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Price Index and Risk and Return þÿModeling: Ethiopia s Agricult Commodities Market in Focus

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By

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PRICE INDEX AND RISK AND RETURN MODELING: ETHIOPIA'S AGRICULTURAL COMMODITIES MARKET IN FOCUS

A DISSERTATION SUBMITTED TO

COLLEGE OF BUSINESS AND ECONOMICS, BAHIR DAR UNIVERSITY, IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN ACCOUNTING AND FINANCE

Tirngo Dinku

Principal Advisor: Gardachew Worku (Associate Professor)

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BAHIR DAR, ETHIOPIA

Declaration

This is to certify that the thesis entitled **"Price Index and Risk and Return Modeling: Ethiopia's Agricultural Commodities Market in Focus**", submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Accounting and Finance, Bahir Dar University, is a record of original work carried out by me and has never been submitted to this or any other institution to get any other degree or certificates. The assistance and help I received during the course of this investigation have been duly acknowledged.

Tirngo Dinku	February 20, 2022	Bahir Dar
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Approval of Dissertation for Defense

I hereby certify that I have supervised, read, and evaluated this dissertation titled "**Price Index and Risk and Return Modeling: Ethiopia's Agricultural Commodities Market in Focus** by Tirngo Dinku prepared under my guidance. I recommend the dissertation be submitted for oral defense.

Gardachew Worku (Associate Professor) ____________ ______________

Advisor's name Signature Date

Bahr Dar University

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Approval of Dissertation for Defense Result

We hereby certify that we have examined this dissertation entitled "**Price Index and Risk and Return Modeling: Ethiopia's Agricultural Commodities Market in Focus**" by *Tirngo Dinku*. We recommend that ____________________ is approved for the degree of "________________________________"

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Abstract

Although the Ethiopian government is engaged in a process of modernization and making major financial reforms, there is no solid financial tool that could assist market participants to analyze risk and return in the agricultural commodity market. Similarly, agricultural policy lacks instruments to shield neither farmers against potential losses induced by a reduction in the price of the crops they produce nor consumers against the increase in the cost of living induced by food price inflation. Accordingly, this study aimed to construct a price index for agricultural commodities, estimate the systematic risk (Beta), and examine the best-fit volatility model. Retail price data of agricultural commodities in five categories: cereals, pulses, oilseeds, root crops, and spices from 2010-2020 from three regions and one city administration were collected from the central statistics agency of Ethiopia (CSAA). The Laspeyres average production quantity weighting index approach was used to construct the index. The systematic risk, or beta, of a commodity was estimated through a market model, and the GARCH family models were used to estimate the volatility of the commodities. The findings show that prices of agricultural commodities revealed an ever increasing trend in all the three regional states and the Addis Ababa city administration despite the fact that there were variations across the areas. The mean monthly returns for each crop were positive while those of the root crops were the highest as compared with the other categories, followed by red pepper. Similarly, commodities having higher returns have higher standard deviations, which imply they are more volatile. It was also found that the systematic risk of agricultural commodities has a significant positive relationship with the return of specific commodities. Moreover, out of the GARCH specifications, the EGARCH was a better fit model for the volatility of "Teff" ," "maize," "Niger," "onion," "potato," and "red pepper," and the TGARCH model fits the data best for "sorghum," "barley," and "beans". In Ethiopia, prices of agricultural commodities have been increasing. Once the price of a crop has increased, its probability of falling below its previous average is very low. Moreover, the return on agricultural commodities is significantly influenced by the overall market return, and there is volatility clustering. "Bad" news has a greater impact on volatility than "good" news of the same magnitude.

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Acronyms

APT: Arbitrage Pricing Theory

ARCH: Autoregressive Conditional Heteroscedasticity

ARIMA: Autoregressive Integrated Moving Average

CAPM: Capital Asset Pricing Model

CPI: Consumer Price Index

CSA: Central Statistics Agency

CLR: Classical Linear Regression

ECX: Ethiopian Commodity Exchange

EGARCH: Exponential Autoregressive Conditional Heteroskedasticity

FAO: Food and Agriculture Organization

FPI: Food Price Index

GARCH: Generalized Autoregressive conditional heteroscedasticity

GJR-GARCH: Glosten Jagannathan Runkle Generalised Autoregressive Conditional Heteroscedasticity

GSCI: Goldman Sachs Commodity Index

MAD: Mean Absolute Deviation

TGARCH: Threshold Autoregressive Conditional Heteroscedasticity

UNCTAD: United Nations Conference on Trade and Development

WRS: Weighted Repeated Sales

CHAPTER ONE: INTRODUCTION

This chapter discusses the background of the study, the statement of the problem, and the objective of the study. It also deals with the significance, and scope of the study.

1.1 Background of the study

Risk and return are the basic concepts that have a strong theoretical backup in finance (Bringham & Houston, 2012; Damodaran, 2020; Pogue, 1973). The tradeoff between risk and return is a key element of effective financial decision making by individuals, firms, and other market participants. An implication of many asset pricing models is that they mostly focus on the tradeoff between risk and return. The market, by its nature, is dynamic and fluctuating (Pindyck, 2001), and it can be impacted by several forces, such as human emotions, the behaviors of producers, and consumer prices. To understand how the market performs, it is important to have key information to succeed in one's investment decision. Price indices are one of the tools that help to measure the movement and performance of the market, such as a stock or commodity market that is offered and which facilitates investors' decisions. A market index is a measurement of the value of a section of the market that serves as a benchmark for the economy or some sectors of the economy (Afriat, 2015). Lo (2016), by giving a historical perspective of the market performance, says that market indexes can provide investors with more insight about the market so that they can easily make their investment decisions. Therefore, a market index is a figure over which investors rely on and make investment decisions given their risk appetite, and it is used as a forecasting tool.

An index number is an instrument that is used to compute a change in the level of a set of variables beginning with a certain reference (base) period. Coelli et al. (2005) defined an index number as a device that is employed to compare prices over time, space, or both; indeed, it is an instrument that is used to measure changes in a variable or group of variables with common features, for example, time and geography. Furthermore, according to Allen (1976), Balk (2008), and Afriat (2015), an index number is a tool of measurement which can fairly combine either similar or different types of data and helps to bring about a single summary value which helps to make an accurate comparison between the given periods, namely time series. There are different types of commonly employed indices, such as price indexes, which can be used to measure percentage changes in price; quantity indexes that are used to measure percentage changes in quantity produced or consumed, and a value index that is employed to measure the percentage change in values (Encyclopedia Britannica, 2014).

Of these, a price index is characterized as a time series index. A time series index, according to Allen (1976) and Allen et al. (1981), helps to make the degree of change easily understandable in the process of constructing values. In this process, the first step is choosing a base year, which is used as the reference period with which one compares the change concerning the selected base year (Ralph et al., 2015). The second step is to scale the reference period using the commonly used reference points, usually 100 or 1000, and the same scaling factor is then applied to the values for other years. The values for the scaled series could be set around the reference points, and this helps to make the degree of changes easily understandable; these scaled values are called index numbers, and the collection of index numbers is called an index series (Ralph, et al. 2015). By creating an index number representation of the time series, it is possible to gain a more direct representation of change, for the focus is primarily on the change in the level of the series instead of the actual amount in billions of dollars (Allen, 1976; Ralph et al., 2015).

The construction of an index number should clearly show the type of the index to be constructed and the method used to construct the index. For example, a market level index is an index that is constructed to measure the overall market performance whereas a sectorial index is a type of index that is used to measure the economic performance of a sector and thus provides investors with summarized, comprehensive, and reliable sectorial information.

Underlying an index number conception is a theory that promotes the aggregation of quantity and prices over commodities (Coyle, 2007). This is termed the "index number theory." In 1936, Frisch distinguished two main schools in the theory of index numbers, namely the atomistic and the functional approaches, where the former considers quantity and price data of the individual products (i=1, 2,…n) to be independent variables, and the task here is to find a functional role for the second independent variable that indicates the changes in the price level and total volume in an acceptable manner; in the functional approach, some characteristic relations are assumed to exist between prices and quantities, which changes the entire nature of the problem; that is, in the former, a logical and unique definition of the index number is impossible, while it is possible in the latter approach (Köves, 1978).

In the process of constructing an index, other important issues to be considered are the selection of the items to be included in the index and the determination of the appropriate weight to be applied. Based on the weighting approach, researchers can categorize an index as either weighted or un-weighted, where they, in the latter, do not apply a weight to the index, but in the former, they apply different bases as weights, such as: equally weighted, quantity weighted, price-weighted, market capitalization-weighted, float-adjusted, and market capitalization-weighted as the most commonly used weighting methods; for example, the indexes developed by Laspeyres in 1971 and Paasche in 1974 (Horner, 1971;Selvathan,1991,1993) are citable in using base year quantity and current year quantity as weighting methods.

Several organizations develop indexes across the globe, both in stock markets and commodity markets, for which they have been used as a barometer of the market's condition. Just to list some, the S&P 500, Dow Jones, NASDAQ, Russell 2000, EGX 30, NIFTY, Bloomberg, and Zimbabwe Industrial Index can be mentioned, as examples. Investors, traders, speculators, governments, and others rely on the information provided by index numbers to understand market characteristics such as relative changes, risk, and return in order to make their own decisions. However, many alternative investment decisions lack this attribute. This is an assured pitfall that an investor and other market participants, including the government, must take into account in their investing plans.

An index, whether it be pre-existing or newly constructed, can serve as an instrument or a benchmark that is commonly used in risk and return analyses, for example, estimating the market return and systematic risk of the so-called beta of any asset. The systematic risk (beta) of each asset could be estimated through different asset pricing techniques as a function of the market index. Indeed, one can get different asset pricing models, such as the Capital Asset Pricing Model (CAPM) (Sharp, 1965), the Arbitrage Pricing Theory (APT) (Ross, 1976), and the Fame-French Three-Factor Model (Fama & French, 1993). Though these asset pricing models were originally developed for the evaluation of risk and return in the capital market, scholars such as Dusak (1973), Turvey and Driver (1987), Barry and Collins (1986), Outinen (2007), Bessembinder and Ghan (2012), and others adapted them for agricultural commodity markets in response to the growing interest in agricultural investments. Asset prices can be determined by investors' risk preferences and the distributions of assets' risky future payments (Drobetz, 2000).

Besides, market instability is a significant issue that needs attention. That is, commodity market instability shows a rising trend in prices (Arezki, 2012; Rezitis & Sassi, 2013), and the existence of such a volatile market results in hazardous conditions. Thus, price stability is one of the main economic goals in any economy, so it is crucial to ensure it and work hard to keep the overall price of agricultural commodities fairly stable. In other words, price stability should be one purpose of an economic policy (Tucheker, 2003). Price stability can be affected by many factors, including inflation, which can negatively affect social welfare and restrict the domestic economy from performing well, thus disturbing price stability (Fullerton & Araki, 1997).

In fact, according to IMF (2007), since 2006, food prices have increased by 45%, which evidences the existence of dramatic price growth of agricultural products; the price increments boom picked up pace; for example, the prices of crude oil, tin, nickel, soybeans, corn, and wheat are presently citable.

The rapid increments in prices were specifically observed in the main food crops such as corn, wheat, and edible oil, even though the same is true in other food crops including, for example, price (Jema et al., 2012).

Specifically, in Ethiopia, since the end of 2005, food prices have shown dramatic increments. For example, successive increments of 15.1%, 28%, and 57.4%, were recorded in 2006, 2007, 2008, respectively (Jema et al., 2012), and 22.22% and 38.4 % in 2019 and 2020, respectively (CSA, 2021) the dramatic increment in agricultural commodity prices has remained a concern not only for policymakers, donor agencies, and economists but also for society at large (Jema et al, 2011) including researchers. This means that food prices in Ethiopia have not shown stability. Regarding this, Zewdu (2015) explains that although food price inflation showed a stable growth rate in the first quarter of 2010, starting from the third quarter of 2010 up to the second quarter of 2012, it showed a high annual food inflation rate which was transformed from single-digit to double-digit. Hence, agricultural commodity price inflation shows more volatile trends than other non-food inflation, and it takes a lion's share of the volatility of headline inflation (Zewdu, 2015).

Generally, the markets in developing countries, including Ethiopia, are often characterized by small trading volumes, lack of competition, and high price volatility (Teshome, 2020). Low trading volume implies that the quantity and quality of information that buyers receive are limited, and thus the price prediction process could be affected. A faulty price prediction results in price volatility, which again brings about inefficient market systems (Mattos & Giarcia, 2009). More specifically, the volatility and rapid growth of agricultural prices have put a great burden on both the farmer and the consumer and also put pressure on the struggle to reduce poverty.

As a change in prices of agricultural products has become a global phenomenon (Shiferaw, 2009), price volatility in markets for major crops remains high in Ethiopia too (Rashid et al., 2010). In line with this, although agricultural product market policies in the country have tried to make dramatic changes over the past number of years. For example, the Imperial Regime (1960-74) market was characterized by limited government intervention, a high volume of marketing relative to production, and very high transport costs due to limited infrastructure followed by the state-controlled markets (1975-1990) which instituted a wide range of controls over cereal production and marketing, including quotas and restrictions on private grain trade. Even the Liberalization and Rapid Growth started in 1991, in which reorganization and re-structuring of public enterprises, and giving the mandate to the Ethiopian Grain Trade Enterprise (EGTE) to (a) stabilize prices with an objective to encourage production and protect consumers from price shocks, (b) earn foreign exchange through exporting grains to the world market, and (c) maintain strategic food reserves for disaster response and emergency food security operations (Rashid et al., 2010).

However, the desired outcomes have not been achieved, and the efforts made to reduce price volatility have remained unsuccessful (Shiferaw, 2009). As a result, it is crucial to maintain efforts in this area in order to develop an appropriate tool capable of accurately modeling and forecasting the agricultural commodity prices, as well as to implement a policy that could help to protect both farmers and consumers from risk. An accurate prediction of future food price increment conditions is a crucial planning tool for the country's governmental and food aid institutions. Indeed, an accurate evaluation of agricultural commodity price movements is important for inflation control and production planning, and it is particularly relevant to developing countries, like Ethiopia, which is in the process of promoting investment in the agriculture sector, and which is required to work hard for poverty reduction (Chen et al., 2010).

Thus, this researcher first tried to (1) develop a market index for agricultural commodities prices, (2) estimate the market return, (3) investigate the systematic risk (beta) of a commodity, and (4) *examine* the best fitted price volatility models for selected agricultural commodities in Ethiopia.

1.2 Statement of the problem

Due to the increasing nature of international investments and the globalization of the market system over recent years, the demand for getting timely, valid, and reliable information regarding a given market is increasing dramatically. Many equity and commodity indices around the world have been providing information based on risk-adjusted returns analysis and asset pricing models that provide strong theoretical support in finance to meet this demand (Bringham & Houston, 2012; Damodaran, 2020; Pogue & Gerald, 1973).

In brief, a market index is a measurement of the value of a section of the market that serves as a benchmark for the economy (Afriat, 2015), which could be used as a tool in risk and return analysis for an investment decision. A market index can provide investors with information about the market, allowing them to make more informed investment decisions. With the construction or development of a global price index for various market segments, one can obtain a variety of price indexes used for various purposes, i.e., different organizations or institutions construct indexes for various types of markets, such as stock and commodity markets.

The stock market index is the most dominant and established, which was developed by various index developers such as Dow Jones, S&P 500, NASDAQ, and others for the US stock market; the Nairobi Securities Exchange, Ghana Stock Exchange, and Egyptian exchanges with an African context are also among the organizations that construct indexes. Apart from these, others build price indexes for distinct market segments and specific commodities. For example, for the real estate and housing segment, price indexes are assembled by applying approaches such as the hedonic approach (Rosen, 1974), repeated sales (Bailey et al., 1963), Case & Shiller (1987), hybrid approaches (Case et al.. 1991), and the autoregressive index introduced by Nagaraja et al. (2011).

Moreover, price indexes are developed for specific commodities as well. Recently, Tuo and Zhang (2020) modeled the iron ore price index for China, which was used to explore the price risk and fluctuation correlations between China's iron ore futures and spot markets and forecast the price index series of the country's and international iron ore spot markets from the futures market. Another study by Yang et al (2020) was conducted with the aim to construct the natural gas price index (NGPI). All of these signify the necessity of index construction for different sectors of the economy. It is not surprising that there is no stock price index and no index developer in Ethiopia, as there is no any stock market in the country.

Specifically, agricultural commodity indices can serve as representative indicators of the commodity markets, measuring the aggregate direction of prices across various commodity sectors. In Ethiopia, agriculture is the backbone of its economy, contributing 27.5 billion dollars, or 34.1% of GDP, accounting for 79% of foreign earnings, being the primary source of raw materials and capital for investment and market (Getachew, 2020), accounting for 80 % of the country's exports (USAID, 2020), and employing the majority (79%) of the population. The majority of the farmers are smallholder farmers, whose output is predominantly cereal crops, which account for 95.0% of the agricultural production in Ethiopia. While construction of the agricultural commodity price index plays a paramount role for the economy's participants, including the government, currently, there is no organization other than Central Statistics Agency (CSA) and FAO somehow providing information related to commodity prices in the agricultural commodity markets of Ethiopia. Even the CSA and FAO's limited indexes could not independently represent domestic agricultural commodity prices.

For example, the CSA consumer price index whose purpose is to measure the average price change of certain consumer goods and services and can give information about inflation and the cost of living over a given period, and it is highly influenced by commodities other than agricultural products, such as energy, construction, transportation, and others (CSA, 2016). Hence, it fails to show the performance of the agricultural commodities market independently. When it comes to the FAO Food Price Index (FPI), its purpose is not just to be used as an indicator on its own to assess the domestic agricultural commodity market; it is based on the export share of a commodity in the international market.

Moreover, methodologically, the CSA, CPI, and FAO FPI indexes make use of different weighting approaches to reflect the relative importance of goods and services, where the former is a base year quantity consumed weighted index and the latter is weighted with an average export share of each of the five groups over 2014-2016 (FAO).

In brief, for the CSA's index, the weight reflects the relative importance of the goods and services as measured by their expenditure weight, that is, the share of a commodity in the total consumption basket of households (CSA, 2016). While for the FAO's FPI, the weight reflects the relative importance of the goods and services as measured by their average export share to the global market (FAO, 2020). Nonetheless, neither of these indexes takes the quantity of production into account when constructing their indexes. That is, it is both supply and demand that mainly determine the price of goods and services. Unlike the stock price, the price of agricultural commodities is subjected to the size of areas covered with that specific commodity and the quantity produced in any given particular year. So, one need to take into accounts those factors while constructing a price index for agricultural commodities as an indicator of relative importance.

Therefore, it is worth establishing a solid price index for the agricultural commodities market, which could be used to measure the economic performance of the sector and provide investors with summarized, comprehensive, and reliable sectorial information.

The second issue worth investigating is risk and return of agricultural commodities. In the process of examining risk and return relationships from investment, Sharp's CAPM is the dominant asset pricing model under the portfolio theory. Even though CAPM was originally developed for market portfolios in the capital market, later on, researchers adopted it to measure risk and return in other sectors, for example, the agricultural commodity market, where it is experiencing inflation (Durevall et al., 2013) and high price volatility (Shiferaw, 2012). Some studies, for example, Dusak (1973); Carter et al. (1983); Driver (1985); Bjornson (1994); Outline (2007); Bessembinder and Ghan (2012) have attempted to apply the CAPM to understand the risk-return relationships in agriculture and estimate systematic risk. In investment and corporate practices, systematic risk (beta) can be estimated using different asset pricing models (Bertomeu & Cheynel, 2016). Scholars such as Dusak (1973); Cornell and Dietrich (1978), Chan and

Lakonishok (1992), Outinen (2007) and Phuoc and Pham (2020) conducted a study of beta estimation.

Briefly, Cornell, and Dietrich's (1978) investigation focused on estimating beta by using 100 randomly selected companies from the S&P 500 index for 13 one-year periods. The authors realized the deficiencies of the OLS estimator and proposed an alternative estimator that gives less weight to outliers. Similarly, Chan and Lakonishok (1992) conducted an estimate of beta using simulated and actual monthly returns data of 50 randomly selected stocks from the NYSE for 1983–1985. The findings of the empirical analysis showed that there is a potential efficiency gain from using robust methods as an alternative to OLS, except for the MAD. Moreover, research by Phuoc and Kim (2020) explored the estimation of the beta coefficient (β) through the Capital Asset Pricing Model (CAPM). The findings pointed out that the robust Least Trimmed Square (LTS) and maximum likelihood type of M-estimator (MM-estimator) performed much better than the ordinary Least Square (LS) in terms of efficiency for large-cap stocks in the United States markets. In practice, using monthly/quarterly, or annual returns data, ordinary least square (OLS) is used to estimate beta. By adapting Dusak's approach Outinen (2007) for estimation of betas for agricultural commodities with a slight modification, where the portfolio consists of 90% S&P 500 index and 10% Dow-Jones, which are both common stocks indices. However there are limitations in these studies related to application of the right proxy variable that is, they used the return on S&P 500 Index and Dow-Jones industrial average index as a proxy variable for the return on the efficient market portfolio, and they were limited to a small set of commodities, namely Wheat, Soybean, and corn.

The other issue that needed to be investigated was the volatility of agricultural commodities. Commodity prices are characterized by a high degree of volatility (UNCTAD, 2019). Agricultural products are major contributors to food price volatility in commodity-dependent developing countries like Ethiopia. Modeling this volatility is highly demanding for investment decisions, policy recommendations, and future forecasting. In line with this, Engle (1982) introduced a volatility model called the Autoregressive Conditional Heteroskedasticity (ARCH) model. Following his model, other scholars introduced different ARCH family models such as Generalized Autoregressive Conditional Heteroscedasticity (GARCH) (Bollerslev, 1986), Threshold GARCH (Zakoian, 1994), and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) (Nelson, 1999).

Assuming the GARCH family of models specifically for agricultural commodity prices, different studies have been done globally and nationally. Musunuru et al. (2013) applied TGARCH and EGARCH models to model and forecast volatility of returns for corn futures prices using data from the Chicago Board of Trade (CBOT). The results show that the TGARCH model is the best fit model in which there is a leverage effect. That is the corn return series reacts differently to good and bad news in which the negative news has a bigger impact on volatility than positive news of the same magnitude. Lama et al (2015) studied the autoregressive integrated moving average (ARIMA) model, generalized autoregressive conditional heteroscedastic (GARCH) model, and exponential GARCH (EGARCH) model along with their estimation procedures for modeling and forecasting of three price series, specifically domestic and international edible oils price indices and the international cotton price 'Cotlook A' index. Their study revealed that the EGARCH model outperformed the ARIMA and the GARCH models in forecasting the international cotton price series primarily due to its ability to capture asymmetric volatility patterns.

Similarly, Le Roux (2018) suggests that volatility is present in the data, whereas overall, GARCH, EGARCH and GJR-GA of RCH was the best fitting model for the S&P GSCI Agriculture Index , for the Brazilian Real, and for cocoa respectively. Through the use of 26 years of T-bill in monthly time series data on the Commodity Food Price Index, Kuhe (2019) also searched for optimal Autoregressive Moving Average and Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) models. According to him, the ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models were fitting in describing the symmetric and asymmetric behaviors of the log-return that best describe the log-returns price volatility of selected agricultural commodity food products in Nigeria. However, the study further shows that the best-fitted models are not necessarily the best forecasting models. With special reference to the context of Ethiopia, researchers, for example, Shiferaw (2012), Muanenda and Yohannes. (2018), and Teshome (2020) have conducted studies that focused on modeling commodity price volatility.

Shiferaw (2012), in his study on selected agricultural products in Ethiopia, found price volatility was persistent in all three categories (cereal, pulse, and oil crops) of selected agricultural goods. In line with this, the results suggested that GARCH (1, 1), GARCH (1,2), and GARCH (2,1) models were the best fit models for the log-returns of cereal, pulse, and oil crop prices, respectively. In addition, Muanenda and Yohannes

(2018) found that ARIMA (0, 1, 1) and ARMA (2, 2)-GARCH (2, 1) with the normal distributional assumption for the residuals were adequate models for modeling and forecasting the volatility of the export price of sesame in Ethiopia. Moreover, recently, Teshome (2020) conducted a study on modeling time-varying coffee price volatility in Ethiopia and found that the multiplicative GARCH-MIDAS model explains stylized facts that cannot be captured by the standard GARCH model.

Furthermore, countries employ agricultural policies to secure food supplies and fair prices for their customers. Brazil's agricultural policy instruments, for example, were devised in a way that could help farmers be safe from unexpected price fluctuations. The government also buys surplus production to equalize prices, gives public and private sales contracts to boost agricultural prices and reduce volatility, and has developed an agricultural risk management strategy that helps farmers be safe from potential losses that could come from reductions in the prices of crops that they plant.

In line with this, the government gives them support via economic subsidies so that they can purchase agricultural insurance policies. Similarly, the Indian agricultural policy incorporates a price policy to encourage farmers to be engaged in large-scale investment; the policy accomplishes this task by fixing the minimum price for what farmers can plant. However, the agricultural policy of Ethiopia could not safeguard both consumers and producers from unexpected agricultural commodity price fluctuations. That is, the Ethiopian agricultural policy has a gap in dealing with price policies on agricultural products, and there is also no mechanism to safeguard farmers from a potential loss that might occur due to a decline in the market price of crops that they are producing. The policy has neither support for a minimum price strategy nor a government purchase policy in a time of large supply, as both appear in other countries' agricultural policies, such as Brazil and India.

Even though presence of reliable, relevant, and timely information about the market performance is able to give more insight into their investment decisions, in Ethiopia however, traders, investors, and those interested in commodities markets have found few comprehensive sources of information available. That is, there has not been an attempt made to develop a financial tool for decision-making purposes concerning the agricultural commodity market to improve the mobilization of financial resources. Moreover, in the context of Ethiopia, no empirical study has been done to estimate the beta of an agricultural asset. Previous studies such as Dusak (1973) and Outinen (2007) have limitations related to use of appropriate benchmark that is, they used the return on S&P Index of' 500 and Dow-Jones as a proxy variable for the return on the efficient market portfolio, and they were limited to a small set of commodities, namely Wheat, Soybean, and corn. Besides, previous studies in Ethiopia regarding volatility modeling, by Muanenda and Yohannes (2018) and Teshome (2020) each focused on a single commodity, such as sesame and coffee, where both of them are export commodities, and experience special volatility compared to other commodities because they are subjected to international prices and foreign exchange issues. Furthermore, as has been witnessed from the literature, there is no one best model that fits all data series.

Therefore, it is worth establishing a solid price index for the agricultural commodities market, which could be used to measure the economic performance of the sector and provide investors with summarized, comprehensive, and reliable sectorial information. Thus, this study could fill the aforementioned gaps in that it constructed commodity price indexes comprised of ten commodities that are supposed to represent agricultural commodities traded in the Ethiopian commodity market as a proxy variable of market return on which market return was estimated, estimated the systematic risk (Beta) for a commodity, and examined the best fit volatility model in the agricultural commodity price index. In line with this, the general and specific objectives of this study are framed as follows:

1.3 Objective of the study

The general objective of the study is to construct price indexes and to model risk and return for Ethiopia's agricultural commodities market

Specific objectives

Specifically, the study aims to:

- ✓ Construct price index for agricultural commodities in Ethiopia,
- ✓ Estimate market return of the agricultural commodity market,
- ✓ Estimate the systematic risk (beta) for selected agricultural commodities, and
- ✓ Examine best fitted price volatility model for agricultural commodities using GARCH family models

In line with these objectives, this study tried to formulate the following basic research questions:

1.4 Research questions

- ✓ What would the price index of agricultural commodities look like in Ethiopia?
- ✓ What would be the estimated market return of the agricultural commodity market?
- ✓ How would the systematic risk (beta) of crops associated with market return in Ethiopia?
- ✓ Which GARCH family model would be best fitted price volatility model for agricultural commodities?

1.5 Scope of the study

This research focuses on the behavior of the commodity market in which agricultural commodities are traded. On top of that, the commodity price index, risk, and return were studied. The Laspeyres average production quantity weighted index is the methodology applied for the construction of the commodity price index. Moreover, market models and GARCH family models were applied to the systematic risk and volatility of agricultural commodities, respectively. The study covers 10 years, which includes the length of time from 2010 up to 2020, and it focused on ten selected agricultural commodities from five categories, namely cereals, pulses, oil seeds, root crops and spices on the basis of an agricultural sample survey that provided the relative importance of the crop in the country's crop production shares for which retail price data is available at CSA for the aforementioned length of time. Furthermore, based on the contribution that each region had to the whole market of the country, three regional states and one city administration, namely Amhara National Regional State, Oromia National Regional State, South Nations Nationalities and Peoples Region, and Addis Ababa City Administration, were included.

1.6 Significance of the study

This research has both theoretical and practical contributions. That is, firstly, the study contributes to the literature in such a way that it constructs an agricultural commodity index with special reference to Ethiopia. Secondly, it contributes to the literature in such a way that it introduces the concept of modern portfolio theory in the Ethiopian context and estimates the systematic risk (beta) for agricultural commodity assets. Furthermore, the study identifies the best fit model for forecasting the volatility of agricultural commodity price indexes with special reference to price data in Ethiopia. And this will serve as a source for other researchers in the fields of finance and economics. For its practical significance, since the Ethiopian government is engaged in a process of modernization and major financial reforms, it is vital to develop financial tools that could be helpful for decision-making concerning the commodity market to improve mobilization of financial resources. Therefore, it is essential to establish a solid index of agricultural commodities to reflect commodity market features and movement. Hence, it will help to inform producers, investors, traders, consumers, and the government about the performance of the commodity market, the associated risk related to the sector, and the systematic risk of a commodity concerning the market, and lastly, it will come up with valid policy recommendations.

1.7 Organization of the study

This dissertation exhibits price index, and risk and return modeling in Ethiopia's agricultural commodity market. It is organized as follows.

Chapter 2 put emphasis on theoretical and empirical studies. Firstly, it deals with the concepts of price indexes, asset pricing, and price volatility. Then, it explains the relationships among price indexes, asset pricing, and price volatility. Next to that, it tries to deal with the modern portfolio theory that can serve as the foundation of the study. Finally, it presents research findings concerning the study. Chapter three provides the methodology that was used to conduct the research. The chapter is further divided into two subsections where the first subsection discusses the theoretical methodology, such as research philosophy, research approach, and research strategy, and the second section deals with practical methodology, including sample size and the sampling strategy, and the data analysis methods used in this study. Chapter four discusses the result and analysis of the data collected from CSA. Firstly, an attempt was made to present the price indexes of agricultural commodities in Ethiopia at both regional and national levels followed by estimation of market return and systematic risk (beta) of the crops. Finally, the price volatilities of the selected crops were estimated using GARCH family models. In chapter five, discussions of the results are presented. Chapter six presents summaries of the key research findings followed by conclusions and recommendations forwarded. Finally, Appendix A contains the regression results for each crop with respect to the market return benchmark, Appendix B, the Breusch–Godfrey serial correlation LM test, the Corrologram of standardized residual squared, a test of the adequacy of the fitted models, and Appendix C, the country level index.

CHAPTER TWO: REVIEW OF RELATED LITERATURE

This chapter focuses on two main issues: theoretical and empirical studies about four main issues. Firstly, it deals with the theory of index numbers and concepts of price indexes, portfolio theory, specifically asset pricing models, and price volatility. Then, it explains the relationships among price indexes, asset pricing, and price volatility. Next to that, it tries to deal with the main theories that can serve as the foundation of the study. Finally, it presents research findings concerning the study.

2.1 Index number theory

An index number is a measure of changes (Ralph eta al, 2015) of magnitudes from one situation to another (Allen, 1976), which may be two time periods (e.g., two years), two situations in a spatial sense (e.g., two regions of a country), or two groups of individuals. Since index numbers measure changes, there should be a reference or base required to compare with, which usually is the period taken at a level of 100.

Traditional index number theory organizes a value ratio into the product of a price index and a quantity index. The price (quantity) index is interpreted as an aggregate price (quantity) ratio. According to Hill (1988), there are two fundamental approaches to index number theory; axiomatic approach and the economic approach. Diewert (2005) takes an alternative approach to index number theory, started by Bennet and Montgomery in the 1920s, which decomposes a value difference into the sum of a price difference plus a quantity difference. Hence axiomatic and economic approaches to this alternative branch of index theory are considered in his paper. The analysis presented has some relevance to accounting theory in which revenue, cost, or profit changes need to be decomposed into price quantity components. In axiomatic price index theory, “tests” or “axioms” indicate numerical properties that are fundamental or necessary for a price record equation, and equations are looked for that show those properties (Reinsdorf, 2007). The term “test” was used by Irving Fisher in two books that viably enforced this field of investigation in the early twentieth century, whereas “axiom” is utilized by later scholars to indicate the core properties that are fundamental for any price index. Two options to the axiomatic approach are too often used to plan or to assess price indexes. The stochastic approach, also called the statistical approach considers the individual person’s price changes as appealing from a statistical distribution whose central tendency is to be evaluated.

The axiomatic approach is one in which the theoretical foundations of index numbers are built on certain postulates, or axioms, which any index must satisfy. For Reinsdorf (2007), the axiomatic approach is adequately versatile to be all-around appropriate, but the applicability of the elective approaches, for the most part, depends on the level of accumulation. At the lowest level of accumulation, the presumptions of the stochastic approach are well-suited for the problem of combining price quotes from different venders into an index for a single product. Most index number issues include higher levels of accumulation, be that as it may. A basic example of one of these problems the weighting of different commodities to reflect their economic significance.

Fisher (1922) is the one who required indices to satisfy certain conditions called axioms, or tests, such as the Monotonicity Axiom or the Linear Homogeneity Axiom, which states the linear homogeneity of a price index with respect to the comparison price, the identity axiom, which states that if all prices remain constant, the value of P equals unity, and so on. The dimensionality axiom states that a dimensional change in the unit of the currency does not change the value of the function P. In other words, if two economies are identical except for the definition of the unit of money, then the values of the respective price indices are the same just to explain some.

The economic theoretic approach, which seeks to define price or volume indices with reference to underlying utility functions with the consumer preference context or production functions in the context of producers. Konus (1924) cited in Diewert (2005) says that an aggregator function is neoclassical if these functions are continuous, positive, and linearly homogeneous, in which the cost function or expenditure function is the solution to the minimization problem. That is, the economic approach models quantities as a function of price and income as a description to solve an optimization problem.

A price index, according to (Diewer, 2007), is a measure or function that summarizes the change in the prices of many commodities from one situation (a time or place) to another; to determine a price index, it is necessary to know the types of commodities or items to be included in the index, the method used to determine the item prices, the types of transactions that involve the items to be included in the index, the type of technique used to determine the weight, and the sources from which the weights are drawn, and the type of formula or mean that should be employed to compute the average value of the selected items relative prices.

2.1.1 Index number construction

In the process of constructing an index number, it is necessary to decide on six factors: they are the purpose of the index, availability of data, selection of items, choice of the base period, selection of the weights, and methods of construction (Tysoe, 1981). In brief, in the process of developing an index number, the first step is to state the purpose for which the index is intended to be used; it is crucial to specify the purpose of an index before any attempt is made to construct it, for stating the purpose helps to influence other factors involved in the construction process of the index. The second step is to ensure the availability of the required data. In other words, it is essential to be sure that the data is continually available and accessible in the right format for the index number construction process. The reason for this is that lack of access to the required data could create a serious problem years after an index number series has been started. If the needed data is not available at the right time and in the right format from the beginning, and if its inaccessibility continues, the index number's future usefulness and reliability will be distorted.

The third step is the selection of the items to be included in the index. Meaning, in the process of constructing a general-purpose index, for example, a consumer price index, it is difficult to include all consumer goods. The only feasible alternative is to take samples in such a way that it may reasonably be presumed that the items that are included adequately reflect, represent, or indicate the overall picture. The fourth step is the choice of the base period. The year or period with which one wants to compare is called 'given year' or 'given period' while the year or period relative to which the comparison is made is called 'base year' or 'base period'. The index number for the base year is taken as 100. Ideally, in the choice of a base year, it is generally desirable to base comparisons on a period of relative economic stability (a period of average steady inflation without any unusual occurrences) as well as a period not too distant in the past. An index based on a period of abnormal economic conditions tends to give the wrong impression of the phenomenon being observed. When the base period is too remote, data related to such a period could be very difficult to collect. The fifth step is the choice of the weights that account for the significance of individual items in the overall that the index is supposed to describe. Choice of the weights, therefore, becomes very important when items being considered in an index are not of equal importance. The weights assigned to the various items must, therefore, be measures of their relative importance and should be carefully chosen to avoid biased and misleading results.

Based on the weighting approach, an index can be categorized as weighted or unweighted, and while the latter does not apply a weight to the index, the former applies different bases as a weight, such as equally weighted, price-weighted, market capitalization-weighted, and float-adjusted market capitalization-weighted. For example, Laspeyres (1971) and Paasche (1974) developed indexes that use base year quantity and current year quantity as weighting methods.

To begin with, an equal-weighted index is the type of weighting index that is used to assign equal value to all the stocks in the index, and therefore, all of the constituent stocks carry equal relative importance or weight in the construction of the index. To create a price-weighted-index, first the average price is computed, and then the percentage change in the average price is calculated. In the price weighted-index method, the highest-priced stocks have the highest weightings within the portfolio regardless of their total market capitalization; price-weighted indices are easy to calculate but generally have arbitrary index weightings (Zeng & Luo, 2013). The Dow Jones industrial average is one of the well-known indexes that use a price.

The third weighting method, namely the market capitalization-weighted index, is a weighting approach in which a company's shares outstanding are multiplied by its per-share market value, and the weight is computed as a proportion of the total market capitalization; the market cap index method is dominantly employed by many index providers, such as the S&P 50, the NASDAQ 100, and the Russell 2000 (Zeng & Luo, 2013). Finally, float-adjusted market-capitalization weighting is another weighting approach by which the weight of each constituent security is determined by adjusting market capitalization for its market float, i.e., the regular shares a company has issued to the public that are available for investors to trade.

The last step is the methods of construction, which is about the choice of appropriate formulas that describe relative changes. The particular formulas that provide the required index numbers could be chosen based on practical considerations. That is, there are different formulas, and some of the most commonly used are the Laspeyres price index and the Paasche price index. The Laspeyres price index was developed by German economist Etienne Laspeyres as a base period quantity index in which the Laspeyres price index is used to measure the change in the prices of a basket of goods and services relative to a specified base period weighting. The Paasche Price Index is another price index method developed by German economist Hermann Paasche to measure the change in the price and quantity of a basket of goods and services relative to a current period price and observation year quantity). The Paasche Price Index is commonly confused with the Laspeyres Price Index. The key distinguishing factor between the Paasche Index and the Laspeyres Price Index is that the Paasche Index uses current-period quantity weightings while the Laspeyres Price Index uses base-period quantity weightings.

2.2 Asset pricing

An asset is defined as a resource owned by a business (Krause, 2001) that is expected to provide future economic benefit (Krause, 2001; Weygandt et al., 2020), and it results from past events. Furthermore, Celik (2012) defines an asset as a generating risk future payoff that can be distributed over time; an asset's value is determined by its future cash flows (Krause, 2001). Thus, pricing an asset is based on its current value of the payoffs of cash flows discounted for risk and time lags; that is, asset pricing means a formal treatment and development of pricing principles together with the resultant models (Celik, 2012). That is, one can get different asset pricing models that have been developed for a variety of situations. Of the well-known asset pricing models, the Capital Asset Pricing Model (CAPM) (Sharp, 1965), Arbitrage Pricing Theory (APT) (Ross, 1976), and the Fama-French Three-Factor Model (Fama & French, 1993) are particularly citable. For example, the Capital Asset Pricing Model (CAPM) results in the birth of asset pricing theory (Fama & French, 2004), which plays a central role in finance theory and application (Chenk & Tong, 2008). That is, the asset pricing theory can help one to understand the prices or values of claims to uncertain payments; a low price implies a high rate of return, so one can think of the theory as explaining why some assets pay higher average returns than others (Cochrane, 2000). In other words, asset pricing theory can provide   insight into the prices, values, or returns of claims to uncertain payments, such as stocks, bonds, and options (Barillas & Shanken, 2018). Asset prices can be determined by investors' risk preferences and the distributions of assets' risky future payments (Drobetz, 2000). In relation to this, the modern portfolio theory, capital asset pricing model, arbitrage pricing theory, and multifactor model are briefly discussed as follows:

2.3 Modern portfolio theory

Modern Portfolio Theory ("MPT") is made up of Markowitz's Portfolio Selection theory, which was first introduced in 1952 by Henry Markowitz, and William Sharpe's contributions to the theory for asset pricing, which were introduced in 1964 and became known as the Capital Asset Pricing Model ("CAPM") (Sharp, 1964).

Modern Portfolio Theory (MPT), developed by Markowitz in 1952, is one of the most important and influential economic theories dealing with finance. MPT is a theory of individual decision making in which Markowitz hypothesized that "investors can design an optimal portfolio to maximize returns by taking on a quantifiable amount of risk." It gives investors a chance to choose different types of investment for diversification. By investing in more than one stock, investors can reduce risk by going in line with the saying: “Do not put your eggs in one basket.” Modern portfolio theory has several assumptions that are implicit and explicit. These assumptions and the critique of the assumptions are discussed here. In other words, the MPT framework includes several assumptions about markets and investors. The following are assumptions that Harry Markowitz hypothesized:

- Returns from the assets are random variables and are normally distributed.
- Investors are rational and need to minimize risk and maximize returns.
- Investors are only willing to accept higher amounts of risk if they are compensated with higher expected returns.
- Investors have the same access to timely receipt of all relevant information.
- Investors can borrow or lend an unlimited amount of capital at a risk-free rate of interest,
- Markets are perfectly efficient,
- There is no transaction cost or tax ,
- It is possible to select securities whose individual performance is independent of other portfolio investments.

Despite its theoretical significance, Markowitz’s MPT received certain criticisms for its assumptions and financial market modeling. The following are some of the critiques:

The first one is based on the assumption that investors are rational. This is in contrast to what may be seen among market participants who become involved in ‘herd behavior’ investment activities. The market is boom or bust owing to speculative immoderations (Morien, n.d.a as cited by (Mangram, 2013), and this critique comes from behavioral economists. Second, Perfect Information assumption MPT assumes that all investors have access to timely and accurate information that is important to their decision-making, while information asymmetry is evident in the real market (Mangram, 2013).The final one is the unrestricted access to Capital assumption. In real-world markets, where only the federal government can regularly borrow at the interest-free treasury-bill rate this assumption of Markowitz attracted a criticism (Morien, n.d. as cited by Mangram, 2013). Theoretically, Markowitz's contributions to MPT are based on the premise that markets are fully efficient (Markowitz, 1952), despite the fact that markets are far from efficient in reality; because the market is subject to environmental, personnel strategic, or social investment decision dimensions, this is the case. Furthermore, it disregards potential market failures such as externalities (Mangram, 2013).

In addition to these, Markowitz's MPT ignores transaction costs (e.g. broker fees, administrative costs, etc.) and tax, which is contradictory to the real investment products, which are subjected to both taxes and transaction costs (Mangram, 2013). As portfolio theory deals with the measurement of risk and the relationship between risk and return, it is concerned with security prices and the portfolio selection decisions made by investors. While all investors maximize portfolio return with the selection of diversified stocks, a model, individually developed by professors, namely Lintner (1965) and Sharpe (1964), called the Capital Asset Pricing Model (CAPM), which is an extension of Markowitz portfolio theory, is used to measure the relationship that exists between required return and risk. The CAPM will be discussed as follows:

2.3.1 Capital asset pricing model (CAPM)

One of Markowitz' doctoral students, William Sharpe, updated his work, Modern Portfolio Theory (MPT), and developed a more accessible approach to diversification known as the Capital Asset Pricing Model (CAPM).

The capital asset pricing model (CAPM) is the risk and return model that has been in use the longest and is still the standard model in most real-world analyses (Damodaran 2020). Treynor (1961) formerly introduced the CAPM model, followed by Sharp (1964), Litner (1965a, 1965b), and Mossin (1966), who independently worked on it. The introduction of the CAPM model provides a useful starting point for the discussion of risk and return models, even though it is not free from critique (Damodaran, 2020) with respect to its unrealistic assumptions. The Capital Asset Pricing Model expands Modern Portfolio Theory in two ways. First, it considers both risky and risk-free assets. Second, it breaks down investment risk into two distinct components – systematic and unsystematic risk (CCC, 2021). The CAPM model is based on the assumption that any stock's required rate of return is equal to the risk-free rate of return plus a risk premium that reflects only the risk remaining after diversification (Drobetz, 2000; Damodaran, 2020; Fama & French, 2004; Fernandez, 2017).

2.3.2 CAPM Assumptions and Conditions

Since the CAPM is an extension of modern portfolio theory, most of its assumptions are derived from modern portfolio theory. The assumptions are about the behavior of investors and the condition of the capital market. These assumptions are listed as follows (Sharpe, 1965):

-Investors are risk-averse.

-Investors have a common time horizon for investment decision making

-Any investor has the same expectation about future security returns and risks.

-Perfect capital markets have no transaction costs or differential taxes, and borrowing and lending rates are equal each other and the same for all investors (Sharp, 1965).

Therefore, based on its assumptions, the Capital Asset Pricing Model (CAPM) measures the relationship that exists between required return and risk on a mathematical equation basis as follows:

$E(R) = Rf + \beta i\ (ERm - Rf)$

E(R) - expected return

Rf- risk free rate

β- Beta of asset i

E (Rm) - expected return on the market portfolio

The implications of CAPM for investors is that investors can adjust their risk preferences, in their allocation decisions between how much to invest in a riskless asset and how much in risky assets (market portfolio); the rate of return is only valid as long as the inputs are valid, i.e., the risk free rate, beta, and market risk premium.

There is an argument about the market model to trace the difference between the market model and the one being used by Sharpe in its CAPM, particularly in estimating the beta. One single factor that is very important in that model is market beta.

Market model:

$$\boldsymbol{R}_i = \boldsymbol{a_j} + \boldsymbol{\beta_j} \boldsymbol{R_m} + \boldsymbol{e_j}$$

$\boldsymbol{R_i}$ = historical (realized) rate of return on commodity j

$\boldsymbol{R_m}$ = historical (realized) rate of return on the market

$\boldsymbol{a_j}$ = vertical axis intercept term for commodity j

$\boldsymbol{\beta_j}$ = beta, coefficient, for commodity j

$\boldsymbol{e_j}$ = random error

Thus, what it is seen as trying to do here is regress the asset's realized return against the markets realized return. If one looks at the SML of the CAPM, the realized return is a bit different from the market model. To be theoretically correct in CAPM, both dependent and independent variables in the regression should have excess returns over the risk-free rate. In most cases, both the market model and the CAPM can produce a single result with no significant differences. So, it is safe to use the market model in estimating the beta without having to use the SML of the CAPM.

It is essential to note that CAPM has its fair share of critics; for example, taking beta as the only measure of risk in a single factor concept is the one and only element that has prompted other researchers to extend the CAPM. As a result, Ross developed an alternative asset pricing theory known as Arbitrage Pricing Theory (APT) in 1976. The APT considers multiple factors instead of only one factor when calculating the expected return and risk premium in the CAPM. APT conveys the ability to construct a new portfolio with any level of sensitivity to each of the other factors. Hence, the unsystematic risk will be low as one can increase the number of factors. The model will capture one or more variations in the return of the security. Similar to the CAPM, APT also has its own assumptions. Investors are assumed to be rational and risk-averse. The market is assumed to be efficient so that it provides information perfectly; it is also assumed that there is no information cost to permit arbitrage. Another assumption in the arbitrage pricing model is that factors that are included in the model are not correlated with each other. Though the APT model could give room for multiple variables to explain the expected return, it is criticized in that it says nothing about specifying the factors to be included in the model.

Fama and French (1992) developed an alternative model that helps to specifically identify the factors that the APT model fails to do. The model developed by Fama and French (1992) is a three-factor model that is an extension of the capital asset pricing model that includes two other factors: size risk (size of the firm or market capitalization) and value risk (book to market value) factors in addition to the market risk factor in CAPM. The authors expanded the three-factor model to a five-factor model in which they include profitability and internal investment. The former refers to the concept that companies reporting higher future earnings have higher returns in the stock market, and the latter implies that companies directing profit towards major growth projects are likely to experience losses in the stock market.

Although APT and multifactor models were provided as alternatives to the CAPM, they did not show a significant improvement in terms of estimating expected returns (Damodaran, 2020). That is, even though the APT gives room for multiple variables to explain the expected return; it fails to specify those factors to be included in the model. When it comes to the multifactor model, the data is supposed to determine multifactor models rather than extensive economic rationale. Hence, as Damodaran (2020) notes, CAPM is still predominantly used to estimate the expected return of an asset. Thus, it is possible to take the stance that judicious use of the CAPM is the most effective method of dealing with risk and return valuation. Next, the concept of 'risk and return trade-off' in relation to Markowitz's basic principles will be discussed.

2.4 Return and risk

Return is defined as the total gain or loss from an investment over a specific time period, taking into account both changes in market value and cash distributions. It is a measure derived from the overall gain or loss incurred by the owner in relation to an asset (share or bond) over a particular period of time (Guinea, 2016).

Risk is a difficult concept to understand, and attempts to define and evaluate it have sparked heated debate. People, in their traditional view, use the word “risk” to describe the likelihood that something bad will happen, as a negative exposure to danger or hazard. As a result, when investing in a stock, investors may consider risk as the likelihood that the stock price will fall before the investor sells it, resulting in a loss. Guinea (2016) defines risk as the probability of loss; when an asset has a higher probability of loss it is termed as a “risky asset.” But other writers, for example, Damodaran (2020), define risk as both a hazard and an opportunity; it is impossible to have one without the other, and that is why he combines danger with opportunity in risk. The more you are interested in accepting the danger, the more you will be rewarded by it. Hence, for this study to deal with risk, consideration is given as it is a deviation from expectation; that is both the pain and the gain.

Though everyone does not agree on defining risk, in general, investment opportunities that offer higher returns also entail higher risks. Here it is necessary to note that even though the term "risk" may imply the chance of injury or loss, the term used in this study has a broad definition and is employed to reflect volatility in stocks’ or other assets' rates of return, and it should not be confused with risk and uncertainty in the production process (Hotvedt & Tedder, 1978).

Investment diversification, or the purchase of various types of assets (stocks, bonds, securities, real estate, and so on) and the purchase of ties, real estate, and so on, can minimize the total risk of an investor's investment portfolio (Hotvedt & Tedder, 1978). However, risk can only be reduced to a certain extent in this manner because changes in overall market conditions affect price fluctuations in all stocks and other assets, and this diversification cannot completely eliminate this variability (Hotvedt & Tedder, 1978).

As a result, it is desirable to classify total risk into two components: one reflecting the portion of an asset's price movements caused by changes in the market as a whole, and the second reflecting that portion of an asset's price movements caused by factors unique to the company or industry itself. The former is called "systematic risk" (and is non-diversifiable) and the latter "unsystematic risk" (diversifiable) (Hotvedt & Tedder, 1978), and each of them is discussed in detail as follows:

Systematic risk refers to the risk inherent in the entire market, so it is also known as market risk or volatility, and it affects the overall market, not just a particular stock or industry (Bringham & Houston, 2012; Ross et al., 2001). That is, systematic risk is inherent in the market as a whole, and it reflects the impact of economic, geopolitical, and financial factors.

Unsystematic risk is a company-specific or specific risk that is attributable or specific to a single investment or small group of investments (Bringham & Houston, 2012; Ross et al., 2001); it is uncorrelated with stock market returns and is thus termed as a specific risk, diversifiable risk, idiosyncratic risk, and residual risk.

The relationship between risk and return is a fundamental concept in finance theory, and it is the most important point for investors to understand. The ‘risk and return trade-off’ is related to Markowitz’s basic principle that the higher the risk, the larger the expected return. That is, investors will keep a risky security only if the expected return is sufficiently high enough to compensate them for assuming the risk (Ross et al, 2001). Some risks can be avoided and, as such, bear no expected reward; it is only those risks that cannot be easily avoided that are compensated for (Bradford & Miller, 2009).

The first theoretical attempt to quantify the relationship between risk and return was made by Markowitz in 1952. The name of the theory is often called Modern Portfolio Theory or MPT, which uses the application of statistical measures of risk such as variance and standard deviation. In Markowitz's portfolio selection theory, risk is synonymous with volatility—the greater the portfolio volatility, the greater the risk. Volatility refers to the amount of risk or uncertainty related to the size of changes in the value of a security (Volatility/Investopedia, n/d). This volatility is measured by a number of portfolio tools, including: (1) calculation of expected return; (2) the variance of an expected return; (3) the standard deviation from an expected return; (4) the covariance of a portfolio of securities; and (5) the correlation between investments (Ross & Westerfiels, 2018). These measures of risk/volatility are listed as follows:

- The first step is to calculate the expected return or mean from the given observations
- Second, deduct the expected return from the possible returns in the observation and square the result to calculate the variance of the expected return
- Third, calculate the standard deviation from the expected return.
- Forth ,calculates the covariance of a portfolio of securities, and
- Finally, calculate the correlation between investments.

2.5 Risk-free rate

Risk-free rate is the crucial component of CAPM that could be considered in one's investment decision. As a result of this, the empirical literature uses various approaches for the estimation of this element. A risk-free rate is theoretical and even practically unavailable. A risk-free investment is one on which an investor certainly knows the expected return. The government of any country is said to have no risk of default because they can print money to repay the debt when required. Consequently, the interest rates on non-tender government securities such as the government's long term T bond rate, treasury bills, bills, and promissory notes are often considered a proxy for the risk-free rate of return in most corporate finance analysis (Bodie et al., 2003; Bringham & Houston, 2012). Theoretically, for an investment to be called risk-free, it has to meet some conditions, such as the entity issuing the security is default free, the cash flows from this investment can have no reinvestment risk (Damodaran, 2020); zero volatility; zero interest rate risk; zero covariance with the market portfolio; zero exposure to inflation risk; and zero liquidity risk (Strydom & Charteris, 2009). It is apparent that a review of U.S. research and Rexts advocates T-Bills as the most suitable proxy (Bodie et al., 2003; Reilly & Brown, 2006).

2.6 Price volatility

In a strictly descriptive context, volatility refers to changes in economic variables over time; it is a measure of market differences from the previous period to the current period. Volatility is a measure of price variation from the previous period to the current period. Variation is not always problematic, such as when prices move along a smooth and well-established trend reflecting market fundamentals and well-known seasonal patterns (Shiferaw, 2009). But price variations become problematic when they are large and become unpredictable, and consequently, they create a level of uncertainty that increases risks for producers, traders, consumers, and governments and may lead to sub-optimal decisions.

Volatility can be measured in two ways: realized volatility and implied volatility. Realized volatility is commonly referred to as historical volatility because it can be calculated from previous pricing. This measure forecasts the future based on the past. Implied volatility, on the other hand, is computed using the market's consensus on a derivative instrument's fair value, such as the S & P500 index option contract. Implied volatility is a "future" or "forward-looking" expectation estimate. Brook (2002) describes historical volatility as the computation of variance or standard deviation of returns in a conventional statistical approach across some historical era, which may then become a forest of all future periods.

The evolution of price fluctuation was originated by Markowitz's (1952) study, which focused on the concept of the uncertainty of asset prices that is based on price movement and dynamics. As documented by Mandelbort (1963) volatility clustering and leptokurtosis are the main characteristics of financial time series, among others.

Traditional econometric models assume a one-period forecast variance that is constant. Engle (1982) was the first to develop a modern volatility model, in which he used autoregressive conditional heteroscedasticity (ARCH) to deal with shifting variance. These are mean zero, serially uncorrelated processes with non-constant variances conditional on the past but constant unconditional variances (Teshomeet al., 2020). The recent past provides information on the one-period forecast variance for such systems.

The basis of an ARCH model is that there is a time-varying mean (hetroschdastic) that is dependent on (conditional) on a lagged effect; as a result, large and small errors tend to cluster together when a big shock occurs in the preceding period. It is more likely that the variance of the current period will also be bigger than the vice versa (Teshome et al., 2020).

After Engle’s (1982) Autoregressive conditional heteroscedasticity (ARCH) was implemented, several other models were introduced to volatility modeling, including a generalized version Called generalized autoregressive conditional heteroscedasticity GARCH model, which was introduced four years later by Bollerslev (1986). Then it is followed by the Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model (Nelson, 1991), the Threshold Generalized Autoregressive Conditional Heteroskedastic (TGARGH) model (Zakoian, 1994), and others that become dominant in modeling conditional variance and risk prima.

The conditional variance in the ARCH (q) process is only specified as a linear function of past sample variances, whereas the GARCH (p, q) (Bollerslev, 1986) process also allows lagged conditional variances to enter the model, with the conditional variance expressed as a linear function of past squared innovations and their past values with a non-negativity constraint. The degree of unforeseen excess returns determines feature variance in GARCH models, not their positivity or negativity. The leverage effect is what the EGARCH (Nelson, 1991) model captures that the GARCH model does not. That is, negative shocks at time t-1 have a stronger impact on the variance at time t than positive shocks (Nelson, 2011), since the rise in risk is thought to be due to the increased leverage caused by a negative shock, which allows for equalized positive and negative shocks.

The Threshold GARCH model, proposed by Zakoian (1994), is a model similar to the Exponential GARCH model, which permits asymmetric shocks to volatility. Volatility tends to increase with bad news and decrease with good news (Zakoian, 1994). One of the differences between these two models is that the TGARCH makes volatility a function of non-normalized innovations and enables additive modeling, while the EGARCH does not. In modeling asymmetries, EGARCH imposes a stable structure at all lags, whereas TGARCH cases may give opposing contributions at various lags.

The agricultural commodity market reacts more to good news than to bad news where speculative hoarding takes place (Thiyagarajan et al., 2015). According to Thiyagarajan et al. (2015), GARCH (1, 1), for asymmetric modeling P GARCH (1, 1) was found to be the best model, for example, for the Indian and for asymmetric modeling, as they explain volatility better in their category, as the calculated LM test values are the lowest for them, signaling that these models are better at capturing the effect of volatility than others, in the Indian Agricultural market. Agricultural commodity market quantities and prices are often random. This introduces a large amount of risk and uncertainty into Le the process of market modeling and forecasting.

The volatility in the prices of commodities has a direct impact on final consumers as the price of food is impacted by production costs as well as by inflation (Le Roux, 2018). Commodities are used as financial assets in various forms, and understanding the volatility present in the price could be used to the advantage of the investor (Le Roux, 2018).

Roux (2018) empirically examined the GARCH family of models, including the generalized autoregressive conditional heteroscedastic (GARCH) model, the Glosten - Jagannathan-Runkle generalized autoregressive conditional heteroscedastic (GJR-GARCH) model, and the exponential GARCH (EGARCH) model, to determine the best fitting model for various agricultural commodities. The results show that volatility exists in the data; overall, GARCH was the best fitting model for the S&P GSCI Agriculture Index during and after the financial crisis, as was EGARCH for the Brazilian Real, and only the GJR-GARCH results for cocoa indicated the presence of leverage effects.

Lama et al (2015) studied the autoregressive integrated moving average (ARIMA) model, the GARCH model, and the EGARCH model along with their estimation procedures for modeling and forecasting of three price series, specifically domestic and international edible oil price indices and the international cotton price ‘Cotlook A’ index. Their study revealed that the EGARCH model outperformed the ARIMA and the GARCH models in forecasting the international cotton price series, primarily due to its ability to capture asymmetric volatility patterns. Another study by Rahayu et al. (2015) also supports the asymmetric effect return of coffee prices in Indonesia. Hence, EGARCH is an appropriate model for this commodity.

Moreover, the study conducted by Adugh (2019), which focused on modeling volatility of agricultural commodities by using monthly commodity food price index data in Nigeria, shows ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models with student-t innovations were appropriate in describing the symmetric and asymmetric behaviors of the log returns. That is, the study concludes that ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1)models fit symmetric and asymmetric behaviors of the log returns, which could best describe the log returns price volatility of selected agricultural commodity food products in Nigeria. The study further showed that the best fitted models were not necessarily the best forecast models.

With special reference to the context of Ethiopia, researchers, for example, Shiferaw (2012), Ayele et al. (2017), Muanenda and Yohannes (2018), Teshome (2020), and Teshome et al. (2020), have conducted studies that focused on modeling commodity price volatility.

Shiferaw's (2012) study that focused on selected agricultural products, found that the ARCH and GARCH models were appropriate. In line with this, the results suggested that GARCH (1,1), GARCH (1,2), and GARCH (2,1) models were the most appropriate fitted models that a researcher could use to evaluate the volatility of the log-returns of the price of cereal, pulse, and oil crops, respectively. Price volatility was persistent in all three categories (cereals, pulses, and oil crops) of selected agricultural goods. The study conducted by Ayele et al (2017) revealed that the GARCH-M (2,2) was found to be the best fit model for modeling and forecasting the gold price volatility in the Ethiopian market, and Muanenda and Yohannes (2018) found that ARIMA (0,1,1) and ARMA (2,2)-GARCH (2,1) with the normal distributional assumption for the residuals were adequate models for modeling and forecasting the volatility of the export price of sesame in Ethiopia. Moreover, recently, Teshome (2020) also conducted a study on modeling time-varying coffee prices, and found that the multiplicative GARCH-MIDAS model explained stylized facts that could not be captured by the standard GARCH model,

Though most of the volatility models originated in the financial market to capture the conditional volatility of variables such as asset returns and inflation, their application expanded to measure volatility in other situations, for example, in agricultural commodity markets. many scholars have employed GARCH family models to model the volatility of agricultural commodity price indexes by using data from a variety of sources, including both developed and developing countries and at various times. However, they found a different model that fits best with the agricultural commodity price index.

Therefore, this study contributes to modeling the risk and return of agricultural commodities in Ethiopia using data from CSA and examines the best-fit GARCH family model.

2.7 Empirical literature

Some studies that focused on price index construction, asset pricing, and price volatility have been conducted. To begin with the first one, a variety of price indexes for real estate and housing have been developed at different times and by different scholars; for example, the repeated sales index by Bailey et al (1963), hedonic regression by Rosen (1974), weighted repeated sales by Case and Shiller (1987), hybrid approaches by Case et al. (1991), Quigley (1995), and Hill et al. (1997), autoregressive index by Nagaraja et al (2011), and a spatial cost index of housing by Paredes (2011) are citable.

In brief, a study by Bailey et al. (1963) focused on the construction of a real estate price index employing the regression method. According to these researchers, quality differences can help estimate price indexes for real properties difficult. In other words, for them, it is challenging to construct index numbers for the prices of real properties, and the difficulty can result from the high differences in quality among the properties. As a result, index numbers constructed relying on the average sales prices of all properties of certain specific types sold in a given period are likely to be inefficient in two ways: (1) the variation observed in the quality of properties sold from time to time can make the index vary widely more than the value of any given property; and (2) it is the event of a progressive change in the quality of properties which are sold at different times, the index number will be biased over time. One technique that could be employed to avoid these problems is to eradicate the apparently observed quality differences by employing regression analysis. Indeed, the difficulty of merging price relations of repeat sales of properties to get a price index can be converted into a standard regression method, which, in turn, can be used to estimate the index; the regression approach of estimation is more effective than other methods for merging price relations. Furthermore, the regression approach can help one to easily compute standard errors of the estimated index, and it can help to eradicate certain effects on the value of real properties from the index (Bailey et al., 1963).

Rosen (1974) conducted a study that attempted to develop an index using hedonic regression methods; hedonic models indicate that shifts in the quality of one attribute of a product may prompt a shift in the composition of buyers of that product, and a hedonic regression model describes how a product price could be explained by its characteristics; that is to say, it permits various attributes. Indeed, the main idea behind the hedonic model is to decompose the characteristics. It is worth noting that the repeated sales method, which was introduced by Bailey et al. (1963) and further extended by Case and Shiller (1987) as the weighted repeated sales model (WRS), is a type of model that is used as quality control for a property, and it requires very limited data in comparison to hedonic or hybrid methods. The WRS index could be constructed based on non-random samples selected from a population of house sales that could be sold more frequently during a given time interval. Yet, the WRS model is criticized for its failure to address depreciation and normal maintenance as well as problems concerning interpretation and sample selection.

Considering the weakness of the WRS, the hedonic, and repeated sales models, Case et al. (1991), Quigley (1995), and Hill et al. (1997) developed a hybrid model by combining hedonic and repeated sales, which was found to avoid most of the sources of biases and inefficiency, and the autoregressive index model was introduced by Nagaraja, Brown, and Zhao (2011). Paredes (2011) proposes a methodology for a spatial cost index of housing in consideration of spatial heterogeneity in properties across regions by combining quasi-experimental methods, hedonic prices, and Fisher spatial price index techniques to reduce the spatial heterogeneity in housing. In a study he conducted, Paredes (2011) found the existence of a price variation for similar houses in Chilem and he concluded in such a way that, firstly, houses were matched, followed by a hedonic price model computation and the creation of a regional housing price matrix using Fisher spatial price indices.

The aforementioned studies, however, relied on price index construction methodologies that were focused on the real estate sector; they cannot be directly traced to agricultural commodities price indexes, which are fundamentally different from real estate and housing sector prices. Thus, Fernandez (2019) proposed a price index that is an extended version of Grilli and Yang's (1988) non-fuel commodity price index (GYCPI) for the period of 1900–2016 that included thirty-six commodities which were classified into seven categories: beverages, cereals, other foods, agricultural raw materials, energy, metals and minerals, and precious metals. He used the Divisia-based commodity price index and the Divisia-version of the Grilli-Yang non-fuel commodity price index. Each commodity's average export share is taken as weights during the base period of 1977−79; He presented two Divisia commodity indices that can track well-known indices, such as the World Bank and S&P GSCI non-energy indices on annual and monthly bases, both of which can be easily computed and updated using publicly available data.

Fernandez (2019) extended index displays strong co-movement with a Divisia-version of GYC; both indices are capable of tracking well-known indices, such as the World Bank and S&P GSCI non-energy indices.

In addition to the studies conducted on price index construction, there have been some investigations that focused on asset pricing. Studies by Barry (1980), Bjornson and Innes (1992), and Turvey and Driver (1986) could be cited as examples of researches which focused on the application of CAPM in the agricultural sector.

In brief, Barry (1980) studied capital asset pricing and farm real estate, and he used the capital asset pricing model (CAPM) to estimate the risk premium required to hold farm real estate in a well-diversified market portfolio; risk premiums were estimated for farm real estate at the national level and for ten farm production regions of the United States. CAPM results then were evaluated in light of farm real estate's unique characteristics. He found that a significant portion of returns to farmland was not explained by his model and they could, therefore, be classified as "nonmarket" returns. The two major claims of his study were that it provided evidence that farm real estate had low risk relative to other assets and that the CAPM framework provided insights into the effects of nonfarm investor behavior. Empirical support was provided by Barry for the former and little or no discussion was offered by him in relation to the latter. Thus, farmland returns were not dictated by returns in a portfolio comprised of bonds, stocks, and farmland, and it was unsuitable to investigate them with the CAPM model which assumed they were. In addition, Turvey and Driver (1986) examined the systematic risks in agriculture. A Farm Sector Capital Asset Pricing Model (FSCAPM) was developed to examine systematic risks in agriculture. Beta coefficients were derived for various agricultural activities and portfolios. The study revealed that there was a great deal of systematic risk and low compensation for accepting these risks. Thus, an off-farm investment that could help to reduce systematic risk was suggested.

Finally, Bjornson and Innes (1992) investigated risk and return in agriculture, and they developed and estimated an explicit-factor arbitrage pricing theory (APT) model aiming to discover (a) the systematic risk properties of returns to agricultural assets, (b) the relationship between agricultural returns and returns on comparable-risk non-agricultural assets, and (c) the possible relevance of agriculture-related risks in general capital markets. The study concluded that: (a) farmer-held assets had exhibited significant systematic/ factor risk over the 1963-82 estimation interval, although U.S. farmland had not exhibited such risk; (b) a grain-price index had been a pricing factor in general capital markets; and (c) average returns on farmer-held assets had been significantly lower, and average returns on U.S. farmland significantly higher than those on comparable-risk non-agricultural assets. The total risk of an asset can be measured by its variance (Markowitz, 1952). This risk measure can be divided into two general types of risk: systematic risk and unsystematic risk. Systematic risk is defined as the portion of an asset's variability that can be attributed to a common factor, which cannot not be diversified, while unsystematic risk is the portion of an asset's variability that can be diversified away (Sharp, 1964). As a result, estimation of systematic risk (or 'beta') is critical in a variety of finance applications, including estimating costs of capital, capital budgeting decisions, portfolio selections, determining relative risk and testing asset pricing models.

Scholars such as Cornell and Dietrich (1978), Chan and Lakonishok (1992), Fong (1997), Cheng and Boasson (2004), Phuoc et al (2018), and Phuoc and Pham (2020) conducted studies that focused on beta estimation. In brief, Cornell and Dietrich's (1978) investigation focused on estimating beta by using 100 randomly selected companies from the S&P 500 index for 13 one-year periods, with each set of annual betas estimated using weekly data. By realizing the deficiencies of the OLS estimator, the authors proposed Mean Absolute Deviation (MAD), an estimator which gives less weight to outliers compared with the OLS estimator. They hypothesized that MAD could generate a more efficient beta estimation compared to the OLS method. However, the empirical results do not confirm their hypothesis, for the results showed that the MAD estimator did not necessarily produce a more efficient beta estimation than the OLS estimator.

Similarly, Chan and Lakonishok (1992) conducted a study of beta estimation using simulated and actual monthly return data of 50 randomly selected stocks from the NYSE for 1983–1985. The authors described various robust methods, such as minimum absolute deviations (MAD), the trimmed regression quantile estimator (with trimming proportion α set to 0.10, 0.20, or 0.25), and the Trimean and Gastwirth estimators in comparison to OLS. These robust methods are applicable when observations on the dependent variable take on extreme outlying values, not accounted for by movements in the explanatory variables. Based on both simulated and actual return data, except for the MAD, the finding of the empirical analysis showed that there is a potential efficiency gain from using robust methods as an alternative to OLS. The robust methods should be considered as a serious alternative to OLS in estimating cross-sectional betas for a sample of initial public offerings. Considerable progress was also observed from using the robust methods when the simulations were based on the actual distribution of residuals and excess market returns using both monthly and daily data. The other author, Fong (1997), explored how betas could be estimated when the distribution is non-normal; that is, both skewed and leptokurtotic, using monthly returns data of 22 stocks listed on the Singapore Stock Exchange, which is a price-weighted index of 30 leading industrial stocks in Singapore. Fong found that the Generalized Student-t (GET) outperformed the OLS in estimating beta. However, this research employed only one data type, horizon data, and two criteria in comparison.

Cheng and Boasson (2004) conducted a study of beta estimation and proposed a special type of time-weighted least square method (TWLS), which assigns greater weights to the regression errors in more recent periods, for estimating the current beta. They used daily returns of 31 emerging markets stock from 2000 to 2002 and found that the betas for these markets do shift over time.

Moreover, Phuoc et al. (2018) explored the estimation of the beta coefficient (β) through the Capital Asset Pricing Model (CAPM). In the past and in common practice, these coefficients were typically estimated using the ordinary Least Square (LS) regression method and monthly return data in the finance and accounting literature. In addition, it was practically common to estimate through the ordinary Least Square (LS) regression method and monthly return data in the finance literature. With this conception in mind, Phuoc and Kim examined alternative ways of estimating the coefficient of systematic risk, namely the beta coefficient. Their findings revealed that the robust Least Trimmed Square (LTS) and maximum likelihood type of M-estimator (MM-estimator) out performed much better than Ordinary Least Square (LS) in terms of efficiency for large-cap stocks in the United States markets. Additionally, it showed that daily return data would provide more accurate estimation than monthly return data in both ordinary Least Square (LS) and robust Least Trimmed Square (LTS) and maximum likelihood type of M-estimator (MM-estimator) regressions.

Finally, a study conducted by Phuoc and Pham (2020) exhibited that the non-parametric Bayes estimator generated a higher model fit compared with the parametric Bayes estimator. The investigators used 450 stocks from the S&P 500 with monthly data from 07/2007–05/2019. It showed the non-parametric Bayes estimator generated statistically significantly smaller AIC/DIC, model variance, fewer zeroed betas, smaller alpha, and beta standard deviation, and higher model fit compared with the parametric Bayes estimator.

To sum up, in investment and corporate practices, systematic risk (beta) can be estimated using different asset pricing models (Bertomeu & Cheynel, 2016). The Capital Asset Pricing Model (CAPM) is a frequently used asset pricing model among different asset pricing models (Bartholdi & Peare, 2005; Fama & French, 1996b; Jacobs & Shivdasani, 2012; Zhang et al, 2017). The reason for its application is its ability to show a very simple linear relationship between a stock's beta and expected returns and the availability of its components' data, such as the returns on the stocks and market (Phuoc & Pham, 2020). In practice, using monthly/quarterly/annual return data, ordinary least square (OLS) is used to estimate beta.

Furthermore, there have been studies that put special emphasis on price volatility. Of the studies which focused on price volatility, Bonato (2019), Degiannakis et al. (2019), and Yuan et al. (2020) could be cited. For example, Bonato (2019) tried to provide new insights into the changes in the dynamics of price correlations and spillover effects in the commodity market. They employed US-traded futures price data at a 1-minute frequency over the 2002-2017 periods and considered the interaction within soft and grain commodities and between these commodities and oil; they used the recently introduced volatility model, which was known as the realized Beta GARCH model of (Hansen et al., 2014). The study revealed that soft commodities were segmented before 2008 and became correlated thereafter. The nature of the increase in correlation was only temporary, and the correlations within grains (already significant and positive) increased only marginally, indicating that this group had been less affected by recent events. The correlation between oil and agricultural commodities, which reached its peak in 2008, has also reverted to the pre-crisis level. Spillover effects between oil and commodities had become more prominent before the commodity price crash. However, this increase in volatility transmission tends to precede the increase in correlations. The impact of these findings on the performance of hedging strategies and optimal portfolio weights was discussed, and the results were found to be valuable for investors exposed to the commodity market as they showed that while the diversification benefits of investing in this market had decreased, volatility transmission risk and hedging costs had increased.

Similarly, Yuan et al., (2020) conducted a study that focused on modeling co-movement among different agricultural commodity markets using a copula-GARCH approach. Their study aimed to explore the volatility contagion among different agricultural commodity markets. To achieve this objective, the study used the copula-GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model for the daily spot prices of six major agricultural grain commodities, including corn, wheat, soybeans, soy oil, cotton, and oat over the periods from 2000 to 2019. The study revealed that significant contagion effects and risk transmissions existed among different agricultural grain commodity markets, suggesting that potential speculation effects on one agricultural market could be contagious to another agricultural market, resulting in an increase in volatility in agricultural product markets. Secondly, agricultural commodities appeared to co-move symmetrically. The study also found that there were substantial co-movements among agricultural commodity markets, which indicated that agricultural commodity markets tended to crash (boom) together during extreme events. Furthermore, after the food crisis, contagion effects and risk transmissions among different agricultural commodity markets increased substantially. Fourth, the study found that there were the strongest contagion effects and risk transmissions between corn and soybeans, and the weakest contagion effects and risk transmissions were observed between soya oil cotton and between cotton and oat. Last but not least, the study discovered that co-movement varies over time.

These findings have significant implications for modeling the co-movement with the copula-GARCH approach. Degiannakis et al. (2019) conducted a study that aimed to forecast the realized volatility of agricultural commodities. They forecasted the realized and median realized volatility of agricultural commodities using variants of the heterogeneous autoregressive (HAR) model, and they obtained tick-by-tick data on five widely-traded agricultural commodities (corn, rough rice, soybeans, sugar, and wheat) from the CME/ICE. Real out-of-sample forecasts were produced for between 1 and 66 days ahead. Their in-sample analysis showed that the variants of the HAR model that decomposed volatility measures into their continuous path and jump components and incorporated leverage effects offered better fitting in the predictive regressions. However, they demonstrated convincingly that such HAR extensions did not offer any superior predictive ability in their out-of-sample results, since none of these extensions produced significantly better forecasts than the simple HAR model. The findings remained robust even when the researchers evaluated them in a value-at-risk framework. Thus, there was no benefit from including more complexity, related to the volatility decomposition or relative transformations of the volatility, in the forecasting models.

To come to local studies (studies conducted in the context of Ethiopia), one can get studies that have focused on factors that could affect price volatility and inflation. In particular, previous studies that have been conducted on the agricultural commodities market have mainly focused on examining factors that could affect food prices and modeling inflation. For instance, Hilegebrial (2015) investigated the determinants of food price inflation in Ethiopia using food price inflation recorded from 1971-2013. He developed a regression model in which food price inflation was taken as the dependent variable and money supply, real GDP, inflation expectation, and world food price were taken as independent variables. His findings revealed that food prices in Ethiopia were determined by both demand (money supply and expectation) and supply (output and world food price) factors. Durevall et al. (2013) estimate models of inflation to identify the importance of the factors contributing to CPI inflation using monthly data over the past decade. Durevall et al. (2013) found similar results with Hilegebrial (2015) in some variables, such that agricultural supply shocks in the short run and monetary policy and international food and goods prices affected inflation in the long run.

Tassew & Yisak (2015) conducted another study on food price volatility in Ethiopia with the objective of examining how people and the government dealt with the extraordinary levels of food price volatility. Their study was qualitative; data were gathered from those engaged in grain production (rural) and traders (urban) by using focus group discussion and interviews. Their findings showed a global market, variable agricultural production, and irregular trading practices had marked food price volatility in Ethiopia over the last decade. Yet there is no reliable quantitative measure that shows the overall performance of the agricultural commodity market on which investors, farmers, government bodies, and other interested groups relay on. So current research intends to fill this gap by constructing a solid index readily used to show the performance of the agricultural commodities market.

Secondly, there have been certain local studies that focused on price volatility. For example, Ayele et al (2017) conducted a study that aimed at modeling and forecasting the gold price volatility in the Ethiopian market, and they used the exponentially weighted moving average (EWMA) and the generalized autoregressive conditional heteroscedasticity (GARCH) models for analyzing the retail data, which were recorded starting from 1998 up to 2014. Their finding dictates that the price return series of gold shows the characteristics of financial time series, such as leptokurtic distribution, data dependence, and strong serial correlation in squared returns. So, the series can be modeled using both EWMA and GARCH-type models. In a comparison made between the GARCH and the EWMA models, using the relative mean squared error & mean absolute error measures, Ayele et al (2017) suggest GARCH models with explanatory variables are superior in forecasting volatility. Hence, GARCH-M (2, 2) was found to be the best fit model for the data series among the GARCH-type models. In addition to this, they found certain explanatory variables which had significant impacts on gold price volatility, such as interest rates, exchange rates, and crude oil prices.

With special reference to modeling and forecasting the volatility of the export price of sesame in Ethiopia, a study was conducted by Muanenda and Yohannes (2018). In the study, ARIMA and GARCH family models were used. Monthly observations of the export price of sesame, the food price index, the fuel oil price, and the exchange rate from January 1998 to June 2013 were the data used for their analysis. Statistical tests from the study revealed that all the series were non-stationary at the level and stationary after the first difference. Muanenda and Yohannes (2018) ARIMA (0, 1, 1) and ARMA (2, 2)-GARCH (2, 1) with the normal distributional assumption for the residuals were adequate models for the sesame export price data. There is an increasing trend observed in the out-of-sample forecasts of sesame export prices, while the in-sample forecast using the best-fit the GARCH model indicates that the export price volatility of sesame steadily increased at the beginning of the study period, remained at an almost constant level till 2007 and then exhibited a downward trend around the end of the study period.

Based on the DM test, Abebe (2020), in his research which focused on modeling the average daily coffee price volatility from January 2010 to June 2019 in Ethiopia, discovered that statistic multiplicative GARCH-MIDAS model could explain stylized facts that the standard GARCH model could not capture. The GARCH-MIDAS component model decomposes the conditional variance into short-run components and long-run components; the former follows a mean-reverting unit GARCH process and the latter considers different frequency macroeconomic indicators via mixed interval data sampling (MIDAS) specification. Additionally, the estimated GARCH-MIDAS model with money supply as the main driver was used for the out-of-sample forecast.

In conclusion, studies by Muanenda and Yohannes (2018) and Abebe (2020) focused on single commodity, such as sesame and coffee, respectively, and each of them is basically an export commodity. Export commodities in the country experience greater price volatility than other commodities since they are influenced by external factors, for example, the world production quantity and exchange rate currency, since most globally traded commodities are priced in USD. Data used by both Muanenda & Yohannes (2018) and Abebe (2020) were the export price, in which prices of export commodities were subject to extreme volatility (Kindie, 2009) with a considerable impact on the level of uncertainty. On one hand, as it is seen from the literature, there is no one best model which fits all data series and the nature of the commodity. On the other hand, the aforementioned studies included very limited commodities in their model, and even the commodity they incorporated in their volatility models did not explain the domestic market on a broader basis.

Therefore, this study tries to add its contribution to the literature in the field by documenting the best fit volatility model which can be used to forecast prices of several agricultural commodities with the use of different data (retail price data) in the local markets. To summarize, in both the international and local studies conducted on price indexes, application of CAPM and volatility modeling, certain gaps have been apparently observed. Firstly, it has been hardly attempted to develop an index that can serve as a reliable quantitative measure that could show the overall performance of the agricultural commodities market in Ethiopia, which is useful for investment and policy-making decisions. To begin with the CSA CPI, firstly, its purpose has been to measure the overall inflation level in the country. As a result, it was based on a basket of commodities which consisted of both agricultural and non-agricultural commodities.

Furthermore, the weighting strategy was based on the relative importance of each commodity in household consumption. That is, it was a base year quantity weighted index (CSA). Therefore, it has failed to demonstrate the quantity produced to signify the performance of the agricultural commodities market.

The FAO Food Price Index (FFPI) was introduced in 1996 as a public good to help the development of the global agricultural commodities market. The purpose of the index was not to use it as an indicator on its own to assess the domestic agricultural commodities market. In addition, it has focused on the export share of a commodity in the international market. In other words, the FAO FPI have been used as a measure of the monthly change in international prices of a basket of food commodities weighted by the average export shares of each of the groups. By implication, the FAO FPI has relied on commodities that could be exported from the country and imported into the country (FAO, 2021). But there are many agricultural commodities that are dominantly produced and consumed in the local market that the FAO FPI could not address because the indexes were based on global export share and the actual price paid by individuals is quite differences. Secondly, there has not been explicit research yet conducted to estimate the beta of a capital asset with the application of CAPM because there has not been stock market in Ethiopia.

Similarly, even though there has been a commodity market in the country, an attempt has not been made to estimate beta for any commodity in Ethiopia. Thirdly, the studies on volatility modeling revealed that the different models used to measure volatility were found to be context-dependent. That means a model that could fit for a particular data may not be appropriate for forecasting another data. Furthermore, the scope of the local studies in terms of their coverage of commodity numbers has been very limited, and they have focused on data related to the export price of those commodities.

Therefore, this study tried to fill the aforementioned gaps. That is, it attempted to develop price indexes for agricultural commodities; using these indexes, it estimated market return and the betas of agricultural commodities. Finally, this study tried to add its own contribution to the literature in documenting the best fit volatility model used to forecast prices of relatively large numbers of agricultural commodities with the use of retail price data with special reference to Ethiopia.

2.8 Theoretical framework

This study can be anchored to modern portfolio theory, which is a philosophy of individual decision making in which it gives investors a chance to design an optimal portfolio that could help to maximize returns with a given level of risk or minimize risk with a given level of return (Markowitz, 1952). In this regard, investors select an asset to be included in a portfolio if it helps to diversify the portfolio's risk. The capital asset pricing model (CAPM) is an acceptable approach for the diversification of risk that includes both risky and risk-free assets in the portfolio. That is, CAPM classified total risk into systematic and unsystematic components, where only the latter is to be diversified with an efficient portfolio.

According to portfolio theory, the portfolio return is calculated as a weighted average of individual assets' returns. In the same theory, risk is defined as the deviation of return from the expected return, which is measured by variance and standard deviation, and volatility as the risk of a portfolio. Thus, taking the portfolio theory as a basis, it is attempted to design a model which shows the conceptual relationships of the variables of the study. See the figure below.

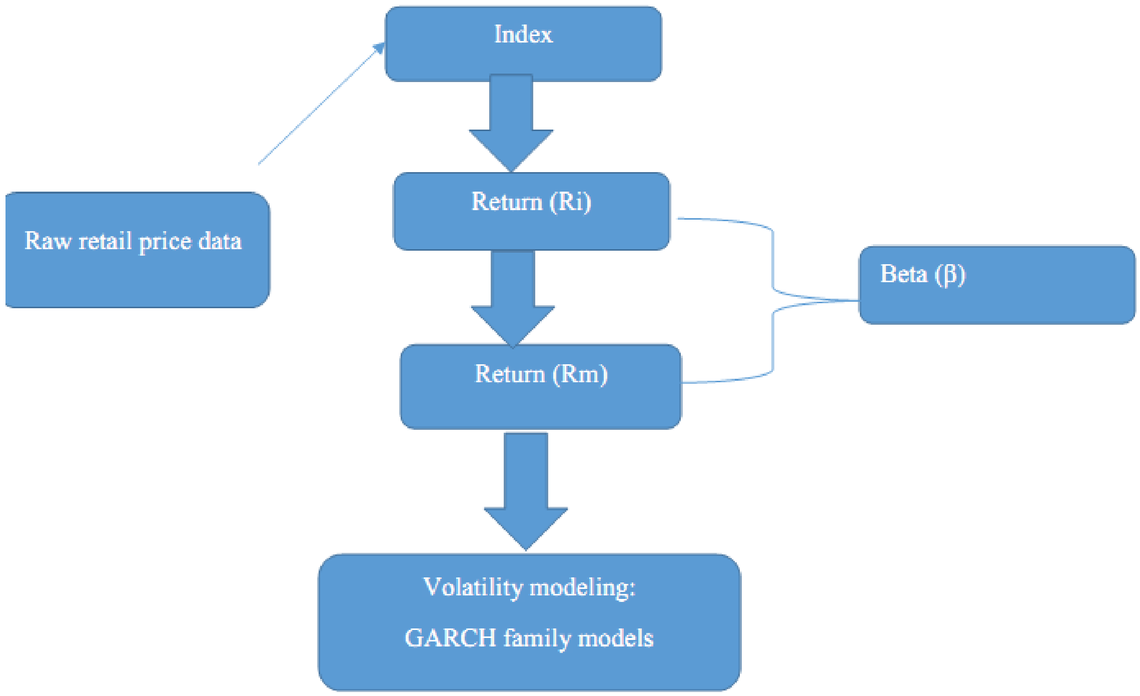


Figure 1: Theoretical framework of the study (Source: Sharpe 1964)

The above model shows how the different variables in this study are related to one another. In brief, the raw monthly retail price data obtained from the Central Statistics Agency over time is aggregated to realize the overall market condition, the so-called market index. Accordingly, this construction of the index is a key to figuring out the price changes and overall market conditions for the agricultural commodities market in Ethiopia.

Following the index development or having an index that shows the overall change in the price of agricultural commodities/ crops in the above mentioned years, the next task is to lend a hand to estimate the systematic risk (beta) of each crop, which is a constituent of a well-known CAPM model, in a similar fashion to what has been done in the capital markets. That is, once the index is developed and the market return is obtained, the systematic risk (beta) of each commodity is estimated as the function of the market index by the menses of a market model very close to the CAPM, where the whole idea of the CAPM is beta.

Using the developed market index and the estimated systematic risk, the last turn for the study comes to modeling volatility of the agricultural commodities market using GARCH family models and identifying the best fit models appropriate for agricultural commodity/crop prices.

Operational definitions

Market: in this study, refers to the market areas which are listed as major markets in Ethiopia by Central Statistics Agency (CSA) specifications.

Agricultural commodities: in this research, refer to the ten crops, such as teff, barley, wheat, maize, sorghum, bean, potato, onion, red paper and niger that are selected as sources of data for this study.

Raw retail price data refers to average monthly retail prices of the ten agricultural commodities in Ethiopian market as collected by CSA.

Index is a measure which shows how prices changes over the period of time; that is, the measure which illustrates how the changes in prices of ten selected agricultural commodities have been occurring beginning from 2010 up to 2020.

Commodity price index is a weighted average of price relatives for the ten selected agricultural commodities in ANRS, ONRS, SNNP, and Addis Ababa during the year 2011 up to 2021which will show changes in price of agricultural commodities.

Return means Logarithmic return, which is calculated as the difference between the natural logarithm of the crops price at the end of the period and the natural logarithm of the crop price at the beginning of the period.

Systematic risk (beta) refers to a measure of commodity prices responsiveness with respect to the market (commodity prices index): in other words, it is measure of the relative risk exposure of holding a particular agricultural commodity of the ten selected commodities in relation to the Ethiopian market**.**

CHAPTER THREE:RESEARCH METHODOLOGY

This chapter presents the methodology that was used to conduct the research. The chapter is further divided into two subsections where the first subsection discusses the theoretical methodology, such as research philosophy, research approach, and research strategy, and the second section deals with practical methodology, including sample size and the sampling strategy, and the data analysis methods used in this study. Here, the researcher describes the methods that were chosen during the research and explains why they were preferred over the available alternative methods.

3.1 Research paradigm

A study has a philosophy or paradigm on which it is based. A research paradigm is the world view of the researcher that could hold about an issue to be investigated (Creswell & Clark, 2011). There are different types of paradigms. According to Denzin and Lincoln (2018), research paradigms can involve four types of views, such as axiological beliefs (which deal with the nature of ethics), epistemological assumptions (which focus on the nature of knowledge), ontological beliefs (that deal with the nature of reality), and methodological philosophies (which are about the nature of inquiry). In brief, an ontology that refers to “the study of being” (Crotty, 2003, p.10) is concerned with the kind of world the researcher is investigating, with the nature of existence, and the structure of reality. According to Guba and Lincolin (1989, p. 83), the ontological assumptions are those that respond to the questions” what is there to be known’ or what is the nature of reality?” (p.83).

This study has adopted a realistic ontology in which the researcher assumes that there are some realities, i.e., risks and returns, which exist in the current market for agricultural commodities in Ethiopia. According to Pring (2004), one purpose of a research is to explain what has happened and predict the future based on pre-existing conditions. A reason for seeking explanations might be to predict what will happen in the future. It is based on historical data that actually happened in the market and was documented for different purposes. Moreover, this study intends to use mathematical models to show the associations among variables that reveal the existence of objective or factual data. This is clearly shown in the objectives of this study, which aimed to predict systematic risk, risk-free rate, and price volatility of agricultural commodities in Ethiopia using GARCH family models. Secondly, according to Crotty (2003), epistemology is 'a technique of comprehending and explaining how a researcher knows what s/he knows'. Objectivism is the epistemological view taken in this study, which believes that the researcher's thinking, exists apart from the reality sought. As a result, the researcher's subjective or value judgment had no place in this study. The researcher tried to construct a price index, estimate the systematic risk (Beta) of commodity assets by making use of a capital asset pricing model and model price volatility for selected agricultural commodities in Ethiopia. Based on the aforementioned ontological and epistemological stances, a positivist paradigm was used to inform the methodology of this study. A new paradigm has important implications for every decision that could be made in a research process (Kivunja & Kuyini, 2017). That is, this study is grounded in a positivist paradigm that is aligned with a quantitative approach. A positivist view supports a quantitative approach that focuses on measuring phenomena to answer predetermined research questions

(Deribsa, 2017). It focuses on prior hypotheses (or theories) or predetermined basic research questions.

3.2 Research approach

Among the two types of reasoning, namely inductive and deductive, deductive reasoning was chosen for this study. Deductive reasoning is the process of drawing a conclusion based on premises that are generally assumed to be true. For the reason that the purpose of the study is to quantitatively associate variables based on an established theory or framework, it is creditable that deductive reasoning was fitting to this research. This dissertation made use of a predominantly quantitative approach. A quantitative approach focuses on numerical information, and by employing this method, a researcher can construct a statistical model to explain her/his observations of facts (Deribsa, 2017). In this study, the researcher attempted to construct price indexes, apply a capital asset pricing model to estimate market return, systematic risk beta for agricultural commodities, and model price volatility for agricultural commodities.

3.3 Sampling techniques

Purposeful sampling techniques were used to collect the data. Ten years data on the prices of the agricultural commodities which were recorded from 2010-2020 were chosen. The reasons for selecting these years were that these years were considered as the most recent periods which could help the researcher be in a position to reflect the current situation and forecast the future market better. That is, if the data included the long past, it might be far in time and could not reflect the current market conditions due to the dynamic nature of the market. Secondly, only major market areas which were supposed to represent the market in the country were chosen purposefully. Out of the nine regions and two city administrations, three regions, and one city administration that share at least ten percent of the overall Ethiopian major markets were selected. Specifically, of the nine regions, three regional states, namely Amhara National Regional State, Oromia National Regional State, South Nations Nationalities and Peoples Regional State were chosen, and of the two city administrations, Addis Ababa was selected. As shown in table 1, the selected three regional states accounted for more than 63% of the overall Ethiopian market (CSA, 2016). Similarly, Addis Ababa City Administration which is the capital city of the country and the country's major political and economic center accounted for about 10% (CSA, 2016).

Table 1: Major markets in Ethiopia and their respective percentages

Region/ Administrative City	Number of Market outlets	Percentage
Tigray	8	6.72
Afar	4	3.36
Amhara	20	16.8
Oromia	24	20.2
SNNP	31	26.1
Somali	6	5.04
Benishangul Gomuz	6	5.04
Gambella	3	2.52
Harari	2	1.68
Addis Ababa	12	10.1
Dire Dawa	3	2.52
Total	119	100

Source: (CSA, 2016)

The above Table shows the major markets in Ethiopia along with their respective contributions to the whole market of the country. In Ethiopia, there are nine regions and two administrative cities. In the country, there are a total of 119 representative market outlets in which the CSA price survey data collection had been basically focused on. So, based on the contribution that each region had to the whole market of the country, the sampling selection tasks were accomplished. As it is mentioned above, those regions and administrative cities that had greater contributions to the market were chosen. For better understanding, the contributions of the four selected study sites are indicated in the following Table.

Table 2: Rescaled weight for market centers

Region/ Administrative City	Weight	Scaled weight
Amhara	16.8%	22.94%
Oromia	20.2%	27.66
SNNP	26.1%	35.66%
Addis Ababa	10.1%	13.8%
Total	73.2%	100%

Source: (CSA, 2016)

Table 2 shows the weights and scaled weights of the four study sites.

3.4 Selection criteria

An index is a group or basket of securities, derivatives, or other instruments that represent and measure the performance of a specific market, asset class, market sector, or investment strategy. That means, an index is a statistically representative sampling of any set of observable securities in a given market segment. Therefore, while constructing an index, the selection of commodities to be included in or excluded from the model should be specified. For this research purpose, the total population covered retail price data for commodities, including agricultural and non-agricultural, which have been collected by the Central Statistics Agency for the last ten years, starting from the year 2010 up to the year 2020. To be selected for inclusion in the index, the commodity should be agricultural. For each commodity to be included in the index there should be retail price data collected throughout these periods without any significant missing. That is, the agricultural commodities should be traded and the monthly retail data should be recorded for the whole twelve months of a given year. The representative item method was also used to sample a commodity; that is, for crops that might have different quality levels, the crop with the best quality level was selected for inclusion in the indexes. For example, out of Barley White, Barley Mixed, and Barley Black, Barley White was taken as a representative item. Therefore, the price change for the three items was measured using a sampled price change for Barley White.

3.5 Data types and sources

The average monthly prices of some selected agricultural commodities (crops) obtained from CSA for the selected regions and city administration were used to have relevant data for the study. The periods covered in this study were about ten years; that is, the prices of the agricultural commodities recorded from 2010 to 2020 were taken. As explained in section 3.3, the reason for selecting the time periods from 2010 to 2020 was its relevance in reflecting the current condition of the agricultural commodities market in the country.

3.6 Data analysis techniques

Firstly, descriptive statistics such as, mean, and standard deviation were employed to develop the price index of the selected agricultural commodities.

3.6.1 Index construction

To construct the index for the selected agricultural commodities, the Laspeyres production quantity weighting index approach was used because it was found to be appropriate for the nature of the data and the objective of the index construction process in the current study. Crops are categorized as cereals, pulses, oilseeds, spices, and root crops. For this study's index construction, cereals take the lion's share, which constitutes about 80% of the overall selected agricultural commodities prices indexes. It is because cereals are crops, by far the most important Ethiopian agriculture products, which are produced in a greater volume compared to the other chosen crops, for they are the principal staple crops. Unlike the CSA price index, the price index in the current study used production quantity weighting. However, to ensure that the weights were stable and did not reflect short-term and seasonal fluctuations in production, the index was calculated using a three-year average production quantity weighted, for the years around the base year, i.e., 2014-2016. Therefore, production quantity data for these years was obtained from CSA for the determination of an appropriate weight of each commodity in the index. The three-year weight reference period, 2014 - 2016 , was chosen for the indices in this study because it was thought to be the most representative period for most regions in the country for the past years as: (i) it was recent, so the production share data was unlikely to have been subjected to significant adjustments; (ii) the productions of the selected crops in those regions were relatively stable relative to their trend volumes, so they were fundamentally representative of recent years; and (iii) it was contested with the FAO price indices base period and also included the CSA December 2016 base period CPI to help for an easy comparison. The index's basket was determined on the basis of an agricultural sample survey that which provided the relative importance of the crop in the country's crop production shares. Accordingly, the index comprised of the categories and proportionate shares such as cereal (80%), root crop (5%), pulse (5%), spice (5%), and oilseeds (5%) (CSA, 2016). The details of the selected commodities representation in subgroup and the overall price index are presented as follows in Table 3.

Table 3: Subgroup and the overall price index of selected commodities

Group	Index commodity item	Subgroup	Weights as a percentage of the index
Cereals	Teff	20.83%	16.65%
	Barley	8.40%	6.70%
	Wheat	18.83%	15.00%
	Maize	32.55%	26.00%
	Sorghum	19.71%	15.65%
	Subtotal	100%	80%
Pulse	Beans	100%	5%
	Sub total	100%	5%
Root crop	Potato	76%	3.80%
	Onion	24%	1.2%
	Subtotal	100%	5%
Spice	Red Pepper	100%	5%
	Subtotal	100%	5%
oilseeds	Niger	5%	5%
	Subtotal	100%	5%
Price index all group			100%

Source: Author's computation from (CSA, 2016)

There are different approaches and stages of aggregations which can be used for the calculation of elementary indices and upper level aggregations.

The first elementary item indexes are calculated as follows;

$$\boldsymbol{p_{i,j}^{t}} = \frac{\boldsymbol{p_{i}^{t}}}{\boldsymbol{p_{i}^{0}}}\ \boldsymbol{x100}$$

$\boldsymbol{p_{i,j}^{t}}$ is the price index for item i in region j at period t

$\boldsymbol{p_{i}^{t}}$ is average monthly price of a commodity i in region j at period t

$\boldsymbol{p_{i}^{0}}$ is the price of item i in region j as an average monthly price over the three-year base period 2014–2016.

The elementary item indexes were then aggregated via their region weights to derive the overall national item index. After the elementary indices were computed, indices at the upper level were calculated as weighted averages of the elementary indices by using the Laspeyres formula where the weights were the share of the average of the quantity produced.

The formula for aggregation of items in areas to derive a national item index is:

$$\boldsymbol{p_{I}^{t}} = \sum_{j=1}^{4} \boldsymbol{w_{i}}\left(\boldsymbol{p_{i,j}^{t}}\right) / \sum_{j=4}^{4} \boldsymbol{w_{j}}$$

Where;

$\boldsymbol{P_I^t}$ is national index for item i in period t

$\boldsymbol{w_j}$ is the national weight of region j weighted as a an overall share of Ethiopian major markets

The overall country levels all items index compiled by aggregation of items across areas using national item weight.

$$\boldsymbol{p_n^t = \sum_{i=1}^{10} w_i(p_I^t) \,/ \sum_{i=1}^{10} w_i}$$

Where;

$\boldsymbol{p_n^t}$ - is the national all items index at period t

$\boldsymbol{w_i}$ - is the weight for item i as an average over the three-year base period 2014–2016 quantity produced

3.6.2 Estimating market return and systematic risk /beta

The market returns and the systematic risk or beta estimations are discussed in detail as follows:

3.6.2.1 Estimating market return

A market return is the return on a theoretical portfolio of all assets. The Oxford dictionary (publication year?) defines the return as defined by Oxford dictionary, is a profit on an investment over a period of time, expressed as a proportion of the original investment. Returns are calculated as a simple return or log return.

(Tsay, 2005) the simple net return of an asset can be defined in an equation form as:

$R = \left(\frac{Pt - Pt-1}{Pt-1}\right)$ and the logarithmic return $R = \boldsymbol{ln} \left(\frac{\boldsymbol{p_t}}{\boldsymbol{p_{t-1}}}\right)$.

Calculating the return on an asset in a particular period as the difference between the natural logarithm of the asset price at the end of the period and the natural logarithm of the asset price at the beginning of the period (referred to as a logarithmic return) is a very commonly used procedure in mathematical finance. The log return series was chosen because it could provide better evidence of stylized facts of financial time series, such as leptokurtic distribution, volatility clustering, and existence of leverage effect (Rachev et al, 2011).

Hence, the return of each commodity is calculated as follows:

$$\boldsymbol{R_{i,}^{t}} = \boldsymbol{ln} \left(\frac{\boldsymbol{p_i^t}}{\boldsymbol{p_i^{t-1}}}\right)$$

$\boldsymbol{R_{i,}^{t}}$- return of commodity i at period t.

$\boldsymbol{p_i^t}$- is average monthly price of commodity i at period t.

$\boldsymbol{p_i^{t-1}}$ – is average monthly price of price of commodity I at period t-1.

Then the market return, the return on portfolio of all assets is calculated as follows:

$$\boldsymbol{R_m} = \boldsymbol{ln} \left(\frac{\boldsymbol{p_t}}{\boldsymbol{p_{t-1}}}\right)$$

Where: p_{t} - is average monthly price of the commodity market index at period t.

P_{t-1} is average monthly price of the commodity market index at period t-1.

R_m is return of the commodity market index.

3.6.2.2 Estimating beta (systematic risk)

Beta can be estimated using the variance and covariance methods, the correlation method or as the slope of the CAPM. In this study, with a specified and observed market index being constructed, the systematic risk or beta of a commodity or crop was estimated with the use of a market model very close to the CAPM. The market model, also called index model, states that the return on a security is determined by the return on the market portfolio and the extent of the security`s responsiveness as measured by beta. The market model beta coefficient turns out to be the same as the CAPM expected return beta relationship except that it replaces the theoretical market portfolio of CAPM with the well specified and observed market index (Bodie et al, 1999).

The Market model:

$$\boldsymbol{R_i = a_j + \beta_j R_m + e_j}$$

$\boldsymbol{R_i}$ = historical (realized) rate of return on commodity j

$\boldsymbol{R_m}$ = historical (realized) rate of return on the market

$\boldsymbol{a_j}$ = vertical axis intercept term for commodity j

$\boldsymbol{\beta_j}$ = beta, coefficient, for commodity j

e_j = random error

3.6.3 Volatility models

Traditional econometric models assume a one-period forecast variance that is constant. Engle (1982) was the first to develop a modern volatility model, in which he used autoregressive conditional heteroscedasticity (ARCH) to deal with conditional variance. Following his model, other scholars introduced different ARCH family models, such as symmetric and asymmetric models, including Generalized Autoregressive Conditional Heteroscedasticity (GARCH) (Bollerslev, 1986), Threshold GARCH (Zakoian, 1994), and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) (Nelson, 1991). Based on its statistical significance and model adequacy tests, the best fitting volatility models, among them, were selected for specific crops.

3.6.3.1 Autoregressive Conditional Heteroskedastic ARCH model

An ARCH model is an important tool that is used to analyze time series data; it is predominantly used as a financial application, which was originally proposed by Engle (Engle, 1982). It is employed to specify the conditional distribution of εt given the information available up to time t-1.

These models are especially useful when the goal of the study is to analyze and forecast volatility.

The model is specified as;

$$\boldsymbol{Y_t = \mu_t + \varepsilon_t}$$

$$\boldsymbol{\delta^2 = \omega + \alpha_1 \varepsilon^2{}_{t-1} + \alpha_2 \varepsilon^2{}_{t-2} + \alpha_3 \varepsilon^2{}_{t-3} + \cdots + \alpha_{1q} \varepsilon^2{}_{t-q}}$$

Where: $\boldsymbol{\varepsilon_t}$ is the shock at time t

$\boldsymbol{\delta}^2$ is volatility at time t and

$\boldsymbol{\varepsilon^2_{t-1}}$ is squared shock at time t-1

3.6.3.2 Generalized Autoregressive Conditional Heteroskedastic GARCH Model

The generalized ARCH model was developed by Bollerslev (1986). A Generalized Autoregressive Conditional Heteroskedasticity process is said to be a GARCH (p, q) process, and the model is variance and covariance stationary where it imposes non-negativity constraints for α, β, and ω.

The model is being expressed as a linear function of past squared innovations and their past values.

The basic GARCH (1, 1) is expressed as;

$$\boldsymbol{\delta^2 = \omega + \alpha_1 \varepsilon^2_{t-1} + \delta^2_{t-1}}$$

3.6.3.3 Exponential Generalized Autoregressive Conditional Heteroskedastic Model

Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model is another volatility model proposed by Nelson (1991) as it is shown below:

$$Ln\delta^2 = \omega + \beta Ln\delta_{t-1}^2 + \alpha_1 \frac{\left|\varepsilon_{t-1}^2\right|}{\delta_{t-1}^2} + \gamma \frac{\varepsilon_{t-1}^2}{\delta_{t-1}^2}$$

where α represents the symmetric effect of the model, β_1 measures the persistence of conditional volatility shock. Large value of β_1 implies that volatility will take a long time to die out following a crisis in the market. The volatility shock is asymmetric when $\gamma \neq 0$; if $\gamma = 0$ then the model is symmetric (positive and negative shocks of the same magnitude have the same effects on volatility). When $\gamma < 0$ it implies the existence of the leverage effect, negative shocks (bad news) can generate more volatility than positive shocks (good news) of the same magnitude, and $\gamma > 0$ implies that positive shocks generate more volatility than negative shocks of the same modulus.

3.6.3.4 Threshold Generalized Autoregressive Conditional Heteroskedastic

The Threshold GARCH (TGARCH) model, which was proposed by Zakoian (1994), allows for asymmetric shocks to volatility, which again permits positive and negative shocks of equal size to have a different impact on volatility.

The Simple Threshold GARCH specified as;

$$\delta^2 = \omega + \alpha_1 \delta_{t-1}^2 + \beta \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1}$$

Where dt =1 if it is negative and 0 otherwise. In the TGARCH (1, 1) model, volatility tends to decrease with good news.

CHAPTER FOUR: RESULTS

This chapter deals with data analyses of the data collected from CSA. Firstly, an attempt is made to present the price indexes of agricultural commodities in Ethiopia at both regional and national levels. Next, the estimation of market return in the index is dealt with, followed by the estimation of systematic risk (beta) of the crops. Finally, the price volatility of the selected crops is indicated using GARCH family models.

4.1 Results

4.1.1 Data coding and organization

Data coding refers to giving codes to the subjects of the study (Dornyei, 2007) and the coding tasks can be accomplished before and/or after data collection. Accordingly, the present researcher assigned codes to agricultural commodities collected from three regional states and one city administration. The codes assigned to each of the commodities are indicated in the following table.

Table 4: Codes assigned to different commodities with their respective regions

TeffAA	Teff of Addis Ababa City Administration
TeffAmhR	Teff of Amhara Region
TeffSNNNP	Teff of South Nations and Nationality People
TeffOroR	Teff of Oromia Region
WheatAA	Wheat of Addis Ababa City Administration
WheatAmhR	Wheat of Amhara Region
WheatSNNP	Wheat of South Nations and Nationality People
WheatOroR	Wheat of Oromia Region
BarleyAA	Barley of Addis Ababa City Administration
BarleyAmhR	Barley of Amhara Region
BarleySNNP	Barley of South Nations and Nationality People
BarleyOroR	Barley of Oromia Region
MaizeAA	Maize of Addis Ababa City Administration
MaizeAmhR	Maize of Amhara Region
MaizeSNNP	Maize of South Nations and Nationality People
MaizeOroR	Maize of Oromia Region
SorghumAA	Sorghum of Addis Ababa City Administration
SorghumAmhR	Sorghum of Amhara Region
SorghumSNNP	Sorghum of South Nations and Nationality People
SorghumOroR	Sorghum of Oromia Region
NigerAA	Niger of Addis Ababa City Administration
NigerAmhR	Niger of Amhara Region
NigerSNNP	Niger of South Nations and Nationality People
NigerOroR	Niger of Oromia Region
BeansAA	Beans of Addis Ababa City Administration
BeansAmhR	Beans of Amhara Region
BeansSNNP	Beans of South Nations and Nationality People
BeansOroR	Beans of Oromia Region
OnionAA	Onion of Addis Ababa City Administration
OnionAmhR	Onion of Amhara Region
OnionSNNP	Onion of South Nations and Nationality People
OnionOroR	Onion of Oromia Region
PotatoAA	Potato of Addis Ababa City Administration
PotatoAmhR	Potato of Amhara Region
PotatoSNNP	Potato of South Nations and Nationality People
PotatoOroR	Potato of Oromia Region
Redpepper AA	Red Paper of Addis Ababa City Administration
RedpeperAmhR	Red Paper of Amhara Region
RedpeperSNNP	Red paper of South Nations and Nationality People
RedpeperOroR	Red paper of Oromia Region

4.1.2 Price index

One of the objectives of this study was to construct price indexes for agricultural commodity prices in Ethiopia. To construct the price index, 10 years of average monthly retail price data of selected 10 corps in the five categories were collected from three regions, namely Amhara National Regional State (ANRS), South Nations and Nationalities People's Regional State (SNPRS), Oromia National Regional State (ONRS), and one city administration, namely Addis Ababa, which were selected based on their lion's shares of contributing to the Ethiopian major market areas. The indices monitor the price developments over the period 2010–2020 as a production-weighted average, based on production quantity over a chosen three-year base period of 2014–2016. The price indexes were computed starting from the lower level aggregations and followed by the upper level aggregations. The descriptive statistics of the raw price data are presented in Table 5, at the regional level, and in Table 6, at the national level, and they are presented as follows:

Table 5: Descriptive statistics, regional level

a. Descriptive statistics - Cereal

teffAA	19.68	7.68	8.97	41.89
TeffAmhR	17.33	7.34	4.24	38.86
TeffSNNNP	18.58	7.30	7.72	40.60
TeffOroR	18.64	7.07	7.69	40.37
WheatAA	13.01	4.80	5.75	25.30
WheatAmhR	11.09	4.00	5.03	21.50
WheatSNNP	11.59	4.01	5.28	20.99
WheatOroR	11.24	3.86	5.14	20.89
BarleyAA	13.72	4.77	6.60	26.18
BarleyAmhR	11.53	3.82	5.04	22.21
BarleySNNP	11.47	4.10	4.85	23.66
BarleyOroR	11.14	3.76	4.88	21.42
MaizeAA	8.58	2.85	3.58	15.22
MaizeAmhR	6.73	2.22	2.74	13.05
MaizeSNNP	6.43	2.10	2.19	11.48
MaizeOroR	6.54	2.21	2.30	12.23
SorghumAA	13.00	4.70	5.91	24.14
SorghumAmhR	9.79	4.42	3.18	31.84
SorghumSNNP	7.99	3.07	2.57	22.48
SorghumOroR	8.84	3.28	2.99	18.50
Valid N (list wise)				

Source: EViews 10 output based on CSA data from 2010-2020

b. Descriptive statistic Oilseed, Pulses and root crop

NigerAA	30.95	11.55	1.84	57.82
NigerAmhR	26.82	12.04	5.57	95.32
NigerSNNP	29.29	11.91	1.33	94.92
NigerOroR	26.21	9.69	11.28	57.19
BeansAA	19.76	9.04	6.27	54.04
BeansAmhR	15.28	6.91	0.42	35.40
BeansSNNP	15.64	6.14	6.39	33.62
BeansOroR	16.92	10.90	5.61	110.00
OnionAA	15.70	12.33	2.86	61.01
OnionAmhR	15.00	10.96	3.46	65.47
OnionSNNP	13.58	6.16	3.87	38.17
OnionOroR	13.04	5.97	4.61	44.20
PotatoAA	7.14	2.85	2.87	16.89
PotatoAmhR	8.74	8.17	3.30	69.80
PotatoSNNP	7.12	2.74	3.27	16.96
PotatoOroR	6.95	2.84	3.09	16.52
Redpepper AA	98.58	35.92	27.63	188.82
RedpeperAmhR	68.82	38.61	5.24	355.59
RedpeperSNNP	67.43	24.37	24.27	164.60
RedpeperOroR	72.62	25.75	23.06	123.05
Valid N (list wise)				

Source: EViews 10 output based on CSA data from 2010-2020

All the prices are stated in Ethiopian Birr (ETB) per kilogram. In areas included in the study average prices of cereals such as Teff, wheat, barley, maize, and sorghum over the period were ETB 18.55, 11.73, 11.96, 7.06, and 9.90, respectively. Of the prices indicated above (see Table 5), the highest price of the commodities in hand is observed in Addis Ababa. However, the lowest prices are observed at ANRS for Teff and wheat, with average prices of ETB 17.3251 and 11.0858, respectively, and the lowest prices for maize and sorghum are observed in SNNP, with average prices of ETB 6.4318 for maize and ETB 7.9889 for sorghum, correspondingly, the lowest average price of barley is witnessed in ONRS.

Table 6: Descriptive Statistics of the ten selected commodities a weighted average of areas included in the study

Descriptive Statistics				
	Average	Std. Deviation	Min	Max
Teff	18.56	7.28	7.82	40.43
Wheat	11.73	4.13	5.31	22.17
Barley	11.97	4.08	5.36	23.37
Maize	7.07	2.29	2.73	12.95
Sorghum	9.90	3.61	3.76	21.58
Niger	28.32	10.28	12.18	54.08
Beans	16.90	7.25	6.40	38.27
Onion	14.33	8.21	3.98	47.94
Potato	7.49	3.21	3.43	20.77
Red pepper	77.28	28.60	25.71	168.13
Number of observations	120.00			

Source: EViews 10 output based on CSA data from 2010-2020

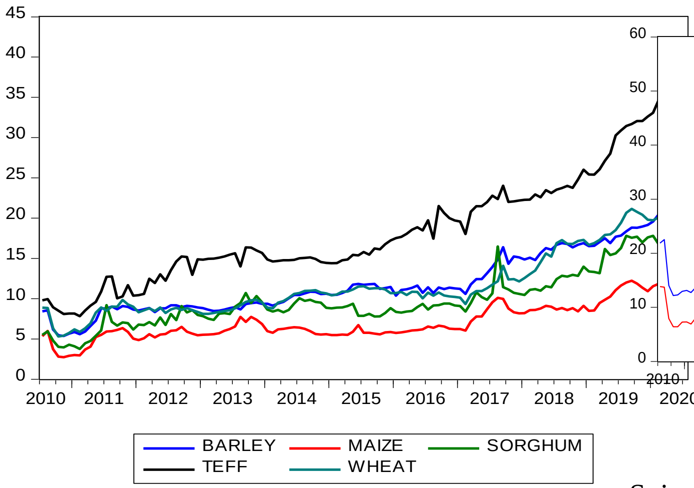
The standard deviations of the above commodities, as indicated in Table 6, for cereals, namely Teff, Wheat, Barley, Maize, and Sorghum, are 7.28, 4.13, 4.07888, 2.29, and 3.61, respectively. The lowest average values were recorded in different regions; for example, the average prices of oilseed and pulse were observed to be the lowest in ANRS, while the average prices of onion and potato were seen as relatively the lowest in ONRS, and the average price of red pepper was the lowest in SNNP, which was about

ETB 67.43 over the study periods. But the highest prices for all groups of the commodities were observed in Addis Ababa, the city administration.

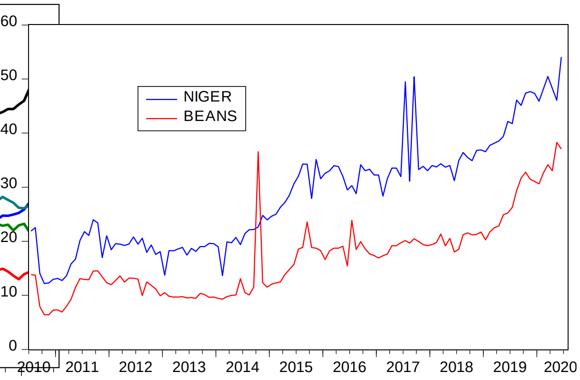
Next, prices of crops in Ethiopia are shown in the following figures:

Figure 2: Raw price data of agricultural commodities in Ethiopia

Cereals

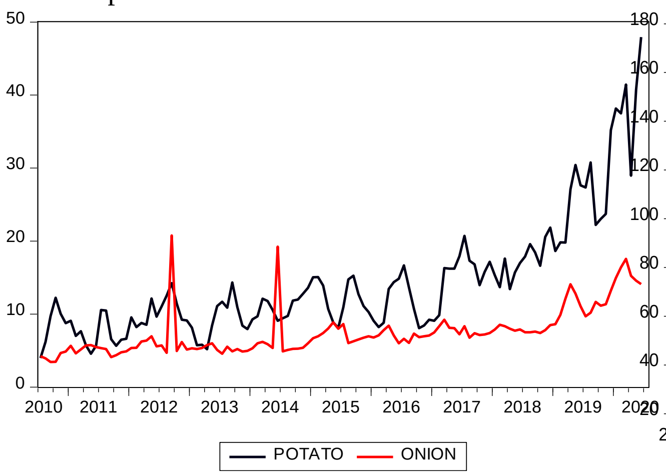


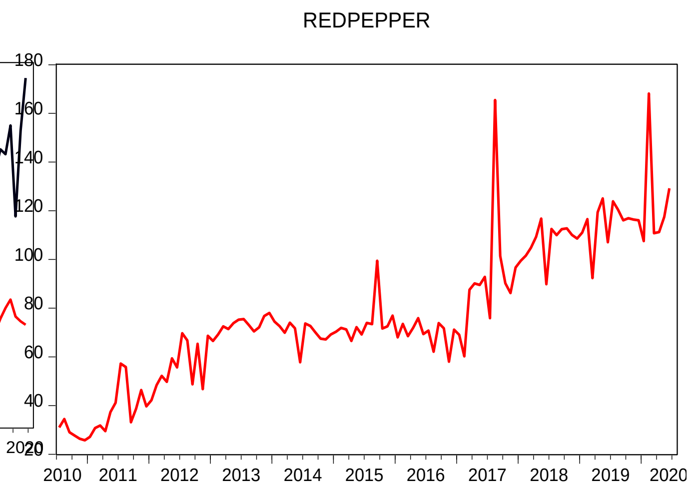
Oilseed and pulses



Spices

Root crop





As indicated in figure 2, prices of agricultural commodities exhibits sustainable rise over time. The lower level price indices were computed using the formula

$$\boldsymbol{p_{i,j}^{t} = \frac{p_i^t}{p_i^0}\, x100},$$

at commodity level, and the results are presented as follows;

Cereals are the first group of commodities that account for the largest share, i.e., 80% of the overall index. Under cereal, five crops, namely teff, wheat, barley, sorghum, and maize, were included.

When one wants to see the overall weighting proportions of the four chosen sites for the study, Addis Ababa accounted for 13.8% of the weightings in the overall agricultural commodities price index, considered in average values over the market share of the country. The elementary price index of Addis Ababa, for cereals, namely teff, wheat, maize, barley, and sorghum, rose steadily from 2010 to 2020. In the period between July 2010 and March 2011, slight decrements in prices of some cereals were recorded, but from 2011 to 2013, prices again were seen to show increments; for example, the maize price index reached 129 (taking into account 2014-2016 average= 100).

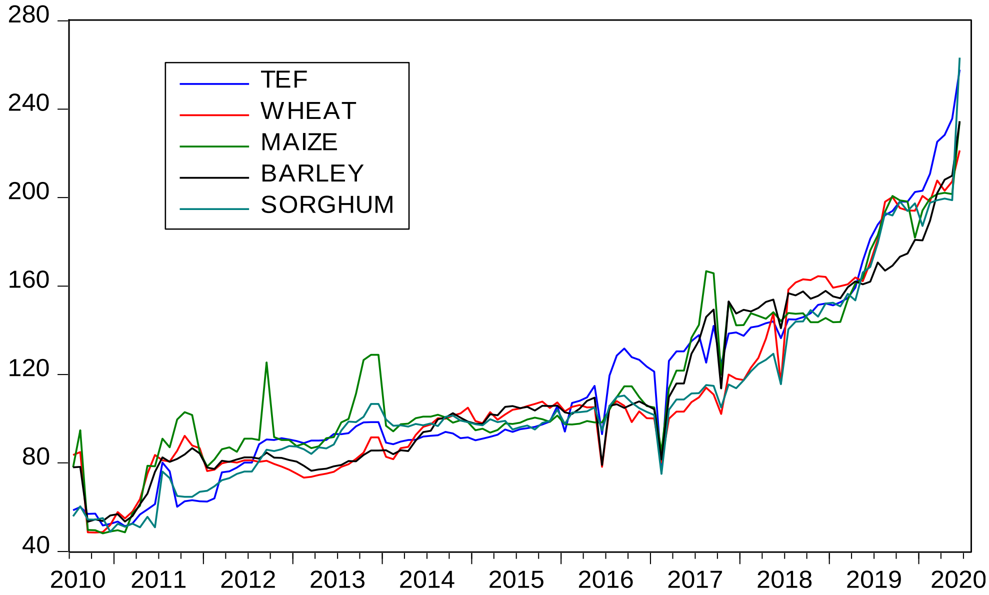
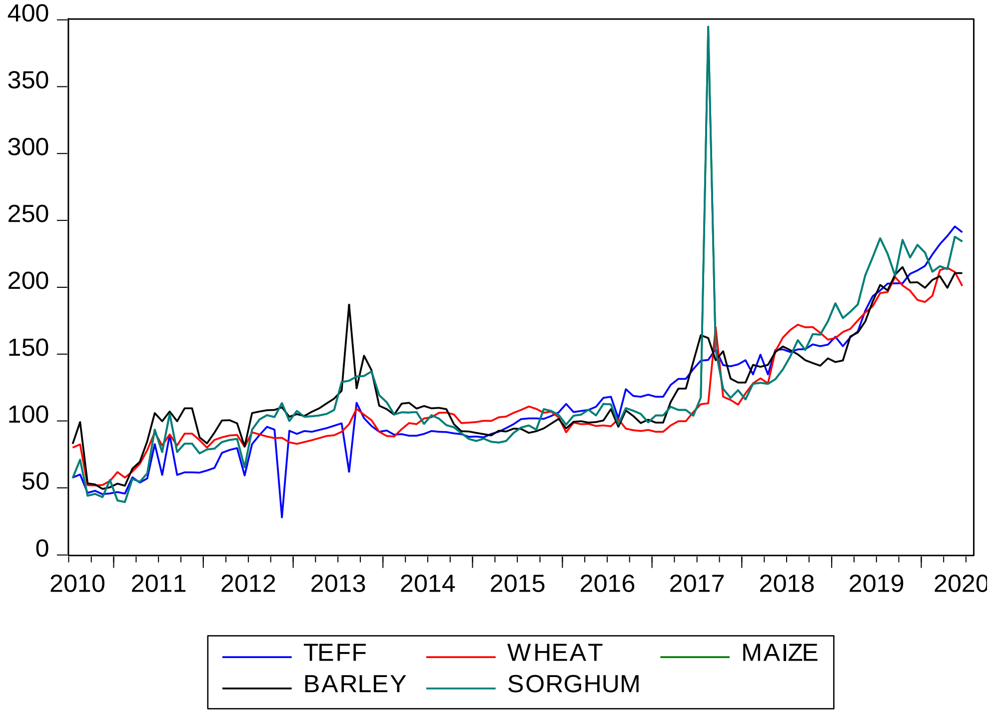


Figure 3: Elementary price index of cereal in Addis Ababa

The elementary price indexes of teff, wheat, barley, and sorghum rose slowly from 2010 to 2016, but in 2017, the elementary price indexes of some crops increased rapidly compared to the prices recorded in the previous periods; for example, the elementary indices of maize, barley, and teff were recorded as reaching the levels of 167, 149, and 146, respectively. After 2017, the price indexes of all cereal crops continued to rise steadily and reached their picks in 2020, when the price indexes of sorghum, teff, maize, wheat, and barley are 263, 258, 235, 221, and 235, respectively.

Secondly, Amhara National Regional State accounts for 22.94% of the weightings in the total Ethiopian agricultural commodities price index. From 2010 to 2013, the overall *teff* price index of ANRS increased sustainably, with high volatility. From the end of 2013 up to 2017, the index continued to show a slight growth, reaching 154 index level in the mid of 2017, and after a slight decrease for few months; it continued to grow sharply. The 2020 price index of teff in the Amhara region reached its peak of up to 245 index level.

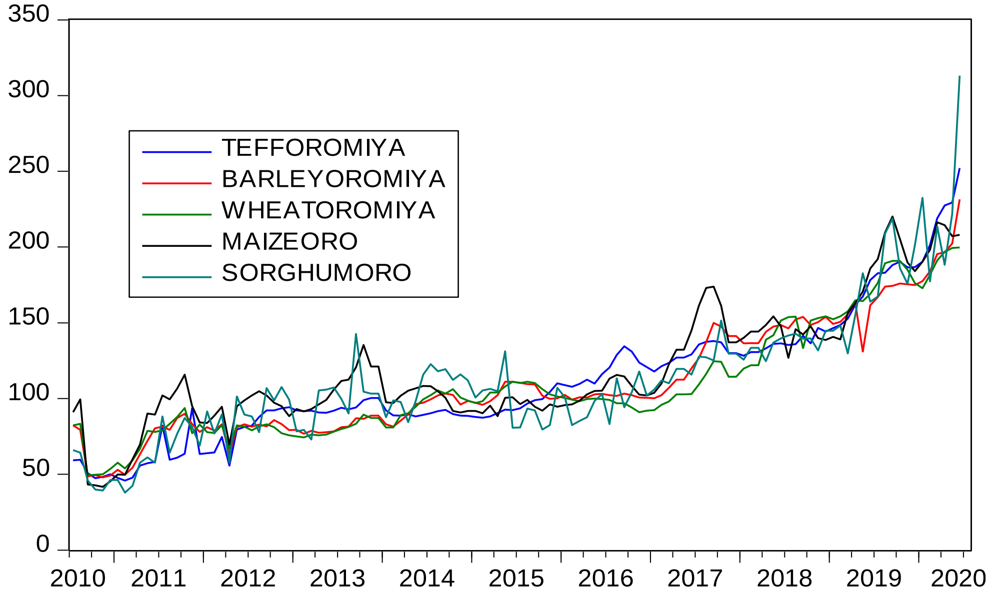
Figure 4: Elementary level price index of cereals, in Amhara Region



Wheat and Barley price indices at ANRS showed higher volatility than other price indexes; prices fell slightly in the early years (from 2010 to 2011), but price indexes rose again in late 2011, 2012, and 2013; for example, barley reached 187 in the eighth month of 2013.

Contrary to Wheat's and Barley's price indexes, sorghum's price index was relatively stable; that is, before the year 2017, its index showed slow growth , but in 2017, a sudden increment was exhibited in the sorghum's price index, which was similar to the price indexes of other crops in hand.

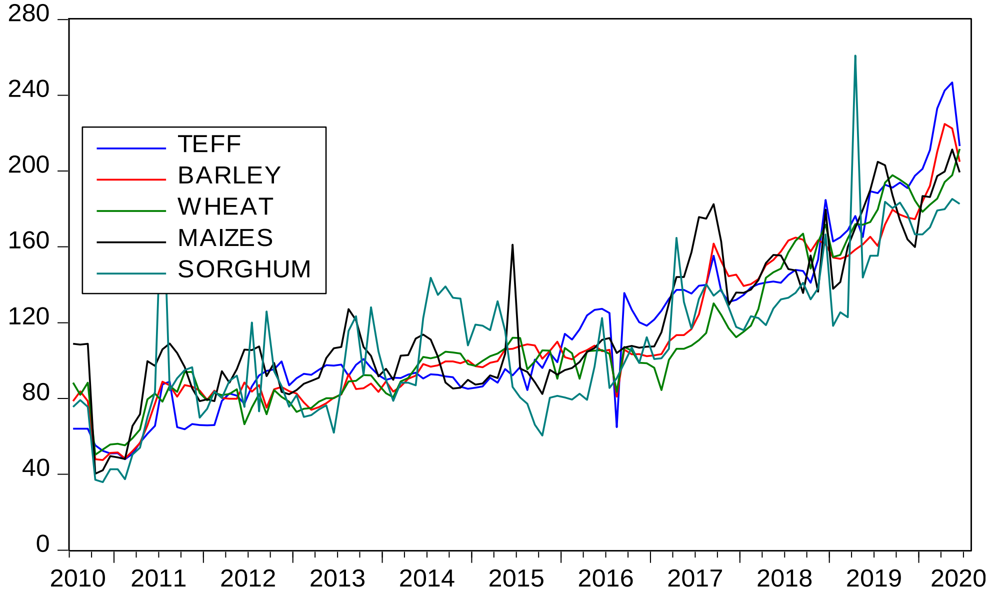
Figure 5: Price index of Cereal of Oromia Region



Thirdly, Oromia National Regional State accounted for 27.66% of the weightings in the Ethiopian agricultural commodities price index. The ONRS price of cereals at an index level moved in a similar pattern to the other regions in an overall situation. At the beginning of the study period, the price index of teff showed declines, followed by increments from 2011 to the end of 2013. In the years starting from 2014 up to the beginning of 2017, the index was relatively stable before it began rising in 2017. September 2019 was a period when the highest ever index point of 220 was recorded in ONRS's maize price.

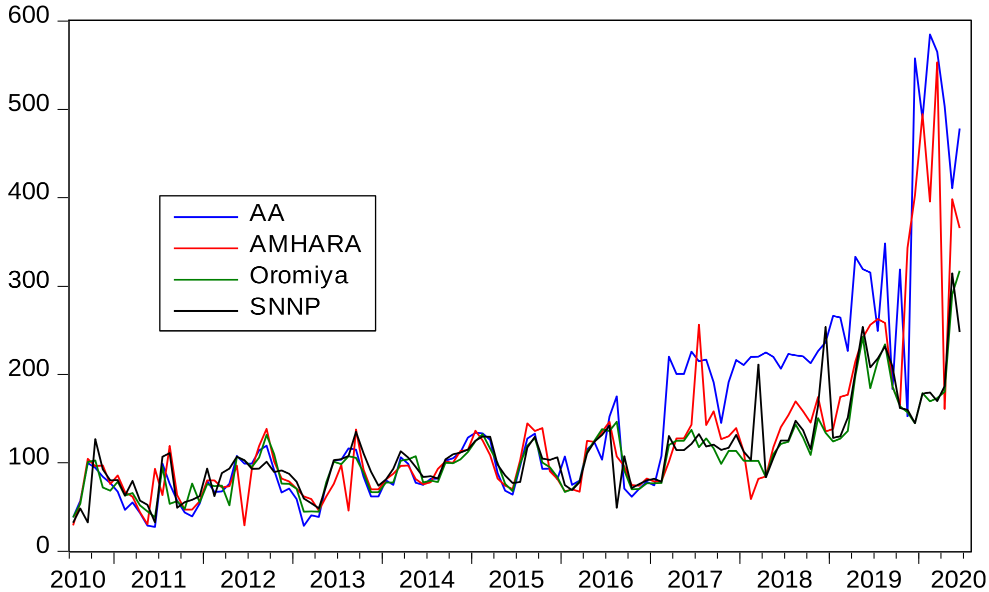
Lastly, the Southern Nation Nationalities and Peoples Region (SNNP) accounted for 35.66% of the weightings in the overall agricultural commodities price index. Very similar to the price indexes of the other regions, in the mid of 2017, the price indexes of sorghum, wheat, maize, and barley rose rapidly. In addition to this, the maize price index exhibited high rises in the years 2011, 2013, 2015, and 2020 in this particular region. Following the declines from 2010 to 2011, the index of barley and wheat in SNNP was relatively stable starting from the end of 2011 up to 2016, while the steady rise was exhibited after the rapid increment of 2017. Sorghum was the most volatile cereal crop in the SNNP markets during the study periods as compared to the degree of volatility of other selected commodities.

Figure 6: Price index of Cereal of SNNP



Root crops took the second stage in the groups of the index, which accounted for a share of 5% of the national index, two crops, namely onions and potatoes, were included in this group. Onion and potato price indexes from the years 2010 to 2020 showed variations by indicating remarkable fluctuations in the three regional states starting from 2010 to 2016. In Addis Ababa, the index, from 2010 to 2016, was found in the range of the lowest (27) in June 2011 and the highest in August 2016 (taking the average value of 2014-2016 as 100). In early 2017, the index rose noticeably to a level of 220 from 79 in its immediate past; this increment was the highest. Following this rapid increase, the price index continued to rise substantially up to the year 2019, whereas in late 2019 there was a certain decrease in prices. But it was again very high, and in 2020, it reached a high level, resulting in an index of about 585 in Addis Ababa.

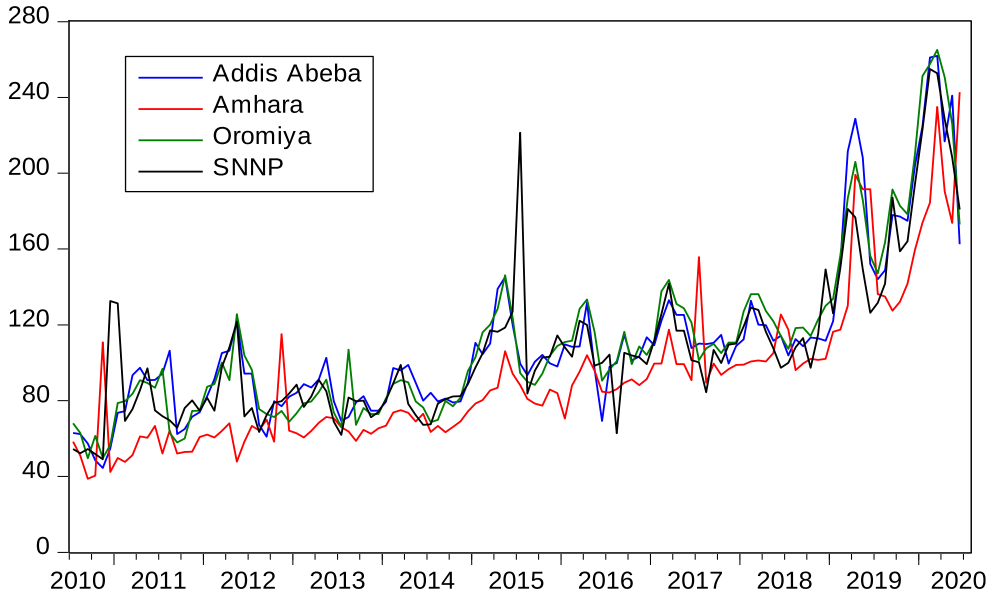
Figure 7: Price index of Onion in the four study areas



In the Amhara Region, the price index of onions, between 2010 and 2016, demonstrated frequent fluctuations; that is, it followed neither an increasing nor a decreasing trend, and it did not show a fixed tendency either: a one period increase was observed in the price index of onions, followed by a decrease and vice versa. By contrast, since 2017, the highest index price increase was recorded as compared with the price index of the previous periods; there was a slight decrease in late 2018, but it still remained relatively higher than that which was observed in 2010-2016. The index reached its peak level of 553 as of March 2020. In SNNP and Oromia, similar patterns were demonstrated in the price index of onions. That is, before 2016, it was fluctuating frequently, but, generally, it was of a smaller magnitude; after the rapid increment in 2017, it showed a steady rise and reached its highest peak in 2020.

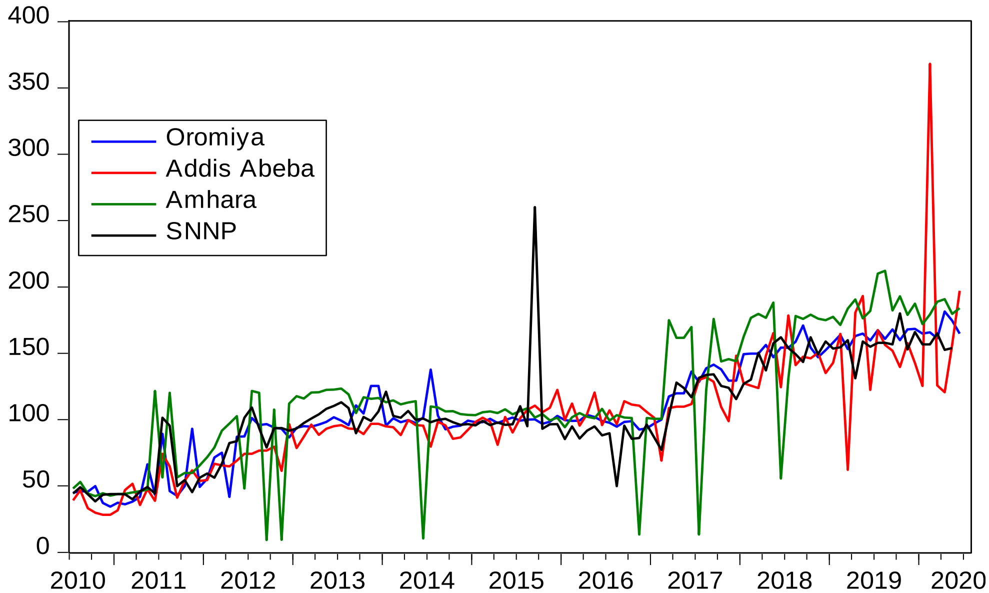
Concerning potato, in the periods from 2010 to 2020, the price index demonstrated an increment in Addis Ababa, ANRS, ONRS, and SNNP. In Addis Ababa, for example, the index was seen to move from a range of 49 index levels in 2010 to a level of 235 in March 2020; similarly, ANRS showed an index increment by moving from the level of 39 in 2010, to the level of 243 in 2020; SNNP showed index movements beginning from 52 in 2010 to 255 in 2020, and ONRS from 50 in 2010 to 265 in 2020. For all the study areas and in all the years under study, the price index of potatoes rose in certain months (such as March, April, and May) of the year and decreased in some others (such as June, July, and August).

Figure 8: Price index of potato in the four study sites,



The third group of commodities in the index is spices, which accounts for 5% of the index. Red pepper is the crop, specifically, included in the index representing the spice category. Since 2010, the price index of red pepper in Amhara Region has increased from 48 index level to 120 index level, followed by showing declines for certain periods. Except for very low index levels in some months during 2014, it was stable from 2013 to 2016. Starting from late 2016, it began to rise and reached its maximum peak in 2017, followed by a decline in 2018, but it still remained relatively higher than the indexes observed in the periods starting from 2013 to 2016. In Addis Ababa, it increased substantially from 2010 to 2020. A special decline was recorded in 2019, unlike the decrements seen in the rest of the periods. The price index for red pepper reached its maximum peak level of 368 in 2020. Similarly, in Oromia Regional State, a progressive rise was recorded in the index.

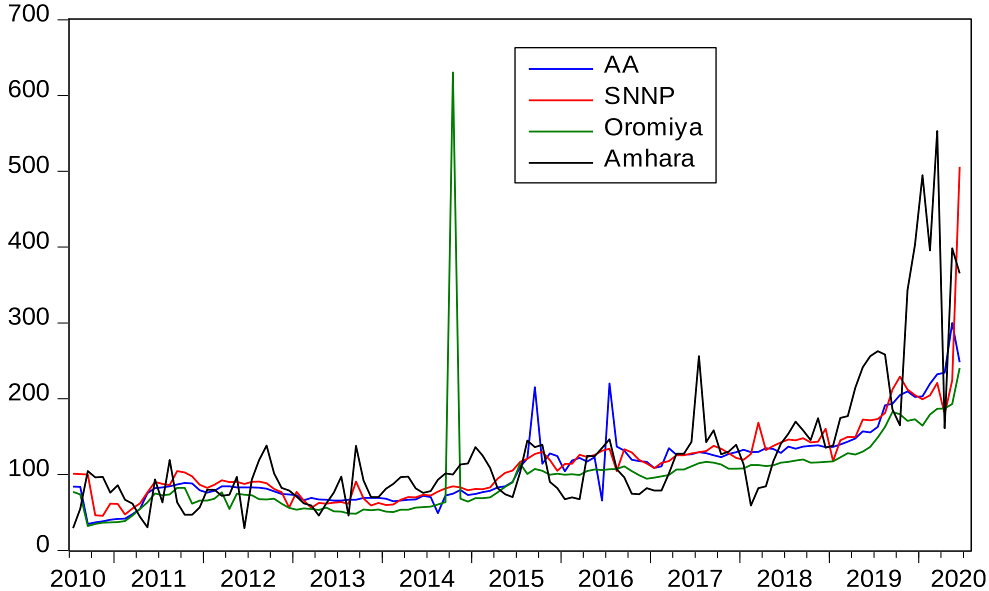
Figure 9: Price index of Red pepper in the four study areas



The red paper price index was seen to be high between 2012 and 2014, but it declined from late 2014 to the beginning of 2016, but it began to rise in 2017 and continued to rise with significant increments until it reached its peak in 2020.

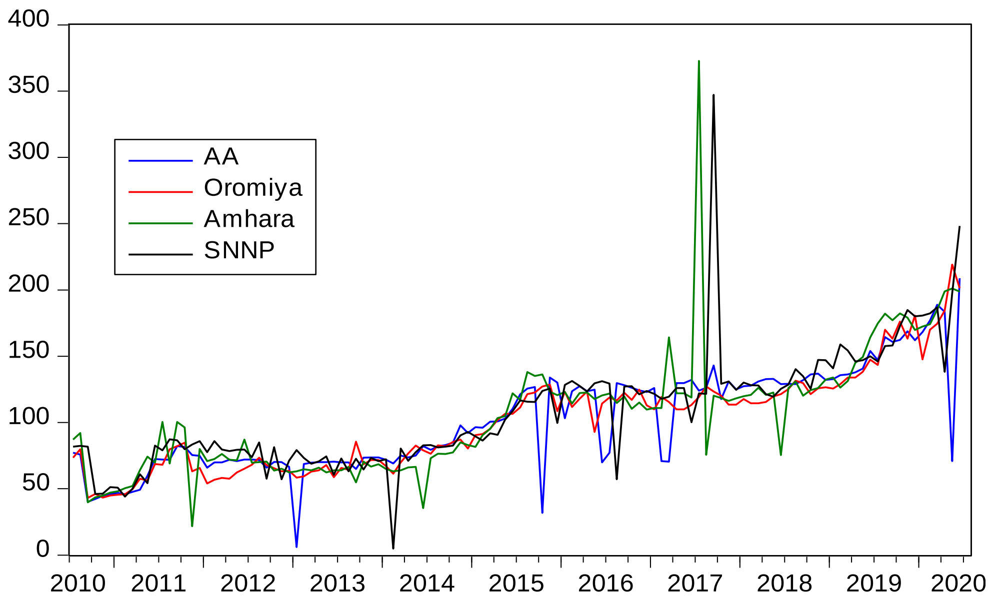
The red pepper price index, in SNNP exhibited an increasing trend, an exceptional rapid increase that reached a peak level of 260, and demonstrated decrement reaching its lowest level of 50 in 2015 and 2016, respectively. Correspondingly, the price indices of pulses and oilseeds in the study areas displayed increasing trends.

Figure 10: Overall elementary price index of pulses



As Figure 10 indicates, in Addis Ababa the price of Pulses' (Beans') started to increase as of early 2011 reaching their peak between 2015 and late 2016; then it started to drop in early 2017, and it then rose again reaching their peak in 2020, and finally started to drop in late 2020. Concerning the index of beans, more frequent fluctuations were observed in the Amhara Region than in its indexes in other regions. In the ONRS, the highest price index of beans was recorded in 2014, while it was in 2020 for the SNNP. The price index for Niger reached its peaks in 2017 in Addis Ababa, ANRS, SNNP, and ONRS. In Addis Ababa, it was lower in the periods 2013, 2015, and 2020, while it was lower in 2014 and 2016 in SNNP.

Figure 11: Total elementary price index of oilseed, Niger



Next, the elementary indexes were aggregated by their respective region's weights to derive the overall national item index, and indices at the upper level were calculated as weighted averages of the elementary indices by using the Laspeyres formula. For a better understanding of price developments over the observed periods, sub-indices for regions that have the highest contributions in the country were calculated. The three regional states and the one city administration covered about 63% and 10%, respectively, of the overall Ethiopian market (CSA 2016). Hence, four sub-indices, namely the ANRS index, the ONRS index, the SNNP index, and the Addis Ababa index, were identified.

The formula for aggregation of items in areas to derive a national item index is:

$$p_I^t = \sum_{j=1}^{4} w_i\left(p_{i,j}^t\right) / \sum_{j=4}^{4} w_j$$

Where;

P_I^t is national index for item i in period t

w_j is the national weight of region j weighted as a an overall share of Ethiopian major markets

The overall country level all item index was compiled by the aggregation of items across areas using national item weights. Hence, the basket was determined on the basis of an agricultural sample survey that provided the relative importance of the crop in the country's crop production shares. Accordingly, the index, which comprises five categories with their respective proportionate shares, was identified. The proportionate shares involved 80% for cereal, which included Teff (16.65%), barley (6.70%), wheat (15.00%), maize (26.00%), and sorghum (15.65%), 5% for root crops that involved onion and potato with portions of 3.8% and 1.2%, respectively, 5% for pulses , 5% for Spices , and 5% for Oilseeds.

$$p_n^t = \sum_{i=1}^{10} w_i(p_I^t) \,/ \sum_{i=1}^{10} w_i$$

Where;

p_n^t is the national all items index at period t

w_i is the weight for item i as an average over the three-year base period 2014–2016 quantity produced.

Table 7: Discriptive statistics,overall Country level index

Item	Average	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P value
TEFF	113.76	248.62	47.36	44.64	0.95	3.54	19.47	0.0001
WHEAT	110.45	206.93	50.19	38.58	1.01	3.05	20.55	0.0000
BARLEY	113.34	223.61	48.92	38.03	0.85	3.12	14.53	0.0007
SORGHUM	113.27	263.64	39.93	41.41	0.97	3.98	23.78	0.0000
MAIZE	118.60	217.50	44.46	38.34	0.74	3.07	11.03	0.0040
BEANS	106.34	234.23	41.13	44.86	0.96	3.52	19.79	0.0001
NIGER	103.87	203.69	43.06	38.17	0.54	2.57	6.67	0.0357
ONION	119.94	394.28	34.01	64.29	1.78	6.59	127.96	0.0000
POTATO	107.82	253.37	49.89	43.20	1.57	5.12	71.60	0.0000
REDPEPPER	109.56	194.04	38.77	38.81	0.10	2.21	3.31	0.1907

Source: EViews 10 output based on CSA data from 2010-2020

Table 7 presents the descriptive statistics for the overall country level price index of each crop. In view of that, the average, minimum, and maximum levels of the price indices were displayed.

The average teff price at an index level (taking 2014-2016= 100) was 113.76 with its minimum and maximum values of 47.36 and 248.62, respectively. Based on their means, the average price index of Niger, that is, 103.87, was smaller and that of maize, which is 118.60, was higher as compared to the price indexes of other selected crops. As seen from the above Table, during the study periods, the price indices of onions which were recorded as the highest and the lowest index levels were 34.02 (the minimum) in 2010 and 394.28 (the maximum) in 2020. For red pepper, the highest price index was recorded in February 2020, and the smallest one, which was 38.77, was seen in December 2010. On average, the beans' price index was 106.34, where its standard deviation was 44.86. To display the trend of the price index, graphs are provided for each of the items in the following sections.

Figure 12: The overall price index of cereals

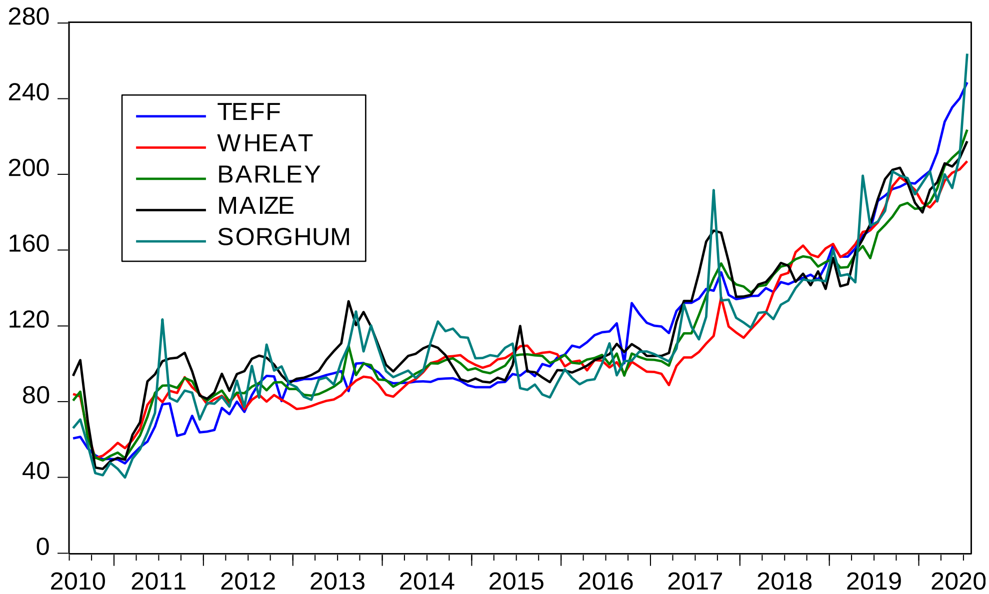
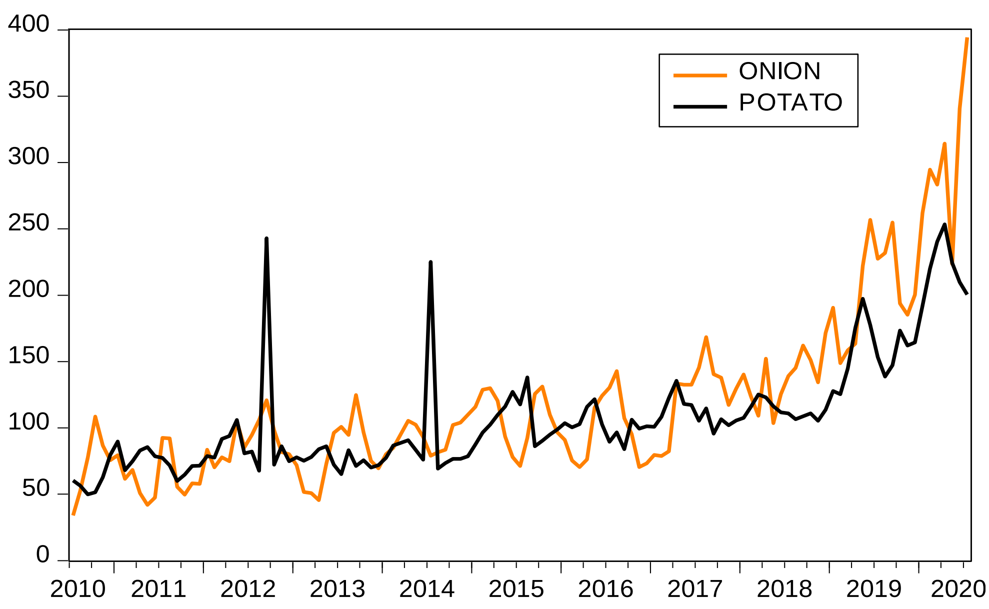


Figure 12 demonstrates the overall price index of cereals in Ethiopia. In Ethiopia, the overall price index of cereals showed a progressive rise starting from the period of 2010 to 2020. Between July 2010 and March 2011, there were slight drops in the prices of some cereals, such as teff, wheat, and sorghum, but in late 2011, they showed sharp growth until they reached their maximum peak in the same year.

In 2012 and 2013, price indices of cereals exhibited stabilization in most of the items until they reached their peaks in September 2013; the price indices of sorghum, maize, and wheat were 128, 133, and 93, respectively (taking the 2014-2016 average as the base =100). In the early 2017's, the price index indicated rapid rises for all crops; in 2018, a slight decline was recorded, but it still remained relatively higher than the indices recorded in the previous periods before 2017, and continued to grow until 2020, when the highest ever recorded price at an index level was recorded over the study periods. Maize and sorghum price indices showed higher volatility than the indices of other crops in this category. After the year 2016, the rises in the price indexes for some crops, for example, teff, wheat and barley were very high as compared to the price indices recorded in the previous periods.

Figure 13: The overall process of root crops

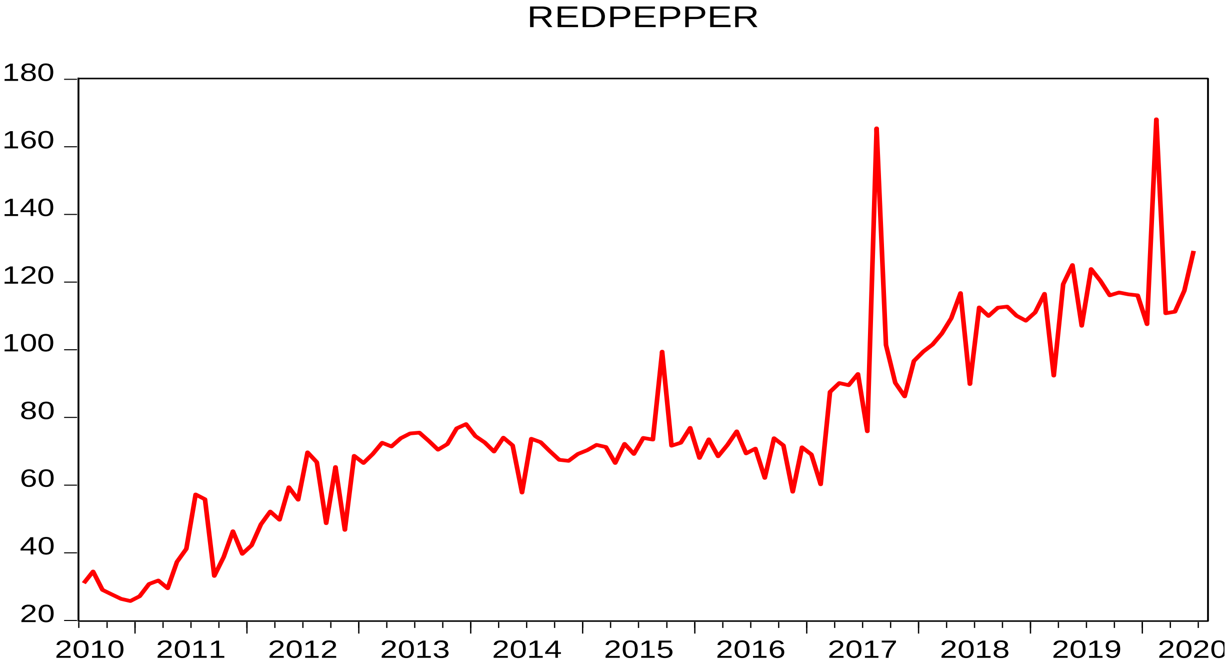


As can be seen from Figure 13, the fluctuations of the potato and onion price indices were high as compared to the other items included in the index. With the exception of September 2012 and

July 2014, the index of potato prices fluctuated frequently, but it was observed to be at a lower speed between 2010 and 2016; that is, it did not follow a similar trend of either rising or declining, as well as it did not follow a fixed tendency; that is, a one period increase in the price index of onions was followed by a decrease and vice versa. Since 2017, a higher price index was recorded as compared to the price indexes of the same crop recorded in the previous periods, and it continued to rise at a higher rate. Even though price indices fell slightly in late 2018, they remained relatively higher than what was observed from 2010 to 2016.

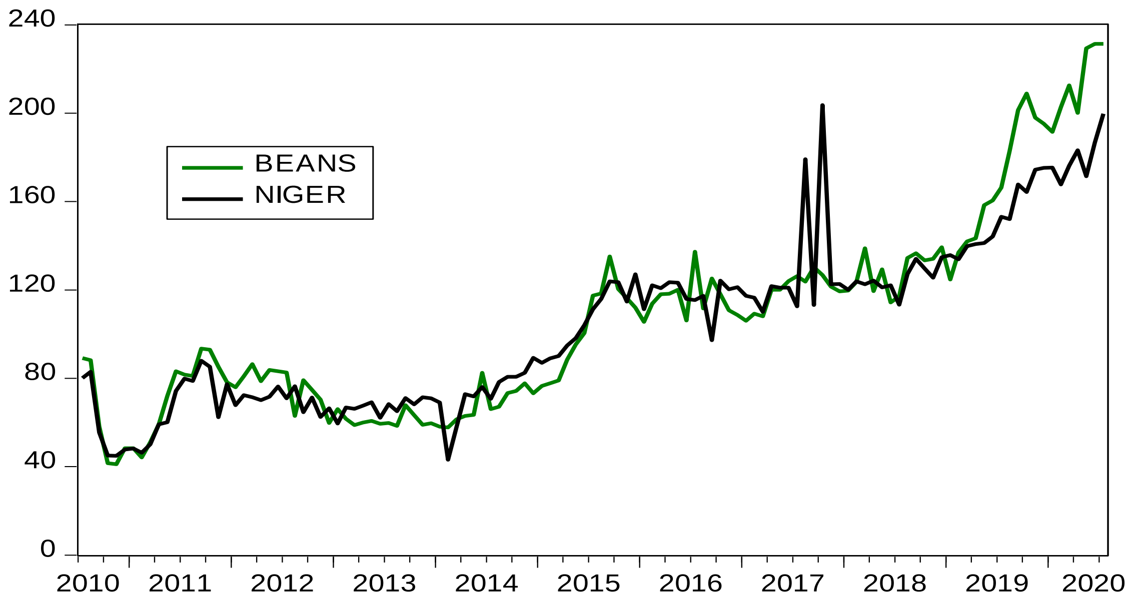
The index reached its peak point of 394 in July 2020. The other root crop included in the index was potato, as shown in figure 13; the potato price index from 2010 to 2020 generally increased in an overall context, but at a lower rate than the index for onion. The highest ever observed index level was 253, which was recorded in March 2020, and the lower one was 46, which was seen in March 2013, for all the study areas. In most of the study periods, the price index of potatoes showed declines in certain months (such as March, April, and May) of the year and falls in some others (such as June, July, and August).

Figure 14: Price indices of spice



The third group of commodities that accounted for 5% of the index was spices, specifically Red pepper. Since 2010, the price index of red pepper in Ethiopia has been steadily increasing, though there were certain declines in certain periods; it was not lower than the amounts observed in the previous periods, except in June 2014. A higher increment was recorded in September 2015, followed by a decline in the following months. In early 2017, it again began increasing, and continued rising until it reached its maximum peak in February 2020, followed by another decline.

Figure 15:The price indecis of pulses and oilseed



The price indices of pulses and oilseed are presented together in Figure 15 above; as it is shown in the figure, the index of pulses at the beginning showed declines for certain months, and then it rose, followed by another decline in the periods between October 2011 and March 2015. From April 2015 to September 2016, it was increasing and then back to declining and continued fluctuating at a smaller rate until January 2019; after that, it increased considerably and reached its peak (231) in June 2020.

With regard to Niger, in the first few months, there was a decline, followed by a rise in the last few months to October 2011. Then, up to 2014, it declined and reached its lowest point in February 2014; after this, it steadily increased in the rest of the periods; the highest ever level of the price index for Niger was recorded in 2017, which was 204 and that was its peak.

4.1.3 Market return and systemic risk (beta)

The second and third purposes of the study were to estimate the market return and the systematic risk (beta) for the 10 selected agricultural commodities in Ethiopia. Note that the same data was employed to compute them. For this purpose, the mean monthly returns for each commodity were also estimated.

The mean monthly return of a specific crop from each of the five categories was first estimated using the following formula.

$$\boldsymbol{R_{i,}^{t} = ln\left(\frac{p_i^t}{p_i^{t-1}}\right)}$$

$\boldsymbol{R_{i,}^{t}}$ is return of commodity i at period t

$\boldsymbol{p_i^t}$ is average monthly price of price of commodity i at period t

$\boldsymbol{p_i^{t-1}}$ is average monthly price of price of commodity I at period t-1

The result showed that the mean monthly returns of the cereals such as teff, maize, barley, wheat, and sorghum were 1.406%, 1.092%, 1.048%, 0.920%, and 2.034%, respectively.

The average monthly price returns of root crops, namely potatoes and onions, were 4.316% and 4.266%, respectively; the average monthly return for red pepper was 2.730%. Beans and Niger had average monthly returns of 2.553% and 1.811%, respectively.

Accordingly, an attempt was made to estimate the market return by computing the monthly log returns using the following equation:

$$Rm_t = ln\left(\frac{p_t}{p_{t-1}}\right)$$

The result specified that the average monthly mean return of the market was 1.12% and its standard deviation was 6.14%. Next, the systematic risk (beta) was computed by employing the market model. The systematic risk, or beta, of a commodity or crop is estimated with the use of the market model.

The Market model:

$$R_i = a_j + \beta_j R_m + e_j$$

R_i = historical (realized) rate of return on commodity j

R_m = historical (realized) rate of return on the market

a_j = vertical axis intercept term for commodity j

β_j = beta, coefficient, for commodity j

e_j = random error

The empirical market model in this study takes the form of a classical linear regression (CLR). The classical linear regression model is subject to some theoretical assumptions that are practically unrealistic. Therefore, to estimate beta of a commodity through a linear regression model, a test of the assumptions of the classical linear regression model and/or a statistical measure for violation of the assumptions needs to be done before the regression. Below are discussed the nature and consequences of these assumptions and how violations of these assumptions are treated to avoid inaccurate inferences in this study.

4.1.3.1 Methodological issues and corrections for the violations of assumptions

4.1.3.1.1 Heteroscedasticity problem

One of the important assumptions of the classical linear regression model is homoscedasticity, or equal variance (Gujarati, 2004). That is, it is assumed that the variance of each disturbance term u_i, conditional on the chosen values of the independent variables, is some constant number equal to sigma square ($\sigma 2$). The opposite of this is heteroscedasticity. That is, when the variance of a disturbance term is not constant, there might be different reasons for the variance of the disturbance term varying. If someone uses the usual testing procedures in the presence of heteroscedasticity, whatever conclusions are drawn or inferences made may be distorted. Consequently, a test for the detection of the presence of heteroscedasticity needs to be conducted, and the White test is used to detect the presence of heteroscedasticity. Thus, remedial measures are used to resolve the heteroscedasticity problem through the Newey-West standard error.

4.1.3.1.2 Autocorrelation

Autocorrelation is defined as the correlation between members of a series of observations ordered in time as in time series data or space as in cross-sectional data (Gujarati 2004). Classical linear regression assumes that there is no serial correlation or autocorrelation among the disturbance terms. However, mostly in time series data, for example, stock price indexes, it is likely that successive observations exhibit inter correlation. For that reason, the assumption of no auto, or serial, correlation in the error terms that underlie the classical linear regression model will be violated. In this study, Breuch-Godfrey (BG) LM tests were used to detect the presence of autocorrelation. For Newey and West (1987), heteroscedasticity and autocorrelation-consistent (HAC) standard errors, or simply Newey-West (N-W) standard errors, are used to correct the standard errors.

4.1.3.1.3 Normality assumption

The residuals, or error terms, are assumed to be normally distributed. Regression analysis depends on the assumption that a dataset is normally distributed, that is, symmetrical around its mean. Kurtosis, skewness, and Jarque-Bera tests are used to detect normality in this study. The high kurtosis values indicated that large shocks of either sign were more likely to appear in the series, indicating that the return series is leptokurtic, the skewness coefficients, did not follow a normal distribution; the result was further confirmed by the Jarque-Bera test too. This problem is minimized by using lognormal returns in return estimates.

4.1.3.1.4 Stationarity

This study uses time series data, and empirical studies based on time series assume that the fundamental time series is stationary. According to Gujarati (2004), if a time series is stationary, its mean, variance, and auto covariance at various lags remain the same no matter at what point one measures them; that is, they are time invariant. In this study, the Augmented Dickey-Fuller (ADF) test is used to check the stationarity of the monthly return series. The null hypothesis of the unit root was rejected; that is, the series was stationary at every level.

EViews package is used to facilitate the estimation procedure see appendix A. See the following table.

Table 8 Systematic risk (beta) of crops

	Beta	Sig.
Teff	.623	.000
Wheat	.645	.000
Sorghum	1.419	.000
Maize	1.130	.000
Barley	.747	.000
Niger	.681	.001
Beans	1.368	.000
Onion	.470	.118
Potato	1.195	.001
red pepper	.911	.000

Table 8 displays the systematic risk of crops; the co-movement of returns of each crop with respect to the market was computed using a market model. The systematic risk (beta) of Teff was 0.623 and that of wheat and barley was 0.645 and 0.747, respectively. Of the cereals, sorghum and maize were observed to have higher betas, with values of 1.419 and 1.13, respectively. Betas of the other crops such as Niger, beans, onions, potato, and red paper were 0.681, 1.368, 0.470, 1.195, and 0.911, respectively (except for onion, the result is statistically significant).

4.1.4 Price volatility

The final objective of this study was to identify the best-fitting GARCH family model. The summary statistics such as monthly mean returns, maximum and minimum returns, standard deviations, skewness, kurtosis, and Jarque-Bera statistics for the commodity price return were computed and presented as follows in Table 9.

Table 9: Descriptive Statistics

Item	Average	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
TEFF	0.014059	0.318	-0.216	0.065776	0.572846	7.867164	123.9677
BARLEY	0.010479	0.208	-0.286	0.059775	-0.74233	8.917582	184.5589
WHEAT	0.009202	0.196	-0.233	0.056551	-0.68038	7.424932	106.2655
MAIZE	0.010924	0.313	-0.35	0.085498	-0.48531	7.917191	124.5576
SORGHUM	0.020336	0.667	-0.336	0.137654	1.285555	8.052755	159.3655
NIGER	0.018109	0.8	-0.398	0.151613	1.777804	12.97527	556.0688
BEANS	0.025529	2.195	-0.668	0.233038	6.598648	65.0373	19946.36
ONION	0.042655	0.95	-0.395	0.2232	1.034845	4.728731	36.05765
POTATO	0.04316	2.591	-0.703	0.32923	5.391311	40.98864	7732.033
REDPEPPER	0.027303	1.394	-0.421	0.19618	2.959798	22.04211	1971.65

Source: EViews 10 output based on CSA data from 2010-2020

As it is shown in Table 9, the summary statistics indicated that the average monthly price returns of root crops, namely potatoes and onions, were 4.316% and 4.266%, respectively, while the average monthly return for red pepper was 2.730%. Beans and Niger had average monthly returns of 2.553% and 1.811%, respectively, with their respective standard deviations of 23.30% and 15.16%.

As compared to the other crop categories, the average monthly returns of cereals were relatively small. Though cereals had small returns in general, in relative terms, sorghum had a higher return than the returns of the other crops in the group, having an average return of about 2.034% with a standard deviation of 13.77. The average monthly returns of the rest of cereals such as teff, maize, barley, and wheat were 1.406%, 1.092%,1.048%, and 0.920%, respectively.

To come to either the acceptance or rejection of the hypothesis, the null hypotheses of zero skewness, and a kurtosis coefficient of 3 were rejected at a 0.01 level of significance. The high kurtosis values indicated that large shocks of either sign were more likely to appear in the series, indicating that the return series is leptokurtic.

Similarly, the skewness coefficients, which suggest the existence of the monthly price return series in the commodities, did not follow a normal distribution; the result was further confirmed by the Jarque-Bera test as the associated p-value was far below the 0.01 level of significance.

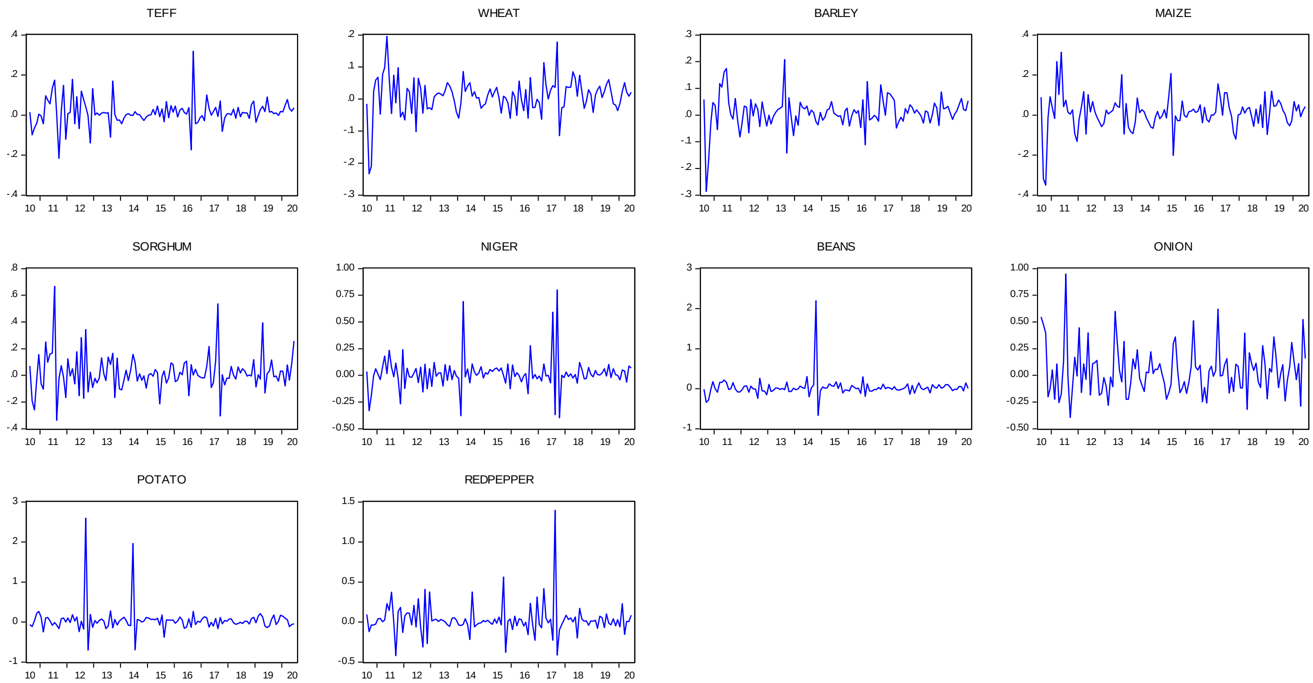
Figure 16: Average Monthly prices

Source: Result of EViews 10 output based on CSA data from 2010-2020

The time plot of the monthly price of the five categories of crops, in the plot was not smooth as it was observed in Figure 17. This indicated that the mean and the variance of the commodities were Heteroskedastic, and the series seemed to be non-stationary. Therefore, transforming the monthly price data (Yt) to natural log returns (r t) was performed.

The graphical properties of the price return series, which are the primary steps in analyzing time series data, are plotted against time in the figure as follows:

Figure 17: Monthly Prices return



Source: Result of EViews 10 output based on CSA data from 2010-2020

The price return time plot revealed that some periods were riskier than others. There was also some degree of autocorrelation in the riskiness of the log returns. The amplitudes of the price returns varied over time, as large changes in returns tended to be followed by other large changes, which again were followed by small changes.

This is one of the stylized facts in the financial time series, the so-called volatility clustering. The volatility clustering, in the series, indicates that the returns are being driven by market forces.

To meet the objective, GARCH family models were applied; the EViews 10 statistical package was used to compute the estimates of the GARCH volatility model parameters. The monthly price series for each selected commodity was used to compute the logarithmic return series as

$$Y_t = ln\left(\frac{p_t}{p_{t-1}}\right)$$

Statistical tests to run GARCH family models

4.1.4 .1 Unit Root Test for Non-stationary Series

For time-series data, one should check for stationarity to find an appropriate model. Therefore, in this study, an Augmented Dickey–Fuller (ADF) unit root test was used to check the stationarity of the monthly return series. The result is presented in Table 10. As it is observed from the table, the null hypothesis of the unit root was rejected; that is, the series were stationary at level; therefore, proceeding to the model, the conditional volatility with GARCH-class models is possible.

Table 10. Unit Root Tests for the Series (at level)

ADF test

Price return series	test equation	ADF Test statistics	P value
Teff	With intercept	-7.759353	0.0000
	with trend and intercept	-7.722723	0.0000
Wheat	With intercept	-9.0742	0.0000
	with trend and intercept	-9.105941	0.0000
Barley	With intercept	-9.578447	0.0000
	with trend and intercept	-9.619655	0.0000
Maize	With intercept	-8.796355	0.0000
	with trend and intercept	-8.78586	0.0000
Sorghum	With intercept	-13.70124	0.0000
	with trend and intercept	-13.64497	0.0000
Niger	With intercept	-19.02211	0.0000
	with trend and intercept	-19.03523	0.0000
Beans	With intercept	-13.4771	0.0000
	with trend and intercept	-13.42674	0.0000
Onion	With intercept	-10.26097	0.0000
	with trend and intercept	-10.2095	0.0000
Potato	With intercept	-15.26639	0.0000
	with trend and intercept	-15.27743	0.0000
red pepper	With intercept	-11.08461	0.0000
	with trend and intercept	-11.05381	0.0000

Source: Result of EViews 10 output based on CSA data from 2010-2020

4.1.4 .2 Test of ARCH effect

The test of the ARCH effect is one of the most important issues to be checked before applying GARCH models. LM test for the squared residuals of the fitted model proposed by Engle (1982) was conducted for testing heteroscedasticity.

Table 11: Hetroskedasticity test: ARCH

Price return series	LM Statistics	Chi square Statistics
Teff	4.288312	4.206049
	(0.0406)	(0.0403)
Wheat	61.93762	40.95625
	(0.0000)	(0.0000)
Barley	46.53749	33.70664
	(0.0000)	(0.0000)
Maize	37.60407	28.83066
	(0.0000)	(0.0000)
Sorghum	22.36661	19.0744
	(0.0000)	(0.0000)
Niger	15.76442	14.10504
	(0.0001)	(0.0002)
Beans	18.54074	16.24423
	(0.0000)	(0.0001)
Onion	0.498272	0.50475
	(0.4817)	(0.4774)
Potato	12.03613	11.08525

	(0.0007)	(0.0009)
red pepper	1.625696	1.630869
	(0.2048)	(0.2016)

Source: Result of EViews 10 output based on CSA data from 2010-2020

The null hypothesis, which states that there is no remaining ARCH effect, is rejected as the finding specifies the existence of the ARCH effect in the commodities. Therefore, it is possible to estimate the ARCH model for a better result since it shows the variance of return series for each commodity is time varying.

4.1.4.1 GARCH component Model Specifications

After confirming the presence of an ARCH effect in the residuals of the mean model, one needs to estimate a GARCH model to test for the presence of asymmetry and time varying unconditional variance in the series. Various symmetric and asymmetric models, specifically GARCH, EGARCH, and TGARCH, were considered. Then, for the model selection procedure, these symmetric and asymmetric GARCH family models were fitted for each series. As a result, under the normal distribution assumption for residuals, the symmetric GARCH model, as well as the asymmetric EGARCH and TGARCH models, were selected as possible models of volatility. Table 12 displays the summary results.

Table 12: Model selection

Crop	Model	AIC	SIC	Likelihood
Teff	ARCH	-2.69485	-2.64814	162.3434
	GARCH 1,1	-2.83491	-2.76484	171.6768
	TGARCH	-2.82369	-2.73027	172.0094
	EGARCH	-2.85321	-2.75979	173.7658
Wheat	ARCH	-2.97149	-2.92479	178.8039
	GARCH 1,1	-3.16703	-3.09697	191.4385
	TGARCH	-3.15146	-3.05804	191.5116
	EGARCH	-3.13961	-3.04619	191.9091
Barley	ARCH	-3.03834	-2.99163	182.7812
	GARCH 1,1	-3.08087	-3.01081	186.3119
	TGARCH	-3.08302	-2.9896	187.4395
	EGARCH	-3.06786	-2.97444	186.5376
Maize	ARCH	-2.23018	-2.18348	134.696
	GARCH 1,1	-2.35094	-2.28087	142.8807
	TGARCH	-2.4334	-2.33999	148.7875
	EGARCH	-2.47705	-2.38363	151.3844
Sorghum	ARCH	-1.28158	-1.23487	78.2537
	GARCH 1,1	-1.26712	-1.19706	78.39374
	TGARCH	-1.29051	-1.1971	80.78547
	EGARCH	-1.22659	-1.13317	76.98196
Niger	ARCH	-1.361	-1.29094	83.97937

	GARCH 1,1	-1.361	-1.29094	83.97937
	TGARCH	-1.444	-1.35059	89.91811
	EGARCH	-1.52077	-1.42735	94.48553
Beans	ARCH	-0.0795	-0.0328	6.730492
	GARCH	-0.17618	-0.10612	13.48284
	TGARCH	-0.60942	-0.516	40.26048
	EGARCH	-0.58006	-0.48664	38.51333
Onion	ARCH	-0.10099	-0.05429	8.009105
	GARCH	-0.16469	-0.09463	12.79894
	TGARCH	-0.14663	-0.05321	12.72433
	EGARCH	-0.30806	-0.21465	22.32978
Potato	ARCH	0.19019	0.236898	-9.316288
	GARCH	0.636607	0.706669	-34.87811
	TGARCH	0.530757	0.624173	-27.58007
	EGARCH	-0.02982	0.063599	5.774135
red pepper	ARCH	-0.74526	-0.69855	
	GARCH	-0.78114	-0.71108	49.47767
	TGARCH	-0.97843	-0.88501	62.21645
	EGARCH	-1.03766	-0.94425	65.74089

Source: Result of EViews 10 output based on CSA data from 2010-2020

Table 12 presents information criteria and the log-likelihood functions for the estimated symmetric and asymmetric models; the results confirm that asymmetric models outperform the symmetric model in most of the crops under consideration. That is, for the fact that most of the criteria for selection of the best fit model are the higher the log likelihood function and the lower the AIC and SIC. However, in some cases, if the three criteria contradict each other, the AIC value is taken into account. Based on this conception, the EGARCH model with a normal distributional assumption performed better in describing volatility for teff, maize, onion, potato, Niger, and red pepper price returns, and TGARCH was found to be the best model in explaining the conditional volatility of sorghum, barley, and beans. However, for wheat coefficients, ARCH, GARCH, and asymmetric terms were not found to be significant; hence, no model was found to be the best fit for wheat price return in the sampled periods.

Table 13 : parameter estimation

	MODEL	ω	α	β	γ
Teff	ARCH	0.002792*	0.416315*		
	GARCH	0.000578*	0.539948*	0.446636*	
	EGARCH	-1.62678*	0.736522*	0.804146*	-0.039079
	TGARCH	0.000645*	0.41489*	0.230032	0.450632*
Wheat	ARCH	0.002254*	0.280818*		
	GARCH	0.000186	0.101969	0.791517*	
	EGARCH	-10.82518	0.896441*	-0.664017*	-0.016344
	TGARCH	0.000178*	0.091929	0.790803*	0.041995
Barley	ARCH	0.001159*	1.088462*		
	GARCH	0.000696**	0.705673**	0.248115**	
	EGARCH	-1.978545*	0.570868*	0.746815*	0.131184*
	TGARCH	0.000692	0.887812**	0.259204**	-0.553951
Maize					

	ARCH	0.003777*	0.609962*		
	GARCH	0.000931*	0.219916*	0.598751*	
	TGARCH	0.000347*	-0.002524	-0.108959*	0.949358
	EGARCH	-0.059781*	-0.269908*	0.956144*	0.051775
Sorghum	ARCH	0.007486*	1.115987*		
	GARCH	0.008021*	1.109539*	-0.02609	
	TGARCH	0.010118*	1.127071*	-0.090085*	-0.75179*
	EGARCH	-1.965463	0.408904	0.601891*	0.234228
Niger	ARCH	0.00888*	0.727594*		
	GARCH	0.009157*	0.732183*	-0.014667	
	TGARCH	0.013139*	0.136661	-0.096237	0.664885
	EGARCH	-3.606661*	0.939767*	0.321029*	-0.563668*
Beans	ARCH	0.050635*	0.059527		
	GARCH	-0.000295	-0.017075	1.028248*	
	TGARCH	0.055157	0.025289	0.280246	-0.265305
	EGARCH	-4.783632*	2.580257*	0.095865	0.757953*
Onion	ARCH	0.049581	0.032254		
	GARCH	0.022346	-0.05668	0.582091*	
	TGARCH	0.02388*	-0.05975	0.56101*	0.071062
	EGARCH	0.00751*	-0.20159*	0.95063*	-0.147774*
Potato	ARCH	0.007286	8.327911		
	GARCH	0.013596	-0.004636	0.88611	
	TGARCH	-0.000309	0.032905*	0.847811	1.816192
	EGARCH	-3.39606*	1.840953*	0.119832	-1.164976*
Red pepper	ARCH	0.012388	1.663435		
	GARCH	0.007357*	2.054468*	0.071576**	

	TGARCH	0.009691*	0.129286	0.000833	5.840678*
	EGARCH	-3.308722*	1.210604*	-0.525129*	0.349798*

* Significant at 1 percent level

** Significant at 5 percent level

Source: EViews 10 output based on CSA data from 2010-2020

As Table 13 shows, the result established the presence of time varying conditional volatility on the returns of most of the agricultural commodities. The coefficients of the asymmetric terms for the TGARCH model ($\boldsymbol{\gamma}$) were negative: 0.75 for sorghum, -0.55 for barley and -0.26 for beans price returns, and they were statistically significant at a .0.01 level of significance. Some of the estimates of time varying volatility are given as follows:

TGARCH specification;

$$\delta^2 = \omega + \alpha_1 \delta_{t-1}^2 + \beta \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1}$$

$$\delta^2{}_{sorghum} = 0.010118 - 0.090085\delta_{t-1}^2 + (1.127071 - 0.751790)\varepsilon_{t-1}^2$$

$$\delta^2{}_{barley} = 0.000692 - 0.259204\delta_{t-1}^2 + (0.887812 - 0.55395)\varepsilon_{t-1}^2$$

$$\delta^2{}_{beansy} = 0.055157 - 0.280246\delta_{t-1}^2 + (0.025289 - 0.265305)\varepsilon_{t-1}^2$$

EGARCH specification;

$$\boldsymbol{Ln\delta^2 = \omega + \beta Ln\delta_{t-1}^2 + \alpha_1 \frac{\left|\varepsilon_{t-1}^2\right|}{\delta_{t-1}^2} + \gamma \frac{\varepsilon_{t-1}^2}{\delta_{t-1}^2}}$$

$$\mathbf{Ln\delta^2{}_{teff} = 1.62678 + 0.804146 Ln\delta^2 + 0.736522 \frac{\left|\varepsilon_{t-1}^2\right|}{\delta_{t-1}^2} - 0.039079 \frac{\varepsilon_{t-1}^2}{\delta_{t-1}^2}}$$

$$\mathbf{Ln\delta^2{}_{red\ pepper} = -3.308722 \pm 0.525129 Ln\delta^2 + 1.210604 \frac{\left|\varepsilon_{t-1}^2\right|}{\delta_{t-1}^2} + 0.349798 \frac{\varepsilon_{t-1}^2}{\delta_{t-1}^2}}$$

Based on the results of the estimated EGARCH model, the differences between the "good" news and the "bad" news, which were the coefficients of the asymmetry term, were 0.039079 for *the Tef*f price return, and 0.34978 for the pepper price return. Moreover, the coefficients of the asymmetric terms for onion and potato were negative 0.15 and negative 1.16, respectively, and both of them were statistically significant at a 0.01 level of significance. Similarly, the asymmetric term coefficient of Niger was negative 0.56, and it was statistically significant; the asymmetric term was also statistically significant for red pepper, with a coefficient of -0.53.

4.1.4.2 **The Adequacy of the Fitted Models**

So far, it has been mentioned that EGARCH was the best model for Teff, Maize, Niger, Onion, potato, and red pepper, and TGARCH was the best model for Sorghum, Barley, and Beans. The Breusch–Godfrey serial correlation LM test, the Corrologram of standardized residual squared, and Jarque –Bera for normality tests were employed to check the adequacy of the fitted models.

Accordingly, the result of the Breusch–Godfrey serial correlation LM test showed that the fitted models did not exhibit any additional ARCH effect for each of the series, as both the F statistics and observed R squared were not significant. Both the autocorrelation function (ACF) and partial autocorrelation function (PACF)fell within the confidence interval, and all the p values were well above 5% (0.05) (see appendix B), which means they were not significant. It indicated that there was no serial correlation in the residuals.

CHAPTER FIVE: DISCUSSION

This study's overall objective was to develop a price index, estimate market return, estimate a commodity's systematic risk (beta), and model price volatility for Ethiopia's agricultural commodities market. In line with this objective, the overall market condition, or market index, was constructed by aggregating raw monthly retail pricing data gathered from the Central Statistics Agency across time (from 2010 to 2020). Indeed, this index's design is critical for determining price movements and overall market conditions in Ethiopia's agricultural commodities market. Following the indexes' development, or having indexes that show the overall change in the prices of agricultural commodities or crops in the years at hand, attempts were made to estimate the systematic risk (beta) of each crop. That is, once the indexes were constructed and the market returns were determined, the systematic risk (beta) of each commodity was estimated as a function of the market index using market model that is very close to the CAPM, where beta is the central concept of the CAPM. Finally, it was attempted to model the volatility of the agricultural commodities market using GARCH family models and determine the best fit models appropriate for agricultural commodity/crop prices using the generated market index and the estimated systematic risk.

In brief, one of the objectives of the study was to construct price indices for agricultural commodities in Ethiopia. In the process of constructing an index number, it is necessary to decide on six factors: the purpose of the index, availability of data, selection of items, choice of the base period, selection of the weights, and methods of construction (Freund & Williams, 1969; Tysoe, 1982). The Laspeyres price index and the Paasche price index are the most commonly used methods of index construction, where the Laspeyres price index is a base period index and the Paasche Price Index is a current period price and observation year quantity.

In this study, the purpose of the index is to provide a basis for price monitoring and analysis that could help market participants, such as, producers, traders, consumers, and the government, with a regular breakdown of price changes for a better understanding of recent market developments. The monthly retail price data were available at CSA for the periods 2010- 2020. For the index construction, agricultural commodities from five categories, namely Cereal, Pulses, Oilseed, Root crop and Spices were taken. From the five categories, a total of ten crops were chosen and included in the index based on their proportionate share in the overall agricultural commodity as weight. Therefore, in this research, the Laspeyres's approach was used; accordingly, the share of the crop in the average production quantity of the country was used as the appropriate weighting scheme. To ensure the stability of the weights and to avoid short-term and seasonal fluctuations in production, the index was calculated using a three-year average production quantity weighted. To this end, the 2014-2016 average production quantity was selected as the base period.

The result revealed that the price of agricultural commodities exhibited an ever increasing trend in all of the regions of the country and in Addis Ababa city administration during the study periods between 2010 and 2020. Some special sudden increases were also recorded in some years as compared to the past, specifically in the year 2017. While providing similarity in the ever increasing trend of crop prices throughout the country, there were some differences in prices of crops across the regional states and the Addis Ababa city administration over the study periods. That is, the price of a specific commodity was relatively low in one region as compared with others, and it might be higher in another crop in comparison to other regional states and the national average. For example, prices of Teff and Wheat were relatively the lowest in ANRS and of the lowest prices for maize and sorghum were observed in SNNP, while the lowest average price of barley was witnessed in ONRS. This might be due to the week market integration and poor supply chain in the marketing of agricultural commodities across regions and even within the region.

Specifically, in the Amhara Region, the index of Teff prices is relatively lower than the national average, while the Sorghum and Wheat indices are a bit higher than the national average. During 2017, price indexes for most of the crops suddenly increased. For example, the sorghum price index dramatically increased to a point of 395, up from 104 points in the previous periods. The same sudden rise in the index was recorded at the national level, which rose from 104 to 192 in the price of sorghum. The price index of maize in most of the periods, especially from 2010 up to 2017, was lower in the region than the national average. After the year 2017, in which the highest ever index level was recorded, the increase in its price at ANRS was far greater than the increases in other regions and the national average comparatively. Starting from mid-2018 up to the end of 2020, the ANRS price index for maize was above the national average.

Concerning barley, a slight decline in the first eight months was recorded both at the national level and at the ANRS level, while a rapid increase followed from June 2011 until November 2013. From 2014 up to the beginning of 2017, lower and relatively stable prices were recorded, followed by a sharp increase in late 2017. In most of the periods, the ANRS barley price index is above the national average, with the highest ever index point of 215 recorded in 2020 at ANRS, where the national average for a similar period was 185.

The price of cereals at an index level moves in a similar pattern to the national average in Oromia national regional state, a region which accounts for 27.66% of the weightings in the Ethiopian agricultural commodities price index. With the exception of the last few months, the price of cereals in this regional state, at an index level, was slightly lower than the national average. Since 2017, the index of sorghum, wheat, and barley has been rising rapidly. A similar sudden rise in the index was recorded at the national level too for the same crops. With respect to teff, its price was declining at the beginning of the study period, but it began to rise between the periods from 2011 to late 2013. Relatively, price stability was observed in the price of Teff in the years from 2014 up to the beginning of 2017, followed by a subsequent rise. In most of the study periods, specifically from 2010 up to 2016, the price of maize in ONRS at index level was lower than the national average. After that, it was higher than the national average. This implies that the increase in prices in the region was higher in magnitude than the increases recorded at the national level on an average. In September 2019, the ONRS maize price reached its highest ever index point of 220. The Southern Nation Nationalities and Peoples region (SNNP) accounts for 35.66% of the weightings in the Ethiopian agricultural commodities price index. The SNNP price of cereals at an index level moves in a similar pattern to the price movements at the national level. Except for a few months in the study periods, the prices of most cereal crops in SNNP were above the national average at index levels.

The year 2017 was a period wherein special increments were observed in most of the commodities in SNNP, the same as in ANRS, ONRS and Addis Ababa too. As compared to other crops, the price indexes of barley and wheat in SNNP were relatively stable from the end of 2011 up to 2016, while the sustainable rise was exhibited following the 2017 increment. In particular, the price of sorghum was found to be the most volatile compared to the prices of other cereal crops in the SNNP markets during the study periods. This might result from the lack of market integration in agricultural commodities and the production quantity of this particular crop in the region. That is, the weak market integration and poor supply chain in the marketing of agricultural commodities across regions can result in the variations in price volatility of agricultural commodities. According to the report of FAO (2015), in Ethiopia, sorghum is the single most important staple in drought-prone areas in which the majority of its imports take the form of food aid, and the sorghum value chain is long and involves too many small operators. In line with this, the main sorghum producing regions are Oromia National Regional State and Amhara National Regional State are the main sorghum producing regions, accounting for nearly 80 percent of total production according to the reports of the Central Statistics Agency. As a result, sorghum from surplus areas is transported to deficit areas, among which SNNP is the one that is considered as deficit area specifically for sorghum as recorded by Famine Early Warning Systems Network (FEWSNET, 2014). In short, it is likely that SNNP's high price volatility of sorghum as compared to other cereal crops can result from a lack of adequate production in the region.

As mentioned above, like SNNP, special increments in price indexes of most agricultural commodities were seen in Addis Ababa in 2017. There might be different reasons for these unique increments. For example, Addis Ababa is the capital city of the country and accounts for 10% of the country's major market areas wherein agricultural commodities from all corners of the country are bought and sold at large. In most of the study periods, the price index of Addis Ababa was found to be above each of the regional states and the national average too. This is because it is receiving city rather than a producing one. Many of the crops under study that were tra in Addis Ababa came from ANRS, ONRS, and SNNP. Hence, the price in Addis Ababa is highly impacted by the prices in those nearby regions, which are major producers of the commodities. Moreover, transportation costs were other factors that impacted its price. The finding of this study shows that the indexes of cereals in Addis Ababa were more volatile than the national averages except for sorghum.

That is, as the price volatility is associated with different factors, the marketing system is one of them. That is, in market areas that are major producers of a specific crop, its price tends to be relatively lower and less volatile than the national average. The Addis Ababa city administration is the one wherein the studied crops are traded but is not a major producer of any of them. That means crops sold in the 12 Addis Ababa market were transported from other regions, hence the prices for almost all crops were high and volatile, with an exception to sorghum.

According to the central statistics agency agricultural sample survey data, sorghum is one of the major staple crops and drought-tolerant crops grown in the poorest and most food insecure regions of Ethiopia. Besides, the consumption of sorghum has increased in areas affected by adverse climate conditions, which favor the production of sorghum over other cereals. According to a USAID (2012) report, sorghum accounts for 10% of the daily caloric intake of households Ethiopia's eastern and north-western parts. That is, where teff is used to make injera (the traditional food) in more productive areas, sorghum grain is used for making injera in these areas as a substitute for teff. Therefore, when teff prices decline, the consumption of sorghum also declines, and when teff prices rise, the consumption of sorghum also rises, in areas affected by adverse climate conditions. However, its consumption in Addis Ababa is insignificant, and so its price volatility is not as high as other cereal crops.

Coming to root crops, they are more volatile than other groups of crops included in this study. From July 2010 to January 2017, Addis Ababa's root crop price index tracked the national root crop price index. The price of onions in Addis Ababa was highly volatile throughout this period. A rapid rise in onion prices has been recorded in March 2017, from an index point of 74 in January 2017 to 220 in March 2017. Following this rise, the index rests within a range of 220 to 264 points, up to the 2019 January index level. Prices have been dramatically rising since November 2019, reaching their peak point of 585 on an index level in February 2020. With the exception of a few months, the price of potatoes in Addis Ababa moves at nearly the same rate as the national average over the study period. The frequent fluctuation and volatility in root crops is not exhibited only in the Addis Ababa city administration but also in other regional states and the national average too.

At the national level, the price indices of pulses and oilseeds initially showed declines for certain months, and then they rose, followed by another decline in the periods between October 2011 and March 2015, specifically for pulses. The price of pulses was in an increasing pattern during the periods between April 2015 and September 2016, and then went back to declining and continued fluctuating at a smaller rate until January 2019; after that, it increased considerably and reached its peak (231) in June 2020. The lowest point in the price of Niger was reached in February 2014; after that, it steadily increased in the rest of the periods; the highest ever level of the price index for Niger was recorded in 2017, which was 204, and that was its peak.

The year 2017 was the period in which special increases in prices were observed in almost all of the crops used for this study. The major reason behind this occurrence might be the currency devaluation that the Ethiopian government has made since 2017. The National Bank of Ethiopia (NBE) has announced a devaluation of the country's currency by 15% effective Wednesday, October 11, 2017. The government of Ethiopia has been implementing a "managed float" exchange rate system for a long period of time. This is because the exchange rate does not have a given path and is, therefore, allowed to fluctuate every day through the authorities' occasional intervention in the foreign exchange market by means of buying and selling currency. However, in all of the previous years, Ethiopia's official exchange rate was fairly stable with a nominal devaluation of 5% per year, with the exception of some significant devaluations but no single instance of appreciation. Countries devalue their currencies for different reasons, such as to boost exports, to improve their balance of payments, or to reduce sovereign debt burdens.

The main argument behind the currency devaluation by the Ethiopian government rests on the first one; that is, devaluation would empower exporters to make more money in the local currency for a given amount of sales abroad, thereby encouraging them to export more. This argument, however, assumes that Ethiopia could earn much more hard currency by exporting more when export prices rise in local currency and that imports would significantly decline when their prices increase in local currency (NBE, 2017). That is, it is based on the assumption that supply of export and demand of import are quite flexible. In addition, to be successful, the devaluation needs to be accompanied by tight monetary and fiscal policy, which the NBE should implement. Theoretically, the devaluation of one currency has both advantages and disadvantages. There is valid evidence which shows the positive impacts of devaluations. Brazil, for example, devalued its currency by 64% in 1999, South Korea devalued its currency gradually in the 1970s, and Egypt devalued Egypt's pounds by approximately 200 % between November 2016 and May 2017. The devaluations of these countries were successful for the reason that they were supported by restrictive monetary and fiscal policies to curb inflation. However, the results of the present study showed that the devaluation is followed by an immediate rise in the prices of major cereal crops in the country, except Teff. This finding is confirmed by the report of the monthly update on the Ethiopian economy (UN, 2020) that stated, in any episodes of significant devaluation in Ethiopia, a significant increase in export earnings and a decline in imports were never witnessed because its exports are still limited to agricultural commodities. In principle, inflation is likely to occur after devaluation due to rising import prices and increased demand for exports. Immediately after the Birr devaluation on October 10, 2017, the prices of almost all commodities and services increased significantly, leading to an increase in the overall price level. Thus, it is in line with the finding of Korsa et al. (2018) and Rajan (2018) that the rise in inflation in Ethiopia following the devaluation once again confirms that there is a direct link between devaluation and inflation. One of the important factors in keeping inflation high in Ethiopia is the frequent devaluation.

In general, despite the differences in its magnitude, the price index of agricultural commodities in Ethiopia has been steadily rising in the three regional states and Addis Ababa City Administration. There were some ups and downs in the patterns, that is, there were periods when declines in prices were recorded, but the declines were still above what they had been in the previous period’s average. It is implied that once the price of a commodity rises, its probability of declining is very low as it becomes the norm to continue rising. Even the seasonal decline at harvest time was not as high in magnitude to offset the previous period's increment.

The regional and national price indices constructed in this research offer advantages for in-depth price monitoring and analysis, and provide a basis for forecasting. In addition, it provides researchers and interested parties, such as producers, traders, cooperatives, consumers, and the government, with a thorough breakdown of price changes that allows them to better understand recent market developments.

Constructing the indexes for the selected agricultural commodities, this researcher looked into the risk and return characteristics of the Ethiopian agricultural commodities market. The Modern Portfolio Theory of Markowitz (1952) provides insight into quantifying the relationship between risk and return. An extension of the Modern Portfolio Theory, the Capital Asset Pricing Model is a single-factor model that divides investment risk into two distinct components: systematic and unsystematic risks. Since the following purpose of the study was to estimate the market return and the systematic risk (beta) for the 10 selected agricultural commodities in Ethiopia, the same data was employed to compute them. In line with this theory, the following objectives were designed: the first one was to estimate the market return of the agricultural commodity market; the second one was to estimate the systematic risk (beta) for selected agricultural commodities.

To meet these objectives, a portfolio of ten agricultural commodities was taken, and for that, a production quantity weighted index has been constructed from the monthly price data of those commodities to be used as a proxy for the market portfolio. Accordingly, an attempt was made to estimate the market return by computing the monthly log returns from the weighted average of individual commodities. Hence, the mean monthly returns for each commodity were also estimated, and the result showed that mean returns were positive. Specifically, the mean monthly returns of cereals such as Teff, maize, barley, wheat, and sorghum were 1.406%, 1.092%, 1.048%, 0.920% ,and 2.034%, respectively. The average monthly price returns of root crops, namely potatoes and onions, were 4.316% and 4.266%, respectively.

The monthly price return of root crops was the highest as compared with other crop categories. This is supposed to be related to the vulnerability of these commodities' spot prices to being highly influenced by seasonality effects, which is the pattern of the commodities' demand and supply. Because these crops are produced more than once in a year in the country, the farmers' production decisions are influenced by what happened in the prices of that specific commodity in the previous season.

That is, if the price of a specific crop, for example, onion is very low and participants incur a loss in some periods, the farmers are discouraged from producing that crop in the following season and shift to other crops. The supply for the following season significantly declines. As a result of this, its price rises significantly, and farmers are able to earn more.

The average monthly return for red pepper was 2.730%. Beans and Niger had average monthly returns of 2.553% and 1.811%, respectively. The result implied that, in comparison to the other crop categories, the average monthly returns of cereals were relatively low, while the mean monthly return of root crops was relatively higher than the other groups, followed by red pepper. The price returns from agricultural commodities are affected by seasonal effects since the prices of agricultural commodities are subject to seasonal variations. That is, most of the cereal crops were harvested once a year, but root crops, specifically onions and potatoes, were cultivated more than once a year. Consequently, price returns of root crops tend to be more volatile than those of cereal crops, which were harvested once a year. Among the cereal categories, too, the return on sorghum was relatively higher than others, while wheat was the lowest. The result specified that the average monthly mean return of the market was 1.12% and its standard deviation was 6.14%. Tracing the findings here, in light of the risk and return tradeoff theory, the volatility of returns of those commodities as measured by their respective standard deviations needs to be inferred. The standard deviation of return for a commodity with a higher return is relatively higher for Sorghum in the cereal groups than for others within the group. Furthermore, on average, the return of potatoes, which has a higher return, deviates from its mean by about 32.92%, which is the highest of all. On the other hand, the volatility of wheat return as measured by its standard deviation was 5.65 %, which is the lowest of all.

Therefore, it implies that the commodity that has a relatively higher return is more volatile in its return, hence having a higher risk, measured by standard deviation, and the commodity that has a relatively lower return is less volatile in its return, hence having a lower risk, measured by standard deviation. The findings of this research confirmed the risk and return tradeoff theory, in which the higher the risk, the higher the return will be and vice versa (Bodie & Kane, 2003). In addition, with respect to whether there is a return or not in the agricultural commodity market, the finding of this study contradicts the finding of Dusak (1973), who found a return on agricultural commodities in the future is not different from zero, while in line with (Carter et al,1983). That is consistent with a previous study because the returns of all of the commodities were nonzero over the period of this study. Given the market return, the proxy in hand, the next task is to estimate the systematic risk beta of the ten commodities.

The third objective of this study was to estimate systematic risk. And, an attempt was made to address this objective. Systematic risk is the portion of an asset's variability that can be attributed to a common factor, and which cannot be diversified away (Sharp, 1964, Fabozzi, 1999). Beta is a measure of systematic risk of an asset which plays a pivotal role in modern finance as an essential parameter of CAPM. The CAPM predicts a linear relationship between asset returns and asset systematic risk by taking into account the market index benchmark as a proxy. For this, the monthly mean returns of each of the ten commodities were used as a dependent variable, and regressed against the proxy of market return, the independent variable.

The finding of this research indicated that the beta of agricultural commodities with respect to the agricultural commodity market index benchmark has a significant relationship to the return of specific commodities. In view of that, the beta of sorghum and maize was high relative to others in the cereal category, with a beta values of 1.419 and 1.13 for sorghum and maize, respectively. The beta for the commodities such as Teff was 0.623 and that of wheat and barley were 0.645 and 0.747, respectively. The betas of the other crops, such as Niger, Beans, potato, and Red paper were 0.681, 1.368, 0.470, and 0.911, respectively, and the result is statistically significant. The beta of onion was 1.13 but it was found to be statistically insignificant. According to Bodie and Kane (2003), theoretically, a beta value that is less than 1.0 means that the security is theoretically less volatile than the market. Comprising this asset in a portfolio makes it less risky than the same portfolio without the asset. A beta that is greater than 1.0

indicates that the asset's price is theoretically more volatile than the market benchmark. Some assets have negative betas. A beta of -1.0 means that the asset is inversely correlated to the market benchmark. The current study found that, with the exception of onion, the betas of entire crops were positive and statistically significant.

The result of the present study complies with the findings of Carter et al. (1983) but contradicts those of Dusak (1973), Kolb (1996), and Outinen (2007). If one compares these results from earlier studies, Dusak (1973) found betas for agricultural commodities with respect to stock market index benchmarks, with the result that she found a beta of 0.0602 for wheat, 0.0410 for corn, and 0.0730 for soybeans.

Similarly, Kolb (1996) found betas of 0.0689 for wheat, 0.0258 for corn, and 0.0733 for soybeans. Moreover, Outinen (2007) found similar results for the same commodities, such as for wheat, corn, and soybean betas, which were, 0.0419, 0.0503, and 0.0385, respectively. The findings of these researchers seem to be in the same direction that systematic risk is not an important determinant of commodity returns, that is, systematic risk is most likely to be absent. The use of the market index used as a proxy and the inclusion of more commodities where there were limitations on their studies were the causes of the nonconformity of the current research results from Dusak (1973), Kolb (1996), and Outinen (2007), in which this researcher found the systematic risk of nine out of ten commodities was positive and statistically significant.

One of the major problems associated with Dusak's analysis was that she used the return on the value-weighted S&P Index of' 500 common stocks as a proxy variable for the return on the efficient market portfolio. Hence, it is said to be based on a miss-specified model. To overcome this problem, Bodie and Rosansky (1980) suggest an alternative proxy (one which gives equal weight to a stock and a commodity index) that has more intuitive demand and is more representative of an efficient portfolio. According to them, a market portfolio comprised of' common stocks accompanied by commodities could result in a one-third reduction in variance with no concomitant decline in mean return. The other problem with Dusak's investigation was that the study was limited to a small set of commodities, namely Wheat, Soybean, and corn. The same was true in the case of Outinen (2007), since he adapted Dusak's mode, with a slight modification, where the portfolio consists of 90% S&P 500 index and 10% Dow-Jones, which are both common stocks. To fill these gaps, this study employs a portfolio of commodity price indexes comprised of ten commodities that is supposed to represent agricultural commodities traded in the Ethiopian commodity market as a proxy variable of market return. The researcher found the systematic risks of nine out of ten commodities were positive and statistically significant in determining commodity returns. This finding is consistent with the findings of Carter et al. (1983), who discovered that the estimated risk coefficients of agricultural commodities were generally significantly different from zero at the 95% level of' significance. This implies that in the agricultural commodity market, using the agricultural commodity market index as a proxy for the market, systematic risk, or beta, of a crop positively and significantly determines its return. This finding is in conformity with CAPM under the asset pricing theory.

The final objective of this study was to model the price volatility of agricultural commodities using GARCH family models. Agricultural commodity log return series were used for volatility modeling because they can provide better evidence of stylized facts of financial time series, such as leptokurtic, volatility clustering, and leverage effects (Rachev et al., 2011). From the result, it is shown that the average monthly price returns of cereals were 1.406%, 1.092%, 1.048%, 0.920%, and 2.034% for teff, maiz, barley, wheat, and soghum, respectively. The mean monthly returns of root crops, namely potatoes and onions, were 4.316% and 4.266%, respectively; the average monthly return for red pepper was 2.730%. Beans and Niger had average monthly returns of 2.553% and 1.811%, respectively, with their respective standard deviations of 23.30% and 15.16%. As compared to the other crop categories, the average monthly returns for cereals were relatively the lowest, and root crops were the highest. To run the volatility model, the null hypothesis of zero skewness and a kurtosis coefficient of 3 were tested. The result showed a nonzero skewness and a kurtosis coefficient greater than 3 for all series; hence, the null hypothesis was rejected. The series' high kurtosis values indicate the large shocks of either sign were more likely to appear in the series, indicating that the return series is leptokurtic.

The time plot of price returns indicated that some periods were riskier than others. There was also some degree of autocorrelation in the riskiness of the log returns. The amplitudes of the price returns varied over time, as large changes in returns tended to be followed by other large changes, which again were followed by small changes. That is, one of the stylized facts in the financial time series, the so-called volatility clustering. The volatility clustering, in the series, indicates that the returns are being driven by market forces. The appropriate statistical tests needed to run GARCH family models were tested. Based on that, the first one was to check the stationarity of the series to keep on proceeding. The Augmented Dickey–Fuller (ADF) unit root test result was tested with intercept and with trend and intercept, which confirmed that the series was stationary at level, hence the null hypothesis of unit root was rejected. Before running the model, a researcher who needs to model volatility is required to ensure that it meets GARCH specifications.

Since the first precondition is met, the researcher needs to further confirm that there is the presence of the ARCH effect. Therefore, the null hypothesis, which states that there is no remaining ARCH effect, was tested via the LM test for the squared residuals of the fitted model proposed by Engle (1982). The LM test result revealed the existence of the ARCH effect in the commodities; hence the null hypothesis wasrejected. From this, it is clear that the data is stationary and the variance of the return series for each commodity is time varying; hence, it is possible to model the conditional volatility with GARCH-class specifications. Accordingly, symmetric and asymmetric models, specifically GARCH, EGARCH, and TGARCH, were considered. As the result shows asymmetric, EGARCH, and TGARCH models under normal distribution assumption for residuals were selected as possible models of volatility. Based on the AIC, SIC, and log likelihood function criteria.

Accordingly, the finding of this research with regard to appropriate volatility models signifies that the EGARCH model with normal distributional assumption performed better in describing volatility for teff, maize, onion, potato, Niger, and red pepper price returns, and TGARCH was found to be the best model in explaining conditional volatility of sorghum, barley, and beans. However, the result for commodity wheat was that most of the coefficients of the ARCH, GARCH, and asymmetric terms were not found to be significant. That is, no model was found to be the best fit for wheat price return in the sampled periods from the volatility models specified in this study.

According to the CSA data, wheat is among the most important crops in Ethiopia, ranking fourth in total cereal production. Unlike other agricultural commodities in Ethiopia, wheat is also the single most important staple imported from abroad. The majority of humanitarian food aid and commercial agricultural commodity imports take the form of wheat. Additionally, wheat imported by the government is sold to poor consumers in urban areas at subsidized prices. Hence, addition to the local demand and supply, similar to other crops, the price of crop wheat is influenced by price incentives. For this reason, none of the Generalized Autoregressive Conditional Heteroscedasticity models were found to be the best fit for wheat.

Specifically, the result showed that the coefficients of the asymmetric terms for the TGARCH model ($\boldsymbol{\gamma}$) were negative: 0.75 for sorghum, 0.55 for barley, and -0.27 for bean price returns, and they are statistically significant at a .0.01 level of significance. Moreover, based on the results of the estimated EGARCH model, the coefficients of the asymmetry term were 0.039079 for *the teff* price return, and 0.34978 for the pepper price return. The coefficients of the asymmetric terms for onion and potato were negative 0.15 and negative 1.16, respectively, and both of them were statistically significant at a 0.01 level of significance. Similarly, the asymmetric term coefficient of Niger was negative 0.56, and it was statistically significant.

So far, it has been stated that EGARCH was the best model for Teff, Maize, Niger, Onion, potato, and red pepper, and TGARCH was the best model for Sorghum, Barley, and Beans. The Breusch–Godfrey serial correlation LM test, the Corrologram of standardized residual squared, and Jarque – Bera normality tests were employed to check the adequacy of the fitted models.

Accordingly, the result of the Breusch–Godfrey serial correlation LM test showed that the fitted models did not exhibit any additional ARCH effect for each of the series, as both the F statistics and observed R squared were not significant. Both the autocorrelation function (ACF) and partial autocorrelation function (PACF) lie within the confidence interval, and all the p values are more than 5% (0.05) which means they are not significant. The results indicated that there was no serial correlation in the residuals; therefore, the null hypothesis of no serial correlation in the residuals was not rejected. That means the data is fitted to run GARCH specifications.

The findings of this study are consistent with Hatane (2011), Kuhe (2019) and Rahayu (2015), findings which support the EGARCH model's applicability. Musunuru et al. (2013) and Le Roux (2013) both support the TGARCH model's suitability for Ethiopian agricultural commodities (2018).

Grounded to the results of the estimated EGARCH model, the difference between "good" news and "bad" news, as the coefficient of the asymmetric term indicated, is -0.039079 for Teff price return, -0.563668 for *niger*. Moreover, the coefficients of the asymmetric terms for onion and potato are negative 0.147774 and negative 1.164976, respectively, and both of them are statistically significant at 0.01. The result implies that past negative shocks have a greater impact on following volatility than positive shocks of similar magnitudes for the root crops. The coefficients are positive at 0.34978 for red pepper and 0.051775 for maize, respectively. This implies that positive shocks in the past have a greater impact on future volatility than negative shocks of similar magnitudes in red pepper and maize

Generally, the results of this study in this context show that the asymmetric effect on the volatility of agricultural commodity prices is confirmed. The conditional volatility of the crop log returns is time-varying and persistent, which implies that in forecasting future volatility, past volatility is quite important. The asymmetric GARCH models are found to be the best fitted models for evaluating the volatility of the log-returns of cereals, spices, pulses, and oil crop price returns. That is, there is a difference between the good and the bad news of the same magnitude. Specifically, as the coefficient of the asymmetric term showed was negative, it indicates that the “bad" news has a larger effect on volatility than the “good" news in "teff," "niger," "barley," "sorghum," "beans," "onion," and "potato,” It implies that volatility spikes sharply when unexpected adverse news reaches the market while remaining unresponsive for the most part to positive news for some crops. While in the cases of "maize" and "red pepper” returns, "good" news has a larger effect on volatility than "bad" news. Because it is difficult for market participants to predict the exact size of the harvest and the demand in advance, the spot price of a commodity is difficult to predict perfectly. For market participants, this has implications for the need to have risk mitigating actions by way of 'hedging' against the noise in the news is warranted.

The current study had some limitations. That is, firstly, the research was limited to agricultural sector items. However, if the research had dealt with a variety of product kinds and industries, it would have been theoretically sound for the use of market proxies. Secondly, the same study relied on monthly retail prices, which would have been preferable if high frequency data, for example, daily data, had been available. Thirdly, it makes use of only CAPM but does not include multi-factor asset pricing models, in addition to applications in the agricultural sector for making comparisons in the models, and emphasizes on estimating only the beta of crops. Fourthly, the study focused solely on the spot market cases, although it would have been beneficial to use both the spot and future markets to demonstrate linkages, such as the relationship between spot market prices and future prices.

Despite these limitations, this research remains important for the following reasons. That is, the findings of the study are quite important both theoretically and practically. Firstly, the regional and national price indices constructed in this research offer advantages for price monitoring and analysis. In addition, it introduces a market return variable to the literature of accounting and finance and thus serves as a benchmark for the market in Ethiopia. Secondly, given the theoretical significance of beta in the risk and return theory, this research introduces crop beta in Ethiopia. Therefore, it could help researchers in the field analyze the risk-return relationship through CAPM or other alternative asset pricing theories or models, which would also help with portfolio selection and investment decisions. Thirdly, the findings of this study have provided important insights into the volatility of prices of agricultural commodities in Ethiopia. Therefore, it could allow researchers and other interested parties, such as producers, traders, and consumers of agricultural commodities, to have a better understanding of the recent market developments. Lastly, by offering an in depth understanding of the volatility of domestic prices, the findings of this research could serve as a policy input for the introduction of future markets in Ethiopia that could help to safeguard both farmers and consumers.

CHAPER SIX: SUMMARY CONCLUSIONS AND RECOMMENDATIONS

This chapter, first, presents summaries of the key research findings, and then it comes up with the conclusions and recommendations forwarded.

6.1 Summary of Key Findings

The aim of this research was to construct a price index and model risk and return in the agricultural commodities market in Ethiopia. Specifically, it aimed to:

- construct price index for agricultural commodities in Ethiopia,
- estimate market returns for the agricultural commodity price indexes,
- estimate the systematic risks (betas) for selected agricultural commodities, and
- examine the best fitted price volatility model for selected agricultural commodities using GARCH family models

To meet these objectives, this study used ten years of monthly price data, which were recorded from 2010 to 2020 by CSA for three regional states, namely ANRS, ONRS, and SNNP, and one city administration, namely Addis Ababa. The first attempt was to construct price indexes for agricultural commodities comprising ten different crops from five groups: cereals, pulses, root crops, oilseeds, and spices. From the cereals category, Teff, Wheat, Barley, Sorghum, and Maize were taken; beans from the category of pulses; Niger from the oil seeds category; onion and potato from root crop categories; and red pepper from spices categories were included in this study based on their relative importance and proportionate share in the Ethiopian crop production survey data.

According to the index number theory, an index number is a measure of changes in magnitude from one situation to another, which may be two time periods or situations in a spatial sense. Taking the 2014-2016 average production quantity as a base or reference, the findings of this research showed that the price indexes of crops have been considerably increasing since 2010 in the ANRS, ONRS, SNNP, and Addis Ababa City Administration, regardless of the fact that there were variations across the areas.

Specifically, the result showed that prices of teff and wheat were relatively lower in ANRS than in other regions. In SNNP, the prices of maize and sorghum were relatively lower, while the prices of barley were lower in ONRS than in other areas in the country. Similarly, the average lowest prices of oilseeds and pulses were recorded in ANRS, while the average prices of onion and potato were relatively the lowest in ONRS, and the average price of red pepper was the lowest in SNNP, which was about ETB 67.43 over the study periods.

The highest prices, for all of those commodities were witnessed in Addis Ababa during the study periods. But the highest prices for all groups of the commodities were observed in Addis Ababa, the city administration. Moreover, in spite of the fact that there were regions in which specific crop prices were lowest in some study areas and highest in others, the price indexes of almost all crops in Addis Ababa were the highest of all.

During the study periods, there were periods when declines in prices were recorded. However, the declines were still above what they had been in the previous period's average. That is, the price increase recorded in one period becomes the basis for the next, causing it to rise further.

The mean monthly returns for each commodity were also estimated, and the result showed that mean returns were positive. Specifically, the mean monthly returns of the cereals such as teff, maize, barley, wheat, and sorghum were 1.406%, 1.092%, 1.048%, 0.920% ,and 2.034%, respectively. The average monthly price returns of root crops, namely potatoes and onions, were 4.316% and 4.266%, respectively. The monthly price returns of root crops were the highest as compared with other crop categories. The average monthly return for red pepper was 2.730%. Beans and Niger had average monthly returns of 2.553% and 1.811%, respectively. The result of the standard deviations of returns of these commodities indicated that a commodity that has a relatively higher return is more volatile in its return, hence has a higher risk, and a commodity that has a relatively lower return is less volatile in its return, hence has a lower risk. The overall average monthly mean return of the market was 1.12% and its standard deviation was 6.14%. Therefore, it can be concluded that the agricultural commodity price return is positive, and it demonstrates the risk and return tradeoff, which specifies that the higher the risk, the higher the expected return could be.

Furthermore, in line with the risk and return tradeoff theory, the systematic risk (beta) of agricultural commodities in Ethiopia was found to have a significant positive relationship to the return of specific commodities using the agricultural commodity market index as a proxy. Explicitly, sorghum and maize had beta values that were higher than other crops in the cereal category, in which the beta of sorghum is 1.419 and that of maize is 1.13. The beta for the commodity Teff was 0.623 and the betas for wheat and barley were 0.645 and 0.747, respectively. Similarly, betas of the other crops such as niger, beans, potato, and red paper were 0.681, 1.368, 0.470, and 0.911, respectively, and the result is statistically significant.

With regard to volatility modeling, the findings of this study showed that the price return series of cereals, root crops, oilseeds, pulses, and spices confirmed the characteristics of financial time series such as leptokurtic distributions and volatility clustering, providing an adequate basis for the use of GARCH family models. The ARCH LM test confirmed the presence of ARCH effects in the conditional mean equation residuals. To model the volatility, both symmetric and asymmetric models were explored.

As a consequence, the results revealed that asymmetric models are the best models for agricultural commodities in Ethiopia. That is, the EGARCH model with the normal distributional assumption fits the data best for "teff," "maize," "niger," "onion," "potato," and "red pepper," whereas the TGARCH model with the normal distributional assumption fits the data best for "sorghum," "barley," and "beans" in Ethiopia. In summary, the results of this study show that there is volatility in the series, as well as the presence of time-varying conditional volatility on crop returns. Furthermore, there is an imbalance in the news, with "bad" news having a greater impact on volatility than "good" news in "teff," "niger," "barley," "sorghum," "beans," "onion," and "potato," while "good" news has a greater impact on volatility than "bad" news in "maize" and "red" maize.

6.2 Conclusions

The present study aimed to develop price indexes, estimate the market return and systematic risk (beta), followed by examining the best fitted price volatility model for agricultural commodities in Ethiopia.

Price indexes of ten agricultural commodities were developed, and the constructed indexes demonstrated a substantial rise in prices since 2010, reaching their highest levels in 2020, taking the 2014-2016 average production quantity as a base; the findings revealed that once the price of a specific crop has increased, its possibility of declining below its previous average is unlikely. Thus, the persistent and continuing trend of agricultural commodity prices is highly likely to worsen consumers' lives and would generally boost the cost of living in Ethiopia. If this trend continues, it would be difficult for the majority of the people of Ethiopia to afford to pay for food items.

Furthermore, the findings showed that the market return of agricultural commodities from 2010 to 2020 was positive and statistically significant; return of each crop was positive, and a crop that has relatively higher standard deviation tends to have higher expected return and be more volatile whereas a crop that has relatively lower standard deviation tends to have lower expected return and be less volatile. Therefore, it can be concluded that the agricultural commodity market in Ethiopia recognized the risk and return theory which specifies that the higher the risk, the higher the expected return could be.

It was found that returns and betas were linearly related to each other during the period of 2010 to 2020, which implies strong support for the capital asset pricing model (CAPM). Accordingly, beta coefficients for five crops, namely teff, wheat, barley, niger, and red pepper, are less than one, and the betas of the other four crops, namely sorghum, maize, beans, and potato, are greater than one. This implies that price returns of crops with a beta of less than one, such as teff, wheat, barley, niger, and red pepper, are expected to experience low variation, and are less risky than the market portfolio. And price returns of crops with a beta of greater than one, namely sorghum, maize, beans, and potato are expected to experience greater variation in returns and are riskier than the market portfolio.

Also, volatility was found to exist in the Ethiopian agricultural commodities market and the EGARCH model with the normal distributional assumption was found to be the best fitted model for "teff," "maize," "niger," "onion," "potato," and "red pepper," whereas the TGARCH model with the normal distributional assumption fits the data best for "sorghum," "barley," and "beans" in Ethiopia, which indicates that there is an asymmetry in the information or news that is the "bad" news having a greater impact on volatility than the "good" news. Therefore, modeling of information, policy, news, or events is a very significant determinant of asset volatility. Meaning, what happed to the price returns of a crop in the previous period is of concern to investors because of the sharp reactions to negative events that characterize the data.

6.3 Recommendations

Based on the aforementioned conclusions of the study, the following recommendations are forwarded:

1. The finding showed that the price of an agricultural commodity indicated continued increase, and it is highly unlikely to fall below its previous average price. And it was concluded that if the ever increasing nature of agricultural commodities price continues in a similar pattern, it is highly likely to worsen the consumers' lives and increase the cost of living in the country since the affordability of many food items would become difficult over time. Therefore, policymakers are recommended to introduce a policy framework that includes, for example, the establishment of a future or contract market and enhancement of investment in agriculture to boost commercial framings so as to safeguard consumers from the effect of price increments in agricultural commodities.
2. Significant price disparities in markets within and across the selected regions were observed at similar periods. It is backed by the insufficiency of market information, the lack of well-established market integration in the commodities market, the weak market integration, and the existence of many intermediaries in the marketing line of agricultural commodities from the farmer to the final consumer. According to the Federal Cooperative Agency's official report (2021), there are about more than 92755 cooperatives in Ethiopia. Therefore, the Federal Cooperative Agency (FCA) should build the capacity of these cooperatives to play a tangible and meaningful role in linking small holder farmers with potential buyers and, reducing the role of avoidable middlemen's so as to ensure mutual benefits.

3. Getting timely and reliable information about the market conditions is fundamental for market players to make sound decisions. So an attempt has been made to construct a price index for the agricultural commodities market in Ethiopia. Following that, it is recommended that the ANRS Trade and Market Development Bureau, ONRS, Trade and Market Development Bureau, SNNP Trade and Market Development Bureau, and Addis Abeba Trade and Market Development Bureau adapt the price index for the release of its future daily, weekly, and monthly agricultural commodities price data to be used by market participants, such as farmers, consumers, cooperatives, investors, and government
4. The prices of some crops, particularly root crops with low duration or storability problems, were more volatile. These crops are seasonal, and, as a result, their prices fall at the time of harvest before rising within a short period. This exposes the producers to a further loss. Though it is difficult to maintain at an individual level, it is recommended that farmers' unions in root crop-producing areas should make ready cold storage that could increase the storability of such crops so that farmers are not forced to sell them at a low price as soon as they harvest them.

5. As this study was limited to selected agricultural products and models, it is suggested that studies incorporating more assets from other sectors; with multi factor asset pricing models that are capable of estimating alpha of crops and risk-free rate of returns be conducted in the future.

REFERENCE

Afriat, S. (2015). A Practical Introduction to Index Numbers. 53.

Allen, R. G. D. (1976). Index Numbers in Theory and Practice. London: Macmillan Press,

Arezki, R. (2012). Commodity Price Volatility and Inclusive Growth in Low-Income Countries.

in Arezki,R [and Three Others. (Eds.). International Monetary Fund.

Ayele, Amare Wubishet, Emmanuel Gabreyohannes, & Yohannes Yebabe Tesfay. (2017). "Macroeconomic Determinants of Volatility for the Gold Price in Ethiopia: The Application of GARCH and EWMA Volatility Models." Global Business Review 18(2):308–26. DOI: 10.1177/0972150916668601.

Bailey, M. J., Muth, R. F., & Nourse, H. O. (1963). A Regression Method for Real Estate Price Index Construction. American Statistical Association Journal, 58, 933-942.

Balk, B. M. (2008). Activities of National Activities Reconsidered. Journal of Economic and Social Measurement. 33(2). 165-178.

Balk, B.M. (2008). Price and Quantity Index Numbers: Models for Measuring Aggregate Change and Difference. Cambridge: Cambridge University Press.

Barry, P. J. (1980). Capital Asset Pricing and Farm Real Estate. American Journal of Agricultural Economics. 62 (3), 549-553. URL: https://www.jstor.org/stable/1240213.

Bartholdy, J. & Peare, P. (2000). Estimating Cost of Equity. Denmark. Aarhus University - Department of Finance.

Bertomeu , J. & Cheynel, E. (2016). Disclosure and the Cost of Capital: A Survey of the Theoretical Literature. Abacus. 52(2), 221-258.

Bessembinder, & Ghan, (2012). Time-Varying Risk Premia and Forecastable Return in Futures Markets. Journal of Financial Economics 32(41):586–613. DOI: 10.1016/0304-405X(92)90017-R.

Bjornson, B. (1994). Asset Pricing Theory and the Predictable Variation in Agricultural Asset Returns. American Journal of Agricultural Economics 76(3):454–64. DOI: 10.2307/1243657.

Bjornson, B. & Innes, R. (1992). Risk and Return in Agriculture: Evidence from an Explicit-Factor Arbitrage Pricing Model. Journal of Agricultural and Resource Economics. 17 (2), 232-252.

Bjorksten, N. & Brook, A, (2002). Exchange Rate Strategies for Small open Developed economies such as New Zealand.

Bollerslev, T. (1986). "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics* 31(3):307–27. DOI: 10.1016/0304-4076(86)90063-1.

Bowman, E.H. (1982). Risk Seeking for Troubled Firms, Sloan Management Review, 23() : 33-42.

Brigham, E. F., & Houston, J. F. (2012). *Fundamentals of Financial Management: Concise*. Cengage Learning.

Bodie, Z., Kane, A., & Marcus, A. (2003). Investments. McGraw-Hill Irwin.

Bodie, Z., & Rosansky, V. I. (1980). Risk and Return in Commodity Futures. *Financial Analysts Journal*, *36*(3), 27-39.

Bonato, M. (2019). Realized Correlations, Betas and Volatility Spillover in the Agricultural Commodity Market: What has Changed? *Journal of International Finance Markets, Institutions and many*. 62, 184-20.

Campbell, J. Y. & Cochrane, J. H. (1999). The poor performance of consumption Based asset pricing Models. National Bureau of Economic research 1050 Massachusetts Avenue Cambridge, MA 02138.

Carter, C. A., Rausser, G. C., & Schmitz, A. (1983). Efficient Asset Portfolios and the Theory of Normal Backwardation. *Journal of Political Economy*, *91*(2), 319-331.

Case, B, Pollakowski, H. O. & Wachter. S.M. (1991). "On Choosing Among House Price Index Methodologies." *Real Estate Economics* 19(3):286–307.

Case, K. E. & Shiller, R. J. (1987). Prices of Single Family Homes since 1970: New Indexes of Four Cities. Working Paper No. 2393. National Bureau of Economic Research 1050 Massachusetts: Cambridge.

Çelik, S. (2012). Theoretical and Empirical Review of Asset Pricing Models: A Structural Synthesis. International Journal of Economics and Financial Issues Vol. 2, No. 2, 2012, pp.141-178.

Chan, L. K. C. & Lakonishok, J. (1992) Robust Measurement of Beta Risk .The Journal of Financial and Quantitative Analysis . 27(2) 265-282.Cambridge: Cambridge University Press.

Cheng, J. & Boasson, V.W. (2004). Using the Time Weighted Method to Estimate Betas of Emerging Markets. Managerial Finance. 30(3), 74-87.

Cheng, B. & Tong, H. (2008). *Asset Pricing: A structural Theory and Its Applications*. Singapore: World Scientific Publishing Co, Plc. Ltd.

Chen, Y., Rogoff, K. S. & Rossi, B. (2010). Can Exchange Rates Forecast Commodity Prices? *The Quarterly Journal of Economics*, Volume 125, Issue 3, August 2010, Pages 1145–1194, https://doi.org/10.1162/qjec.2010.125.3.1145.

Collins, R. A. & Barry, P. J. (1986) . Risk Analysis with Single-Index Portfolio Models: An Application to Farm Planning. *American Journal of Agricultural Economics*. 68(1), 152-16.

Coelli, T.J., O'Donnell, P.R.C J., and Battese, G.E. (2005). An introduction to Efficiency and Productivity Analysis (2nd ed). United States of America: Springer Press.

Cornell, B. & Dietrich, J. K.(1978), Mean-Absolute-Deviation Versus Least-Squares Regression Estimation of Beta Coefficients. *The Journal of Financial and Quantitative Analysis. 13(1), 123-131*.

Coyle, B.T. 92007). Aggregation of price Risk over commodities: An Economic Index Number Approach. 89(4).1085-1097.

Creswell, J. W., & Clark, V. L. P. (2011). Designing and Conducting Mixed Methods Research (2nd ed.). Thousand Oaks, CA: Sage Publications.

Crotty, M. (2003). *The Foundation of Social Research: Meaning and Perspective in the Research Process*. Thousand Oaks, CA: Sage.

Damodaran, A.. (2020.). *Applied Corporate Finance (4th)*. New York: John Wiley & Sons, Inc.

Degiannakis, S. & Filis, G., Klein, T. & Walther, T. (2019). Forecasting Realized Volatility of Agricultural Commodities SSRN Electronic Journal. Online ISSN: 1556-5068

Denzin, N. K. & Lincoln, Y.S. (2018). *The Sage Handbook of Qualitative Research*. Los Angeles: Sage.

Diewert, W. E. (2005). Index Number Theory Using Differences Rather than Ratios. *American Journal of Economics and Sociology*, *64*(1), 311-360.

Diewer, W. E.. (2007). Index Numbers. *Arthur L Bowley*:295–321. doi: 10.1142/9789812835512_0008.

Dörnyei, Z (2007). *Research Methods in Applied Linguistics: Quantitative, Qualitative, and Mixed Methodologies.* Oxford: Oxford University Press.

Driver, Turvey and. ? (1985). “An Examination of Systematic Risks in Agriculture: A Farm Sector Capital Asset Pricing Model Calum Greig Turvey* H.C. Driver**.”

Drobetz, W. (2000). Theory of Asset Pricing. *Global Stock Markets* 9–70. doi: 10.1007/978-3-663-08529-4_2.

Durevall, D., Josef. L., and Yohannes Ayalew . (2013). Inflation Dynamics and Food Prices in Ethiopia. *Journal of Development Economics* 104(478):89–106. doi: 10.1016/j.jdeveco.2013.05.002.

Dusak, K. (1973). Futures Trading and Investor Returns: An Investigation of Commodity Market Risk Premiums. *Journal of Political Economy*, *81*(6), 1387-1406.

Encyclopedia Britanica (2014). *Price Index: Economics*. USA: Focus Multimedia Ltd.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica* 50(4):987. doi: 10.2307/1912773.

Fabozzi, F.j. 1999). *Investment Management for Insurers*. Prentice Hall,

Fama, E.F. & French, K.R. (1996). *Multifactor Explanations of Asset Pricing Anomalies*.

The Journal of finance, LI (1), 55-83.

Fama, E. F., & French, K.R. (2004). The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives* 18(3):25–46. doi: 10.1257/0895330042162430.

Food and Agricultural Organization [FAO] (. (2008). Integrating the Crop and Food Supply and the Emergency Food Security Assessments. FAO/WFP Crop and Food Security Assessment Mission to Ethiopia, http://www.fao.org/decrep/010/ah883e/ah883e00.htm.

Food and Agricultural Organization [FAO] (2020). State of Food and Agriculture Report.

Fernandez, P. (2017). The Capital Asset Pricing Model. *Economic Ideas You Should Forget* 18(3):47–49. doi: 10.1007/978-3-319-47458-8_19.

Fernandez, V. (2019). A Readily Computable Commodity Price Index: 1900–2016. *Finance Research Letters.* 31(1170037):448–57. doi: 10.1016/j.frl.2018.12.015.

Franco M., F. & Gerald A. Pogue, G.A. (1973). An Introduction to Risk and Return Concepts and Evidence. 646-73.

Freund, J. E. & Williams, F.J. (1969). *Modern Business Statistics*. Prentice Hall.

Fong, W. M. (1997), Robust Beta Estimation: Some Empirical Evidence. *Review of Financial Economics*. 6 (2), 167-186.

Fullerton, T.M. & Araki, E. (1997). A Theoretical Model of Industrial Economy Inflatory Dynamics: JEL Category E31, Prices, Bussiness Fluctuations, and Cycles. ELPaso. Universithy of texas.

Getachew Diriba (2020). *Agricultural and Rural Transformation in Ethiopia: Obstacles, Triggers and Reform Considerations*. Agricultural and Rural Transformation in Ethiopia Policy Working Paper 01/2020. Addis Ababa: Ethiopian Economics Association.

Getnet , K. (2009). From Auction Market to Commodity Exchange: Managing Coffee Price Risk in Ethiopia. *Quarterly Journal of International Agriculture*. 48(2), 113-134.

Guba, E. G., & Lincoln, Y. S. (1989). *Fourth Generation Evaluation*. Newbury Park, CA: Sage.Gujarati, D. N., Bernier, B., & Bernier, B. (2004). *Econométrie* (pp. 17-5). Brussels: De Boeck.

Hansen, M. Herwartz, H. Rengel, M. (2014). State Dependence of Aggregated Risk Aversion: Evidence for the German Stock Market. *Journal of Applied Economics*. XVII (2), 257-282.

Hatane, S. E. (2011). GARCH-Type Models on the Volatility of Indonesian Cocoaâ€™ s Spot Price Returns. *Jurnal Manajemen dan Kewirausahaan*, *13*(2), 117-123.

Hill, P.. (1988). Recent Developments in Index Number Theory and Practice. *OECD Journal Economic Studies* 123–48.

Horner, F. B. (1971). Effects of Grouping data on the Divergence between Laspeyers and Paasche form of Quantum Indexes*. *The Review of Income and Wealth*. https://doi.org/10.1111/j.1475-4991.1971.tb00779.x

Kivunja, C., & Kuyini, A. B. (2017). Understanding and Applying Research Paradigms in Educational Contexts. International Journal of Higher Education, 6, 26-41. https://doi.org/10.5430/ijhe.v6n5p26.

Kolb, R. W. (1996). The Systematic Risk of Futures Contracts. *The Journal of Futures Markets (1986-1998)*, *16*(6), 631.

Krause, A. (2001). An Overview of Asset pricing Models. University of Bath: Bath, ac. Uk.

Kuhe . D.A. (2019.) Modeling Volatility of Agricultural Commodity Food Price Index in Nigeria using ARMA-GARCH Models. *Mediterranean Journal of Basic and Applied Sciences (MJBAS).* 3(1), 55-75.

IMF (2007). Reaping the Benefits of Financial Globalization: A Discussion Paper Prepared by IMF staff, or Prepared by the Research Department* (This paper was prepared under the direction of Jonathan D. Ostry by a team led by Paolo Mauro and comprising Giovanni Dell’Ariccia, Julian di Giovanni, André Faria, Ayhan Kose, Martin Schindler, and Marco Terrones.)

IMF (International Monetary Fund). (2008). Federal Democratic Republic of Ethiopia: 2008 Article IV Consultation Staff Report. IMF Country Report 08/264. Washington DC:

Jacobs, M. T. & Shivdasani, A. (2012). Do You Know Your Cost of Capital? *Managerial Accounting*. From a Magazine.

Jema H. and G. Fekadu. (2012). "Determinants of the Recent Soaring Food Inflation in Ethiopia", Universal Journal of Education and General Studies, Vol. 1(8), 225-233.

Kimmel, P.D. Weygandt, J.J, Keiso, D.E.Trenholm, B., Invine, W. & Burnley, C.D. (2020). *Financial Accounting: Tools for Business Decision-Making (8th ed.)*. Canada: John wiley sons Canada, Ltd.

KÖVES, P. (1978). Theory of Index Numbers and Economics Reality. *Acta Oeconomica* , 20 (3), 205-227. URL: https://www.jstor.org/stable/40728608.

Krause, A. (2001). An Overview of Asset pricing Models. Bath.

Lama, A., Jha, G.K. Paul, R. K. & Gurung, B (2015). Modeling and Forecasting of Price Volatility: An Application of GARCH and EGARCH Models. *Agricultural Economics Research Review* 28(1):73. doi: 10.5958/0974-0279.2015.00005.1.

Le Roux, C., L. (2018). Volatility Modeling of Agricultural Commodities: Application of Selected GARCH Models 343–56. doi: 10.1007/978-3-319-70055-7_27.

Lo, A. W. (2016). What Is an Index? *Journal of Portfolio Management* 42(2):21–36. doi: 10.3905/jpm.2016.42.2.021.

Mandelbrot, B. (1963) The Variation of Certain Speculative Prices. *International Statistical Review*, 36, 394-419.

Mangram, M. E. (2013). "A Simplified Perspective of the Markowitz Portfolio Theory." *Global Journal of Business Research* 7(1):59–70.

Mattos, F. & Garcia,P. (2009). The Effect of Prior Gains and Losses on Current Risk-Taking Using Quantile R.egression. " Proceedings of the NCCC134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [http://www.farmdoc.uiuc.edu/nccc134]

Maurer, F. (2008). Risk and Return: New Insights For Theory, Measurement and Management. *The Journal of Applied Business Research.* 24 (4), 51-6.

Muanenda, S., & Yohannes, E. G. (2018). *Modeling and Forecasting the Volatility of the Export Price of Sesame in Ethiopia*. *Journal of Economics and Sustainable Development www.iiste.org ISSN* (Vol. 9). Online.

Musunuru, N., Yu, M., & Larson, A. (2013). Forecasting Volatility of Returns for Corn using GARCH Models. *Texas Journal of Agriculture and Natural Resources*, *26 ()*, 42-55.

Nagaraja, C.H., Brown, L.D. & Zhao, L.H. An Autoregressive Approach to House Price Modeling Stat. 5(1): 124-149 (March 2011). DOI: 10.1214/10-AOAS380

National Bank of Ethiopia (NBE) (2016). Directive Amendments on Foreign Exchange (2016/2017) May 11 Posted by Super User in MTA Legal Update.

Nelson, D., B. (2011). “Conditional Heteroskedasticity in Asset Returns : A New Approach Author (s): Daniel B . Nelson Published by : The Econometric Society Stable URL : Http://Www.Jstor.Org/Stable/2938260. CONDITIONAL HETEROSKEDASTICITY IN ASSET RETURNS : A NEW APPROACH. *Society* 59(2):347–70.

Outinen, S. (2007). Risk and Return and Return in Commodity Futures Markets. Vaasa; (Unpublished Master’s Thesis in Accounting and Finance Finance).

Paredes, D., J. C. (2011). A Methodology to Compute Regional Housing Price Index Using Matching Estimator Methods *Annals of Regional Science* 46(1):139–57. doi: 10.1007/s00168-009-0346-z.

Peterson, P. P., & Fabozzi, F. J. (1999). *Analysis of Financial Statements* 54 () John Wiley & Sons.

Pindyck, R., S. (2001). The Dynamics of Commodity Spot and Futures Markets: A Primer. *Energy Journal* 22(3):1–29. doi: 10.5547/ISSN0195-6574-EJ-Vol22-No3-1.

Phuoc, L.T. & Kim, K.S. Su, Y. (2018). Reexamination of Estimating Beta Coefficient as a Risk Measure in CAPM. *Journal of Asian Finance, Economics and Business*. 5 (1), 11-16. 11 Print ISSN: 2288-4637 / Online ISSN 2288-4645.

Phuoc, L.T. & Pham, C.D.(2020). The Systematic Risk Estimation Models: A Different Perspective. Heliyon. 6(2). doi: 10.1016/j.heliyon.2020.e03371

Pogue, F., M. & Gerald, A. (1973). An Introduction to Risk and Return Concepts an evidence. The Bell Journal of Economics , (21):1154–57.

Pring, R. (2004): Philosophy of Educational Research, (2nd ed.) London: Continuum.

Rachev, S. T., Kim, Y. S., Bianchi, M. L., & Fabozzi, F. J. (2011). *Financial Models with Lévy Processes and Volatility Clustering* (Vol. 187). John Wiley & Sons.

Rahayu, M. F., Chang, W. I., & Anindita, R. (2015). Volatility analysis and volatility spillover analysis of Indonesia's coffee price using Arch/Garch, and Egarch model. *Journal of Agricultural Studies, 3*(2), 37-48.

Raily, F. & Brown, K. (2006). Investment Analysis and Portfolio Management. South. Bend, India, Unites States. Research Gate.

Ralph, J., O'Neill, R. & Winton, J. (2015). *A Practical Introduction to Index Numbers*. UK: John Wiley and sons. Ltd.

Rashid, S. Winter-Nelson, A. & Garcia, P. (2010).Purpose and Potential for Commodity Exchanges in African Economies. IFPRI Discussion Paper 01035. Australia:, INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

Reinsdorf, M. B. (2007). Axiomatic Price index Theory. *Forth Coming in Measurement in Economics: A Handbook, MJ Boumans (ed.), Amsterdam: Elsevier*.

Rezitis, A., N., & Sassi., M.(2013). Commodity Food Prices : Review and Empirics Commodity Food Prices : Review and Empirics.. doi: 10.1155/2013/694507.

Sharpe, W.F. (1964) Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance*, 191(3), 425-442.

Shiferaw, A. Y. (2012). Modeling Volatility of Price of Some Selected Agricultural Products in Ethiopia: Arima-Garch Applications. *SSRN Electronic Journal* 1–13. doi: 10.2139/ssrn.2125712.

Rose, S.A., Westerfield, R, W. & Jordan, B., D. (2018). *Fundamentals of Corporate Finance*. California: McGraw-Hill Education.

Selvanathan, E.A. (1991).Standard errors for Laspeyres and Paasche index numbers. *Economics Letters*. 35(1), 1-116 .

Selvanathan, E.A. (1993). More on Laspeyres price index. *Economics Letters*. 43(2)

125-244 .

Strydom, B. & Charteris, A. (2009). A Theoretical and Empirical Analysis of the Suitability South African Risk- Of South African Risk-Free Rate Proxies Free Rate Proxies Free Rate Proxies. Working Paper No. 02-2009. University of Kwazulu Natal.

Tysoe, B. A. (1981). Construction Cost and Price Indices: Description and Use. London, New York. E.&F.N. Spon.

Teshome Hailemeskel (2020). Modeling time-varying coffee price volatility in Ethiopia. *Journal of Applied Economics*, *23*(1), 497–518. https://doi.org/10.1080/15140326.2020.1804304.

Teshome Hailemeskel, Emmanuel Gabreyohannes & Belaineh Legesse (2020). Statistical Analysis of Price Volatility of Agricultural Commodities Traded at the Ethiopian

Commodity Exchange (ECX) Using Multiplicative GARCHMIDAS Two-component Mode. Global Business Review. SAGE-ournals.sagepub.com/home/gbr

Thiyagarajan, S., . Naresh, G & Mahalakshmic, S. (2015). Forecasting Volatility in Indian Agri-Commodities Market. *Global Business and Finance Review* 20(1):95–104. doi: 10.17549/gbfr.2015.20.1.95.

Tsay, R. S. (2005): Analysis of Financial Time Series, 543. John Wiley & Sons.

Tuo, J. & Fan .Z. (2020). Modeling the Iron Ore Price Index: A New Perspective from a Hybrid Data Reconstructed EEMD-GORU Model. *Journal of Management Science and Engineering* 5(3):212–25. doi: 10.1016/j.jmse.2020.08.003.

Turvey, C. G. & Driver, H.C. (1986). An Examination of Systematic Risks in Agriculture: A Farm Sector Capital Asset Pricing Model. A paper prepared for presentation at the annual meetings of the American Agricultural Economics Association, Reno, Nevada.

Turvey,C.G. &. Driver, H. C (1987). Systematic and Nonsystematic Risks in Agriculture . Canadian Journal of Agricultural Economics. 35 (2) . 387-401. https://doi.org/10.1111/j.1744-7976.1987.tb02236.x

UN (2020). Ethiopia Economy (2020) Monthly Updates on the Ethiopian Economy October 2020. https://theodora.com/wfbcurrent/ethiopia/ethiopia_economy.html.

UNCTAD. (2019). World Investment Report 2019: Special economic zones. New York and Geneva: United Nations, pp. 126-206.

West, G. (2006). An Introduction to Modern Portfolio Theory: Markowitz, CAP-M, APT and Black-Litterman. *Parktown North: Financial Modeling Agency*.

Tassew Woldehanna & Yisak Tafere. (2015). Food Price Volatility in Ethiopia: Public Pressure and State Response. *IDS Bulletin* 46(6):76–83. doi: 10.1111/1759-5436.12189.

Woygandt, J.J., Kimmel, P.D., & Kieso, D.E. (2020). Accounting Principles (13rd ed.) . Chikaso: Wiley.

Yang, X., Dong, X, Kong, Z. Jiang, Q., and Wang, T. (2020). Research on the Construction of a Natural Gas Price Index in China. *Energy Strategy Reviews* 30(July):100521. doi: 10.1016/j.esr.2020.100521.Yuan, X. , Tang, J.,Wong, W.K., Sriboonchitta, S. (2020). Modeling Co-Movement among Different Agricultural Commodity Markets: A Copula-GARCH Approach. *Sustainability*. 12, 393, 2-17. doi:10.3390/su12010393

Zakoian, J. M. (1994). Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control* 18(5):931–55. doi: 10.1016/0165-1889(94)90039-6.

Zewdu Hailegebreil (2015). Determinants of Food Price Inflation in Ethiopia. Food Science and Quality Management..41 , 30-43. www.iiste.org ISSN 2224-6088 (Paper) ISSN 2225-0557 (Online)

Zhang, H., Satchell, S. & Westerholm. P.W. (2017). Asset Pricing Anomalies and The State Ownership Effect In China's Domestic Stock Market. 30th Australasian Finance and Banking Conference . University of Sydney Business School.

Zheng, Y. & Luo, D. (2013). 10 Years Later: Where in the World is Equal Weight Indexing Now? S&PJones Indices. McGraw Hill FinancialIMF (2007). Commoduty Prices :Biofuel Demand Pushes Up Food Prices.

Appendices

Appendix A

Regression results (from Eviews) for the systematic risk (beta) of a crop

Dependent Variable: TEFF

Method: Least Squares

Date: 01/25/22 Time: 17:45

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006500	0.004789	1.357479	0.1772
MARKET	0.622844	0.076027	8.192379	0.0000

R-squared	0.364528	Mean dependent var	0.012101
Adjusted R-squared	0.359096	S.D. dependent var	0.064583
S.E. of regression	0.051703	Akaike info criterion	-3.069941
Sum squared resid	0.312763	Schwarz criterion	-3.023233
Log likelihood	184.6615	Hannan-Quinn criter.	-3.050975
F-statistic	67.11507	Durbin-Watson stat	2.681545
Prob(F-statistic)	0.000000		

Dependent Variable: WHEAT

Method: Least Squares

Date: 01/25/22 Time: 17:46

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001132	0.003640	0.311098	0.7563
MARKET	0. .645798	0.057791	11.72841	0.0000

R-squared	0.540375	Mean dependent var	0.007227
Adjusted R-squared	0.536447	S.D. dependent var	0.057724
S.E. of regression	0.039301	Akaike info criterion	-3.618453
Sum squared resid	0.180717	Schwarz criterion	-3.571745
Log likelihood	217.2980	Hannan-Quinn criter.	-3.599487
F-statistic	137.5555	Durbin-Watson stat	2.296432
Prob(F-statistic)	0.000000		

Dependent Variable: BARLEY

Method: Least Squares

Date: 01/25/22 Time: 17:47

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001798	0.003513	0.511850	0.6097
MARKET	0.747352	0.055768	14.01072	0.0000

R-squared	0.626556	Mean dependent var	0.008824
Adjusted R-squared	0.623364	S.D. dependent var	0.061798
S.E. of regression	0.037926	Akaike info criterion	-3.689718
Sum squared resid	0.168287	Schwarz criterion	-3.643010
Log likelihood	221.5382	Hannan-Quinn criter.	-3.670751
F-statistic	196.3003	Durbin-Watson stat	2.833593

Prob(F-statistic)	0.000000

Dependent Variable: SORGHUM
Method: Least Squares
Date: 01/25/22 Time: 17:47
Sample (adjusted): 2010M07 2020M05
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000829	0.009072	-0.091396	0.9273
MARKET	1.419243	0.144035	9.464668	0.0000

R-squared	0.433633	Mean dependent var	0.011429
Adjusted R-squared	0.428793	S.D. dependent var	0.129604
S.E. of regression	0.097952	Akaike info criterion	-1.792011
Sum squared resid	1.122571	Schwarz criterion	-1.745303
Log likelihood	108.6247	Hannan-Quinn criter.	-1.773045
F-statistic	89.57995	Durbin-Watson stat	2.978675
Prob(F-statistic)	0.000000		

Dependent Variable: MAIZE
Method: Least Squares
Date: 01/25/22 Time: 17:47
Sample (adjusted): 2010M07 2020M05
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	-0.003174	0.004609	-0.688516	0.4925
MARKET	1.130377	0.073179	16.06157	0.0000

R-squared	0.687978	Mean dependent var	0.007395
Adjusted R-squared	0.685312	S.D. dependent var	0.088715
S.E. of regression	0.049766	Akaike info criterion	-3.146294
Sum squared resid	0.289772	Schwarz criterion	-3.099586
Log likelihood	189.2045	Hannan-Quinn criter.	-3.127327
F-statistic	257.9741	Durbin-Watson stat	2.580378
Prob(F-statistic)	0.000000		

Dependent Variable: BEAN

Method: Least Squares

Date: 01/25/22 Time: 17:48

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001314	0.007244	-0.181402	0.8564
MARKET	1.36816	0.115003	9.397264	0.0000

R-squared	0.430126	Mean dependent var	0.008403
Adjusted R-squared	0.425255	S.D. dependent var	0.103162
S.E. of regression	0.078209	Akaike info criterion	-2.242203
Sum squared resid	0.715646	Schwarz criterion	-2.195495
Log likelihood	135.4111	Hannan-Quinn criter.	-2.223236
F-statistic	88.30857	Durbin-Watson stat	2.385740
Prob(F-statistic)	0.000000		

Dependent Variable: NIGER

Method: Least Squares

Date: 01/25/22 Time: 17:48

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000506	0.012426	0.040729	0.9676
MARKET	0. 681875	0.197276	4.120502	0.0001

R-squared	0.126726	Mean dependent var	0.007815
Adjusted R-squared	0.119262	S.D. dependent var	0.142954
S.E. of regression	0.134159	Akaike info criterion	-1.162918
Sum squared resid	2.105841	Schwarz criterion	-1.116210
Log likelihood	71.19362	Hannan-Quinn criter.	-1.143951
F-statistic	16.97854	Durbin-Watson stat	3.363901
Prob(F-statistic)	0.000071		

Dependent Variable: ONION

Method: Least Squares

Date: 01/25/22 Time: 17:48

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016375	0.018821	0.870056	0.3861
MARKET	0. .470540	0.298806	1.474331	0. .1181

R-squared	0.018239	Mean dependent var	0.020336
Adjusted R-squared	0.009848	S.D. dependent var	0.204214
S.E. of regression	0.203206	Akaike info criterion	-0.332532
Sum squared resid	4.831231	Schwarz criterion	-0.285824
Log likelihood	21.78564	Hannan-Quinn criter.	-0.313565
F-statistic	2.173652	Durbin-Watson stat	1.726356
Prob(F-statistic)	0.143078		

Dependent Variable: POTATO

Method: Least Squares

Date: 01/25/22 Time: 17:49

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000621	0.021896	-0.028351	0.9774
MARKET	1.19582	0.347639	3.451516	0.0000

R-squared	0.092411	Mean dependent var	0.010168
Adjusted R-squared	0.084654	S.D. dependent var	0.247105
S.E. of regression	0.236415	Akaike info criterion	-0.029794
Sum squared resid	6.539358	Schwarz criterion	0.016914
Log likelihood	3.772742	Hannan-Quinn criter.	-0.010827
F-statistic	11.91296	Durbin-Watson stat	2.842022

Prob(F-statistic)	0.000776

Dependent Variable: REDPEPPER

Method: Least Squares

Date: 01/25/22 Time: 17:49

Sample (adjusted): 2010M07 2020M05

Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004786	0.012952	0.369476	0.7124
MARKET	.91163	0.205635	3.547362	0.0000

R-squared	0.097109	Mean dependent var	0.011345
Adjusted R-squared	0.089392	S.D. dependent var	0.146547
S.E. of regression	0.139844	Akaike info criterion	-1.079915
Sum squared resid	2.288092	Schwarz criterion	-1.033207
Log likelihood	66.25492	Hannan-Quinn criter.	-1.060948
F-statistic	12.58378	Durbin-Watson stat	2.863180
Prob(F-statistic)	0.000561		

Appendix B

The Breusch–Godfrey serial correlation LM test, the Corrologram of standardized residual squared, test of the adequacy of the fitted models.

Teff

Date: 01/11/22 Time: 04:53

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.057	0.057	0.3905	0.532
.|. |	.|. |	2	-0.058	-0.061	0.7965	0.671
.|. |	.|. |	3	-0.042	-0.036	1.0169	0.797
.|. |	.|. |	4	-0.043	-0.042	1.2432	0.871
.|. |	.|. |	5	-0.057	-0.057	1.6439	0.896
.|. |	.|. |	6	0.009	0.009	1.6542	0.949
.|. |	.|. |	7	-0.019	-0.031	1.7016	0.974
.|. |	.|. |	8	0.038	0.036	1.8857	0.984
.|* |	.|* |	9	0.100	0.091	3.1974	0.956
*|. |	*|. |	10	-0.070	-0.082	3.8384	0.954

.|. |	.|. |	11	-0.009	0.014	3.8482	0.974
.|. |	.|. |	12	-0.013	-0.016	3.8718	0.986
.|. |	.|. |	13	0.016	0.024	3.9055	0.992
.|* |	.|* |	14	0.079	0.082	4.7616	0.989
.|. |	.|. |	15	-0.016	-0.035	4.7986	0.994
.|. |	.|. |	16	-0.053	-0.035	5.1836	0.995
.|. |	.|. |	17	0.064	0.065	5.7628	0.995
*|. |	*|. |	18	-0.070	-0.086	6.4574	0.994
*|. |	.|. |	19	-0.066	-0.032	7.0820	0.994
.|. |	.|. |	20	-0.041	-0.053	7.3279	0.995
.|. |	.|. |	21	-0.001	-0.004	7.3282	0.997
*|. |	*|. |	22	-0.076	-0.096	8.1795	0.997
.|. |	.|. |	23	0.003	-0.020	8.1810	0.998
.|. |	.|. |	24	-0.062	-0.061	8.7615	0.998
.|. |	.|. |	25	-0.005	-0.013	8.7655	0.999
.|. |	.|. |	26	0.004	-0.027	8.7676	0.999
.|. |	.|. |	27	-0.018	-0.012	8.8199	1.000
.|. |	.|. |	28	0.039	0.030	9.0550	1.000
.|. |	.|. |	29	-0.041	-0.052	9.3227	1.000
.|. |	.|. |	30	-0.049	-0.043	9.7113	1.000
.|. |	.|. |	31	-0.043	-0.040	10.015	1.000
.|. |	.|. |	32	-0.045	-0.048	10.341	1.000
.|. |	.|. |	33	-0.056	-0.038	10.857	1.000
.|. |	.|. |	34	0.057	0.027	11.396	1.000
.|. |	.|. |	35	0.003	-0.013	11.398	1.000
.|** |	.|** |	36	0.271	0.294	24.034	0.936

*Probabilities may not be valid for this equation specification.

wheat

Date: 01/11/22 Time: 04:54

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|* |	.|* |	1	0.149	0.149	2.7000	0.100
*|. |	*|. |	2	-0.103	-0.128	3.9921	0.136
*|. |	.|. |	3	-0.082	-0.048	4.8294	0.185
*|. |	*|. |	4	-0.092	-0.088	5.8900	0.208
*|. |	.|. |	5	-0.070	-0.059	6.4959	0.261
.|** |	.|** |	6	0.214	0.221	12.298	0.056
.|** |	.|* |	7	0.230	0.151	19.037	0.008
.|. |	.|. |	8	-0.006	-0.033	19.042	0.015
*|. |	*|. |	9	-0.119	-0.073	20.885	0.013
*|. |	.|. |	10	-0.071	-0.009	21.541	0.018
.|. |	.|. |	11	-0.064	-0.019	22.080	0.024
.|. |	.|. |	12	0.011	-0.008	22.095	0.036
.|* |	.|. |	13	0.087	-0.013	23.120	0.040
.|. |	*|. |	14	-0.001	-0.067	23.120	0.058
.|. |	.|* |	15	0.017	0.074	23.158	0.081
.|. |	.|. |	16	-0.041	-0.014	23.386	0.104
*|. |	.|. |	17	-0.090	-0.058	24.512	0.106
.|. |	.|. |	18	0.037	0.070	24.709	0.133
.|. |	.|. |	19	0.008	-0.048	24.717	0.170
*|. |	*|. |	20	-0.096	-0.104	26.052	0.164
.|* |	.|** |	21	0.183	0.234	30.921	0.075
.|. |	*|. |	22	0.028	-0.070	31.039	0.095
.|. |	.|. |	23	-0.024	0.043	31.123	0.120
*|. |	*|. |	24	-0.090	-0.092	32.351	0.119
.|. |	.|. |	25	-0.020	-0.021	32.414	0.146

.|. |	.|. |	26	-0.040	0.027	32.660	0.172
.|. |	.|. |	27	0.010	-0.022	32.676	0.208
.|. |	*|. |	28	-0.041	-0.173	32.940	0.238
.|. |	.|. |	29	-0.022	-0.005	33.019	0.277
*|. |	.|. |	30	-0.083	-0.042	34.128	0.276
*|. |	*|. |	31	-0.084	-0.070	35.290	0.272
*|. |	.|. |	32	-0.085	-0.054	36.493	0.268
*|. |	*|. |	33	-0.075	-0.122	37.440	0.273
.|. |	.|. |	34	-0.002	-0.014	37.440	0.314
.|. |	.|. |	35	-0.058	-0.016	38.014	0.334
.|. |	.|. |	36	-0.022	-0.050	38.101	0.374

*Probabilities may not be valid for this equation specification.

barley

Date: 01/11/22 Time: 04:55

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.001	-0.001	0.0001	0.991
.|. |	.|. |	2	-0.013	-0.013	0.0205	0.990
.|. |	.|. |	3	0.005	0.005	0.0234	0.999
.|. |	.|. |	4	0.067	0.067	0.5811	0.965
.|. |	.|. |	5	-0.043	-0.043	0.8111	0.976
.|. |	.|. |	6	0.066	0.068	1.3588	0.968
.|. |	.|. |	7	0.060	0.059	1.8184	0.969
.|. |	.|. |	8	0.019	0.017	1.8652	0.985
.|. |	.|. |	9	-0.036	-0.029	2.0299	0.991

<table>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>0.010</td><td>-0.001</td><td>2.0426</td><td>0.996</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>-0.013</td><td>-0.017</td><td>2.0662</td><td>0.998</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.061</td><td>-0.063</td><td>2.5603</td><td>0.998</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>-0.032</td><td>-0.035</td><td>2.6974</td><td>0.999</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>-0.005</td><td>-0.016</td><td>2.7008</td><td>0.999</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.006</td><td>0.010</td><td>2.7052</td><td>1.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>0.053</td><td>0.064</td><td>3.0982</td><td>1.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>-0.026</td><td>-0.023</td><td>3.1923</td><td>1.000</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>18</td><td>-0.089</td><td>-0.081</td><td>4.3084</td><td>1.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.023</td><td>-0.014</td><td>4.3854</td><td>1.000</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>20</td><td>0.106</td><td>0.107</td><td>6.0088</td><td>0.999</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>21</td><td>-0.038</td><td>-0.033</td><td>6.2191</td><td>0.999</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>0.032</td><td>0.034</td><td>6.3741</td><td>1.000</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>23</td><td>-0.098</td><td>-0.114</td><td>7.7986</td><td>0.999</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>24</td><td>-0.016</td><td>-0.023</td><td>7.8357</td><td>0.999</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>25</td><td>-0.104</td><td>-0.085</td><td>9.4862</td><td>0.998</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>26</td><td>0.027</td><td>0.010</td><td>9.5982</td><td>0.999</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>27</td><td>0.099</td><td>0.109</td><td>11.120</td><td>0.997</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>28</td><td>-0.057</td><td>-0.063</td><td>11.640</td><td>0.997</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>29</td><td>0.080</td><td>0.120</td><td>12.663</td><td>0.996</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>30</td><td>0.037</td><td>0.022</td><td>12.888</td><td>0.997</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>31</td><td>-0.056</td><td>-0.055</td><td>13.396</td><td>0.998</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>32</td><td>-0.016</td><td>0.009</td><td>13.441</td><td>0.998</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>33</td><td>-0.011</td><td>-0.041</td><td>13.463</td><td>0.999</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>34</td><td>0.014</td><td>0.024</td><td>13.498</td><td>0.999</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>35</td><td>0.181</td><td>0.181</td><td>19.106</td><td>0.987</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>36</td><td>0.179</td><td>0.157</td><td>24.624</td><td>0.924</td></tr>
</table>

*Probabilities may not be valid for this equation specification.

sorghum

Date: 01/11/22 Time: 04:57

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
*|. |	*|. |	1	-0.095	-0.095	1.0956	0.295
.|. |	.|. |	2	-0.017	-0.026	1.1288	0.569
*|. |	*|. |	3	-0.085	-0.090	2.0137	0.570
.|* |	.|* |	4	0.104	0.088	3.3506	0.501
.|. |	.|. |	5	0.021	0.036	3.4048	0.638
*|. |	.|. |	6	-0.066	-0.065	3.9590	0.682
.|. |	.|. |	7	-0.052	-0.048	4.2993	0.745
*|. |	*|. |	8	-0.114	-0.135	5.9707	0.651
.|. |	*|. |	9	-0.031	-0.078	6.0992	0.730
.|. |	.|. |	10	-0.037	-0.053	6.2797	0.791
.|. |	*|. |	11	-0.060	-0.085	6.7636	0.818
.|. |	.|. |	12	0.010	0.005	6.7781	0.872
.|. |	*|. |	13	-0.064	-0.071	7.3315	0.884
.|* |	.|. |	14	0.103	0.071	8.7788	0.845
.|. |	.|. |	15	-0.059	-0.054	9.2516	0.864
.|. |	*|. |	16	-0.021	-0.071	9.3099	0.900
.|. |	.|. |	17	-0.024	-0.045	9.3933	0.927
.|. |	*|. |	18	-0.047	-0.116	9.7102	0.941
.|. |	*|. |	19	-0.046	-0.110	10.009	0.953
.|** |	.|** |	20	0.285	0.287	21.775	0.353
.|. |	.|. |	21	0.016	0.054	21.812	0.410
.|. |	.|. |	22	0.023	0.066	21.892	0.466
.|. |	.|. |	23	-0.047	0.012	22.216	0.507
.|* |	.|. |	24	0.109	0.024	23.999	0.462

.|. |	*|. |	25	-0.061	-0.105	24.562	0.487
.|* |	.|* |	26	0.162	0.161	28.610	0.329
*|. |	.|. |	27	-0.084	-0.033	29.718	0.327
.|. |	.|. |	28	-0.055	-0.019	30.192	0.354
*|. |	.|. |	29	-0.081	-0.027	31.225	0.355
.|. |	.|. |	30	-0.005	0.005	31.229	0.404
*|. |	*|. |	31	-0.077	-0.086	32.194	0.407
.|. |	.|. |	32	-0.057	-0.033	32.732	0.431
.|. |	.|. |	33	-0.018	0.000	32.787	0.478
.|* |	.|. |	34	0.097	0.057	34.383	0.449
.|. |	.|. |	35	0.020	0.058	34.453	0.494
.|. |	.|. |	36	-0.030	0.009	34.613	0.535

*Probabilities may not be valid for this equation specification.

maize

Date: 01/11/22 Time: 04:58

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|* |	.|* |	1	0.113	0.113	1.5565	0.212
.|. |	.|. |	2	-0.036	-0.049	1.7143	0.424
*|. |	.|. |	3	-0.074	-0.065	2.3898	0.496
.|. |	.|. |	4	-0.064	-0.051	2.9051	0.574
*|. |	*|. |	5	-0.083	-0.077	3.7680	0.583
*|. |	*|. |	6	-0.076	-0.070	4.5039	0.609
.|. |	.|. |	7	-0.003	-0.001	4.5048	0.720
.|. |	.|. |	8	0.037	0.017	4.6767	0.792

.|. |	*|. |	9	-0.065	-0.092	5.2273	0.814
*|. |	*|. |	10	-0.102	-0.102	6.5912	0.763
*|. |	*|. |	11	-0.113	-0.113	8.2738	0.689
*|. |	*|. |	12	-0.077	-0.086	9.0557	0.698
.|. |	.|. |	13	0.004	-0.017	9.0575	0.769
.|. |	.|. |	14	-0.011	-0.061	9.0730	0.826
*|. |	*|. |	15	-0.077	-0.138	9.8815	0.827
.|. |	.|. |	16	0.026	-0.016	9.9767	0.868
.|. |	*|. |	17	-0.032	-0.096	10.120	0.899
.|. |	*|. |	18	-0.057	-0.106	10.575	0.912
*|. |	*|. |	19	-0.091	-0.148	11.771	0.895
.|* |	.|* |	20	0.155	0.096	15.245	0.762
.|** |	.|** |	21	0.311	0.221	29.333	0.106
.|* |	.|* |	22	0.188	0.120	34.553	0.043
.|* |	.|* |	23	0.089	0.086	35.731	0.044
.|. |	.|. |	24	-0.019	-0.007	35.788	0.058
*|. |	.|. |	25	-0.096	-0.051	37.196	0.055
*|. |	.|. |	26	-0.102	-0.033	38.800	0.051
.|. |	.|* |	27	0.063	0.148	39.409	0.058
.|. |	.|. |	28	-0.029	-0.037	39.543	0.073
.|* |	.|* |	29	0.157	0.187	43.443	0.041
*|. |	*|. |	30	-0.074	-0.081	44.320	0.045
*|. |	.|. |	31	-0.095	-0.009	45.778	0.042
*|. |	.|. |	32	-0.080	0.029	46.825	0.044
*|. |	.|. |	33	-0.130	-0.061	49.636	0.032
.|. |	.|. |	34	-0.042	-0.006	49.937	0.038
*|. |	.|. |	35	-0.066	-0.051	50.672	0.042
.|. |	.|. |	36	0.011	0.027	50.691	0.053

*Probabilities may not be valid for this equation specification.

onion

Date: 01/11/22 Time: 05:02

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.011	-0.011	0.0138	0.907
*|. |	*|. |	2	-0.094	-0.094	1.0881	0.580
*|. |	*|. |	3	-0.090	-0.093	2.0897	0.554
.|. |	.|. |	4	0.028	0.017	2.1898	0.701
.|* |	.|* |	5	0.104	0.089	3.5435	0.617
.|. |	.|. |	6	-0.021	-0.022	3.6003	0.731
.|. |	.|. |	7	-0.036	-0.016	3.7696	0.806
.|. |	.|. |	8	0.035	0.048	3.9270	0.864
*|. |	*|. |	9	-0.098	-0.112	5.1767	0.819
*|. |	*|. |	10	-0.084	-0.097	6.1071	0.806
.|. |	.|. |	11	-0.012	-0.022	6.1272	0.865
.|. |	.|. |	12	0.063	0.033	6.6586	0.879
.|* |	.|. |	13	0.079	0.061	7.4898	0.875
*|. |	*|. |	14	-0.186	-0.160	12.209	0.589
*|. |	*|. |	15	-0.135	-0.116	14.729	0.471
.|. |	.|. |	16	0.032	0.000	14.871	0.534
.|. |	.|. |	17	0.016	-0.047	14.905	0.602
*|. |	*|. |	18	-0.068	-0.108	15.570	0.623
.|. |	.|. |	19	0.035	0.062	15.746	0.674
.|* |	.|* |	20	0.087	0.091	16.833	0.664
*|. |	*|. |	21	-0.075	-0.111	17.654	0.671
.|. |	.|* |	22	0.063	0.115	18.246	0.691

.|. |	.|. |	23	-0.028	-0.021	18.362	0.738
.|. |	*|. |	24	0.016	-0.072	18.399	0.783
.|* |	.|* |	25	0.158	0.147	22.212	0.623
.|. |	.|* |	26	0.054	0.097	22.653	0.652
.|. |	.|. |	27	0.015	0.030	22.687	0.702
*|. |	.|. |	28	-0.070	-0.055	23.458	0.710
*|. |	*|. |	29	-0.067	-0.075	24.176	0.720
.|* |	.|. |	30	0.105	0.065	25.944	0.678
*|. |	*|. |	31	-0.080	-0.109	26.998	0.672
.|. |	*|. |	32	-0.042	-0.097	27.294	0.704
.|. |	.|* |	33	0.052	0.083	27.743	0.726
*|. |	.|. |	34	-0.092	-0.036	29.170	0.703
.|. |	.|. |	35	0.047	0.013	29.552	0.728
.|. |	.|* |	36	0.015	0.084	29.589	0.766

*Probabilities may not be valid for this equation specification.

Potato

Date: 01/11/22 Time: 04:52

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.034	-0.034	0.1436	0.705
.|. |	.|. |	2	-0.053	-0.054	0.4838	0.785
.|. |	.|. |	3	-0.007	-0.011	0.4895	0.921
.|. |	.|. |	4	-0.060	-0.064	0.9372	0.919

*|. |	*|. |	5	-0.082	-0.088	1.7730	0.880
.|. |	.|. |	6	-0.031	-0.046	1.8967	0.929
.|. |	.|. |	7	-0.033	-0.048	2.0345	0.958
*|. |	*|. |	8	-0.079	-0.095	2.8300	0.945
.|. |	.|. |	9	0.060	0.035	3.2998	0.951
.|. |	.|. |	10	-0.032	-0.054	3.4306	0.969
.|. |	*|. |	11	-0.061	-0.077	3.9207	0.972
.|* |	.|* |	12	0.179	0.154	8.2236	0.767
.|. |	*|. |	13	-0.059	-0.072	8.6961	0.795
.|* |	.|* |	14	0.167	0.186	12.488	0.567
.|. |	.|. |	15	-0.038	-0.052	12.690	0.626
*|. |	.|. |	16	-0.073	-0.053	13.431	0.641
.|. |	.|. |	17	-0.062	-0.042	13.969	0.669
.|. |	*|. |	18	-0.065	-0.081	14.575	0.691
.|. |	.|. |	19	-0.028	-0.015	14.689	0.742
.|. |	.|. |	20	-0.060	-0.055	15.203	0.765
.|*** |	.|*** |	21	0.367	0.359	34.918	0.029
.|. |	.|. |	22	0.032	0.061	35.073	0.038
.|. |	.|. |	23	-0.005	0.037	35.076	0.051
.|* |	.|. |	24	0.083	0.072	36.121	0.053
.|. |	.|. |	25	-0.041	0.009	36.373	0.066
.|. |	.|* |	26	0.069	0.086	37.097	0.073
.|. |	.|. |	27	-0.003	0.050	37.098	0.093
.|. |	.|. |	28	-0.057	-0.033	37.610	0.106
*|. |	.|. |	29	-0.068	0.030	38.336	0.115
.|. |	*|. |	30	-0.064	-0.069	38.995	0.126
.|. |	.|. |	31	-0.029	0.014	39.136	0.150
.|. |	.|. |	32	-0.032	0.054	39.306	0.175
.|. |	*|. |	33	-0.005	-0.172	39.310	0.208
.|. |	.|. |	34	-0.018	0.039	39.366	0.242

.|* |	*|. |	35	0.104	-0.089	41.205	0.218
.|. |	.|. |	36	0.017	-0.014	41.256	0.252

*Probabilities may not be valid for this equation specification.

Red pepper

Date: 01/11/22 Time: 05:03

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.026	-0.026	0.0788	0.779
.|. |	.|. |	2	0.064	0.064	0.5859	0.746
.|. |	.|. |	3	-0.054	-0.051	0.9385	0.816
.|. |	.|. |	4	0.073	0.067	1.5921	0.810
*|. |	*|. |	5	-0.087	-0.079	2.5498	0.769
*|. |	*|. |	6	-0.085	-0.100	3.4535	0.750
*|. |	.|. |	7	-0.076	-0.064	4.1858	0.758
.|. |	.|. |	8	-0.053	-0.060	4.5407	0.805
*|. |	*|. |	9	-0.089	-0.085	5.5794	0.781
.|. |	.|. |	10	-0.024	-0.025	5.6569	0.843
.|. |	.|. |	11	0.026	0.023	5.7463	0.890
.|* |	.|. |	12	0.084	0.070	6.6991	0.877
*|. |	*|. |	13	-0.084	-0.098	7.6529	0.865
.|* |	.|* |	14	0.188	0.161	12.447	0.570
.|* |	.|* |	15	0.182	0.192	16.994	0.319
.|. |	.|. |	16	-0.006	-0.052	16.999	0.386

*|. |	.|. |	17	-0.070	-0.063	17.685	0.409
.|. |	.|* |	18	0.072	0.075	18.424	0.428
.|. |	.|. |	19	-0.036	-0.038	18.608	0.482
*|. |	*|. |	20	-0.095	-0.070	19.916	0.463
.|. |	.|* |	21	0.010	0.090	19.932	0.526
.|. |	.|* |	22	0.047	0.079	20.264	0.567
.|. |	.|. |	23	-0.028	-0.017	20.378	0.619
.|. |	.|. |	24	-0.056	-0.022	20.854	0.647
.|. |	.|. |	25	-0.065	-0.064	21.490	0.665
.|. |	*|. |	26	-0.053	-0.143	21.916	0.693
*|. |	*|. |	27	-0.083	-0.094	22.986	0.686
.|. |	.|. |	28	-0.057	-0.039	23.491	0.708
.|. |	*|. |	29	-0.033	-0.122	23.665	0.745
*|. |	*|. |	30	-0.080	-0.172	24.704	0.739
*|. |	.|. |	31	-0.075	-0.044	25.625	0.739
.|. |	*|. |	32	-0.058	-0.108	26.179	0.756
.|* |	.|* |	33	0.184	0.089	31.790	0.527
.|. |	.|. |	34	-0.058	-0.040	32.351	0.549
.|. |	.|. |	35	-0.006	-0.059	32.356	0.596
.|** |	.|* |	36	0.222	0.200	40.840	0.266

*Probabilities may not be valid for this equation specification.

niger

Date: 01/11/22 Time: 05:05

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*

.|. |	.|. |	1	-0.029	-0.029	0.1043	0.747
.|. |	.|. |	2	0.025	0.024	0.1822	0.913
.|. |	.|. |	3	-0.059	-0.058	0.6150	0.893
.|. |	.|. |	4	-0.034	-0.038	0.7557	0.944
.|. |	.|. |	5	0.007	0.007	0.7611	0.979
.|. |	.|. |	6	-0.059	-0.061	1.2077	0.977
.|. |	.|. |	7	-0.001	-0.009	1.2080	0.991
.|. |	.|. |	8	-0.016	-0.014	1.2426	0.996
.|. |	.|. |	9	-0.034	-0.042	1.3968	0.998
.|. |	.|. |	10	-0.012	-0.019	1.4170	0.999
.|. |	.|. |	11	-0.002	-0.003	1.4174	1.000
.|. |	.|. |	12	-0.032	-0.042	1.5572	1.000
.|. |	.|. |	13	0.004	-0.003	1.5598	1.000
.|. |	.|. |	14	0.005	0.004	1.5636	1.000
.|. |	.|. |	15	0.005	-0.005	1.5674	1.000
.|. |	.|. |	16	-0.045	-0.051	1.8513	1.000
.|. |	.|. |	17	0.031	0.027	1.9825	1.000
.|. |	.|. |	18	-0.053	-0.057	2.3809	1.000
.|. |	.|. |	19	-0.007	-0.020	2.3879	1.000
.|. |	.|. |	20	-0.036	-0.036	2.5712	1.000
.|. |	.|. |	21	-0.037	-0.048	2.7701	1.000
.|. |	.|. |	22	-0.027	-0.043	2.8754	1.000
.|. |	.|. |	23	-0.050	-0.054	3.2459	1.000
.|. |	*|. |	24	-0.049	-0.072	3.6101	1.000
.|. |	.|. |	25	-0.033	-0.052	3.7769	1.000
.|. |	.|. |	26	-0.043	-0.064	4.0645	1.000
.|** |	.|** |	27	0.325	0.309	20.488	0.810
.|. |	.|. |	28	-0.047	-0.056	20.835	0.832
.|. |	*|. |	29	-0.031	-0.071	20.986	0.860
.|. |	.|* |	30	0.060	0.094	21.568	0.869

.|. |	.|. |	31	-0.029	-0.025	21.702	0.892
.|. |	.|. |	32	0.043	0.006	22.001	0.907
.|. |	.|. |	33	-0.044	-0.001	22.320	0.920
.|. |	.|. |	34	0.037	0.018	22.546	0.933
.|. |	.|. |	35	-0.038	-0.044	22.793	0.944
.|. |	.|. |	36	-0.011	0.002	22.815	0.957

*Probabilities may not be valid for this equation specification.

bean

Date: 01/11/22 Time: 05:06

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|** |	.|** |	1	0.225	0.225	6.1509	0.013
.|. |	*|. |	2	-0.055	-0.111	6.5198	0.038
.|. |	.|. |	3	-0.021	0.020	6.5716	0.087
.|. |	.|. |	4	0.048	0.045	6.8522	0.144
*|. |	*|. |	5	-0.121	-0.155	8.6910	0.122
*|. |	*|. |	6	-0.139	-0.069	11.145	0.084
*|. |	.|. |	7	-0.076	-0.048	11.878	0.105
*|. |	*|. |	8	-0.079	-0.083	12.680	0.123
.|. |	.|* |	9	0.052	0.103	13.038	0.161
.|. |	*|. |	10	-0.014	-0.076	13.062	0.220
.|. |	.|. |	11	-0.041	-0.037	13.289	0.275
.|. |	.|. |	12	0.027	0.039	13.389	0.341
.|. |	.|. |	13	0.062	-0.008	13.900	0.381
.|. |	*|. |	14	-0.064	-0.079	14.459	0.416

.|* |	.|* |	15	0.082	0.149	15.380	0.424
.|. |	*|. |	16	-0.040	-0.154	15.601	0.481
*|. |	*|. |	17	-0.136	-0.086	18.198	0.376
.|. |	.|* |	18	0.038	0.130	18.405	0.429
.|. |	*|. |	19	0.021	-0.105	18.467	0.491
*|. |	.|. |	20	-0.079	-0.029	19.369	0.498
.|. |	.|. |	21	-0.014	0.067	19.397	0.560
.|** |	.|* |	22	0.217	0.124	26.318	0.238
.|* |	.|. |	23	0.077	0.013	27.208	0.247
.|* |	.|* |	24	0.100	0.127	28.717	0.231
.|* |	.|* |	25	0.184	0.137	33.865	0.111
.|. |	.|. |	26	0.034	-0.040	34.044	0.134
*|. |	*|. |	27	-0.147	-0.120	37.384	0.088
*|. |	.|. |	28	-0.073	0.015	38.224	0.094
.|. |	.|. |	29	-0.031	0.039	38.375	0.114
.|. |	.|. |	30	-0.056	-0.024	38.876	0.129
.|. |	.|. |	31	-0.005	0.043	38.881	0.156
.|. |	.|. |	32	-0.048	-0.001	39.255	0.177
.|. |	.|. |	33	0.027	0.004	39.373	0.206
.|. |	.|. |	34	0.019	-0.047	39.432	0.240
.|. |	.|. |	35	0.038	0.069	39.683	0.269
*|. |	*|. |	36	-0.090	-0.089	41.087	0.257

*Probabilities may not be valid for this equation specification.

Date: 01/11/22   Time: 05:05

Sample: 2010M07 2020M07

Included observations: 118

Autocorrelation	Partial Correlation		AC	PA
.|. |	.|. |	1	-0.029	
.|. |	.|. |	2	0.025	
.|. |	.|. |	3	-0.059	
.|. |	.|. |	4	-0.034	
.|. |	.|. |	5	0.007	
.|. |	.|. |	6	-0.059	
.|. |	.|. |	7	-0.001	
.|. |	.|. |	8	-0.016	
.|. |	.|. |	9	-0.034	
.|. |	.|. |	10	-0.012	
.|. |	.|. |	11	-0.002	
.|. |	.|. |	12	-0.032	
.|. |	.|. |	13	0.004	
.|. |	.|. |	14	0.005	
.|. |	.|. |	15	0.005	
.|. |	.|. |	16	-0.045	
.|. |	.|. |	17	0.031	
.|. |	.|. |	18	-0.053	
.|. |	.|. |	19	-0.007	
.|. |	.|. |	20	-0.036	
.|. |	.|. |	21	-0.037	
.|. |	.|. |	22	-0.027	
.|. |	.|. |	23	-0.050	
.|. |	*|. |	24	-0.049	
.|. |	.|. |	25	-0.033	
.|. |	.|. |	26	-0.043	
.|** |	.|** |	27	0.325	
.|. |	.|. |	28	-0.047	

month	$P_{i,j}^t$ is national index for item teff in period t	$P_{i,j}^t$ is national index for item wheat in period t	$P_{i,j}^t$ is national index for item Barley in period t	$P_{i,j}^t$ is national index for item Maize in period t	$P_{i,j}^t$ is national index for item Sorgum in period t	$P_{i,j}^t$ is national index for item Niger in period t	$P_{i,j}^t$ is national index for item Bean in period t	$P_{i,j}^t$ is national index for item Onion in period t	$P_{i,j}^t$ is national index for item potato in period t	P_i^t is national index for item in period t

.|. |	*|. |	29	-0.031
.|. |	.|* |	30	0.060
.|. |	.|. |	31	-0.029
.|. |	.|. |	32	0.043
.|. |	.|. |	33	-0.044
.|. |	.|. |	34	0.037
.|. |	.|. |	35	-0.038
.|. |	.|. |	36	-0.011

*Probabilities may not be valid for this equation specification.

Appendix C: Country level index

Jul-10	60.50	84.05	80.58	93.56	65.92	80.06	89.11	34.01	60.35	44.60
Aug-10	61.33	82.82	85.26	101.91	70.51	82.94	88.18	52.59	56.35	48.80
Sep-10	55.24	63.51	60.90	69.44	57.07	55.53	58.22	77.69	49.89	42.97
Oct-10	51.63	50.19	50.38	45.12	42.30	44.98	41.54	108.47	51.45	41.28
Nov-10	49.54	51.41	48.92	44.46	41.18	44.94	41.13	86.75	62.83	39.76
Dec-10	49.74	54.43	51.21	48.50	47.60	47.73	48.36	75.62	79.65	38.77
Jan-11	49.52	58.14	53.05	50.23	44.53	48.20	48.39	79.30	89.77	40.31
Feb-11	47.36	55.39	50.19	49.39	39.93	46.29	44.15	61.56	68.00	42.13
Mar-11	51.90	59.67	56.13	62.57	49.90	50.08	51.05	68.22	74.73	42.27
Apr-11	55.79	65.55	62.03	69.02	54.78	59.14	59.20	50.75	83.03	43.31
May-11	58.93	78.39	72.01	90.64	63.48	60.17	72.02	41.92	85.55	53.32
Jun-11	66.85	83.46	84.58	94.41	74.01	74.28	83.25	47.45	78.56	61.07
Jul-11	78.57	79.72	88.45	101.37	123.40	79.84	81.68	92.52	77.40	83.87
Aug-11	79.03	85.64	88.54	102.80	81.99	78.79	81.04	92.02	71.67	83.00
Sep-11	61.94	84.57	87.17	103.18	80.00	87.89	93.38	55.69	59.90	48.06
Oct-11	63.12	92.85	92.54	105.84	85.81	85.23	92.98	49.73	64.71	54.33
Nov-11	72.48	87.63	90.76	95.89	84.71	62.40	85.20	58.13	71.17	64.28
Dec-11	63.75	84.07	83.30	83.21	70.55	77.36	78.22	57.79	71.41	56.04
Jan-12	64.17	78.57	80.57	81.48	79.31	67.87	75.92	83.56	78.75	60.33
Feb-12	65.01	81.18	83.32	84.79	78.82	72.39	80.96	70.18	77.70	67.13
Mar-12	76.63	83.07	85.80	94.69	82.68	71.47	86.41	77.71	91.69	74.60
Apr-12	73.28	79.34	80.07	85.74	77.37	70.13	78.73	74.86	93.81	71.89
May-12	80.03	84.55	84.69	94.51	91.06	71.60	83.80	104.74	105.87	86.93
Jun-12	74.59	75.96	84.40	96.05	77.16	76.24	83.24	85.39	80.79	81.36
Jul-12	83.46	80.91	87.96	102.59	98.89	71.00	82.56	94.69	82.12	104.85
Aug-12	89.83	83.65	89.78	104.25	82.02	76.44	62.92	105.87	67.62	97.96
Sep-12	93.61	80.00	85.91	103.12	110.04	64.60	79.19	120.81	242.85	67.53
Oct-12	93.36	83.45	90.15	99.57	96.35	71.32	74.78	98.29	72.20	94.94
Nov-12	80.25	80.91	90.32	93.81	98.54	62.44	70.38	81.73	86.07	69.57

Dec-12	90.82	78.75	86.65	89.90	89.58	66.37	59.81	80.12	74.80	95.63
Jan-13	90.94	76.13	86.62	92.07	87.56	59.47	66.12	71.86	77.75	97.00
Feb-13	91.92	76.58	83.65	92.64	82.60	66.72	61.62	51.69	75.18	99.58
Mar-13	91.89	77.63	83.23	94.04	80.95	66.18	58.84	50.90	77.96	102.98
Apr-13	92.81	79.11	84.04	96.17	91.59	67.57	60.03	45.55	83.98	103.46
May-13	94.02	80.34	85.78	102.05	92.72	69.19	60.66	72.84	86.04	106.57
Jun-13	95.00	81.14	87.93	106.61	89.00	62.18	59.39	96.29	72.21	108.67
Jul-13	96.12	83.28	90.75	110.78	101.14	68.33	59.75	100.89	65.05	109.09
Aug-13	85.58	87.50	109.59	133.00	109.48	65.17	58.40	94.69	83.15	105.33
Sep-13	100.17	91.10	94.02	120.42	127.59	71.05	67.90	124.77	71.29	99.57
Oct-13	100.32	93.24	100.10	127.36	106.47	68.25	63.34	96.65	75.67	104.34
Nov-13	97.70	92.65	99.31	119.61	120.20	71.38	58.92	75.01	70.16	109.89
Dec-13	95.34	88.95	91.66	109.66	107.97	70.97	59.68	69.48	71.81	112.57
Jan-14	91.12	83.62	91.42	99.43	96.14	69.08	58.05	80.13	77.38	108.39
Feb-14	89.74	82.67	87.91	95.91	92.89	43.06	57.71	84.98	86.67	103.77
Apr-14	89.93	89.79	92.15	104.07	96.38	72.83	61.44	105.33	90.72	100.92
May-14	90.58	91.93	94.79	105.28	92.53	71.80	62.94	102.44	83.34	105.08
Jun-14	90.61	95.59	96.95	108.09	96.19	76.09	63.48	93.08	76.04	101.80
Jul-14	90.39	100.45	100.29	109.87	111.37	70.73	82.52	79.07	225.12	79.47
Aug-14	91.91	101.36	100.16	108.47	122.35	78.35	66.08	81.56	69.22	109.29
Sep-14	92.15	103.67	101.96	104.58	117.13	80.66	67.13	83.60	73.50	102.63
Oct-14	92.32	104.01	102.89	98.26	118.50	80.71	73.31	102.11	76.57	98.95
Nov-14	91.01	104.56	100.30	91.75	114.13	82.44	74.23	103.88	76.64	97.25
Dec-14	88.53	101.48	96.69	90.56	113.73	89.21	77.74	109.96	78.69	96.38
Jan-15	87.67	99.42	97.63	92.15	102.86	86.98	73.21	115.91	87.48	98.30
Feb-15	87.56	97.89	95.82	90.53	103.07	88.97	76.55	128.69	96.46	98.46
Mar-15	87.63	99.20	95.04	90.13	104.55	90.03	77.68	129.92	102.29	100.54
Apr-15	90.17	102.38	96.85	92.59	103.84	94.85	78.99	120.51	109.62	99.91
May-15	90.39	103.04	99.06	91.16	108.39	98.17	88.43	93.47	116.08	96.97

Jun-15	94.49	105.54	104.11	99.33	110.66	104.06	95.31	78.00	127.15	100.51
Jul-15	93.76	109.32	104.81	120.01	87.03	111.31	100.45	71.22	117.67	98.79
Aug-15	96.69	109.61	104.91	95.93	86.17	115.86	117.47	92.45	138.15	104.98
Sep-15	93.50	104.84	104.40	95.58	89.00	123.84	118.40	125.62	86.20	101.24
Oct-15	99.85	105.75	104.19	92.79	83.79	123.56	135.18	131.12	90.36	157.91
Nov-15	98.60	106.15	100.45	90.28	82.16	114.70	120.40	109.92	94.76	98.45
Dec-15	103.26	104.90	102.10	96.60	89.83	127.08	116.28	96.61	98.84	99.39
Jan-16	104.81	98.65	104.73	96.43	97.06	111.21	112.03	90.98	103.53	103.09
Feb-16	109.55	100.96	100.48	95.41	92.47	122.14	105.50	75.52	100.48	93.39
Mar-16	108.59	101.66	100.17	97.05	89.19	120.77	113.81	70.47	102.77	100.03
Apr-16	111.35	96.47	102.20	98.99	91.23	123.55	118.04	76.23	115.80	95.25
May-16	115.11	101.91	102.96	101.97	91.73	123.28	118.31	115.20	121.69	99.14
Jun-16	116.63	101.70	104.67	103.30	100.12	115.85	120.11	124.21	102.57	101.81
Jul-16	117.09	98.00	99.76	105.15	110.85	115.37	106.09	130.36	89.53	96.86
Aug-16	121.38	100.80	105.45	110.53	93.90	117.36	137.31	142.74	96.59	96.46
Sep-16	100.24	94.80	93.75	106.17	101.30	97.21	111.58	107.40	84.00	81.23
Oct-16	132.08	101.14	105.44	110.34	101.64	124.21	125.22	95.31	106.05	100.17
Nov-16	126.32	98.39	103.52	107.91	106.35	120.35	118.01	70.42	99.31	96.49
Dec-16	121.65	95.83	102.18	104.10	106.48	121.25	110.76	73.27	101.17	74.58
Jan-17	120.07	95.73	102.04	104.17	105.09	117.33	108.62	79.49	100.81	97.90
Feb-17	119.74	94.70	101.34	104.15	103.17	116.50	106.03	78.78	108.42	94.77
Mar-17	116.27	88.77	99.00	105.66	101.27	110.05	109.28	82.39	122.58	87.84
Apr-17	127.87	98.85	110.16	122.12	107.99	121.77	108.09	133.44	135.48	124.43
May-17	132.12	103.33	116.01	133.07	131.29	121.04	120.11	132.51	118.00	130.85
Jun-17	132.12	103.33	116.01	133.07	119.49	121.04	120.11	132.51	117.33	129.39
Jul-17	134.32	106.18	125.71	147.92	112.82	112.60	123.94	145.44	105.38	133.74
Aug-17	139.53	110.65	135.74	164.44	124.83	179.22	126.29	168.30	114.72	103.22
Sep-17	138.57	114.66	145.16	170.29	191.69	113.19	123.74	140.42	95.65	147.15
Oct-17	148.26	135.12	153.02	169.24	133.35	203.69	130.23	137.95	106.52	145.01

Nov-17	136.30	119.69	145.57	153.93	133.86	122.55	126.76	117.28	101.94	130.89
Dec-17	134.07	116.43	141.88	135.30	124.30	122.73	121.54	129.49	105.52	126.95
Jan-18	134.83	113.69	140.73	135.49	121.74	120.04	119.32	140.19	107.49	130.47
Feb-18	135.74	118.10	137.51	136.29	118.92	123.84	119.70	123.69	115.79	141.46
Mar-18	135.87	122.34	140.84	141.81	126.91	122.52	123.58	109.09	125.08	145.65
Apr-18	140.00	126.89	141.64	143.06	127.27	124.20	138.83	152.17	122.97	153.23
May-18	137.78	137.70	147.00	147.55	123.55	121.14	119.52	103.66	116.26	153.09
Jun-18	143.14	146.71	151.28	153.32	131.25	122.08	129.28	125.46	111.64	162.71
Jul-18	141.97	147.98	152.33	151.75	133.44	113.31	114.39	139.03	110.86	130.17
Aug-18	143.88	158.93	155.25	143.28	139.95	127.15	117.14	145.24	106.59	152.19
Sep-18	145.40	162.46	156.66	147.61	144.53	134.04	134.48	162.01	108.81	157.36
Oct-18	146.94	157.68	155.97	141.52	143.82	129.64	136.55	151.22	110.84	159.17
Nov-18	144.42	156.34	151.30	148.79	144.21	125.57	133.37	134.22	105.35	161.59
Dec-18	151.79	160.93	153.68	139.54	143.53	134.85	134.05	171.53	113.77	154.88
Jan-19	162.46	163.29	155.41	155.84	160.28	135.76	139.30	190.51	127.78	157.38
Feb-19	156.63	156.35	150.71	140.94	146.48	133.85	124.65	148.77	125.37	158.82
Mar-19	156.62	158.46	151.04	141.98	147.24	139.81	136.97	158.42	144.71	162.42
Apr-19	160.85	163.09	157.78	158.92	143.02	140.81	141.97	163.51	175.24	149.75
May-19	167.75	169.60	162.09	165.89	199.36	141.25	143.39	222.13	197.35	160.68
Jun-19	170.61	170.46	155.78	173.71	172.80	144.15	158.36	256.88	177.46	169.32
Jul-19	186.02	174.56	169.33	186.77	175.02	153.07	160.48	227.46	153.37	157.84
Aug-19	188.84	182.63	173.23	197.53	180.71	152.04	166.28	231.91	138.73	173.89
Sep-19	192.23	193.82	177.70	202.32	201.58	167.71	182.90	254.81	147.24	170.95
Oct-19	193.48	198.47	183.49	203.42	199.27	164.31	201.45	193.85	173.32	165.05
Nov-19	195.55	195.52	184.95	195.71	198.13	174.39	208.93	185.18	161.96	171.71
Dec-19	195.16	191.80	181.78	185.09	189.44	175.27	197.90	200.37	164.48	163.83
Jan-20	198.66	184.88	182.31	179.84	195.63	175.33	195.26	261.94	192.04	168.28
Feb-20	201.80	182.46	185.30	191.81	201.57	167.72	191.49	294.72	219.95	158.11
Mar-20	211.42	186.93	192.55	195.89	185.65	176.16	202.76	283.29	240.33	194.04

Apr-20	227.80	196.48	204.45	205.79	199.96	183.26	212.64	314.22	253.37	163.93
May-20	235.37	200.87	208.82	204.19	192.75	171.49	200.10	223.42	224.27	164.98
Jun-20	240.06	202.69	212.33	208.68	209.51	186.61	229.38	340.59	209.85	166.01
Jul-20	248.62	206.93	223.61	217.50	263.64	199.70	231.40	394.28	200.57	179.88