3.231831	0.0012
MA(1)	0.449520	0.114851	3.913948	0.0001
MA(3)	0.753975	0.106880	7.054428	0.0000
MA(4)	0.605103	0.084988	7.119861	0.0000
MA(6)	0.207084	0.083338	2.484863	0.0130
SIGMASQ	0.000538	2.43E-06	221.0203	0.0000

R-squared	0.010002	Mean dependent var	0.000304
Adjusted R-squared	0.008307	S.D. dependent var	0.023304
S.E. of regression	0.023207	Akaike info criterion	-4.686792
Sum squared resid	2.516182	Schwarz criterion	-4.674388
Log likelihood	10978.44	Hannan-Quinn criter.	-4.682430
Durbin-Watson stat	1.964148		

Inverted AR Roots	.55-.75i	.55+.75i	.12-.57i	.12+.57i
	-.87-.34i	-.87+.34i		
Inverted MA Roots	.54-.75i	.54+.75i	.10+.51i	.10-.51i
	-.87+.35i	-.87-.35i		

Eviews add in ARIMA Model

Dependent Variable: D(PA)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/30/1998 10/05/2018
Included observations: 4681
Convergence achieved after 38 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.212904	0.122380	1.739692	0.0820
AR(2)	0.096368	0.083524	1.153775	0.2487
AR(3)	-0.863260	0.078543	-10.99093	0.0000
AR(4)	0.432125	0.092014	4.696270	0.0000
AR(5)	-0.043616	0.098878	-0.441107	0.6592
AR(6)	-0.703196	0.086137	-8.163726	0.0000
AR(7)	0.117754	0.011821	9.961576	0.0000
AR(8)	-0.023233	0.018123	-1.281915	0.1999
MA(1)	-0.134781	0.122724	-1.098246	0.2722
MA(2)	-0.116380	0.083796	-1.388847	0.1649
MA(3)	0.815072	0.081016	10.06068	0.0000
MA(4)	-0.329938	0.088242	-3.739020	0.0002
MA(5)	-0.002884	0.092697	-0.031117	0.9752
MA(6)	0.684312	0.088338	7.746486	0.0000
SIGMASQ	0.000535	2.50E-06	214.0533	0.0000

R-squared	0.013897	Mean dependent var	0.000304
Adjusted R-squared	0.010938	S.D. dependent var	0.023304
S.E. of regression	0.023176	Akaike info criterion	-4.688157
Sum squared resid	2.506284	Schwarz criterion	-4.667485
Log likelihood	10987.63	Hannan-Quinn criter.	-4.680888
Durbin-Watson stat	2.000074		

Inverted AR Roots	.75+.53i	.75-.53i	.17+.96i	.17-.96i
	.08-.16i	.08+.16i	-.90-.24i	-.90+.24i
Inverted MA Roots	.77-.53i	.77+.53i	.18+.96i	.18-.96i
	-.88+.24i	-.88-.24i		

Platinum

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 4/29/1997 10/14/2018
Included observations: 4739
Convergence achieved after 129 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(2)	-0.687792	0.070276	-9.787019	0.0000
AR(3)	-0.180134	0.072715	-2.477268	0.0133
MA(2)	0.631626	0.072157	8.753561	0.0000
MA(3)	0.196898	0.076680	2.567792	0.0103
SIGMASQ	0.000360	9.80E-07	366.9897	0.0000

R-squared	0.006810	Mean dependent var	0.000172
Adjusted R-squared	0.005971	S.D. dependent var	0.019030
S.E. of regression	0.018973	Akaike info criterion	-5.090569
Sum squared resid	1.704070	Schwarz criterion	-5.083750
Log likelihood	12067.10	Hannan-Quinn criter.	-5.088173
Durbin-Watson stat	2.121557		

Inverted AR Roots	.12-.86i	.12+.86i	-.24
Inverted MA Roots	.14-.83i	.14+.83i	-.28

Eviews add in ARIMA Model

Dependent Variable: D(PL)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/06/20 Time: 12:11
Sample: 4/29/1997 10/14/2018
Included observations: 4739
Convergence achieved after 280 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.061643	0.003359	-18.35151	0.0000
AR(2)	-0.071115	0.008759	-8.118678	0.0000
AR(3)	0.005059	0.010561	0.479076	0.6319
AR(4)	0.044553	0.017153	2.597378	0.0094
SIGMASQ	0.000358	1.09E-06	327.8419	0.0000

R-squared	0.010742	Mean dependent var	0.000172
Adjusted R-squared	0.009906	S.D. dependent var	0.019030
S.E. of regression	0.018935	Akaike info criterion	-5.094537
Sum squared resid	1.697324	Schwarz criterion	-5.087717
Log likelihood	12076.50	Hannan-Quinn criter.	-5.092140
Durbin-Watson stat	1.998994		

Inverted AR Roots	.42	-.02-.50i	-.02+.50i	-.43

Rice

Custom ARIMA Model

Dependent Variable: D(LOG(CLOSE_PRICE_RR))
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/12/20 Time: 18:44
Sample: 3/22/2000 6/18/2018
Included observations: 4551
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(5)	-0.776502	0.125642	-6.180289	0.0000
AR(6)	0.053867	0.012334	4.367412	0.0000
MA(1)	0.057240	0.012431	4.604527	0.0000
MA(5)	0.755016	0.130562	5.782829	0.0000
SIGMASQ	0.000305	1.88E-06	161.6859	0.0000

R-squared	0.004608	Mean dependent var	0.000185
Adjusted R-squared	0.003732	S.D. dependent var	0.017498
S.E. of regression	0.017465	Akaike info criterion	-5.256147
Sum squared resid	1.386629	Schwarz criterion	-5.249090
Log likelihood	11965.36	Hannan-Quinn criter.	-5.253662
Durbin-Watson stat	1.997603		

Inverted AR Roots	.75-.56i	.75+.56i	.07	-.31+.90i
	-.31-.90i	-.96		
Inverted MA Roots	.75+.56i	.75-.56i	-.30-.90i	-.30+.90i
	-.96			

Eviews add in ARIMA Model

Dependent Variable: D(LOG(CLOSE_PRICE_RR))
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/12/20 Time: 20:00
Sample: 3/22/2000 6/18/2018
Included observations: 4551
Convergence achieved after 6 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	0.057412	0.012410	4.626348	0.0000
SIGMASQ	0.000305	1.72E-06	177.2762	0.0000

R-squared	0.003120	Mean dependent var	0.000185
Adjusted R-squared	0.002901	S.D. dependent var	0.017498
S.E. of regression	0.017472	Akaike info criterion	-5.255977
Sum squared resid	1.388701	Schwarz criterion	-5.253154
Log likelihood	11961.98	Hannan-Quinn criter.	-5.254983
Durbin-Watson stat	2.000216		

Inverted MA Roots	-.06

Silver

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2/29/2000 10/12/2018
Included observations: 4648
Convergence achieved after 85 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.017591	0.045898	-22.17058	0.0000
AR(3)	0.531926	0.040550	13.11766	0.0000
MA(1)	1.004673	0.048900	20.54538	0.0000
MA(3)	-0.522339	0.043763	-11.93564	0.0000
SIGMASQ	0.000378	3.67E-06	102.9781	0.0000

R-squared	0.001384	Mean dependent var	0.000228
Adjusted R-squared	0.000524	S.D. dependent var	0.019455
S.E. of regression	0.019450	Akaike info criterion	-5.040828
Sum squared resid	1.756515	Schwarz criterion	-5.033896
Log likelihood	11719.89	Hannan-Quinn criter.	-5.038390
Durbin-Watson stat	2.014882		

Inverted AR Roots	.58	-.80+.53i	-.80-.53i
Inverted MA Roots	.58	-.79-.53i	-.79+.53i

Eviews add in ARIMA Model

Dependent Variable: D(SI)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2/29/2000 10/12/2018
Included observations: 4648
Convergence achieved after 80 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.400663	0.451684	-0.887042	0.3751
AR(2)	-0.141104	0.166873	-0.845578	0.3978
AR(3)	0.676077	0.179884	3.758402	0.0002
AR(4)	0.684546	0.433880	1.577731	0.1147
AR(5)	0.006434	0.012598	0.510684	0.6096
AR(6)	-0.013400	0.010251	-1.307191	0.1912
MA(1)	0.380229	0.451693	0.841786	0.4000
MA(2)	0.145624	0.174553	0.834267	0.4042
MA(3)	-0.672151	0.181867	-3.695850	0.0002
MA(4)	-0.687605	0.439417	-1.564810	0.1177
SIGMASQ	0.000377	3.79E-06	99.51739	0.0000

R-squared	0.003834	Mean dependent var	0.000228
Adjusted R-squared	0.001686	S.D. dependent var	0.019455
S.E. of regression	0.019439	Akaike info criterion	-5.040642
Sum squared resid	1.752205	Schwarz criterion	-5.025391
Log likelihood	11725.45	Hannan-Quinn criter.	-5.035277
Durbin-Watson stat	1.999843		

Inverted AR Roots	.96	.13	-.16	-.31+.94i
	-.31-.94i	-.70		
Inverted MA Roots	.96	-.31+.95i	-.31-.95i	-.72

Soybean meal

Custom ARIMA Model

Dependent Variable: D(LOG(CLOSE_PRICE_SM))
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 7087
Included observations: 7086
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.022936	0.007773	2.950890	0.0032
MA(5)	-0.049173	0.008641	-5.690831	0.0000
SIGMASQ	0.000322	2.05E-06	156.7937	0.0000

R-squared	0.002914	Mean dependent var	7.70E-05
Adjusted R-squared	0.002632	S.D. dependent var	0.017970
S.E. of regression	0.017946	Akaike info criterion	-5.202451
Sum squared resid	2.281196	Schwarz criterion	-5.199544
Log likelihood	18435.28	Hannan-Quinn criter.	-5.201450
Durbin-Watson stat	2.000065		

Inverted AR Roots	.02			
Inverted MA Roots	.55	.17+.52i	.17-.52i	-.44-.32i
	-.44+.32i			

Eviews add in ARIMA Model

Dependent Variable: D(LOG(CLOSE_PRICE_SM))
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 7087
Included observations: 7086
Convergence achieved after 43 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.627473	0.230237	-2.725333	0.0064
AR(2)	0.520253	0.251337	2.069940	0.0385
AR(3)	0.662764	0.038251	17.32670	0.0000
AR(4)	-0.378599	0.153846	-2.460899	0.0139
AR(5)	-1.017816	0.039247	-25.93369	0.0000
AR(6)	-0.373362	0.246310	-1.515824	0.1296
AR(7)	0.425341	0.203065	2.094604	0.0362
MA(1)	0.650848	0.232867	2.794931	0.0052
MA(2)	-0.508509	0.255194	-1.992637	0.0463
MA(3)	-0.682009	0.041744	-16.33802	0.0000
MA(4)	0.355172	0.163410	2.173496	0.0298
MA(5)	0.998490	0.042196	23.66296	0.0000
MA(6)	0.409757	0.244373	1.676766	0.0936
MA(7)	-0.389039	0.205136	-1.896487	0.0579
SIGMASQ	0.000320	2.22E-06	144.0389	0.0000

R-squared	0.009740	Mean dependent var	7.70E-05
Adjusted R-squared	0.007779	S.D. dependent var	0.017970
S.E. of regression	0.017900	Akaike info criterion	-5.205900
Sum squared resid	2.265580	Schwarz criterion	-5.191366
Log likelihood	18459.51	Hannan-Quinn criter.	-5.200895
Durbin-Watson stat	2.004372		

Inverted AR Roots	.83-.54i	.83+.54i	.48	-.46-.86i
	-.46+.86i	-.92-.34i	-.92+.34i	
Inverted MA Roots	.83-.53i	.83+.53i	.45	-.46-.85i
	-.46+.85i	-.92+.35i	-.92-.35i	

Soybean oil

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 9416
Included observations: 9415
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.923171	0.154682	-5.968197	0.0000
AR(2)	-0.629155	0.099960	-6.294063	0.0000
MA(1)	0.961855	0.154017	6.245102	0.0000
MA(2)	0.644836	0.099856	6.457660	0.0000
SIGMASQ	0.000227	2.22E-06	102.1791	0.0000

R-squared	0.002562	Mean dependent var	3.00E-05
Adjusted R-squared	0.002138	S.D. dependent var	0.015077
S.E. of regression	0.015061	Akaike info criterion	-5.552856
Sum squared resid	2.134568	Schwarz criterion	-5.549058
Log likelihood	26145.07	Hannan-Quinn criter.	-5.551566
Durbin-Watson stat	1.997964		

Inverted AR Roots	-.46+.65i	-.46-.65i
Inverted MA Roots	-.48-.64i	-.48+.64i

Eviews add in ARIMA Model

Dependent Variable: D(BO)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 9416
Included observations: 9415
Convergence achieved after 212 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.906416	0.278541	3.254151	0.0011
AR(2)	-0.778312	0.338959	-2.296179	0.0217
AR(3)	0.413581	0.317025	1.304570	0.1921
AR(4)	-0.216019	0.256417	-0.842450	0.3996
AR(5)	0.553218	0.203826	2.714172	0.0067
MA(1)	-0.867704	0.278210	-3.118884	0.0018
MA(2)	0.725739	0.329027	2.205712	0.0274
MA(3)	-0.372928	0.299917	-1.243436	0.2137
MA(4)	0.206143	0.243095	0.847992	0.3965
MA(5)	-0.570262	0.189026	-3.016837	0.0026
MA(6)	0.010960	0.022696	0.482913	0.6292
MA(7)	0.001577	0.015209	0.103663	0.9174
SIGMASQ	0.000226	2.22E-06	101.7036	0.0000

R-squared	0.004523	Mean dependent var	3.00E-05
Adjusted R-squared	0.003252	S.D. dependent var	0.015077
S.E. of regression	0.015053	Akaike info criterion	-5.553114
Sum squared resid	2.130371	Schwarz criterion	-5.543241
Log likelihood	26154.28	Hannan-Quinn criter.	-5.549762
Durbin-Watson stat	1.999837		

Inverted AR Roots	.96	.42-.90i	.42+.90i	-.44-.63i
	-.44+.63i			
Inverted MA Roots	.95	.41+.90i	.41-.90i	.06
	-.04	-.47+.62i	-.47-.62i	

Soybeans

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 7123
Included observations: 7122
Convergence achieved after 103 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.969459	0.024495	39.57824	0.0000
AR(2)	0.472751	0.030952	15.27348	0.0000
AR(3)	-1.501121	0.039604	-37.90295	0.0000
AR(4)	0.384171	0.037083	10.35984	0.0000
AR(5)	0.889122	0.036246	24.53014	0.0000
AR(6)	-0.857497	0.026712	-32.10111	0.0000
MA(1)	-0.967749	0.023463	-41.24559	0.0000
MA(2)	-0.472714	0.028419	-16.63366	0.0000
MA(3)	1.510722	0.034754	43.46853	0.0000
MA(4)	-0.395800	0.033337	-11.87277	0.0000
MA(5)	-0.916165	0.030936	-29.61523	0.0000
MA(6)	0.893387	0.023649	37.77678	0.0000
SIGMASQ	0.000237	1.36E-06	173.7096	0.0000

R-squared	0.007015	Mean dependent var	7.17E-05
Adjusted R-squared	0.005339	S.D. dependent var	0.015434
S.E. of regression	0.015393	Akaike info criterion	-5.507933
Sum squared resid	1.684475	Schwarz criterion	-5.495391
Log likelihood	19626.75	Hannan-Quinn criter.	-5.503615
Durbin-Watson stat	2.004673		

Inverted AR Roots	.89-.42i	.89+.42i	.51+.81i	.51-.81i
	-.92+.34i	-.92-.34i		
Inverted MA Roots	.89+.42i	.89-.42i	.51-.82i	.51+.82i
	-.92-.35i	-.92+.35i		

Eviews add in ARIMA Model

Dependent Variable: D(S)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/06/20 Time: 18:45
Sample: 2 7123
Included observations: 7122
Convergence achieved after 148 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.280178	0.032763	8.551638	0.0000
AR(2)	0.182704	0.032284	5.659267	0.0000
AR(3)	-0.212496	0.034349	-6.186360	0.0000
AR(4)	-0.220778	0.032369	-6.820689	0.0000
AR(5)	-0.332621	0.030964	-10.74221	0.0000
AR(6)	0.152895	0.032401	4.718856	0.0000
AR(7)	0.261388	0.032282	8.097077	0.0000
AR(8)	-0.826259	0.032655	-25.30232	0.0000
AR(9)	0.005587	0.008652	0.645723	0.5185
AR(10)	-0.026064	0.010146	-2.568825	0.0102
MA(1)	-0.280284	0.032815	-8.541445	0.0000
MA(2)	-0.191644	0.031479	-6.087992	0.0000
MA(3)	0.226455	0.031057	7.291550	0.0000
MA(4)	0.209954	0.028779	7.295295	0.0000
MA(5)	0.307177	0.027502	11.16932	0.0000
MA(6)	-0.146971	0.029380	-5.002454	0.0000
MA(7)	-0.275908	0.028865	-9.558631	0.0000
MA(8)	0.869968	0.028888	30.11526	0.0000
SIGMASQ	0.000236	1.41E-06	166.9696	0.0000

R-squared	0.009084	Mean dependent var	7.17E-05
Adjusted R-squared	0.006573	S.D. dependent var	0.015434
S.E. of regression	0.015384	Akaike info criterion	-5.508321
Sum squared resid	1.680965	Schwarz criterion	-5.489991
Log likelihood	19634.13	Hannan-Quinn criter.	-5.502010
Durbin-Watson stat	1.999713		

Inverted AR Roots	.89+.42i	.89-.42i	.52-.80i	.52+.80i
	-.00+.18i	-.00-.18i	-.35-.92i	-.35+.92i
	-.92-.34i	-.92+.34i		
Inverted MA Roots	.90+.42i	.90-.42i	.52-.82i	.52+.82i
	-.35-.93i	-.35+.93i	-.92-.34i	-.92+.34i

Sugar

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 6/29/2016
Included observations: 9191
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(3)	0.017339	0.007563	2.292547	0.0219
MA(2)	-0.062553	0.006429	-9.729878	0.0000
SIGMASQ	0.000817	3.48E-06	234.4673	0.0000

R-squared	0.004409	Mean dependent var	2.55E-05
Adjusted R-squared	0.004192	S.D. dependent var	0.028648
S.E. of regression	0.028588	Akaike info criterion	-4.271353
Sum squared resid	7.508956	Schwarz criterion	-4.269027
Log likelihood	19632.00	Hannan-Quinn criter.	-4.270562
Durbin-Watson stat	2.177634		

Inverted AR Roots	.26	-.13-.22i	-.13+.22i
Inverted MA Roots	.25	-.25	

Eviews add in ARIMA Model

Dependent Variable: D(SB)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 12/28/1979 6/29/2016
Included observations: 9191
Convergence achieved after 331 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.535685	0.005755	-93.07525	0.0000
AR(2)	-0.020939	0.007292	-2.871373	0.0041
AR(3)	-0.463549	0.009039	-51.28213	0.0000
AR(4)	-1.018395	0.005783	-176.0931	0.0000
AR(5)	-0.126977	0.005686	-22.33057	0.0000
AR(6)	-0.062769	0.008060	-7.787693	0.0000
AR(7)	0.013792	0.008067	1.709586	0.0874
MA(1)	0.446368	0.003508	127.2283	0.0000
MA(2)	-0.089498	0.002331	-38.38793	0.0000
MA(3)	0.452497	0.002423	186.7535	0.0000
MA(4)	0.992930	0.003469	286.2486	0.0000
SIGMASQ	0.000808	4.03E-06	200.6515	0.0000

R-squared	0.015140	Mean dependent var	2.55E-05
Adjusted R-squared	0.013960	S.D. dependent var	0.028648
S.E. of regression	0.028447	Akaike info criterion	-4.280007
Sum squared resid	7.428024	Schwarz criterion	-4.270703
Log likelihood	19680.77	Hannan-Quinn criter.	-4.276844
Durbin-Watson stat	1.999466		

Inverted AR Roots	.62+.79i	.62-.79i	.14	-.12+.30i
	-.12-.30i	-.84-.53i	-.84+.53i	
Inverted MA Roots	.62-.79i	.62+.79i	-.84+.53i	-.84-.53i

Tin

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 7/08/2008 5/20/2019
Included observations: 2650
Convergence achieved after 71 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.223981	0.126546	9.672222	0.0000
AR(2)	-1.919734	0.064003	-29.99456	0.0000
AR(3)	1.698715	0.201243	8.441117	0.0000
AR(4)	-1.216851	0.061983	-19.63203	0.0000
AR(5)	0.737455	0.112668	6.545393	0.0000
MA(1)	-1.186969	0.120414	-9.857429	0.0000
MA(2)	1.887043	0.054237	34.79241	0.0000
MA(3)	-1.677347	0.189775	-8.838624	0.0000
MA(4)	1.197505	0.052233	22.92606	0.0000
MA(5)	-0.768283	0.107040	-7.177506	0.0000
SIGMASQ	0.000316	3.52E-06	89.97596	0.0000

R-squared	0.019324	Mean dependent var	-6.01E-05
Adjusted R-squared	0.015608	S.D. dependent var	0.017963
S.E. of regression	0.017822	Akaike info criterion	-5.212475
Sum squared resid	0.838193	Schwarz criterion	-5.188058
Log likelihood	6917.530	Hannan-Quinn criter.	-5.203637
Durbin-Watson stat	1.998511		

Inverted AR Roots	.82	.39-.88i	.39+.88i	-.19-.96i
	-.19+.96i			
Inverted MA Roots	.84	.38-.90i	.38+.90i	-.21-.96i
	-.21+.96i			

Eviews add in ARIMA Model

Dependent Variable: D(T)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 7/08/2008 5/20/2019
Included observations: 2650
Convergence achieved after 124 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.387766	0.023581	58.85126	0.0000
AR(2)	-1.013621	0.035963	-28.18502	0.0000
AR(3)	0.597614	0.030330	19.70393	0.0000
AR(4)	0.667497	0.028506	23.41562	0.0000
AR(5)	-1.054915	0.032788	-32.17411	0.0000
AR(6)	1.268173	0.034852	36.38745	0.0000
AR(7)	-0.881788	0.021283	-41.43171	0.0000
MA(1)	-1.344111	0.022235	-60.45064	0.0000
MA(2)	0.963832	0.034565	27.88432	0.0000
MA(3)	-0.595844	0.028614	-20.82331	0.0000
MA(4)	-0.669934	0.026720	-25.07190	0.0000
MA(5)	1.012254	0.030194	33.52545	0.0000
MA(6)	-1.246971	0.033514	-37.20713	0.0000
MA(7)	0.911670	0.020798	43.83357	0.0000
SIGMASQ	0.000315	3.68E-06	85.68040	0.0000

R-squared	0.023006	Mean dependent var	-6.01E-05
Adjusted R-squared	0.017815	S.D. dependent var	0.017963
S.E. of regression	0.017802	Akaike info criterion	-5.212939
Sum squared resid	0.835046	Schwarz criterion	-5.179643
Log likelihood	6922.145	Hannan-Quinn criter.	-5.200887
Durbin-Watson stat	2.015771		

Inverted AR Roots	.99-.07i	.99+.07i	.39-.89i	.39+.89i
	-.19-.96i	-.19+.96i	-.99	
Inverted MA Roots	.99-.07i	.99+.07i	.38-.90i	.38+.90i
	-.21-.96i	-.21+.96i	-1.00	

Wheat

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/24/2000 7/02/2018
Included observations: 4571
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(2)	-0.795925	0.323592	-2.459653	0.0139
MA(2)	0.786953	0.329410	2.388976	0.0169
SIGMASQ	0.000329	5.09E-06	64.66512	0.0000

R-squared	0.000187	Mean dependent var	0.000103
Adjusted R-squared	-0.000251	S.D. dependent var	0.018143
S.E. of regression	0.018146	Akaike info criterion	-5.180130
Sum squared resid	1.504059	Schwarz criterion	-5.175912
Log likelihood	11842.19	Hannan-Quinn criter.	-5.178645
Durbin-Watson stat	1.929099		

Inverted AR Roots	-.00+.89i	-.00-.89i
Inverted MA Roots	-.00+.89i	-.00-.89i

Eviews add in ARIMA Model

Dependent Variable: D(KW)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 3/24/2000 7/02/2018
Included observations: 4571
Convergence achieved after 55 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.742599	0.084802	-8.756829	0.0000
AR(2)	-0.891952	0.049261	-18.10652	0.0000
AR(3)	-0.370545	0.066840	-5.543752	0.0000
AR(4)	-0.875260	0.058622	-14.93064	0.0000
AR(5)	-0.758321	0.054578	-13.89424	0.0000
AR(6)	-0.844800	0.073474	-11.49791	0.0000
MA(1)	0.767995	0.084088	9.133257	0.0000
MA(2)	0.905959	0.046483	19.48997	0.0000
MA(3)	0.394499	0.064712	6.096256	0.0000
MA(4)	0.890508	0.055974	15.90929	0.0000
MA(5)	0.797180	0.052928	15.06166	0.0000
MA(6)	0.860824	0.073684	11.68259	0.0000
SIGMASQ	0.000327	5.15E-06	63.51907	0.0000

R-squared	0.006228	Mean dependent var	0.000103
Adjusted R-squared	0.003611	S.D. dependent var	0.018143
S.E. of regression	0.018110	Akaike info criterion	-5.181766
Sum squared resid	1.494972	Schwarz criterion	-5.163487
Log likelihood	11855.93	Hannan-Quinn criter.	-5.175330
Durbin-Watson stat	1.979494		

Inverted AR Roots	.67-.73i	.67+.73i	-.28+.94i	-.28-.94i
	-.77+.56i	-.77-.56i		
Inverted MA Roots	.67+.73i	.67-.73i	-.28+.94i	-.28-.94i
	-.77-.56i	-.77+.56i		

Zinc

Custom ARIMA Model

Dependent Variable: R
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2/21/2008 5/08/2019
Included observations: 2729
Convergence achieved after 143 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.115005	0.071149	-15.67143	0.0000
AR(2)	-1.132730	0.061969	-18.27899	0.0000
AR(3)	-0.754955	0.073739	-10.23819	0.0000
MA(1)	1.068533	0.080463	13.27980	0.0000
MA(2)	1.084864	0.070848	15.31260	0.0000
MA(3)	0.691821	0.083099	8.325279	0.0000
SIGMASQ	0.000401	6.00E-06	66.80805	0.0000

R-squared	0.009522	Mean dependent var	4.45E-05
Adjusted R-squared	0.007338	S.D. dependent var	0.020128
S.E. of regression	0.020054	Akaike info criterion	-4.978152
Sum squared resid	1.094732	Schwarz criterion	-4.962989
Log likelihood	6799.689	Hannan-Quinn criter.	-4.972672
Durbin-Watson stat	2.007457		

Inverted AR Roots	-.14-.94i	-.14+.94i	-.84
Inverted MA Roots	-.14-.92i	-.14+.92i	-.80

Eviews add in ARIMA Model

Dependent Variable: D(Z)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/06/20 Time: 23:55
Sample: 2/21/2008 5/08/2019
Included observations: 2729
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.320178	9.575782	-0.033436	0.9733
AR(2)	-0.592367	6.188591	-0.095719	0.9238
AR(3)	-0.478171	7.566297	-0.063197	0.9496
AR(4)	0.187332	7.068107	0.026504	0.9789
AR(5)	-0.060682	0.431924	-0.140492	0.8883
AR(6)	0.004420	0.703803	0.006279	0.9950
AR(7)	0.003793	0.185556	0.020441	0.9837
MA(1)	0.265667	9.574663	0.027747	0.9779
MA(2)	0.562904	5.666016	0.099347	0.9209
MA(3)	0.415984	7.114392	0.058471	0.9534
MA(4)	-0.207611	6.330544	-0.032795	0.9738
SIGMASQ	0.000400	5.87E-06	68.22069	0.0000

R-squared	0.011309	Mean dependent var	4.45E-05
Adjusted R-squared	0.007307	S.D. dependent var	0.020128
S.E. of regression	0.020055	Akaike info criterion	-4.976290
Sum squared resid	1.092756	Schwarz criterion	-4.950295
Log likelihood	6802.148	Hannan-Quinn criter.	-4.966895
Durbin-Watson stat	1.993886		

Inverted AR Roots	.28	.13+.31i	.13-.31i	.06+.92i
	.06-.92i	-.17	-.81	
Inverted MA Roots	.32	.08+.93i	.08-.93i	-.75

11.3 APPENDIX III: Jumps graphs for daily returns

Test for additive jumps in GARCH models of Laurent, Lecourt and Palm (2016)

Gold

series DL_gold

Critical level of the test: 0.25

Number of detected jumps: 42

Proportion of detected jumps: 0.00822401

Critical value, i.e. G(Beta)*Sn+Cn: 3.65537

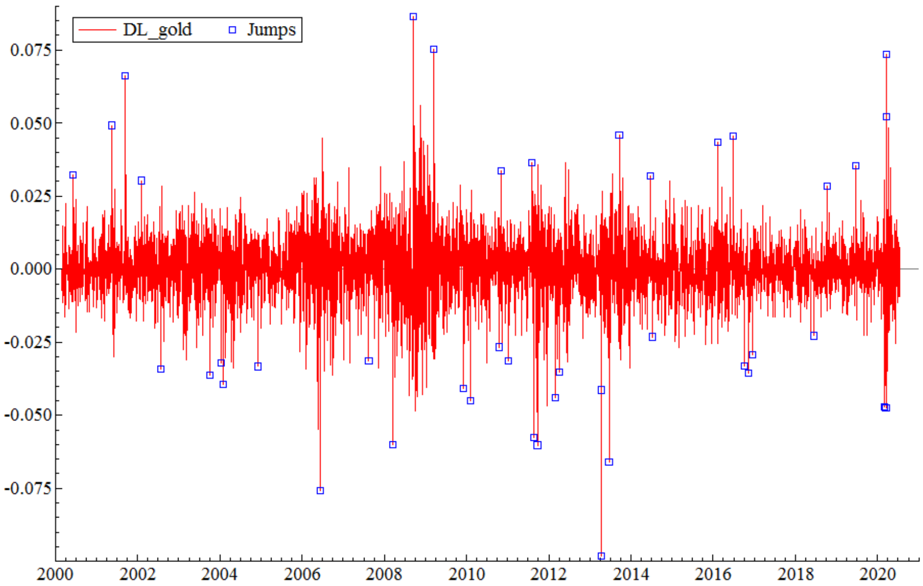

Figure 141: Jumps graph of gold daily log returns

Silver

series DL_silver

Critical level of the test: 0.25

Number of detected jumps: 57

Proportion of detected jumps: 0.0110358

Critical value, i.e. G(Beta)*Sn+Cn: 3.65826

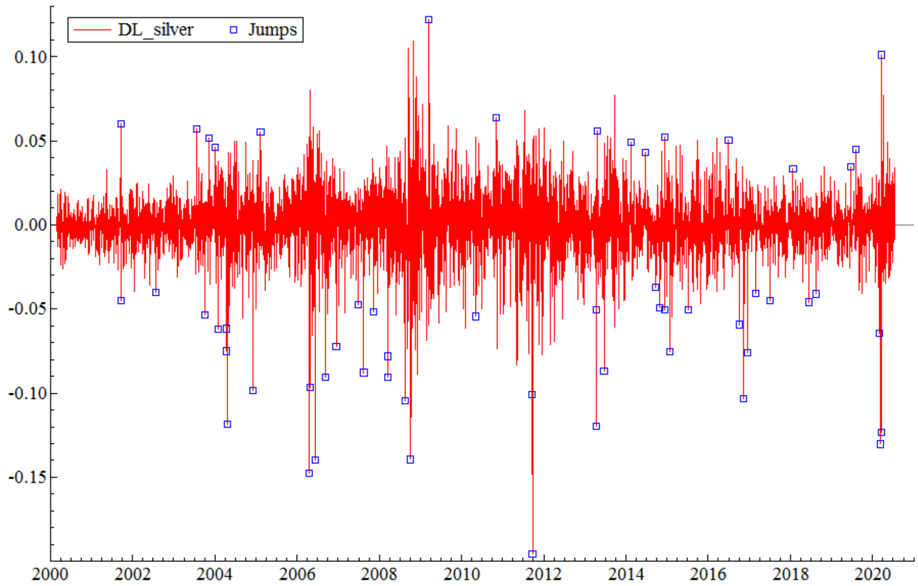

Figure 142: Jumps graph of silver daily log returns

Platinum

series DL_platinum

Critical level of the test: 0.25

Number of detected jumps: 53

Proportion of detected jumps: 0.0100646

Critical value, i.e. G(Beta)*Sn+Cn: 3.6632

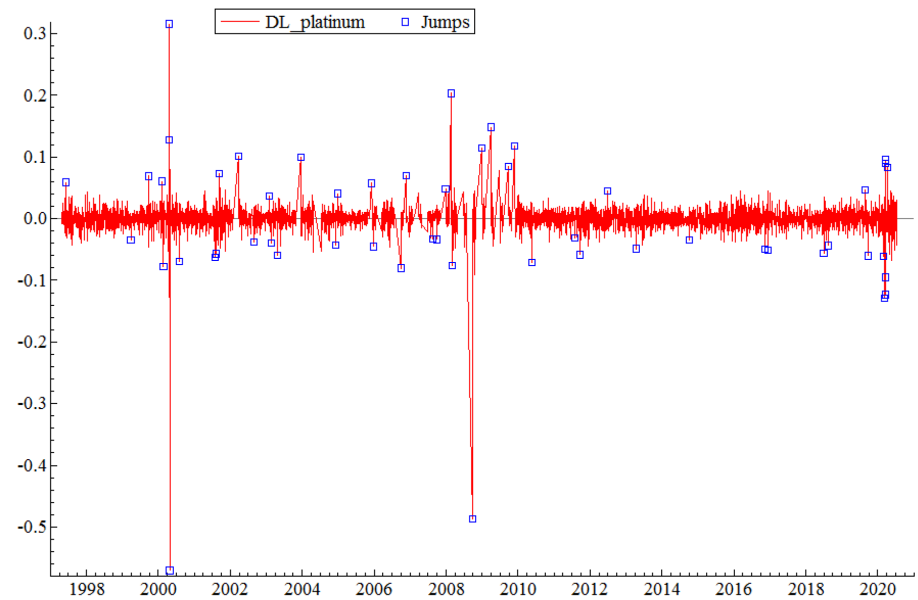

Figure 143: Jumps graph of platinum daily log returns

Paladium

series DL_paladium

Critical level of the test: 0.25

Number of detected jumps: 48

Proportion of detected jumps: 0.00922899

Critical value, i.e. G(Beta)*Sn+Cn: 3.66003

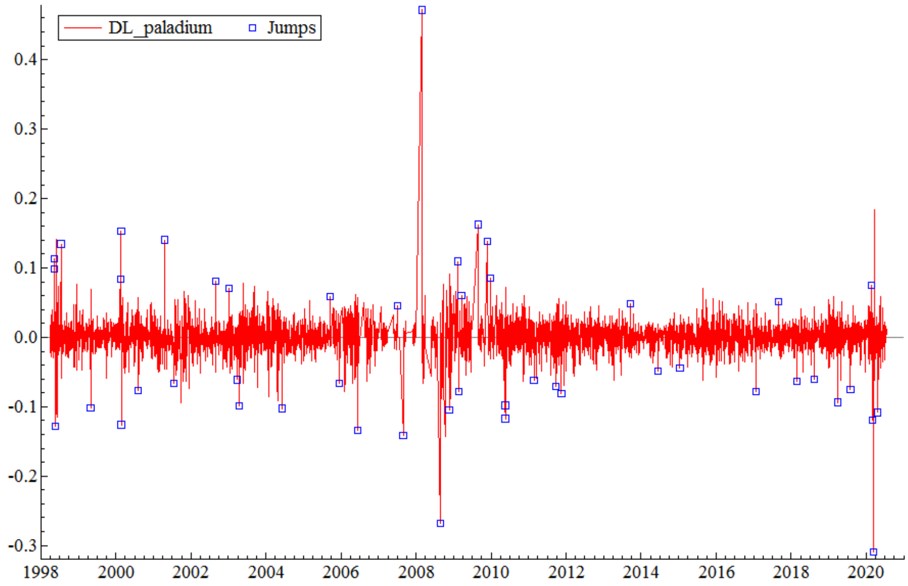

Figure 144: Jumps graph of paladium daily log returns

Aluminum

DL_aluminum

Critical level of the test: 0.25

Number of detected jumps: 6

Proportion of detected jumps: 0.00665927

Critical value, i.e. G(Beta)*Sn+Cn: 3.18515

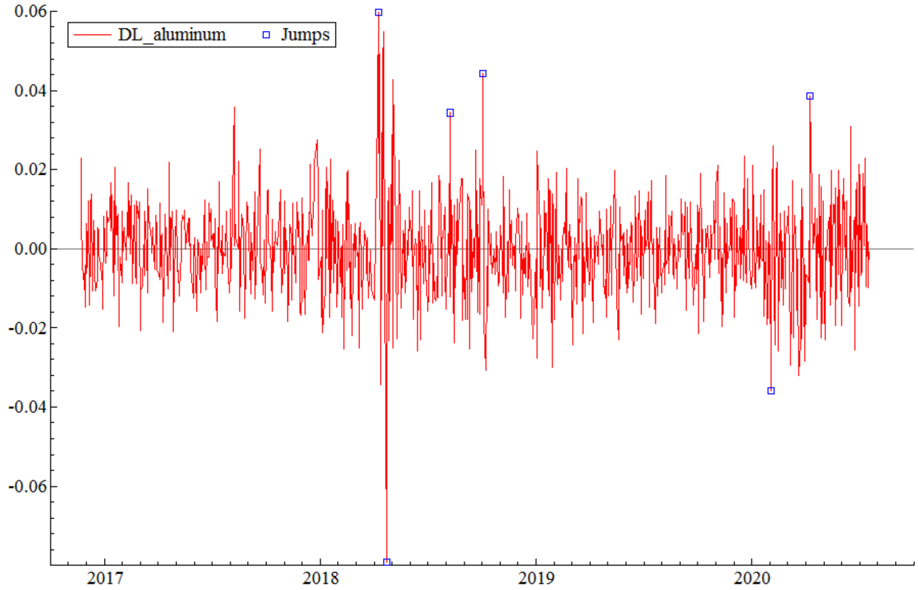

Figure 145: Jumps graph of aluminum daily log returns

Copper

DL_copper

Critical level of the test: 0.25

Number of detected jumps: 34

Proportion of detected jumps: 0.00667714

Critical value, i.e. G(Beta)*Sn+Cn: 3.65462

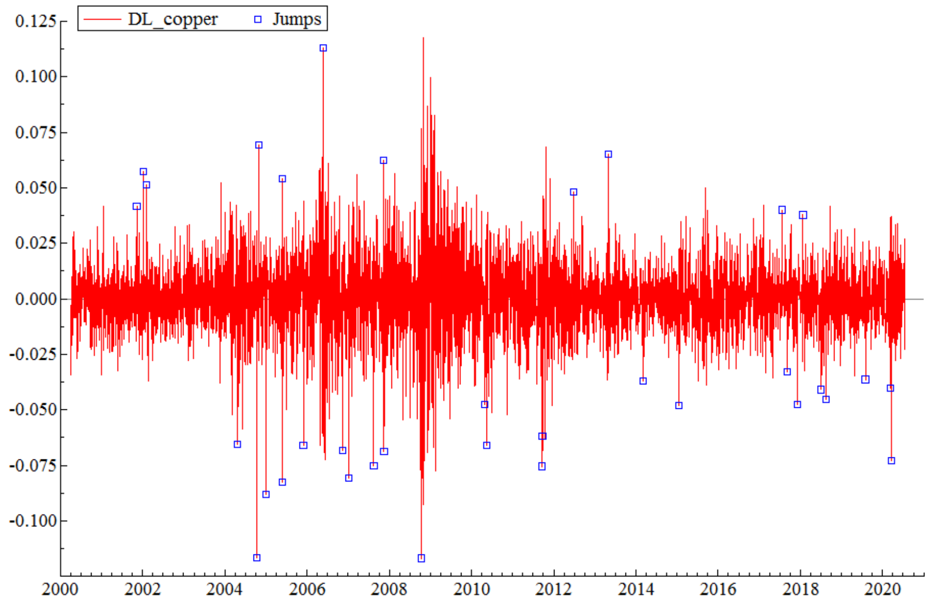

Figure 146: Jumps graph of copper daily log returns

Lead

series DL_lead

Critical level of the test: 0.25

Number of detected jumps: 21

Proportion of detected jumps: 0.00713073

Critical value, i.e. G(Beta)*Sn+Cn: 3.51211

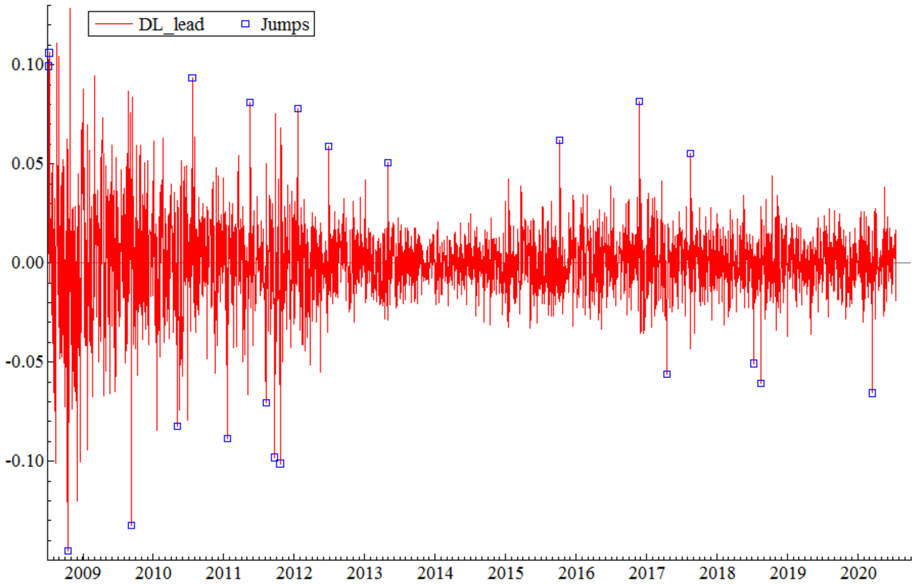

Figure 147: Jumps graph of lead daily log returns

Nickel

series DL_nickel

Critical level of the test: 0.25

Number of detected jumps: 16

Proportion of detected jumps: 0.00543294

Critical value, i.e. G(Beta)*Sn+Cn: 3.51211

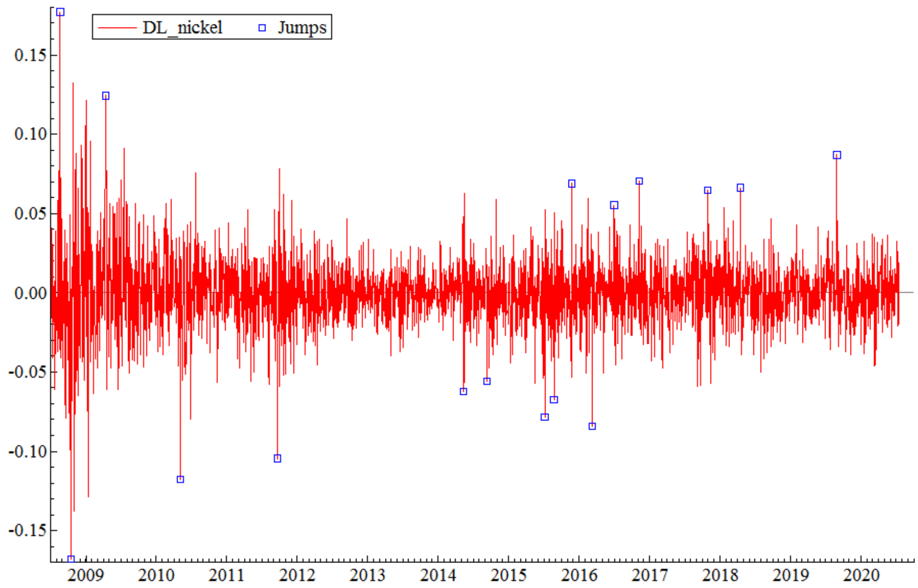

Figure 148: Jumps graph of nickel daily log returns

Tin

series DL_tin

Critical level of the test: 0.25

Number of detected jumps: 37

Proportion of detected jumps: 0.0125637

Critical value, i.e. G(Beta)*Sn+Cn: 3.51211

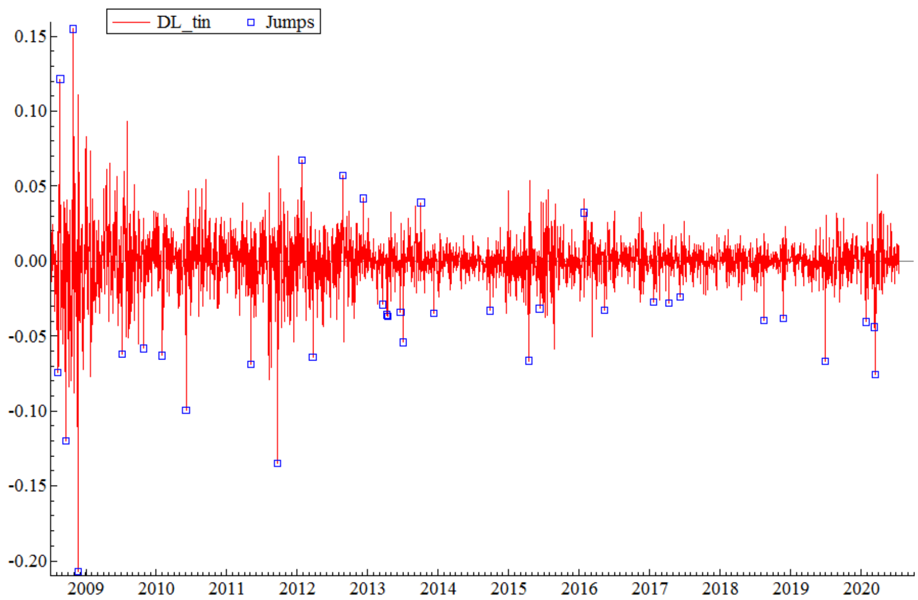

Figure 149: Jumps graph of tin daily log returns

Zinc

series DL_zinc

Critical level of the test: 0.25

Number of detected jumps: 15

Proportion of detected jumps: 0.00494723

Critical value, i.e. G(Beta)*Sn+Cn: 3.51981

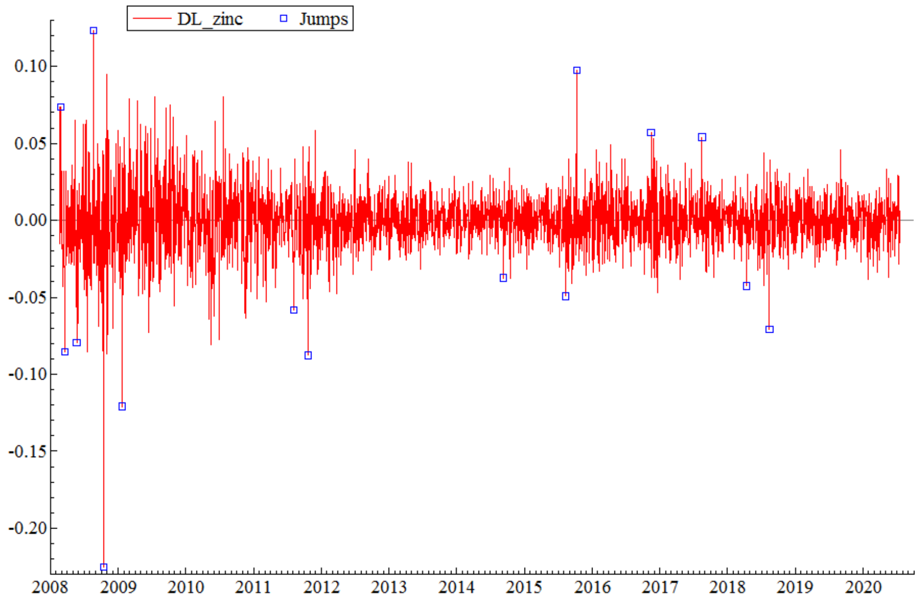

Figure 150: Jumps graph of zinc daily log returns

Crude Oil

DL_crude oil

Critical level of the test: 0.25

Number of detected jumps: 28

Proportion of detected jumps: 0.00549666

Critical value, i.e. G(Beta)*Sn+Cn: 3.65472

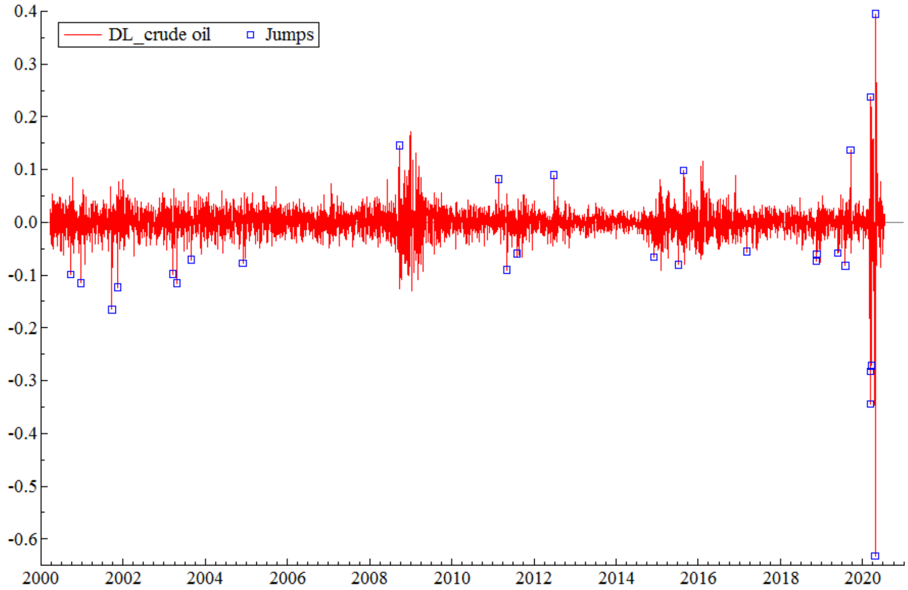

Figure 151: Jumps graph of crude oil daily log returns

Brent Oil

DL_brent oil

Critical level of the test: 0.25

Number of detected jumps: 45

Proportion of detected jumps: 0.00550055

Critical value, i.e. G(Beta)*Sn+Cn: 3.77418

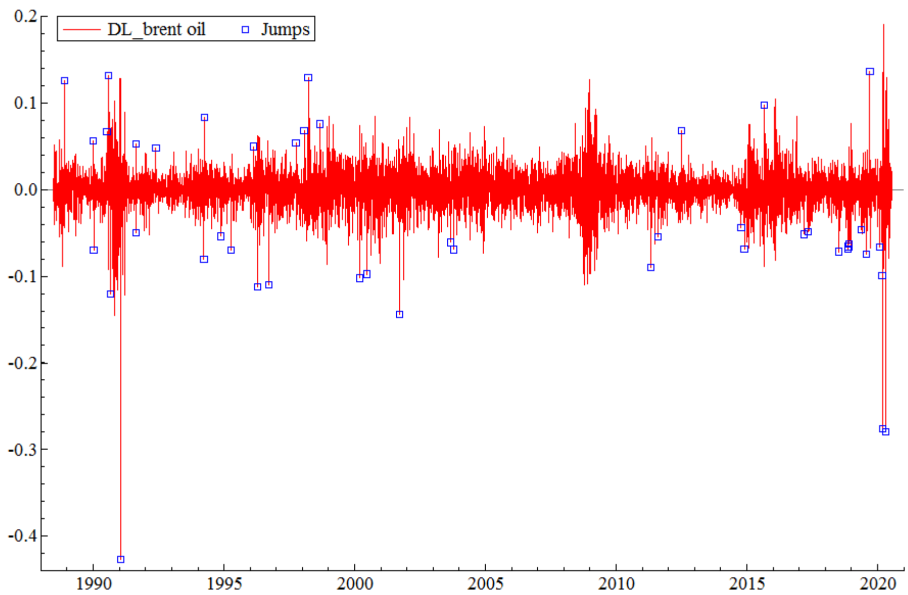

Figure 152: Jumps graph of brent oil daily log returns

Gasoline

series DL_gasoline

Critical level of the test: 0.25

Number of detected jumps: 49

Proportion of detected jumps: 0.0121982

Critical value, i.e. G(Beta)*Sn+Cn: 3.59351

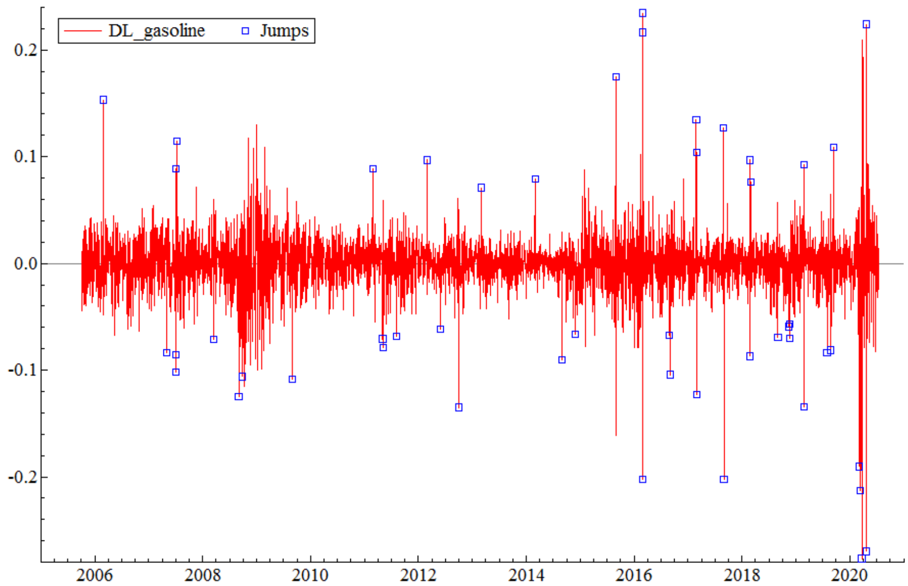

Figure 153: Jumps graph of gasoline daily log returns

Heating oil

DL_heating oil

Critical level of the test: 0.25

Number of detected jumps: 28

Proportion of detected jumps: 0.00547624

Critical value, i.e. G(Beta)*Sn+Cn: 3.65567

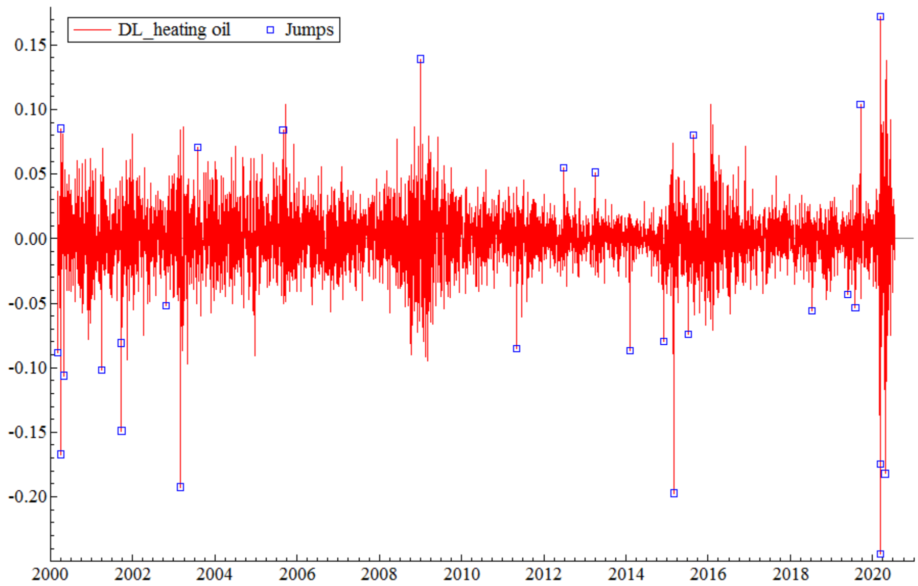

Figure 154: Jumps graph of heating oil daily log returns

Natural gas

series DL_natural gas

Critical level of the test: 0.25

Number of detected jumps: 25

Proportion of detected jumps: 0.00489045

Critical value, i.e. G(Beta)*Sn+Cn: 3.65562

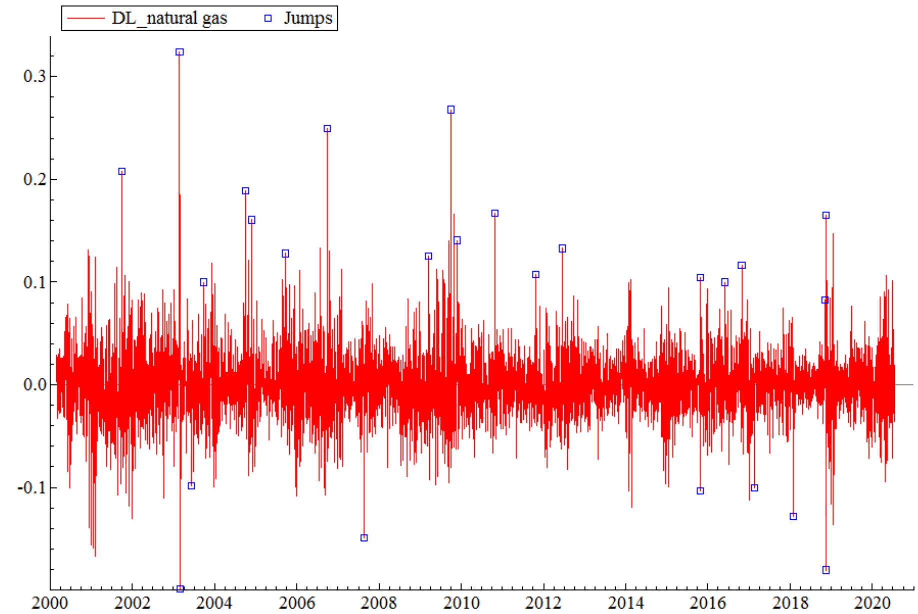

Figure 155: Jumps graph of natural gas daily log returns

Corn

series DL_corn

Critical level of the test: 0.25

Number of detected jumps: 95

Proportion of detected jumps: 0.00909439

Critical value, i.e. G(Beta)*Sn+Cn: 3.83452

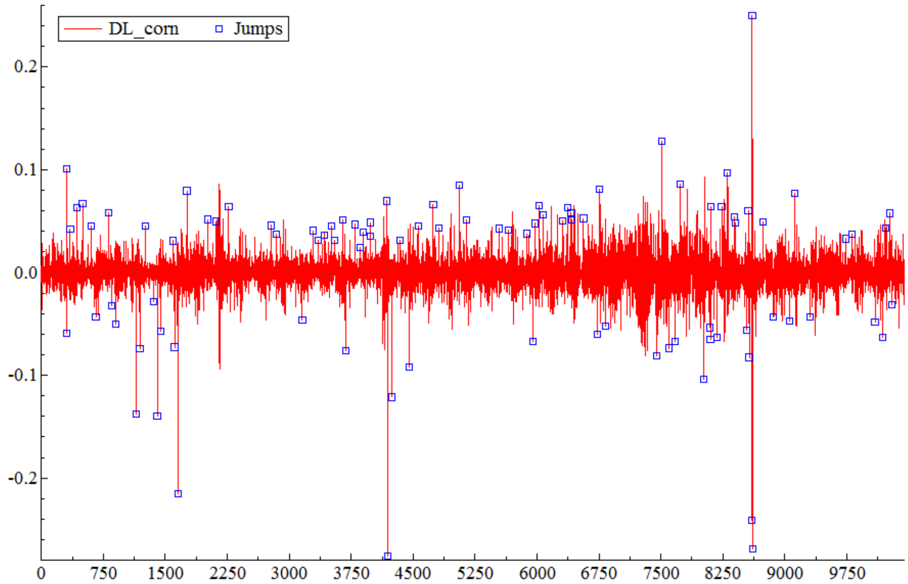

Figure 156: Jumps graph of corn daily log returns

Rice

series DL_rice

Critical level of the test: 0.25

Number of detected jumps: 37

Proportion of detected jumps: 0.00731804

Critical value, i.e. G(Beta)*Sn+Cn: 3.6528

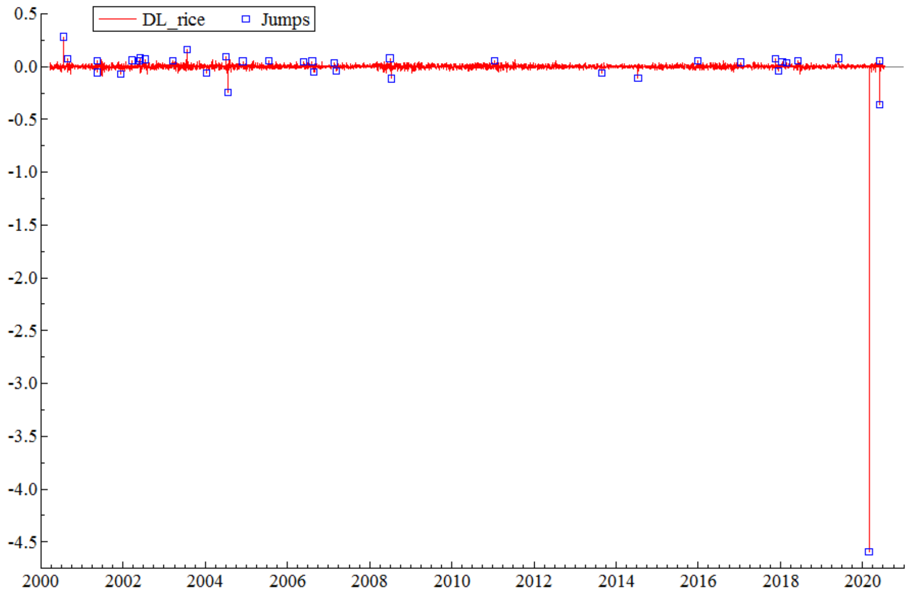

Figure 157: Jumps graph of rice daily log returns

Soybeans

series DL_soybeans

Critical level of the test: 0.25

Number of detected jumps: 52

Proportion of detected jumps: 0.00657146

Critical value, i.e. G(Beta)*Sn+Cn: 3.76589

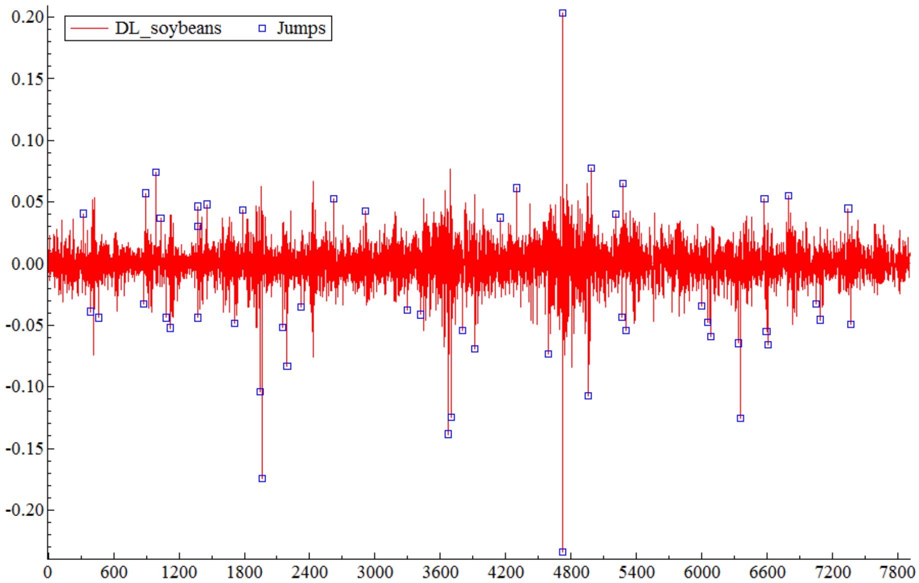

Figure 158: Jumps graph of soybeans daily log returns

Soybean oil

series DL_soybean oil

Critical level of the test: 0.25

Number of detected jumps: 29

Proportion of detected jumps: 0.0027722

Critical value, i.e. G(Beta)*Sn+Cn: 3.83487

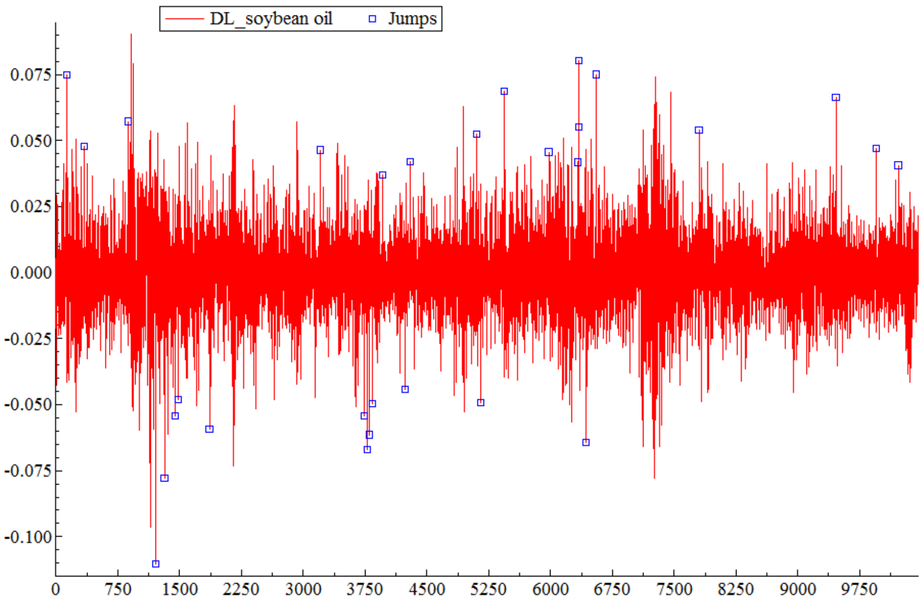

Figure 159: Jumps graph of soybean oil daily log returns

Soybean meal

series DL_soybean meal

Critical level of the test: 0.25

Number of detected jumps: 63

Proportion of detected jumps: 0.00799797

Critical value, i.e. G(Beta)*Sn+Cn: 3.76475

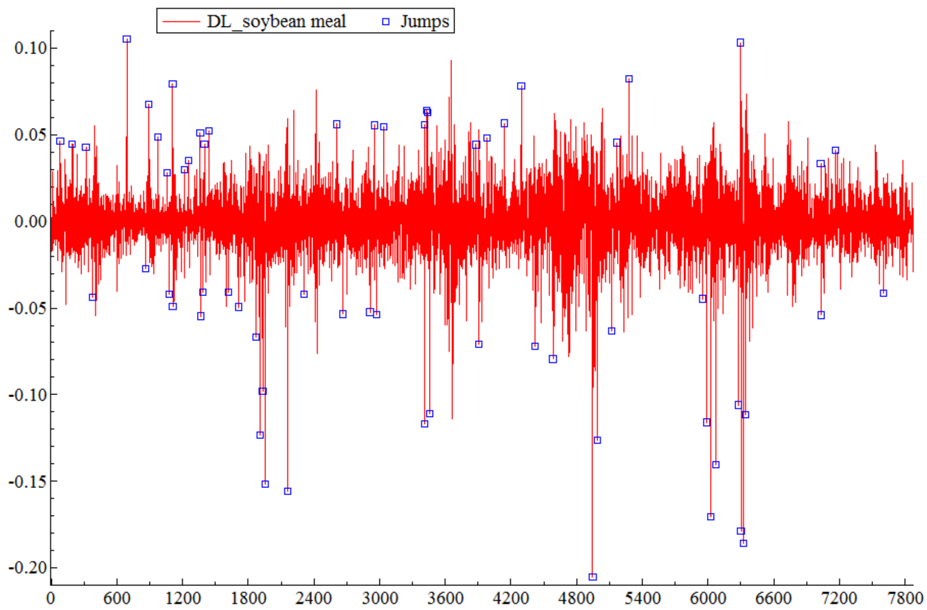

Figure 160: Jumps graph of soybean meal daily log returns

Oats

series DL_oats

Critical level of the test: 0.25

Number of detected jumps: 66

Proportion of detected jumps: 0.0129896

Critical value, i.e. G(Beta)*Sn+Cn: 3.65406

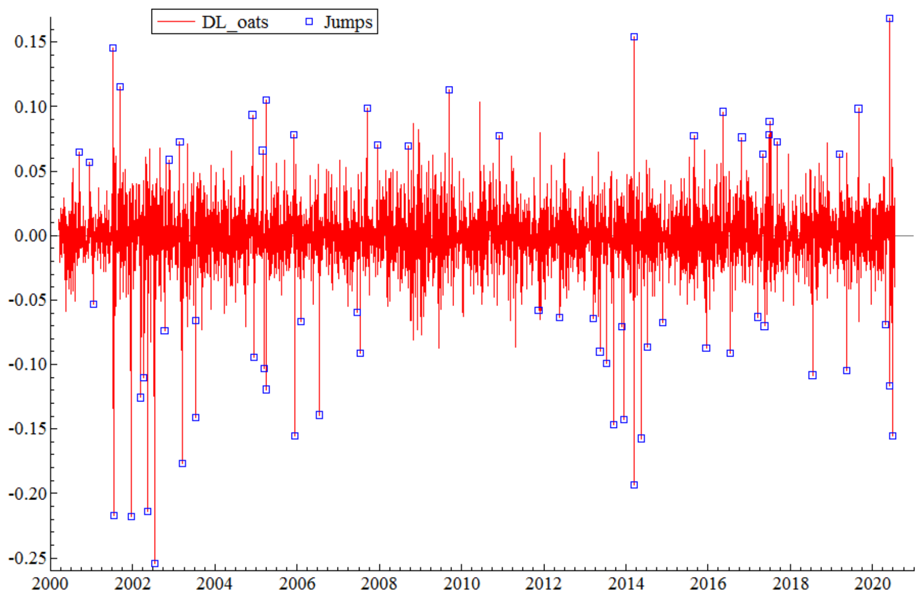

Figure 161: Jumps graph of oats daily log returns

Wheat

series DL_wheat

Critical level of the test: 0.25

Number of detected jumps: 19

Proportion of detected jumps: 0.00374089

Critical value, i.e. G(Beta)*Sn+Cn: 3.65396

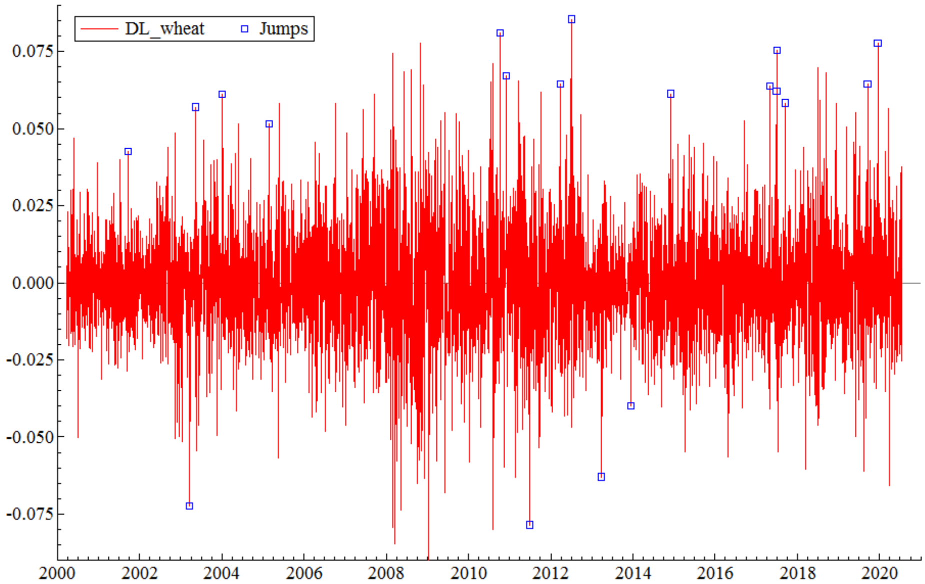

Figure 162: Jumps graph of wheat daily log returns

Coffee

series DL_coffee

Critical level of the test: 0.25

Number of detected jumps: 70

Proportion of detected jumps: 0.00684396

Critical value, i.e. G(Beta)*Sn+Cn: 3.82934

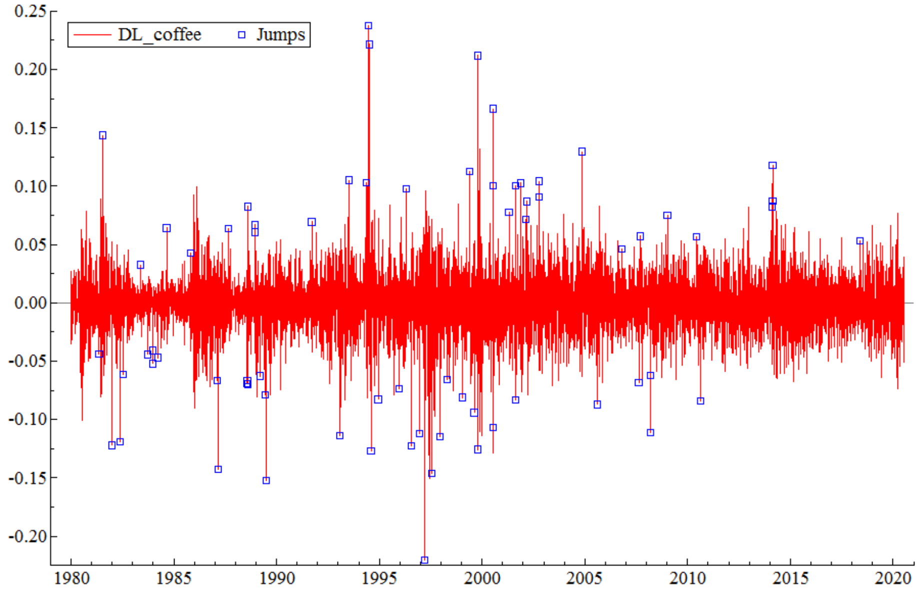

Figure 163: Jumps graph of coffee daily log returns

Cocoa

series DL_cocoa

Critical level of the test: 0.25

Number of detected jumps: 50

Proportion of detected jumps: 0.00491014

Critical value, i.e. G(Beta)*Sn+Cn: 3.82826

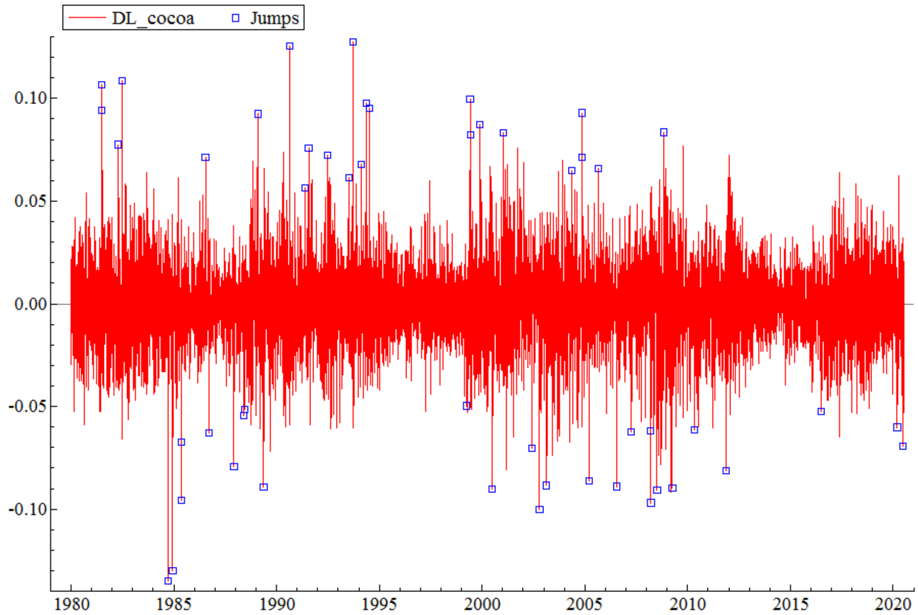

Figure 164: Jumps graph of cocoa daily log returns

Sugar

series DL_sugar

Critical level of the test: 0.25

Number of detected jumps: 101

Proportion of detected jumps: 0.00989033

Critical value, i.e. G(Beta)*Sn+Cn: 3.82896

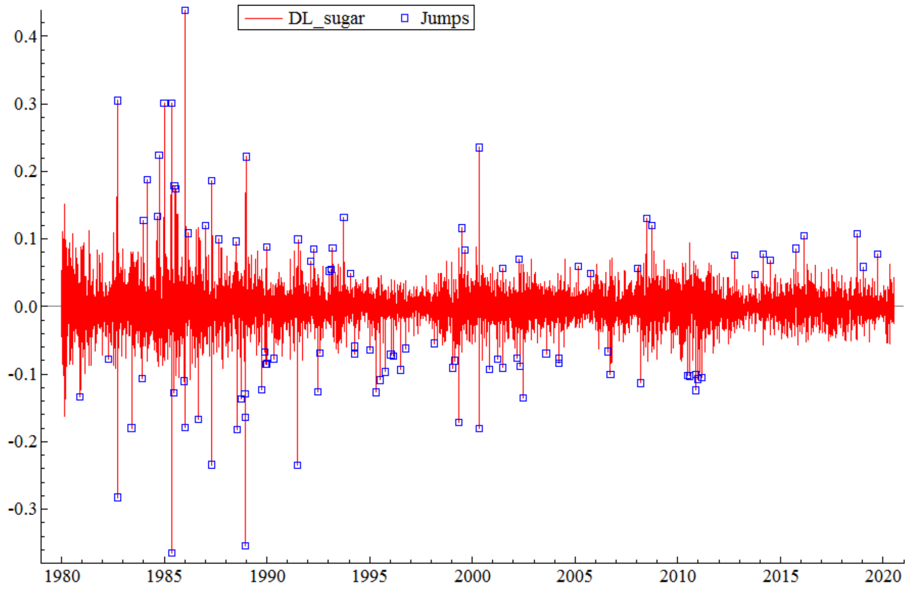

Figure 165: Jumps graph of sugar daily log returns

Cotton

series DL_cotton

Critical level of the test: 0.25

Number of detected jumps: 43

Proportion of detected jumps: 0.00823124

Critical value, i.e. G(Beta)*Sn+Cn: 3.66116

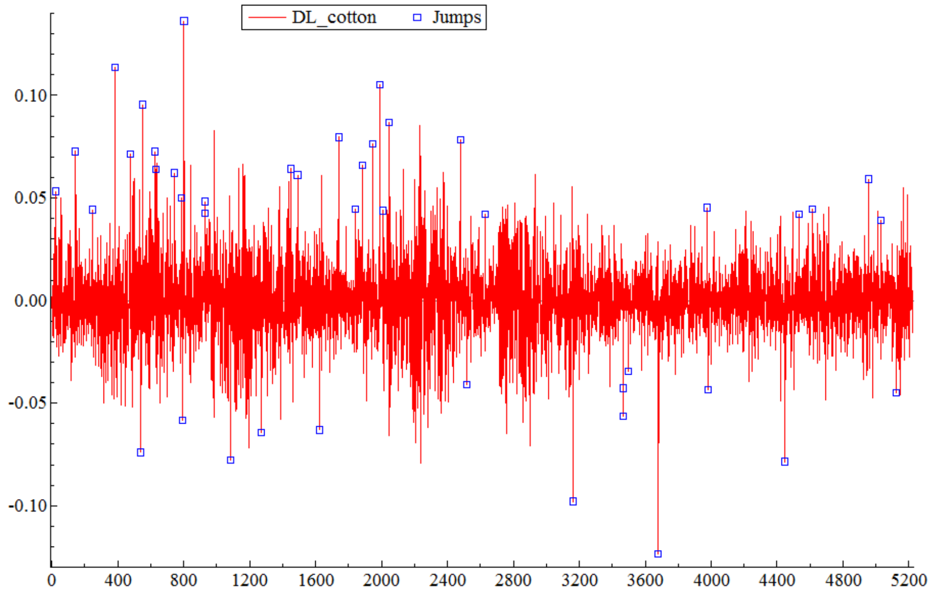

Figure 166: Jumps graph of cotton daily log returns

Lumber

series DL_lumber

Critical level of the test: 0.25

Number of detected jumps: 120

Proportion of detected jumps: 0.0117336

Critical value, i.e. G(Beta)*Sn+Cn: 3.82932

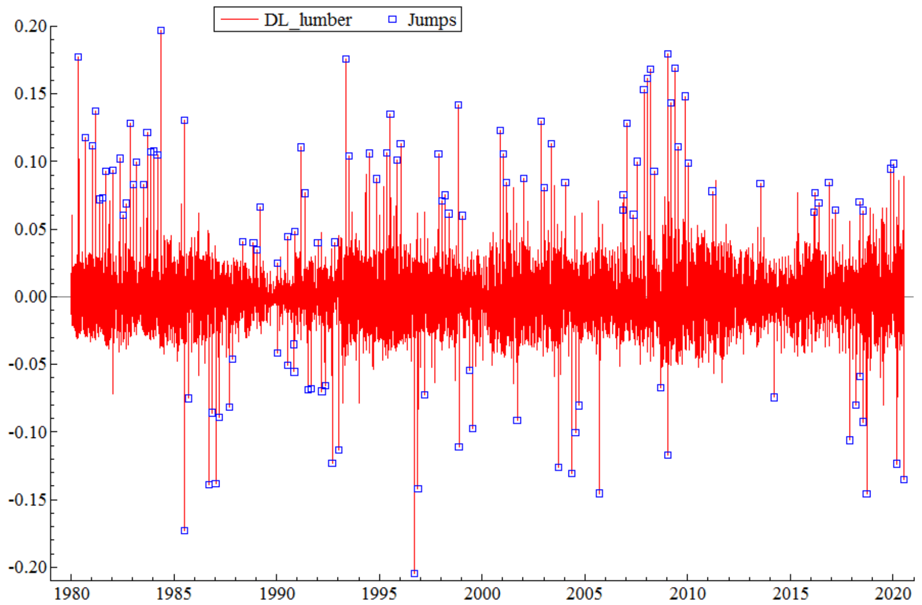

Figure 167: Jumps graph of lumber daily log returns

Lean hogs

series DL_lean hogs

Critical level of the test: 0.25

Number of detected jumps: 206

Proportion of detected jumps: 0.0200878

Critical value, i.e. G(Beta)*Sn+Cn: 3.82999

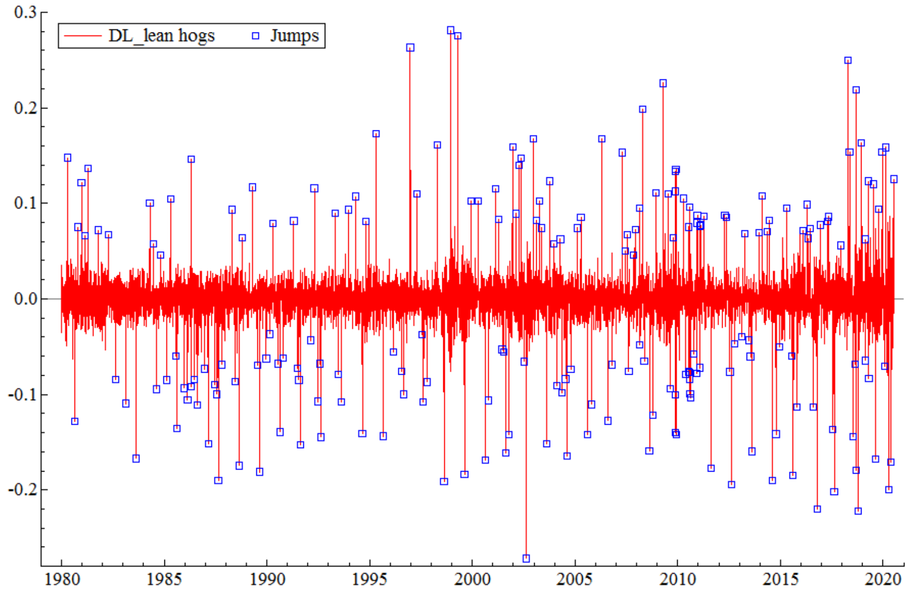

Figure 168: Jumps graph of lean hogs daily log returns

Feeder cattle

series DL_feeder cattle

Critical level of the test: 0.25

Number of detected jumps: 91

Proportion of detected jumps: 0.0178152

Critical value, i.e. G(Beta)*Sn+Cn: 3.65542

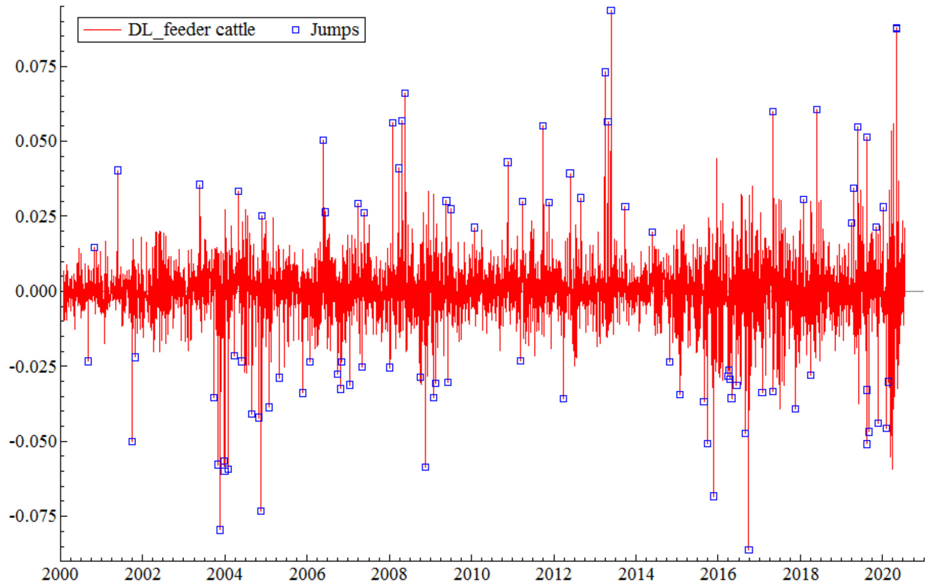

Figure 169: Jumps graph of feeder cattle daily log returns

Live cattle

series DL_live cattle

Critical level of the test: 0.25

Number of detected jumps: 123

Proportion of detected jumps: 0.0120082

Critical value, i.e. G(Beta)*Sn+Cn: 3.8297

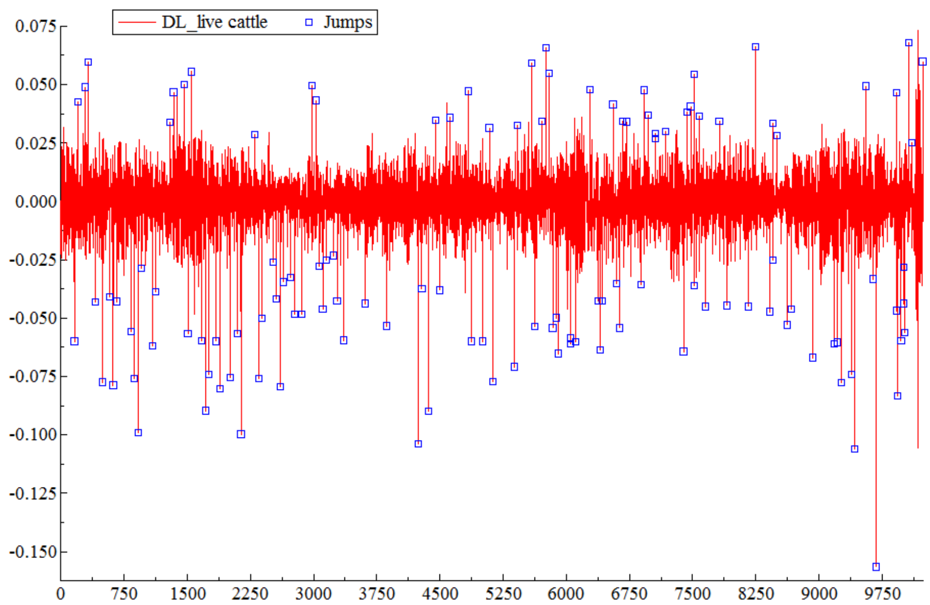

Figure 170: Jumps graph of live cattle daily log returns