Doctoral Thesis

School of Social Sciences

Doctoral School in Economics and Management

COMMODITY PRICE VOLATILITY:

Causes, Effects and Implications

a dissertation submitted to the doctoral school of economics and management
in partial fulfilment of the requirements for the Doctoral degree (Ph.D.) in
Economics and Management

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April 2015

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INTRODUCTION

Agricultural commodities experienced substantial increases in prices over the most recent decade with major surges in both 2007-08 and again in 2010-11. The prices of food commodities such as maize, rice and wheat increased dramatically from late 2006 through to mid-2008, reaching their highest levels in nearly thirty years. In the second half of 2008, the price upswing decelerated and prices of commodities decreased sharply in the midst of the financial and economic crisis. A similar price pattern emerged in early 2009 when the food commodity price index slowly began to climb. After June 2010, prices shot up, and by January 2011, the index of most commodities exceeded the previous 2008 price peak. These price movements coincided with sharp rises in energy prices, in particular crude oil. Sharp increases in agricultural prices were not uncommon, but it is the short period between the recent two price surges that has drawn concerns and raised questions. What were the causes of the increase in world agricultural prices and what are the prospects for future price movements? Were the trend driven by fundamental changes in global agricultural supply and demand relationships that may bring about a different outcome? What are its implication on global food security and sustainability?

Several authors have discussed the factors lying behind the sharp food price increases over the period 2007-11 though no consensus has been reached on the cause of these phenomena. Rapid economic growth in China and other Asian emerging economies, decades of underinvestment in agriculture, low inventory levels, poor harvests, depreciation of the U.S. dollar, and financializiation and speculative influences are among the factors cited as leading to high levels of commodity prices (Abbot et al, 2008, Cooke and Robles, 2009; Gilbert, 2010; Wright, 2011). In addition to the above mentioned factors, the diversion of food crops as bio-fuels stands out as an important and new factor that many have seen as accountable for the food price spikes (Mitchell, 2008).

The price spikes were also associated with increased price volatility in commodity prices. Increasing volatility has been a concern for most agricultural producers and for other agents along the food chain as it renders planning very difficult for all market participants. Price volatility can have a long run impact on the incomes of many producers and the trading positions of countries and can make planning on production more difficult. As argued by Aizenman and Pinto (2005), higher volatility results in an overall welfare loss, though some may benefit from higher volatility. Sudden changes and long run trend movements in agricultural commodity prices present serious challenges to market participants and especially to commodity dependent and net food importing developing countries (FAO 2010). At the national level, food-importing countries face balance-of-payment pressure as the cost of food imports rise. When transmitted to domestic markets, high world prices erode the purchasing power of urban households and other net food buyers (Minot, 2009). Moreover, adequate mechanisms to reduce or manage risk to produces may not exist in some markets and countries or are not easily accessible in others.

Primary commodity prices are variable because short term production and consumption elasticities are low. On the supply side, production responsiveness is low in agriculture because input decisions are made before new crop prices are known. These decisions in turn depend on expected prices and not on price realisations. On the demand side, consumption elasticities, and particularly short-term demand are low because actual commodity price may not be a large component of the overall value of the final product. Low elasticities thus imply that small shocks in production could have substantial price impact.

In agriculture, volatility in food prices is of particular importance as can be noted from different perspectives. Firstly, most of the poor households in developing countries spend large proportions of their incomes on food. Secondly, most farm households in developing countries are small-scale farmers who sell their produce onto the market but also happen to be net buyers. Thirdly and lastly, most small-scale farm households fully rely on the sale of food commodities in order to cover their basic needs and expenditures like health and education expenses. Food price volatility thus feeds directly into the dynamics of poverty. This is so since high food prices can play a major role in moving many vulnerable non-poor households into poverty and low food prices can move non-poor farm households into poverty. Since these households devote a large proportion of their budgets to food price shocks can easily pre-empt their income moving them from sustainability into poverty (Anderson and Roumaset, 1996).

The sudden and unexpected rise in world food prices in recent decade has drawn the attention of policy makers to agriculture and this has led to the debate about the future reliability of world markets as a source for food. The fear of further spells of volatility in food prices has prompted efforts in designing and proposing price stabilizing mechanisms both at international and national levels. This fear has been driven by the recognition that a new set of forces may be driving drive food prices and their volatility trend. These forces emerge from linkages between the agricultural and the energy markets, the role of financial and currency markets, collectively with the wider macroeconomy, which together, render agricultural markets much more exposed to shocks.

Previous research has shown that in the recent decade there has been an increase in volatility grains, vegetable oils and meats. These are commodities which are likely to be affected by the growth of biofuel production. On this view, heightened food price volatility arises due to the importation of oil price volatility. Despite this, crude oil price volatility has not been particularly high over the period considered. This suggests that the relationship between crude oil and grains prices may have changed over the most recent decade resulting in greater transmission of oil price volatility into grains prices. Consistent with this view, grains and crude oil returns have in the recent years been co-moving as shown by the increased correlations between the two groups. These increased correlations may be accounted for either in terms of an increase in the pass-through from the crude oil market to the grains markets or by an increased prevalence of common shocks across the two sets of markets (Tyner, 2010; Serra et al., 2011c; Gilbert and Mugera, 2013)

Increased biofuel production and consumption over the recent decade may have created a new demand side link between energy markets and food commodities by making the demand for grains and vegetable oils sensitive to the price of crude oil. In the United States biofuel production began to rise rapidly in 2003 while in the European Union it accelerated from 2005 (USDA, 2008). Ethanol production (mainly in the United States and Brazil) tripled from 4.9 billion gallons to almost 15.9 billion gallons between 2001 and 2007. In the U.S., corn production used for ethanol production increased from 12.4 percent in the 2004/05 crop year to over 38.5 percent in the 2010/11 crop year (USDA, 2011). Over the same period, biodiesel production, mainly in the European Union and deriving from vegetable oils, rose almost ten-fold, to about 2.4 billion gallons.

A number of authors have documents the increased co-movement and correlation between crude oil prices and food commodity prices over the most recent decade (Tyner, 2010; Serra et al., 2011c; Gilbert and Mugera, 2013). This increase in co-movement appears to have commenced at around the same time as biofuels production took off.

Observers have claimed that the demand for food commodities – in particular, corn, sugar, and vegetable oils – for use as biofuels feedstocks has increased the demand and prices of food commodities (Mitchell, 2008). Agricultural economists for the World Bank and United States Department of Agriculture estimated the share of biofuels' contribution to explaining high grain prices since mid-2007 at between 60 to 75 percent respectively (Mitchell, 2008). Academic analysts on the other hand, placed the share at between 25 and 35 percent (Rosegrant, 2008)[1]. Other commentators were more sceptical about the price impact of biofuels production – see Gilbert and Morgan (2010). They emphasize that biofuels demand may have increased the magnitude of the demand side shocks (that were imported from the energy markets) and reduced the demand elasticity due to restrictive and inflexible mandates.

The hikes in fuel and energy prices are structural as they reflect a long-term imbalance between rising incremental oil demand and relatively stable production and supply (ADB, 2008). Energy prices may affect food commodity prices in two ways. Firstly, an

[1] The IMF estimated that during the commodity spike, the increased demand for biofuels accounted for 70 percent of the increase in maize prices and 40 percent of the increase in soybean prices. In particular, the increase in EU biofuel production raised corn and soybean prices by about around 3 percent around the same period. In Brazil, the increase in sugar-based ethanol production pushed up sugar prices by 12 percent (Abbot *et.al*, 2008).

increase in oil prices exerts more pressure on the production cost through fuel used in tractors and transportation as well as pesticides and fertilizers used in agriculture. This will in turn lead to an upward shift of the supply curve. This pass-through process will partly be through the costs of nitrogen-based fertilizers and partly through transport costs. However, agriculture is not highly energy intensive. Baffes (2007) estimated the pass-through of oil prices into agricultural commodity prices as 17% and this has not changed much over time (Gilbert 2010). Mitchell (2008) estimated 15 – 20% in agricultural production costs in the US was due to the combined effects of higher energy and transport costs.

Secondly, high crude oil prices stimulate biofuel production and increases the demand for agricultural commodities, in particular corn and oil seed rape. This increase results in a rightward shift in the demand curve due to the new demand for food commodities as biofuel feedstocks (Gilbert, 2010). The result is that shocks from the energy demand are transmitted into the food commodities. This then increases the variability of food prices as well as the correlation to energy prices. This increased correlation is predicted by models which emphasize the demand for corn as a biofuel feedstock. In these models, provided the corn price in the absence of biofuels demand allows profitable conversion to biofuels, a rise in the price of crude oil pulls up the corn price – see Schmidhuber (2006). Substitution of land across crops generalizes the corn price increase to other commodities such as wheat and soybeans. Soybeans are most directly affected by the demand for corn-based ethanol as corn and soybeans tend to compete for land area and can be used in rotation. Thus an increase in the demand for corn could reduce soybean production leading to an increase in its price.

The expansion in biofuels production has been driven by a number of economic and environmental factors. High crude oil prices and keenness to promote non-petroleum energy sources to reduce dependence on oil imports have been important policy drivers in the United States, Brazil, and the European Union. Environmental concerns over greenhouse gas emissions and the urge to slow down global warming due to fossil fuel emissions have also contributed to this expansion. Debate remains on whether the increase in biofuels production was primarily market or policy-driven. Some authors believe that the boom was mainly driven by the increase in crude oil prices. Others sustain that the boom resulted from government policies, such as mandates and tax credits in the U.S. aimed at increasing energy self-sufficiency and, in Europe, environmental pressures to reduce emissions (DeGorter and Just, 2009; Abbot, 2013; Peri and Baldi, 2013).

In particular in the United States, July 2005 marked the beginning of what Abbot (2013) termed as the "ethanol gold rush which coincided with policy interventions such as the 2005 Renewables Fuels Standards was enacted (U.S. Congress, 2005). In 2007 then followed the Energy Policy Act which significantly increased the mandated RFS minimum levels of ethanol production (U.S. Congress, 2007). Tyner (2010) confirms that the correlation between energy and agricultural markets has been strong since the 2006 start of the ethanol boom. He highlights the summer of 2008 as the period where these two markets were closely linked. As the crude oil price increased so did the price of corn and other agricultural commodities.

Increasing globalisation and market liberalisation have fostered linkages between markets and have thus influenced volatility in individual markets. To some extent, financial market upheavals over the past few years have also played a role in determining major price shocks but whether this will turn out to be the pattern for future volatility developments still remains unclear. In particular, we have observed strong linkages between international and domestic markets in countries that trade on international markets. Most developing countries consume grains such as corn and wheat (mainly in East Africa and rice (in most of West Africa) as staples. Most of these countries are not self-sufficient and thus depend heavily on either direct (through international markets) or indirect imports (through regional markets). Shocks in international markets are therefore transmitted to domestic markets (Rapsomanikis and Mugera, 2011). Recent food spikes in international markets mainly affected grains such as corn, wheat, rice and soybeans. Increased international food commodity prices were in large measure transmitted back to domestic markets in developing countries where poor households, particularly those in urban areas, spend a large proportion of their incomes on food (World Bank, 2008) thus threatening food security and poverty (FAO, 2008).

Governments as well as policy makers are becoming more and more aware that policies that help households manage risks and cope with shocks should form an integral part of poverty eradicating strategies (Holzmann and Jorgensen, 2001). The renewed focus by policy makers to address risk and vulnerability in formulating policies to reduce poverty has motivated a series of studies aimed at measuring and assessing household vulnerability empirically.

While it is increasingly recognized that household vulnerability mitigating interventions must be an integral part of any poverty reduction strategy (World Bank, 2001), the quantitative links between risks and poverty have not been fully documented. Risk and its contribution to poverty dynamics is of growing importance in the poverty literature.

Risks contribute to poverty dynamics in a number of ways. Firstly, risks may blunt the adoption of technologies and strategies of specialization necessary for agricultural efficiency (Carter, 1997). Risks may drive farmers to apply less productive technologies in exchange for greater stability (Morduch, 2002, Larson and Plessman, 2002). Secondly, risks may function as a mechanism for economic differentiation within a population, deepening poverty and food insecurity of some individuals even as aggregate food availability improves (Carter, 1997).In the absence of risk management instruments, risk events may plunge highly vulnerable households into poverty (Holzmann and Jorgensen, 2000). From a policy perspective, risks are detrimental to the welfare of (poor) households and that ensuring security is an essential ingredient of any poverty alleviation strategy (World Bank, 2001). A household facing a risky situation is subject to future welfare loss. The likelihood of experiencing future loss of welfare, generally weighted by the magnitude of expected welfare loss, is called vulnerability (Sarris and Panayiotis, 2006).

Poverty and vulnerability are basic aspects of well-being. Exposure to risk and uncertainty about future events and its adverse effects to wellbeing is one of the central views of the basic economic theory of human behavior, embodied in the assumption that individuals and households are risk averse. Most poverty and vulnerability measures are unidimensional, focusing on a single measure of wellbeing such as income or consumption expenditure to identify who is poor or vulnerable. There is need to develop a multi-dimensional measure that incorporates different aspects of poverty especially for poor and developing countries. Ligon (2008) empirically shows that the main consequence of increased food prices is that poor consumers, that devote a larger share of their budgets to food consumption expenditure is on the reduction of other expenditures such as investments in health, education, as well as other non-food items. The negative impact of high food prices is not highly visible in a reduction of food consumption but is likely to be visible in other dimensions such as decreases in schooling rates, health expenditures, and other similar investments, as the need to purchase food at higher prices overwhelms the need to spend on other goods. This result not only questions the use of food consumption as a proxy to poverty and vulnerability as it also prompt the need to incorporate other issues of household's well-being that may be affected when households are hit by shocks such as high food prices.

Policy makers are mainly interested in applying appropriate forward-looking anti-poverty interventions (i.e., interventions that aim to go beyond the alleviation of current poverty to prevent or reduce future poverty), the critical need thus to go beyond a classification of who is currently poor and who is not, to an assessment of how households' are vulnerability to poverty. Creating awareness of the potential of such irreversible outcomes may drive individuals and households to engage in risk mitigating strategies to reduce the probability of such events occurring. Moreover, focusing on vulnerability to poverty serves to distinguish ex-ante poverty prevention interventions and ex-post poverty alleviation interventions. Policies directed at reducing vulnerability–both at the micro and macro level– will be instrumental in reducing poverty.

The first chapter of this thesis examines food and energy commodity price volatility over the past decade. The objective of this chapter is to analyse the evolution of this relationship considering the role played by biofuels. It aims at verifying whether the increased grains-crude correlations has led to greater grains volatility as shocks from the crude oil markets are transmitted into the grains market. If this is the case, one would expect there to be a pass-through mechanism of crude oil shocks into the grains markets.

It focuses on two main issues. Firstly, it establishes whether food and energy commodity markets have become more volatile in recent times. Secondly, it analyses the nature of relationship between food and crude oil prices. In particular, it investigates whether the volatility in food commodities is now driven by the transmission of shocks from the crude oil market as a result of increased biofuel production and consumption. A short and a long term historical volatility measure are calculated for different commodities in order to evaluate whether commodity markets have become more volatile in recent times. Multivariate General Autoregressive Heteroskedasticity (MGARCH) models are implemented to establish the nature of the relationship between food and energy prices. Using estimates from the Dynamic Conditional Correlation (DCC) Multivariate GARCH models specification, it decomposes volatility of food commodities into its main components. Conditional correlations are calculated from MGARCH models estimated on daily data over the twelve year sample 2000-2011. Increased commodity comovement implies a rise in inter-commodity correlations. An advantage of the DCC framework is that it allows the investigator to focus specifically on changes in pass-through from the crude oil market to the grains markets.

The second chapter of this thesis focuses on the structural changes in food and energy prices and price relationships given the role of biofuels and biofuel policies in the United States. Increases in energy prices, the boom in biofuel production and government policy interventions have led to questions in relation to the stability in the long run relationships between food and energy commodity prices. This chapter investigates the assertion that the advent of biofuels has altered the nature of the relationship between energy and agricultural markets. The main hypothesis of this second chapter is that recent market and policy events may have induced changes in the relationship between food and energy markets.

Using the Bai and Perron structural break methodology this chapter analyses price relationships between grains and energy prices over the period since 2000 and relates the structural breaks to changes in U.S. biofuel policy. It thus tests whether there have been any structural changes in relationships between energy and commodity prices and if so, whether any such breaks may be modelled as shifts in the mean of the food price processes. It further tests for the presence of multiple structural breaks in the single price series of crude oil, gasoline, ethanol corn, and wheat without pre-specifying the dates of any such breaks. The main focus of this chapter is the United States. This choice is driven by several factors. Firstly, the United States is one of the largest producers and exporters of grains and oilseeds. Secondly, the United States is the world's largest producer and consumer of biofuels. Thirdly, in the recent decade, the United States has experienced a large number of policy and regulatory changes that may have affected both the energy and food commodity markets and their inter-relationship.

The third chapter quantitatively assesses households' welfare dynamics in the recent years. Given the recent international shocks and market related shocks, the objective of this chapter is to quantitatively assess poverty and vulnerability dynamics in Tanzania. This chapter generates a unidimensional and a multidimensional poverty indicator. The Multi-dimensional Poverty Indicator (MPI) is generated implementing the Alkire and Foster (2011) multidimensional methodology. This measure proposes a dual cut-off at the identification step of poverty measurement and it provides an aggregate poverty measure that reflects the prevalence of poverty and the joint distribution of deprivations.

Based on the above poverty indicators this chapter runs a series of logit models for the 2008-09 and 2010-11 survey conditioned upon covariates of 2008-09 and 2010-11 respectively. These include household characteristics including asset ownership, geographical attributes such as location in rural or urban settings and shocks. The models are run using the MPI poverty measure and our baseline measure which is consumption expenditure (income poverty indicator). Using both a unidimensional a multidimensional poverty measure, we analyse both poverty and vulnerability in Tanzanian households.

Tanzania is selected as the country of analysis because maize is the staple food in all households. Maize is one of the food commodities most severely affected by the recent food spikes. Tanzania has also been recently both economically and politically stable and is thus conducive for conducting a survey analysis. Tanzania is a relatively large country and also trades on the international markets. Household quantitative and qualitative information have also been well documented for the relative period of analysis. This analysis is conducted using two waves 2008-09 and 2010-11 household survey panel datasets that have been collected and compiled by the Living Standards Measurement Study (LSMS-ISA, World Bank).

To understand poverty, it is essential to examine the economic and social contexts of the households which include the characteristics of local institutions, markets, and communities. Poverty differences cut across gender, ethnicity, age, rural versus urban location, and income source. Rural poverty accounts for nearly 63 percent of poverty worldwide, and is between 65 and 90 percent in sub-Saharan Africa (IMF, 2001). This chapter also separately analyses urban and rural households.

CHAPTER 1:

VOLATILITY IN FOOD COMMODITY PRICES AND THE CO-MOVEMENT WITH CRUDE OIL PRICES

In 2008, the world experienced a dramatic surge in the prices of commodities. The prices of food commodities, in particular maize, rice and wheat increased dramatically from late 2006 through to mid-2008, reaching their highest levels in nearly thirty years. Prices stabilized in the summer of 2008 and then decreased sharply in the midst of the financial and economic crisis. A similar price pattern emerged in early 2009 when the food commodity price index slowly began to climb. After June 2010, prices shot up, and by January 2011, the index of most commodities exceeded the previous 2008 price peak. Sharp increases in agricultural prices are not uncommon, but it is rare for two price spikes to occur within 3 years as they normally occur with 6-8 year intervals. The short period between the recent two price surges has therefore drawn concerns and raised questions. What are the causes of the increase in world agricultural prices and what are the prospects for future price movements? Will the current period of high prices end with a sharp reversal as in previous price spikes, or have there been fundamental changes in global agricultural supply and demand relationships that may bring about a different outcome?

A number of authors have discussed the factors lying behind the spikes though no agreement has been reached on the cause of these phenomena. Rapid economic growth in China and other Asian emerging economies, decades of underinvestment in agriculture, low inventory levels, poor harvests, depreciation of the U.S. dollar, and speculative influences are some of the factors considered and cited as leading to high levels of commodity prices. In addition, the diversion of food crops as bio-fuels stands out as an important and new factor that many have seen as accountable for the food price spikes.

The recent price spikes were also accompanied by volatile commodity prices. There is evidence of increased price volatility from mid-2000 for most food commodities in particular those of grain prices. Price volatility in commodities has been considerable, making planning very difficult for all market participants. Sudden changes and long run trend movements in agricultural commodity prices present serious challenges to market participants and especially to commodity dependent and net food importing developing countries. At the national level, food-importing countries face balance-of-payment pressure as the cost of food imports rise. When transmitted to domestic markets, high world prices erode the purchasing power of urban households and other net food buyers. Poor urban households are particularly affected because they spend a large share of their income on food.

A majority of analyses examining biofuels impacts on energy and food commodity markets have focused the attention on price-level links while price volatility has received much less attention. An increased correlation between food and energy prices is likely to yield stronger volatility spillovers between prices in these two markets. The recent 2007/08 crisis has stimulated research in the area of commodity price volatility, which can usefully complement the larger body of research which looks at price level impacts.

The aim of this chapter is to analyse the nature and cause of food commodity price volatility. It has two main objectives. Firstly, it establishes whether commodity markets have become more volatile in recent times. Secondly, it analyses the nature of relationship between commodity and crude oil prices. In particular, it aims at studying the evolution of this relationship considering the role played by biofuels. A short and a long term historical volatility measure are calculated for different commodities in order to evaluate whether commodity markets have become more volatile in recent times. It investigates whether the volatility in food commodities is now driven by the transmission of shocks from the crude oil market as a result of increased biofuel production and consumption. This chapter employs Multivariate General Autoregressive Heteroskedasticity (MGARCH). Conditional correlations are calculated from MGARCH models estimated on daily data over the twelve year sample 2000-201Using estimates from the Dynamic Conditional Correlation (DCC) Multivariate GARCH models specification, it decompose volatility of food commodities into its main components. An advantage of the DCC framework is that it allows one to focus specifically on changes in pass-through from the crude oil market to the grains markets.

This chapter focuses on grains food commodities since these are overall the most important food crops. Grains are the major staple food across the globe and also are an input into the production of meat products. Moreover, grains were the main commodities that have been affected in the recent food spikes and are thus are crucial within the food price volatility question.

It examines the prices of:

- Maize (corn): The analysis of corn price volatility is for three reasons. First, maize (white) is a staple food in eastern and southern Africa. Second, it forms the main ingredient in animal feed in the United States. Third, it is the main biofuel feed stock in the United States;
- Wheat: It is the most important grain in temperate regions; in recent times it has been used as a substitute to maize in animal feed;
- Soybeans: It is important both as an animal feedstock and, when crushed, as a vegetable oil. It also competes for land with corn in the United States.

1. HAVE COMMODTIES BECOME MORE VOLATILE?

1.1 Volatility in food commodity prices

An increase in food commodity price volatility can be due to one or more of the following four factors:

- An increase in the variance of demand shocks; the diversion of food crops into biofuel production could lead to increased demand variability. Increased demand for food commodities, in particular corn, in the recent decade sugar and vegetable oils, as biofuel feedstocks has increased the correlation between agricultural prices and the oil price. This allows transmission of oil price volatility to agricultural prices, in effect increasing the variance of demand shocks;
- An increase in the variance of supply shocks; Poor harvests such as those experienced Australian wheat harvests in 2006 and 2007 and a poor European

2007 harvest have been mentioned as possible causes of the recent food price spikes. However, these poor harvests were offset by good harvests elsewhere in the world, notably Argentina, Kazakhstan and Russia, and 2008 harvests were good;

- A decline in the elasticity of demand; elasticity in demand depends on the response of consumers to price changes and this in turn depends on the price transmission i.e. the extent to which prices on world markets are passed through to local prices. Government interventions such as subsidies in response to higher food prices may diminish price responsiveness on the part of consumers thus rendering markets and prices highly inelastic. US government policy interventions through tax credits, mandates and subsidies have been identified as some policy interventions that affected the responsiveness of corn and biofuel markets to changes in crude oil and gasoline prices;
- A decline in the elasticity of supply: Grain inventories have fallen over time since the millennium. Increased demand for corn and other feeedstocks for biofuel production have in turn reduced the responsiveness of supply to the demand shocks thus increasing volatility in these commodities.

1.2 Historical Volatility

Many commentators have maintained that commodity markets have generally become more volatile over the recent decade compared to the past. In this section of the chapter we look at the volatility of agricultural food commodity and crude oil prices both over a long as well as a short and more recent time horizon. We calculate historical volatility, i.e., the standard deviation of monthly price returns, over each calendar year. Monthly returns are converted to an annual rate by multiplying by $\sqrt{12}$[2]. We conduct both a long term and short term volatility analysis. In the long-term volatility analysis we compare the volatility measures of two-decade samples i.e., 1970-1989 with 1990-2011. In the short term analysis we compare volatilities between two- five year sub-samples, i.e., 2000-2006 and 2007-2011.The main data sources are the International Financial Statistics of the IMF and the Chicago Board of Trade (CBOT).

Historical Volatility in Commodity Markets

Gilbert and Morgan (2010) compared volatilities of food commodity prices over the two decades 1990-2009 with those over the immediately prior two decades 1970-1989. For the majority of the commodities they considered, volatility was lower in the later period, and in many cases this decline was statistically significant. We update the analysis by comparing 1970-89 with 1990-2011 and include crude oil to this comparison. The results are similar to those reported by Gilbert and Morgan (2010).

Figure 1 shows that even if volatility has risen recently, it remains substantially lower than in the 1970s. Importantly, crude oil prices show a significantly lower volatility in the later period relative to the earlier. Crude oil prices appeared to be more volatile in the 1970-1989 sub-period as compared to the 1990-2010 sub-period. There is a 4 percentage point statistically significant difference in the volatility measure between the two sub-samples.

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[2] It is convenient to use this standard conversion factor as it is in line with the efficient market theory of independence of the asset price returns be independent over time.

Turning to the shorter comparison of 2007-11 against 2000-06, there is clear evidence that volatility for some commodities has increased – see Figure 2. Specifically, volatility shows a significant increase for seven out of 19 food commodities analysed. There are significant volatility increases for all four grains considered (maize, rice, sorghum and wheat), and also for sunflower oil and beef. Other agricultural commodities either show a volatility decrease or a statistically insignificant increase. For purposes of comparison, crude oil prices show a small and statistically insignificant rise in volatility over the same period.[3]

One can therefore conclude that although there has not been any general increase in agricultural price volatility, there has been an increase in the volatility of grains prices and that this increase extends to some vegetable oils and meat prices. Despite this, food price volatility remains lower than in the 1970's. The concentration of volatility increases on grains, sunflower oil and beef is consistent with biofuels, having played a major role. Notably, however, there does not appear to be a significant increase over this comparison period in crude oil volatility[4].

[3] This comparison is based on an average of WTI and Brent prices on the basis that the WTI price was the more representative of world oil price is the first part of the period but, because of limitations in storage capacity at the Cushing (OK) hub, Brent became the more representative price in the final years of the sample.

[4] Similar results are obtained for the some of the metals. In the long-run comparison, aluminium and copper prices were more volatile in the 1970-1989 sub-sample compared to the 1990-2010 sample. Nickel showed an increase in volatility over the same period. Looking at the same metals over a shorter and more recent sample, volatility statistically increased in all three metals in the 2007-2011 sub-sample as compared to the earlier 2000-2006 subsample.

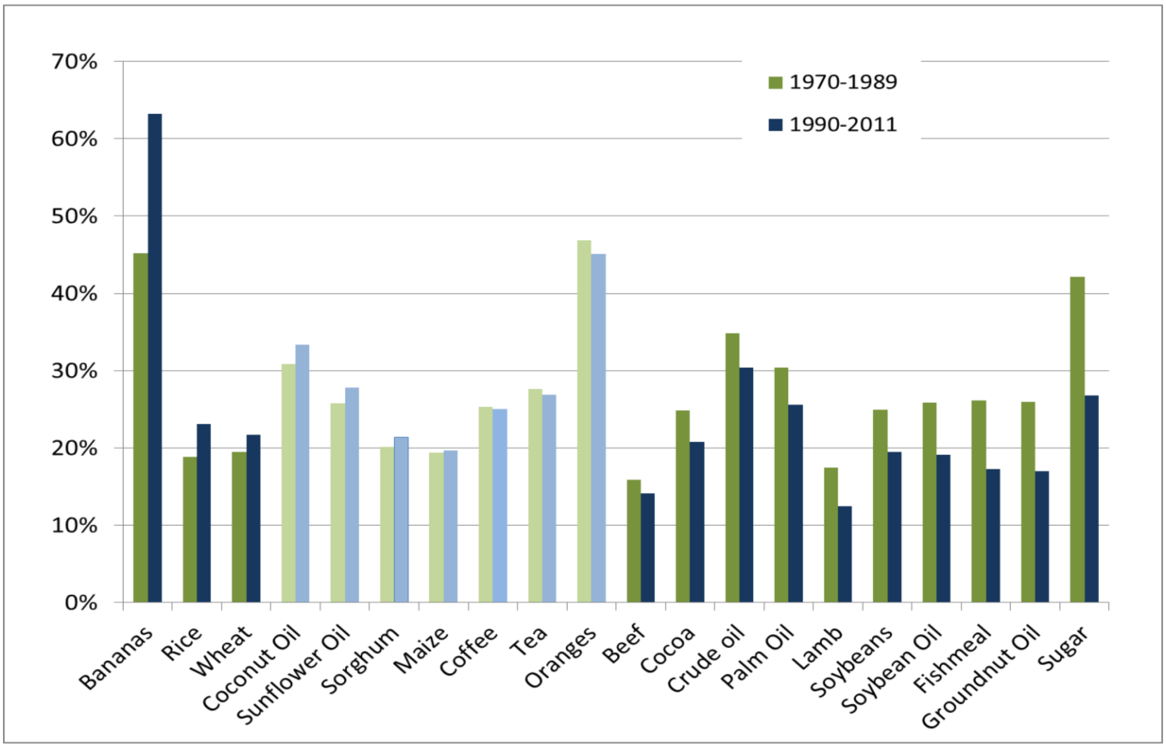

Figure 1: Volatilities 1970-89 and 1990-2011

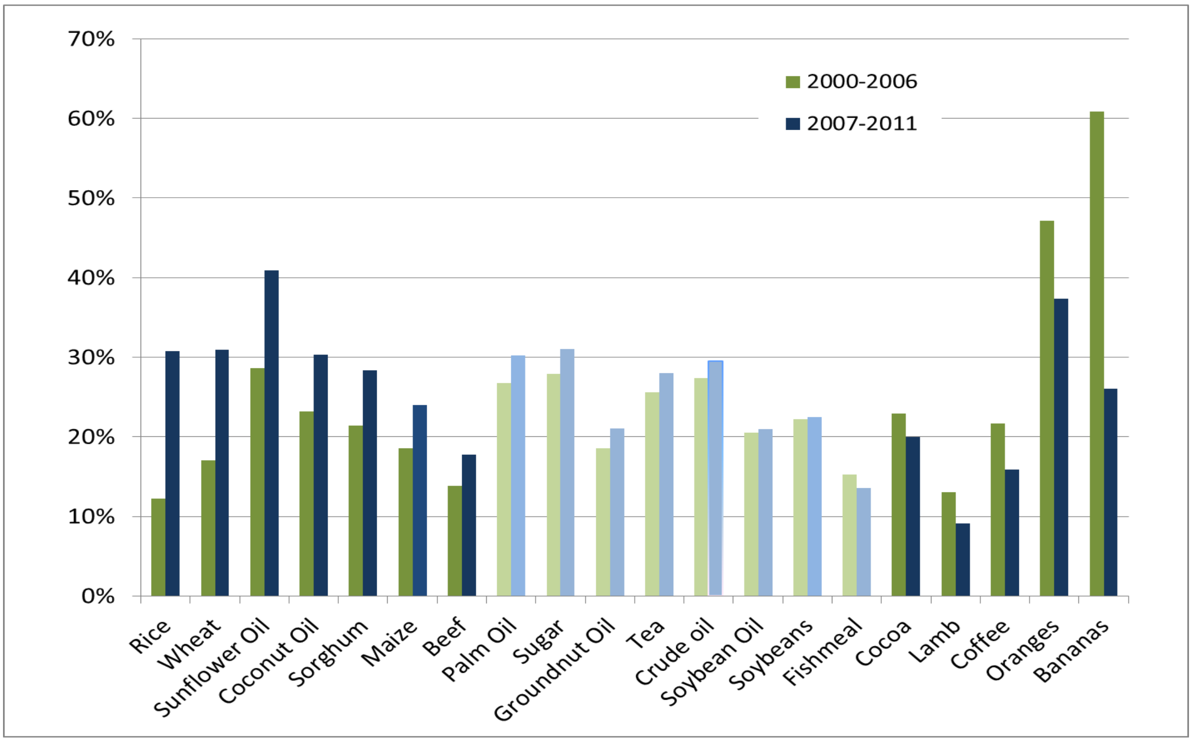

Figure 2: Volatilities 2000-06 and 2007-11

2. THE CO-MOVEMENT OF CRUDE OIL AND FOOD COMMODITY PRICES

2.1 Crude Oil and Commodity Markets

Global biofuel production has increased rapidly over the last 20 years. In the US this began to rise rapidly in 2003 while in the EU it accelerated in 2005 (USDA, 2008). According to FAO (2008), demand for cereals for industrial use, including biofuels, rose by 25 percent from 2000 to 2008 against a 5 percent increase in global food consumption. Moreover, increased biofuel production contributed to a 97 percent increase of the price of vegetable oils in the first three months of 2008 (FAO, 2008).

Crude oil prices can affect the prices of food commodities in two distinct ways. First, crude oil enters the aggregate production function of most primary commodities through the use of various energy-intensive inputs such as fertilizers, heating, pesticides and transportation. However, agriculture is not highly energy-intensive so this impact is unlikely to be large and there is no reason to suppose that it has increased markedly in recent years.

Secondly, some commodities can be used to produce substitutes for crude oil. This is true in particular for maize and sugarcane in ethanol production and oil seed rape and other vegetable oils for biodiesel production. The attractiveness to produce ethanol and biodiesel, and to invest in refining capacity to produce these products, depends directly on the price of crude oil. One should thus expect to find a relationship between food commodity prices and crude oil prices. Although the impact of higher crude prices on the demand and supply of grains and oilseeds takes time, efficient futures markets should anticipate these effects.

2.2 Price Co-movement: Correlations

A number of authors have emphasized the increased co-movement of food prices (and indeed on commodity prices generally) with crude oil prices, stock market returns and exchange rate changes over the recent past. There is little dispute in relation to the facts. Büyükşahin, Haigh and Robe (2010) document that the correlation between equity and commodity returns increased sharply in the latter part of 2008 following the Lehman collapse. UNCTAD (2011) reports that the rolling correlation between crude oil returns and returns and on the S&P 500 equity index has grown steadily since 2004. Tang and Xiong (2012) find similar rises in the rolling correlations between crude oil returns and both agricultural and non-agricultural commodity futures prices. Bicchetti and Maystre (2012) use high frequency data to document a jump in the moving correlation in the returns on various commodity futures (including CBT corn, soybeans and wheat, CME live cattle and ICE sugar) and S&P 500 futures returns.

Gilbert and Mugera (2012) show that the conditional correlations, generated from a multivariate Dynamic Conditional Correlation (DCC) GARCH model (see Engle, 2002), between daily returns on WTI crude oil and respectively CBOT corn, soybeans and wheat rose sharply from around 2006.

We estimate monthly logs averages of agricultural food commodities and Brent (ICE) crude oil prices. We then estimate and statistically test the correlations between the two sets of prices. The correlations are estimated for two sub-periods 2000-06 and 2007-11. We then test whether the change in correlations between the two periods respectively is statistically significant. These estimates are charted and represented in Figure 3. Dark colours indicate statistically significant increases in correlation (at the 5% significance level).

With the single exception of bananas, price changes are all positively correlated with changes in the price of crude oil in the 2007-11 sub-period while in the earlier period they are small and do not exhibit any consistent sign. The correlation between crude oil and the commodities increases from 2000-06 to 2007-11 with the exception of the crude oil-bananas correlation. 11 out of 19 of the increased correlations are statistically significant. This is particularly the case for all the grains except rice, all the oil seeds and additionally for lamb. This is the same broad group of food commodities for which the volatility increases were seen as significant.

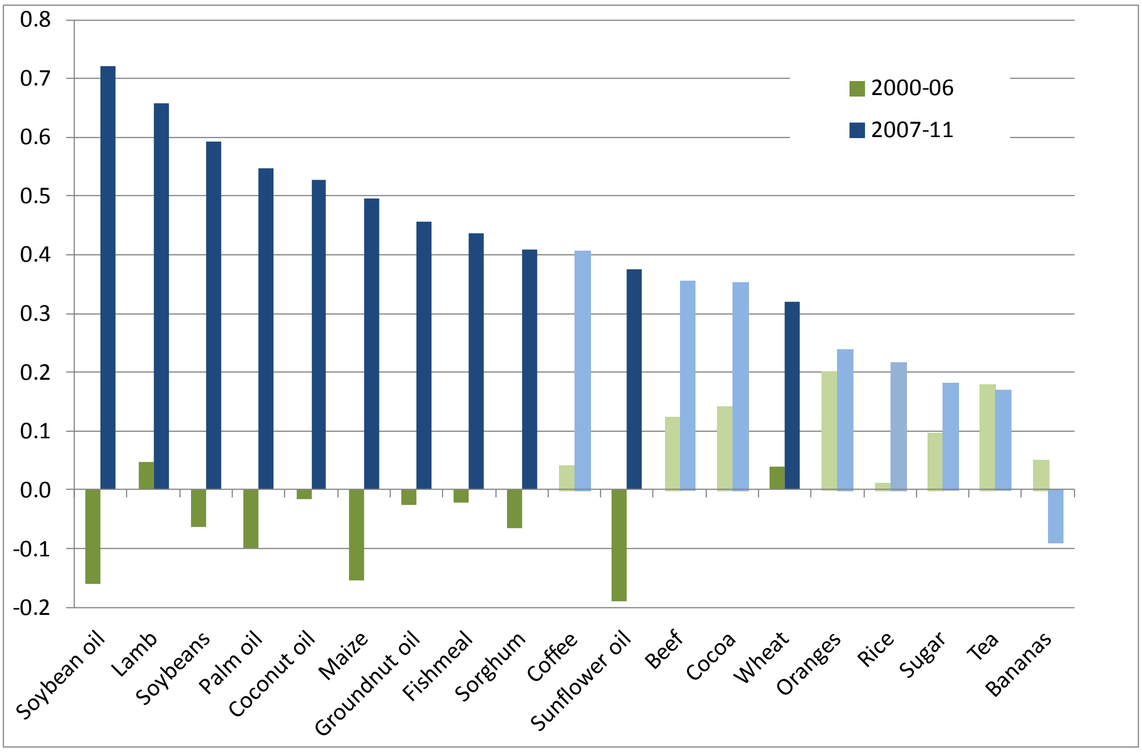

Figure 3: Correlations, Changes in Food and Crude Oil Prices, 2000-06 and 2007-11

Figure 4 repeats the same exercise substituting S&P industrial monthly returns for crude oil price changes. The same pattern of increased correlations can be observed but in this case, the magnitude of the 2007-11 correlations are generally lower (except for coconut oil) and very few of the increased correlations observed and tested are statistically significant (only 6 out of 11 are statistically significant).

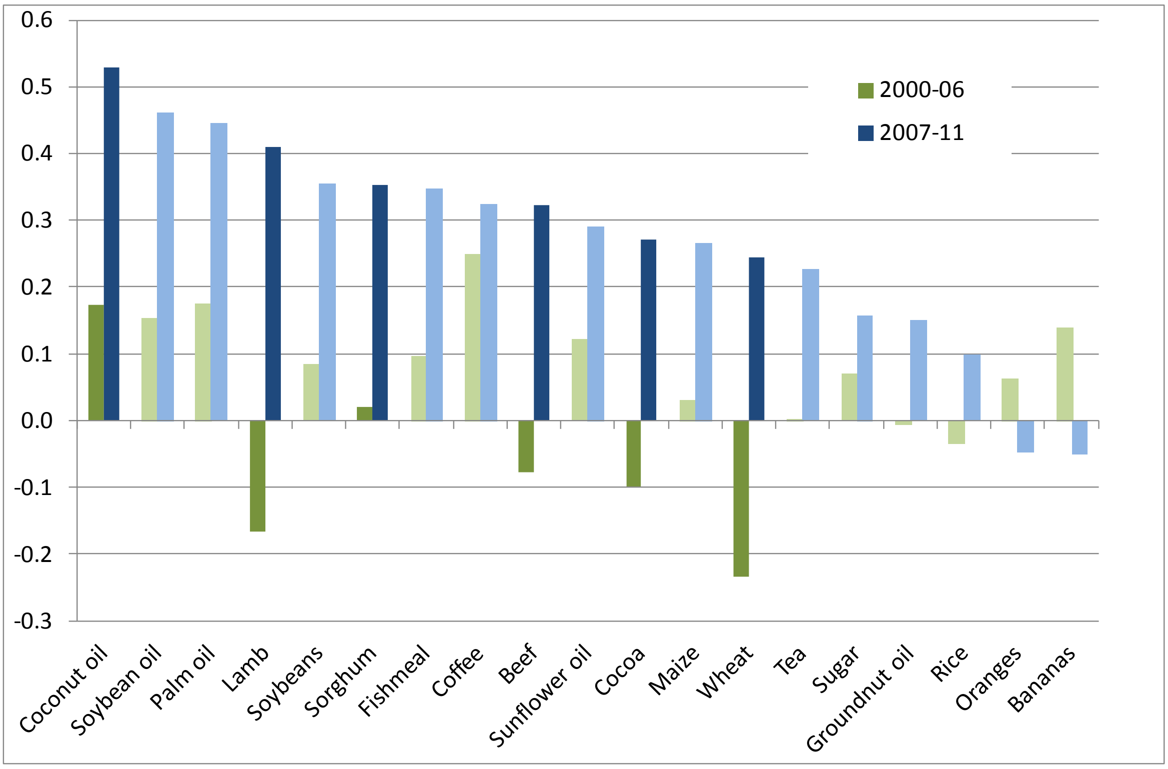

Figure 4: Correlations, Changes in Food Prices and S&P Returns, 2000-06 and 2007-11

The correlations reported in Figures 3 and 4 demonstrate that the increase in co-movement between agricultural food commodities has been more dramatic with crude oil prices than that with share prices. Since changes in crude oil prices are themselves correlated with equity returns, it seems possible that co-movement of food commodity prices with equity prices, stressed by Büyükşahin, Haigh and Robe (2010) and Bicchetti and Maystre (2012) may be largely accounted for as an indirect impact of changes in crude prices.

We therefore estimate and statistically test the partial correlations first of food commodities and equity, holding crude oil prices constant and then food commodities with crude oil, holding equity returns constant.. Table 1, which reports the partial correlations of food commodity prices and respectively crude oil prices and equity returns, demonstrates that this is indeed correct. The partial correlations of food commodity prices and the equity returns, holding crude oil prices constant, showed only a modest increase between 2000-06 and 2007-11 (Table 1, columns 3 and 4) while that between food commodity and crude oil prices, holding share prices constant, rose sharply (Table 1, columns 1 and 2).

It is therefore the increased comovement of food commodity crude oil prices which requires explanation, as emphasized by UNCTAD (2011), Tang and Xiong (2012) and Gilbert and Mugera (2012) provide two rival explanations. Tang and Xiong (2012) see this as a financialization effect. According to their view, the increased correlation arises as index investors buy or sell “on block” the entire range of commodity futures included in the two major commodity indices of which crude oil is the single most important by index weight. They claim that the comovement is greater for commodities included in indices than for those less liquidly contracts outside the indices. Figure 5 fails to bear out this contention with respect to the comovement of food commodity and crude oil prices.

The alternative view, stressed by Gilbert and Mugera (2012), is that the comovement arises instead from the biofuels link whereby the profitability of diverting grains (essentially corn) into ethanol production and vegetable oils (largely oil seed rape and palm oil) into the production of biodiesel.

Table 1 **Partial Correlations**				
	Brent crude		S&P Industrials	
	2000-06	2007-11	2000-06	2007-11
Cocoa	0.1277	0.2615	-0.0762	0.2615
Coffee	0.0883	**0.3007**	**0.2604**	0.1428
Tea	0.1833	0.0686	0.1058	0.1673
Sugar	0.1105	0.1204	0.0889	0.0794
Oranges	**0.2163**	**0.3013**	0.1068	-0.1934
Bananas	0.0768	-0.0755	0.0500	0.0000
Beef	0.1131	0.2387	0.0566	0.1808
Lamb	0.0200	**0.5739**	-0.1616	0.1304
Wheat	0.0000	0.2360	**-0.2313**	0.1058
Rice	0.0624	0.1944	0.0100	-0.0100
Maize	-0.1513	**0.4343**	0.0000	0.0283
Sorghum	-0.0624	**0.2879**	0.0100	0.1903
Soybeans	0.0500	**0.5138**	0.0742	0.0900
Coconut oil	0.0141	**0.3604**	0.1726	**0.3633**
Soybean oil	-0.1378	**0.6392**	0.1288	0.1764
Groundnut oil	-0.0283	**0.4441**	-0.0100	-0.0964
Palm oil	-0.0707	**0.4199**	0.1606	0.2410
Sunflower oil	-0.1720	**0.2782**	0.0933	0.1304
Fishmeal	0.0000	**0.3245**	0.0943	0.1694
Average	0.0232	0.3117	0.0491	0.1135

Columns 1 and 2 give the partial correlations of the change in the row price holding the Brent crude price constant. Columns 1 and 2 give the partial correlations of the change in the row price holding the S&P Industrials index constant. Bold face indicates statistical significance at the 95% level.

2.3 Effects of Biofuels

Biofuels have two main distinguishable effects. The first effect is that it raises the price levels due to diversion of supplies from food and feed consumption. This happens directly via competition between food and feed users and biofuel users for the same grain, but also indirectly, through the substitution of one grain, such as maize diverted to biofuel feedstock from use as food or feed rations, leading to substitution of a food grain, such as wheat, into animal feed. Soybeans are most directly affected by the demand for corn-based ethanol as corn and soybeans tend to compete for land area and can be used in rotation[5].

The U.S. expanded maize area by 23 percent in 2007 in response to high maize prices and rapid demand growth for maize for ethanol production. This expansion resulted in a 16 percent decline in soybean area which reduced soybean production and contributed to a 75 percent rise in soybean prices between April 2007 and April 2008. The expansion of biodiesel production in the EU diverted land from wheat and negatively affected wheat production and stock levels. This was in response to the increased demand and rising prices for oilseeds, land cultivated for oilseeds - particularly rapeseed - increased. Oilseeds and wheat are grown under similar climatic conditions and in similar areas and most of the expansion of rapeseed and sunflower displaced wheat or was on land that could have been used for wheat cultivation (Mitchell, 2008).

Grains prices also affect the price of meat and dairy products because grain is used as feed. Livestock feeding is the largest single use of corn and cattle, hogs, and poultry all use corn feed, thus the expansion in the ethanol industry does affect livestock

[5] In 2007-2008, the price of corn rose substantially reflecting the increase in demand, the cropping pattern changed, with more corn production relative to soybeans. This led to a decrease in overall soybean production and increased its price.

production. Prices will adjust quickly for some such as chicken, milk and eggs, but take more time for others such as beef and pork. The price adjustment period reflects the length of time farmers need to adjust their stock (supply) in response to the higher feed prices (Gilbert 2010).

The second effect of biofuels is it may increase the volatility of food prices. Gilbert and Morgan (2010) note that the volatility of any commodity price depends on the variances of shocks to production and consumption in conjunction with the elasticity of supply and demand. Within this framework, the biofuels link may be seen as introducing an additional source of demand variability – see Wright (2011) who emphasizes the transmission of energy market shocks into food commodity markets – and, if biofuel mandates are inflexible, as decreasing demand elasticities. The main focus of the current chapter is on these volatility links.

2.4 Linkages between Commodity and Crude Oil Markets

The direct production function that links crude oil prices to food commodity prices is well-documented. Using different methodologies, Baffes (2007), Mitchell (2008) and Gilbert (2010) agree in seeing an energy price pass-through to grains prices of between 15 and 20 per cent. It is unlikely that this has changed over recent years. The indirect links, via the use of food commodities as biofuel feedstocks, are more difficult to quantify, in part because of the shortness of the relevant biofuels time series. Moreover, few of the formal models have been able to capture the cross-commodity supply and demand linkages between corn – the primary grain used to make ethanol – and other commodities such as soybeans, wheat, and other feed grains.

Gilbert (2010) used Granger-causality (GC) tests to examine the link between crude oil prices and both the IMF's agricultural food price index and a grains sub-index. In both cases, his results showed a negative impact Granger-causal in the two decades up to 1989 and a positive Granger-causal impact in the two more recent decades. The pre-1989 results may reflect the fact that, over that period, the developed economies lacked a clear monetary anchor and hence a rise in oil prices would likely be met by a tough anti-inflationary monetary tightening. The production function pass-through-impact of higher oil prices only becomes apparent once the credibility of inflation targeting had been established.

Tyner (2010) confirms that since the ethanol boom took off in 2006, the correlation between energy and agricultural markets has been strong. He highlights the summer of 2008 as the period where these two markets were closely linked. As crude oil price increased so did the price of corn and other agricultural commodities. And when crude oil prices started to decline after the summer of 2008, so did the prices of most agricultural commodities. He highlights the blending wall as the determinant to this link. This factor is particularly influential in the case of high crude oil prices. Since ethanol production is limited by the blending wall, when crude oil prices are high, and the corn price increase is dampened. Thus the crude-corn price link that has been established could be significantly weakened at high crude oil prices because of the blending wall limit (Tyner, 2010).

By conducting forward looking analysis, Thompson et al., (2009) use the results of partially stochastically simulations to assess correlations of key market indicators. Their results show that market developments and policy changes not only determined the intensity of links between energy and agricultural markets but also changed the nature of these links (Thompson et. al., 2009).

Tang and Xiong (2010) emphasize financialization as an alternative explanation of the increased correlation between crude oil and food prices. Food commodities are considered as part of the “commodity asset class”. Financial flows into commodity futures, including those for food commodities; - result from - calculations of likely returns on commodities, generally considered as a group, relative to those on equities and bonds. On this view, financialization implies that food commodity prices may be influenced by financial market factors, such as the aggregate risk appetite for financial assets, and investment behaviour of diversified commodity index investors, as well as by demand and supply of the physical market fundamentals. Their research is based on empirical evidence from a 5 year-database as some of their data are only available from 2004. The length of the database is relatively short to be able to fully capture the changes in the commodity risk premium, which is one of the key financial factors identified in determining investment behaviour and the prices of individual commodities.

2.5 The Generalised Autoregressive Conditional Heteroskedasticity Framework

The AutoRegressive Conditional Heteroscedasticity (ARCH) process was first introduced by Engel (1982) in order to allow for conditional variance to vary as a function of past shocks while maintaining the unconditional variance constant. The now standard Generalized ARCH (GRACH) process, introduced by Bollerslev (1986), allows a more flexible and parsimonious representation of the variance (scedastic) process. GARCH models specify an AutoRegressive Moving Average (ARMA) process for the scedastic process followed by a time series to yield an estimate of the conditional variance of the process at each date in the sample. We follow standard practice in adopting a GARCH (1,1) specification which includes a single lagged squared error (the ARCH term) and a single lag on the lagged conditional variance (the GARCH term). The model is represented as follows:

$$r_t | r_{t-1}, r_{t-2}, \dots \sim N(\mu, h_t)$$

$$h_t = \omega + \alpha(r_{t-1} - \mu)^2 + \beta h_{t-1}$$

$$\text{where } \omega > 0 \; and \; \alpha, \beta \geq 0 \tag{1.1}$$

Multivariate GARCH (MGARCH) Models

Bollerslev et al. (1988) provided a framework for multivariate GARCH (MGARCH) analysis. The multivariate framework allows one to jointly estimate volatilities measures. The general MGARCH (1,1) model for an *m*-dimensional vector *r* of returns is

$$r_t \,|\, r_t, r_t, \dots \sim N(\mu, H_t)$$

$$h_{jit} = \omega_{ji} + \sum_{k=1}^{m} \sum_{l=1}^{k} \alpha_{jik}(r_{k,t-1} - \mu_k)(r_{l,t-1} - \mu_l) + \sum_{k=1}^{m} \sum_{l=1}^{k} \beta_{jkl}\, h_{kl.t-1}$$

$$h_{ijt} = h_{jit} \qquad (j = 1, \dots, m; i = 1, \dots, j)$$

$$(j = 1, \dots, m; i = 1, \dots, j-1)$$

$$\tag{1.2}$$

This representation is problematic if the dimensionality *m* of the return vector exceeds two, firstly because the model becomes highly parameterized – the number of parameters is $2m+½m^2(m+1)^2$ – and secondly because it is difficult to impose positive definiteness of the conditional variance matrix H_t at every date in the sample. For these reasons, the literature has tended to work with simplified versions of the general MGARCH model.

Two radically simplified versions of the MGARCH model are commonly used. The first is the constant conditional correlation MGARCH (CCC-MGARCH) model introduced by Bollerslev (1990). In the diagonal case, this has the structure

$$\begin{gathered} r_t \mid r_{t-1}, r_{t-2}, \ldots \sim \mathrm{N}(\mu, \mathrm{H}_t) \\ h_{jjt} = \omega_{jj} + \alpha_{jj}\left(r_{j,t-1} - \mu_j\right)^2 + \beta_{jj} h_{jj,t-1} \qquad (j = 1, \ldots, m) \\ h_{jit} = \rho\sqrt{h_{jjt} h_{jit}} \\ (j = 1, \ldots, m; i = 1, \ldots, j) \qquad h_{ijt} = h_{jit} \\ (j = 1, \ldots, m; i = 1, \ldots, j-1) \end{gathered} \tag{1.3}$$

The scedastic equation in (1.3) may be written more compactly as:

$$H_t = D_t R D_t \text{ where } D_t = \mathrm{diag}\left(h_{11t}^{-\frac{1}{2}}, \ldots, h_{mmt}^{-\frac{1}{2}}\right)' \tag{1.4}$$

and $R = (\rho_{ij})$ is a constant positive definite correlation matrix. This reduces the parameterization to $4m+\frac{1}{2}m(m+1)$ but the imposition of positive definiteness remains difficult except in the equicorrelation case in which $R = \begin{pmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \cdots & \rho \\ \vdots & \vdots & \ddots & \vdots \\ \rho & \rho & \cdots & 1 \end{pmatrix} = (1-\rho)I + \rho\ell\ell'$ where ℓ is the vector of units.

The second model is dynamic conditional correlation (DCC-MGARCH) model introduced by Engle (2002) and is defined by:

$$r_t \mid r_{t-1}, r_{t-2}, \ldots \sim \mathrm{N}\left(\mu, \mathrm{H}_t\right)$$

$$H_t = (1-\alpha-\beta)\bar{H} + \alpha\left(r_{t-1}-\mu\right)\left(r_{t-1}-\mu\right)' + \beta H_{t-1}$$

(1.5)

where $\bar{H}$ is the unconditional variance-covariance matrix and α and β satisfy $\alpha, \beta > 0$ and $\alpha + \beta < 1$. The time-varying conditional correlation matrix is now $R_t = D_t^{-1} H_t D_t^{-1}$.

This is a highly parsimonious specification – given the unconditional matrix n$\bar{H}$, the model contains only 3 additional parameters. Positive definiteness is guaranteed by the conditions on α and β.

Consider a model for *k* > 1 commodity futures prices. Set crude oil as commodity 1 so that the remaining commodities are 2, …, *k*. The standard DCC model treats the *k* prices symmetrically so that equation (4) states

$$h_{jj,t} = \left(1-\alpha-\beta\right)\bar{h}_{jj} + \beta h_{jj,t-1} + \alpha\left(r_{jt}-\mu_{jt}\right)^2 \qquad \left(j=1,\ldots,k\right)$$
$$h_{ji,t} = h_{ij,t} = \left(1-\alpha-\beta\right)\bar{h}_{ji} + \beta h_{ji,t-1} + \alpha\left(r_{jt}-\mu_{jt}\right)\left(r_{it}-\mu_{it}\right) \quad \left(j=1,\ldots,k; i=1,\ldots,j-1\right)$$

(1.6)

We first estimate univariate CCC-MGARCH (1,1) models for the three major Chicago Board of Trade (CBOT) grains included in the tradable indices (wheat, corn and soybeans) and also crude oil[6] over the complete sample of daily observations from January 2000 to December 2011 (2972 observations). In each case, data are for the daily front futures contract rolled on the first day of the expiration month.

6 We use the ICE Brent contract rather than the NYMEX WTI contract since limitations on the availability of storage in Cushing (OK) in 2010-11 resulted in the WTI price becoming less representative of world prices than Brent over that period.

In each of the MGARCH models we include corn, wheat and crude oil over the complete sample of daily observations from January 2000 to December 2011.

We estimate the model over the entire sample of daily data from 2000 to 2011 as well as for two sub-samples 2000-06 and 2007-11[7].

2.6 Grains market volatilities

Tables 2 and 3 report estimates of the CCC-MGARCH model for crude oil and the three grains (corn, wheat and soybeans). The algorithm calculates the univariate GARCH(1,1) model for each series and then estimates the correlations from the GARCH residuals. The CCC-MGARCH estimates are given in Table 2 and the associated correlation matrices in Table 4.

There are some notable features of these estimates.

- Although the volatility processes are close to being non-invertible, we fail to reject the restriction $\alpha + \beta = 1$ only in the case of corn estimated over the complete sample. The same restriction is rejected over the two sub-samples. (Table 2, penultimate row).
- The Chow test rejects decisively homogeneity across the two sub-samples. (Table 2, final row).
- The correlations between Brent crude returns and grains returns rise dramatically across the two sub-periods from under 0.1 to between 0.3 and 0.5. The most dramatic rise is in the soybean-crude oil correlation with wheat being the least affected.

[7] Results for the CCC-DCC MGARCH analysis for corn, wheat and soybeans are reported. Further empirical analysis is available upon request.

- Return correlations for the three grains are broadly constant across the two sub-periods in the 0.5-0.6 range with the only marked change being the rise in the wheat-soybeans correlation. (Upper rows of Table 4).
- The final two rows of Table 4 test the hypothesis that the correlations ρ_{0j} (j = 1,2,3) between crude oil (0) and that the three grains are equal and that the correlations λ_{ij} (i,j=1,2,3) between the three grains are equal. The latter hypothesis is decisively rejected while the former is only rejected for the 2007-11 sub-period.

In summary, volatilities appear to have increased across the board but also have a different character over the most recent five years when grains prices have moved much more closely than previously with crude oil prices.

Table 2

CCC-GARCH Estimates

	Brent crude			**Wheat**			**Corn**			**Soybeans**		
	2000-11	2000-06	2007-11	2000-11	2000-06	2007-11	2000-11	2000-06	2007-11	2000-11	2000-06	2007-11
Intercept ω	0.215	0.476	0.066	0.018	0.025	0.276	0.030	0.075	0.156	0.030	0.032	0.037
	(0.071)	(0.155)	(0.032)	(0.011)	(0.017)	(0.162)	(0.013)	(0.029)	(0.155)	(0.010)	(0.014)	(0.017)
ARCH α	0.092	0.105	0.056	0.031	0.021	0.062	0.057	0.082	0.049	0.052	0.049	0.059
	(0.020)	(0.024)	(0.015)	(0.009)	(0.007)	(0.021)	(0.012)	(0.019)	(0.028)	(0.008)	(0.011)	(0.013)
GARCH β	0.864	0.794	0.930	0.965	0.969	0.895	0.936	0.884	0.920	0.936	0.935	0.930
	(0.030)	(0.044)	(0.019)	(0.011)	(0.011)	(0.041)	(0.014)	(0.027)	(0.056)	(0.010)	(0.015)	(0.015)
Log-likelihood	7264.73	4194.31	3081.74	7484.12	4646.95	2851.90	7901.41	4908.14	3012.75	8266.47	4926.52	3346.67
IGARCH	7249.94	4178.31	3078.41	7482.53	4644.50	2845.52	7898.38	4900.95	3006.83	8261.22	4922.29	3334.65
$\alpha + \beta$	0.957	0.899	0.985	0.996	0.991	0.958	0.992	0.965	0.969	0.988	0.984	0.957
$H_0 : \alpha + \beta = 1$	29.58	32.00	6.66	3.18	4.90	12.76	6.06	14.38	11.84	10.50	8.46	24.04
$\chi^2(1)$	[0.0000]	[0.0000]	[0.0099]	[0.0745]	[0.0269]	[0.0004]	[0.0138]	[0.0001]	[0.0006]	[0.0012]	[0.0036]	[0.0000]
Chow test		22.64			38.96			29.46			13.44	
$\chi^2(4)$		[0.0001]			[0.0000]			[0.0000]			[0.0093]	

Sample: 2000-11, 5 January 2000 – 30 December 2011 (2972 observations); 2000-06, 5 January 2000 – 29 December 2006 (1716 observations); 2006-11, 3 January 2000 – 30 December 2011 (1256) observations). Robust standard errors in (.) parentheses; tail probabilities in [.] parentheses.

Table 3

CCC-GARCH Estimates

	Crude oil			**Wheat**			**Corn**			**Oats**		
	2000-11	2000-06	2007-11	2000-11	2000-06	2007-11	2000-11	2000-06	2007-11	2000-11	2000-06	2007-11
Intercept ω	0.214	0.475	0.066	0.018	0.025	0.276	0.030	0.075	0.156	0.248	0.252	0.245
	(0.071)	(0.155)	(0.032)	(0.011)	(0.017)	(0.162)	(0.013)	(0.029)	(0.155)	(0.105)	(0.156)	(0.112)
ARCH α	0.092	0.105	0.056	0.031	0.021	0.062	0.057	0.082	0.049	0.079	0.082	0.077
	(0.020)	(0.024)	(0.015)	(0.009)	(0.007)	(0.021)	(0.012)	(0.019)	(0.028)	(0.019)	(0.027)	(0.022)
GARCH β	0.864	0.794	0.930	0.965	0.969	0.895	0.936	0.884	0.920	0.867	0.862	0.872
	(0.030)	(0.044)	(0.019)	(0.010)	(0.011)	(0.041)	(0.014)	(0.027)	(0.057)	(0.036)	(0.054)	(0.039)
Log-likelihood	7264.86	4194.35	3081.82	7484.22	4647.07	2851.89	7901.34	4908.75	3012.73	7341.38	4285.29	3058.58
IGARCH	7250.09	4178.35	3078.5	7482.64	4644.62	2845.51	7898.31	4900.91	3006.81	7318.76	4272.1	3049.1
$\alpha + \beta$	0.956	0.899	0.985	0.996	0.991	0.958	0.992	0.965	0.969	0.986	0.944	0.949
$H_0 : \alpha + \beta = 1$	29.54	32	6.64	3.16	4.9	12.76	6.06	15.68	11.84	45.24	26.38	18.96
$\chi^2(1)$	[0.0000]	[0.0000]	[0.0099]	[0.0755]	[0.0268]	[0.0004]	[0.0138]	[0.0001]	[0.0006]	[0.0000]	[0.0000]	[0.0000]
Chow test		22.62			29.48			40.28			4.98	
$\chi^2(4)$		[0.0001]			[0.0000]			[0.0000]			[0.2893]	

Sample: 2000-11, 5 January 2000 – 30 December 2011 (2972 observations); 2000-06, 5 January 2000 – 29 December 2006 (1716 observations); 2006-11, 3 January 2000 – 30 December 2011 (1256) observations). Robust standard errors in (.) parentheses; tail probabilities in [.] parentheses.

Table 4

CCC Correlation Matrices

	2000-11			**2000-06**			**2007-11**		
	Wheat	Corn	Soybeans	Wheat	Corn	Soybeans	Wheat	Corn	Soybeans
Brent crude	0.182	0.219	0.234	0.073	0.087	0.064	0.330	0.389	0.456
	(0.018)	(0.018)	(0.018)	(0.024)	(0.024)	(0.024)	(0.026)	(0.024)	(0.022)
Wheat		0.622	0.478		0.599	0.426		0.657	0.546
		(0.012)	(0.015)		(0.015)	(0.019)		(0.017)	(0.022)
Corn			0.619			0.593			0.649
			(0.014)			(0.020)			(0.020)
$H_0 : \rho_1 = \rho_2 = \rho_3$	$\chi^2(2)$ = 6.06 [0.0484]			$\chi^2(2)$ = 0.75 [0.6873]			$\chi^2(2)$ = 32.92 [0.0000]		
$H_0 : \lambda_{12} = \lambda_{23} = \lambda_{31}$	$\chi^2(2)$ = 149.3 [0.0000]			$\chi^2(2)$ = 116.9 [0.0000]			$\chi^2(2)$ =48.72 [0.0000]		

Notes: see Table 2.

The CCC-MGARCH and DCC-MGARCH models simplify the general model in different directions. The CCC-MGARCH model imposes constancy on the conditional correlations but allows the univariate variance processes to remain unrestricted. The DCC-MGARCH model on the other hand, allows the conditional correlations to be time varying but imposes homogeneity on the variance processes. In comparing the CCC-GARCH estimates over the earlier and later sub-periods, it was the correlations that varied more than the variance parameters. This motivates the use of the DCC-GARCH model. Results are reported in Table 5.

The DCC-GARCH model registers higher log-likelihoods both for each sub-sample and for the entire sample compared to the CCC-GARCH model reported in Table 6. As in the CCC-GARCH model case, the Chow test rejects homogeneity.

Table 5

DCC-GARCH Estimates

	2000-11	**2000-06**	**2007-11**
ARCH α	0.018 (0.003)	0.012 (0.007)	0.021 (0.003)
GARCH β	0.971 (0.005)	0.979 (0.022)	0.964 (0.007)
Log-likelihood	32646.3	19484.8	13239.2
Chow test $X^2(24)$	155.4 [0.0000]		

Sample: 2000-11, 5 January 2000 – 30 December 2011 (2972 observations); 2000-06, 5 January 2000 – 29 December 2006 (1716 observations); 2006-11, 3 January 2000 – 30 December 2011 (1256) observations). Robust standard errors in (.) parentheses; tail probabilities in [.] parentheses.

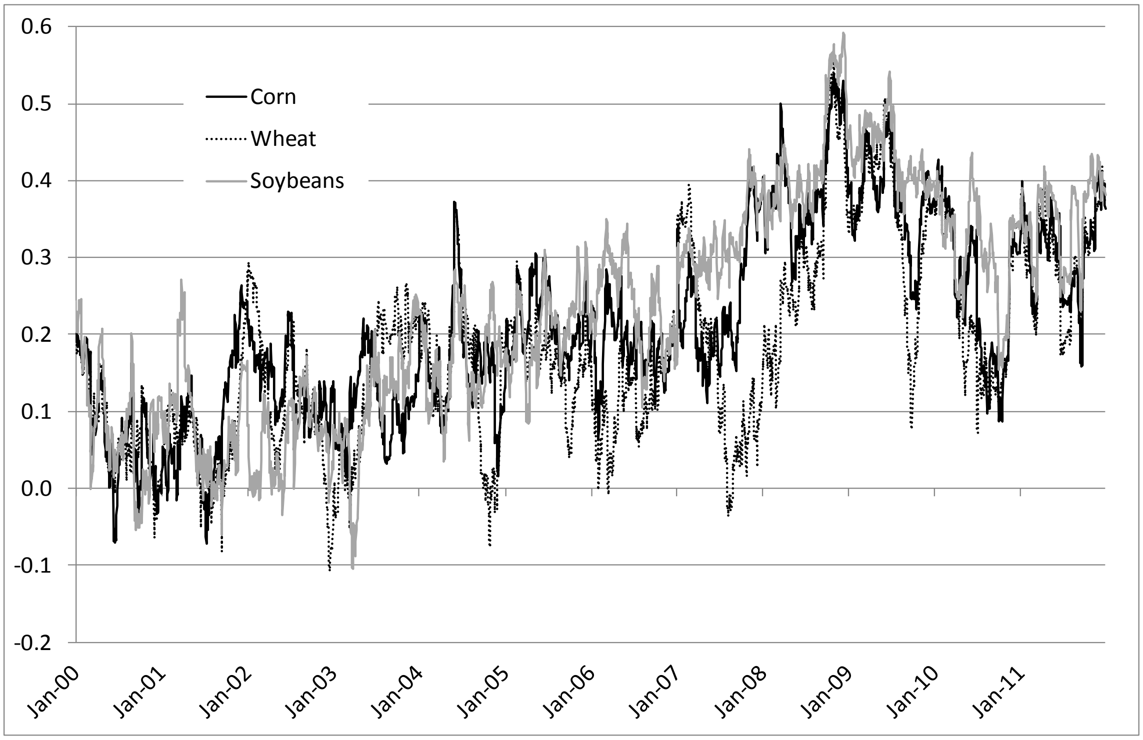

Figure 5: Conditional correlations – grains and crude oil

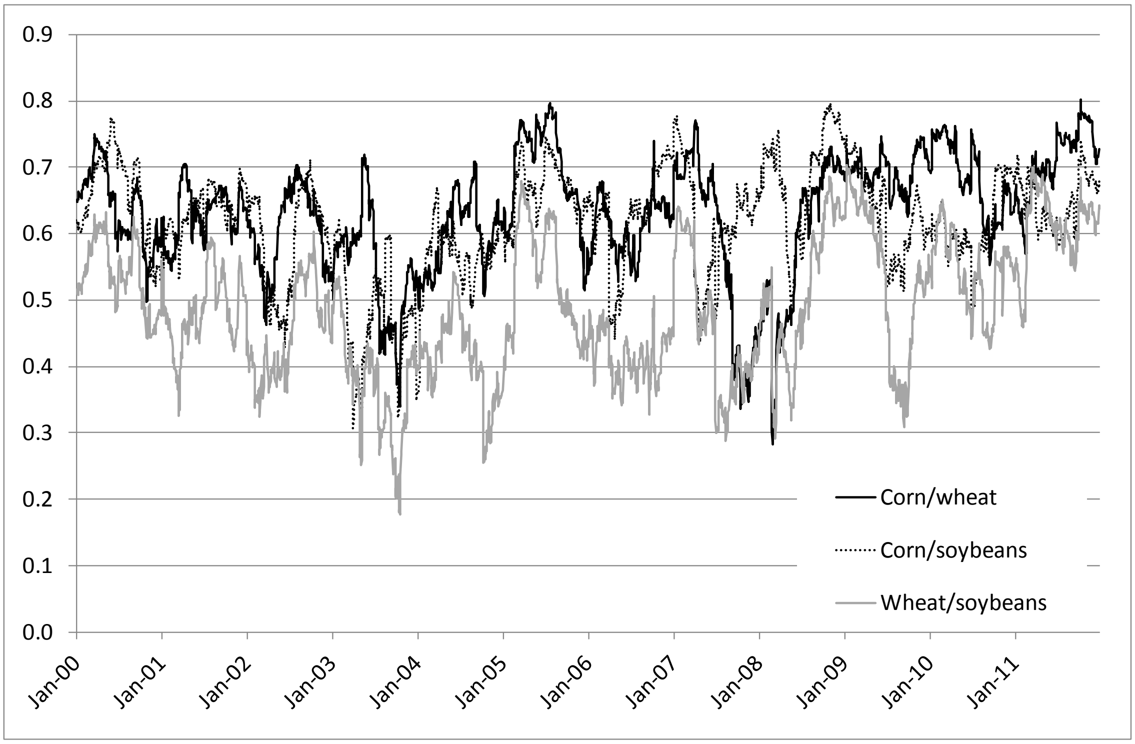

Figure 6: Conditional grains correlations

Figure 5 shows the conditional correlations of Brent crude returns with the three grains taken from the model estimated over the complete sample.[8] These conditional correlations rise from around 0.1 in 2000-03 to around 0.2 in 2004-06, to over 0.4 in 2008-10 and then fall back to around 0.3 in 2011. The corn and conditional crude oil correlations move closely together (r = 0.872) while the wheat conditional correlation is more idiosyncratic (r = 0.781 with corn and r = 0.719 with soybeans).

Figure 6 charts the inter-grain conditional correlations. Although the conditional correlations vary over time, they do not show any tendency to move out of their long term

[8] The conditional correlations from the models from the two sub-samples show a sharp jump at the break date.

0.4 – 0.7 range. These charts confirm the CCC-GARCH finding that it is the crude oil – grain correlations that have changed.

2.8 Volatility decomposition

The proposed decomposition model is based on the simple regression

$$\Delta \ln p_{jt} = \kappa_{jt} + \gamma_{jt} \Delta \ln q_t + \varepsilon_{jt} \tag{1.7}$$

where:

$\ln p_j$: logarithmic prices of corn, wheat and soybeans

$\ln q$: logarithmic price of crude oil

ε_j: idiosyncratic error

First consider the standard representation in which the two coefficients κ_j and γ_j are constant over time. The result is a two-way decomposition.

The regression (1.7) is not proposed as structural or causal but is simply a means of obtaining the standard orthogonal decomposition of the variance of each price into a component which lies in the crude oil price space and one in the corresponding null space. We nevertheless interpret the γ_j coefficients as measures of pass-through on the basis that the grains tail cannot wag the crude oil dog. However, it remains true that elevated γ_j coefficients may also reflect an increase in shock commonality.

We use the DCC-MGARCH model to allow κ_j and γ_j to evolve over time. This is comparable to, but not identical to, estimating regression (1.7) recursively or using a rolling window. It generates a third element to the decomposition arising out of the changing correlation between crude oil and grains prices.

This methodology therefore allows one to decompose the conditional volatilities for corn, wheat and soybeans into variations in three main components:

- commodity specific volatility;
- crude oil volatility;
- the pass-through coefficient.

The conditional volatility for each of the three grains is therefore:

$$Var\left(\Delta \ln p_j\right) = \gamma_j^2 Var\left(\Delta \ln q\right) + Var\left(\varepsilon_j\right) \tag{1.8}$$

We apply this decomposition to the DCC conditional variances discussed in the previous section estimating the pass through coefficients γ_j by the ratio of the conditional grain-crude oil covariances to the conditional crude oil variance. Using the estimated DCC-MGARCH we conduct counterfactual decompositions for each of the grains conditional volatilities. From these estimates we are able to retrieve the three components. Estimate the average volatility values of 2000-05. We simulate the volatility components of each of the grains, holding constant the other components. In this way we are able to isolate the effects of each of the components over time.

The DCC-MGARCH model gives continuous estimates which can be comparable to a recursive regression. While the recursive regression estimates constant parameters over time. DCC-MGARCH model gives an estimate of evolving parameter over time (given that $\beta<1$).

Figure 7 shows the volatility decomposition for corn. Corn volatility is dominated by idiosyncratic volatility. The gamma and crude oil volatility components remain relatively stable and insignificant from 2005. They become very significant from mid-2008 when crude oil prices are high. In particular the WTI-γ component that represents the pass-through coefficient of shocks from crude oil to corn rises in 2008. The high crude oil prices are transmitted into corn price volatility as both the «pass-through coefficient» beta and crude oil volatility are significant. Crude oil prices are important in explaining the 2008-09 increase in grains volatility.

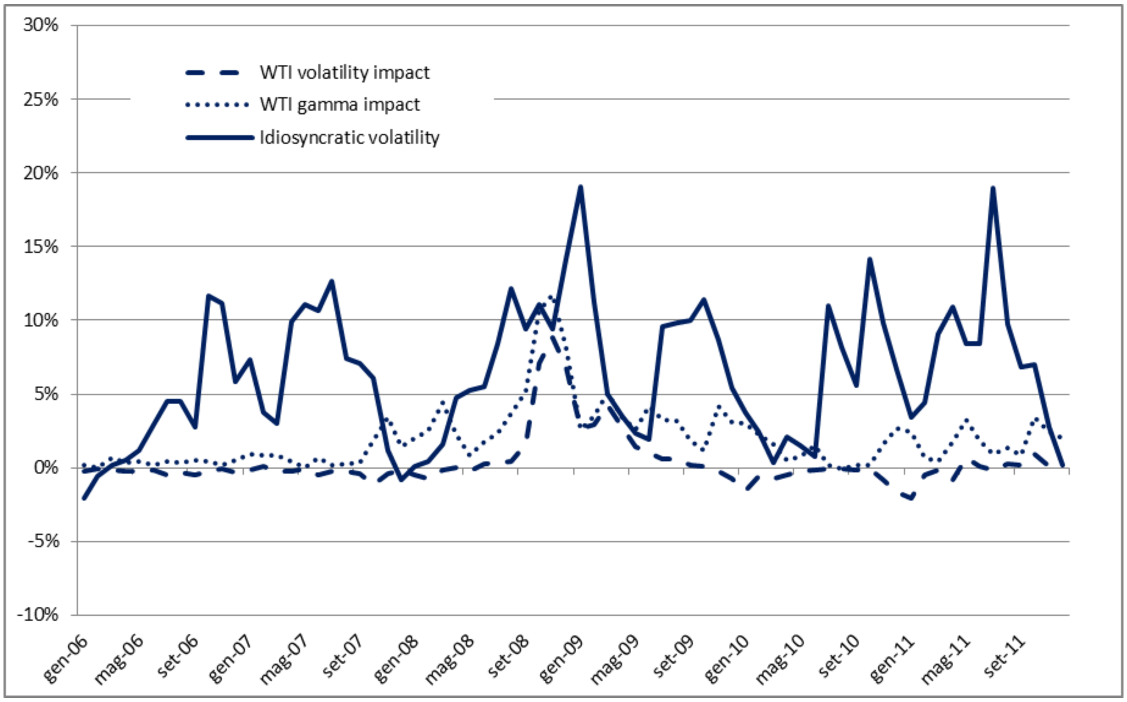

Figure 7: Corn price volatility decomposition

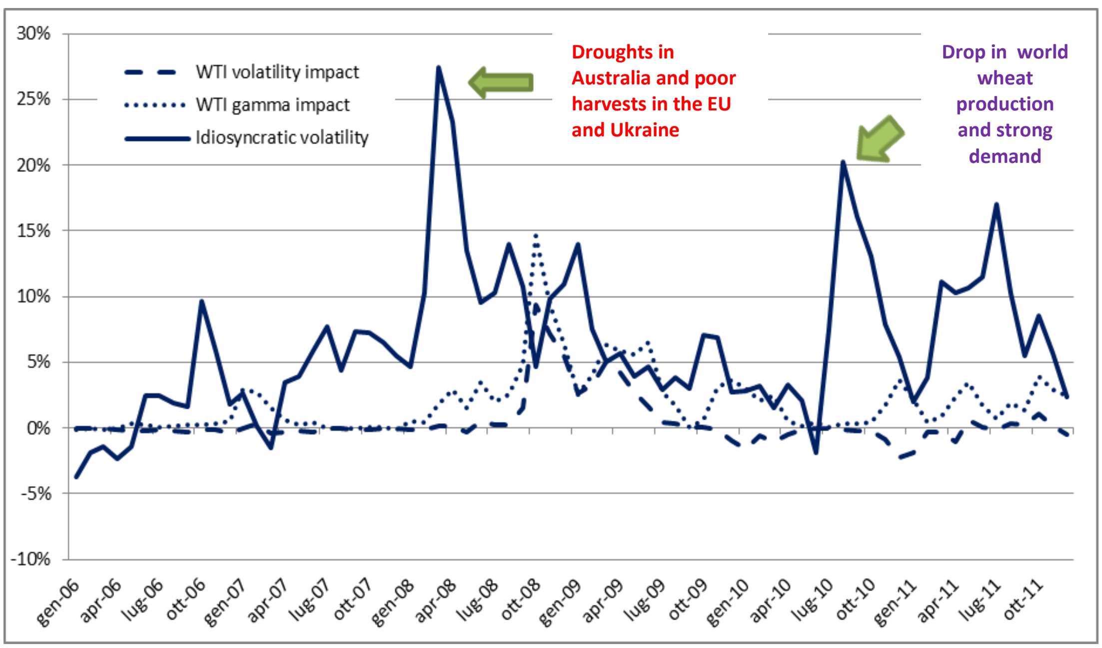

Figure 8: Wheat price volatility decomposition

Figure 8 reports the volatility decomposition over time for wheat. As in the case of corn, both the WTI-γ and WTI volatility components remain dormant from 2006 and then sharply rise in 2008. The idiosyncratic component is also relatively stable over time apart from two significant peaks. The first occurs in 2008 where droughts in the Australia and poor harvests in the European Union and Ukraine rendered wheat prices volatile. The second is in 2010 where the combined effects of a strong demand and fall in world wheat production increased volatility in wheat prices.

The soybeans volatility decomposition is represented in Figure 9. The idiosyncratic component of volatility is important and relatively stable over time. As in the previous cases, both the WTI-volatility and WTI-γ components are important in 2008 in explaining the conditional volatility of soybeans.

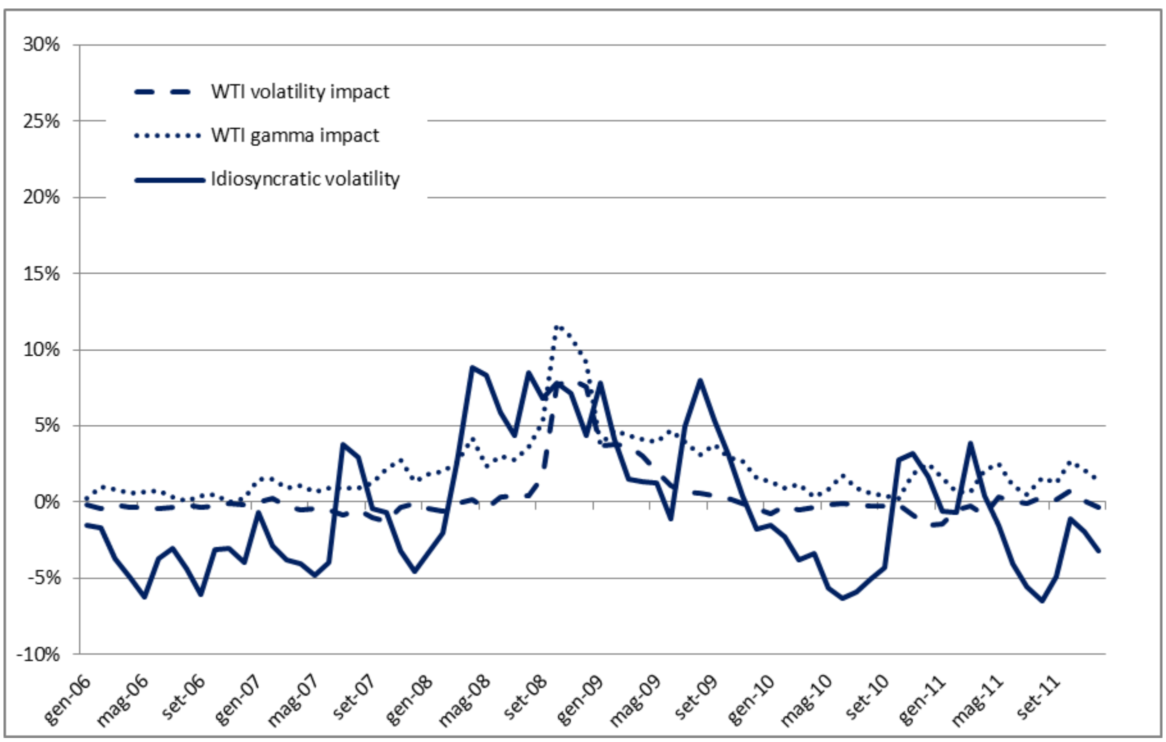

Figure 9: Soybeans price volatility decomposition

Table 6 looks specifically at the volatility impacts of changes in the pass-through coefficients γ_j over the period of the food price spike and the financial crisis. The first three columns give actual conditional volatilities; the second block of three columns gives the counterfactual volatilities obtained by holding the pass-through coefficients γ constant at their average 2000-05 values; while the third block reports the differences.

The differences are all positive indicating that increased pass-through was seen as a contributory factor to higher grains volatility over this period. However, the effects are generally modest accounting for only around 2% - 3% of the 10% - 15% volatility increases. The single exception is the final quarter of 2008 when both crude oil and grains prices suffered a sharp fall. The impact of increased pass-through rises to over 10% in this quarter.

Table 6
Volatility impacts of elevated pass-through

	Actual Volatility			**Counterfactual Volatility**			**Pass-through Impact**		
	Corn	**Wheat**	**Soybeans**	**Corn**	**Wheat**	**Soybeans**	**Corn**	**Wheat**	**Soybeans**
2007q1	29.2%	30.4%	22.7%	28.3%	28.0%	21.4%	0.9%	2.4%	1.3%
2007q2	34.5%	32.4%	20.3%	34.1%	32.0%	19.5%	0.4%	0.4%	0.9%
2007q3	32.9%	33.8%	27.2%	32.6%	33.8%	26.2%	0.3%	0.0%	1.0%
2007q4	28.3%	34.0%	23.2%	26.0%	34.0%	21.0%	2.3%	0.0%	2.1%
2008q1	27.3%	43.0%	25.2%	24.3%	42.1%	23.0%	3.0%	0.9%	2.2%
2008q2	30.7%	47.2%	35.9%	29.0%	44.6%	32.7%	1.6%	2.6%	3.2%
2008q3	38.8%	43.6%	35.5%	35.1%	40.5%	31.6%	3.7%	3.1%	3.9%
2008q4	50.2%	49.2%	44.2%	40.1%	39.0%	33.7%	10.1%	10.2%	10.6%
2009q1	41.2%	42.5%	34.1%	37.5%	38.2%	29.8%	3.8%	4.3%	4.3%
2009q2	30.0%	39.9%	29.2%	26.8%	33.8%	25.2%	3.2%	6.1%	4.1%
2009q3	36.4%	33.3%	33.7%	33.4%	31.2%	29.8%	3.0%	2.0%	3.8%
2009q4	35.7%	35.9%	27.0%	32.9%	33.5%	24.7%	2.8%	2.4%	2.4%

The table compares actual conditional volatilities (daily, converted to an annual rate) with counterfactual conditional volatilities holding the pass-through coefficients γ constant at their average 2000-05 values.

CONCLUSIONS

Food commodities prices increased and become more volatile in the recent decade attracting the attention of market participants and policy makers. Sharp increases in agricultural prices are not uncommon, but it is rare for two price spikes to occur within 3 years as they normally occur with 6-8 year intervals. The short period between the recent two price surges has therefore drawn concerns and raised questions on the causes and future prospects of commodity markets. The price spikes were also accompanied by more volatile food commodity prices. There are many competing explanations for the rise in food price volatility over recent years. Biofuels have been identified as one of the main drivers of high and volatile food prices in the recent decade. High fuel prices combined with legislative policies have been accused of increasing biofuel production causing high food prices and potentially established a link between energy and agricultural prices.

There has always been a direct impact of energy prices on food prices through input and transportation costs. However, the intensity of the link between the oil price and food prices has increased over the most recent period and it may have been driven by an increased biofuel production.

This chapter has two main objectives. Firstly, it established whether commodity markets have become more volatile in recent times. Secondly, it analysed the nature of relationship between commodity and crude oil prices. In particular, it aimed at studying the evolution of this relationship considering the role played by biofuels. A short and a long term historical volatility measure were calculated for different commodities in order to evaluate whether commodity markets have become more volatile in recent times. It investigated whether the volatility in food commodities is now driven by the transmission of shocks from the crude oil market as a result of increased biofuel production and consumption. This chapter employed Multivariate General Autoregressive Heteroskedasticity (MGARCH). Conditional correlations were calculated from MGARCH models estimated on daily data over the twelve year sample 2000-201. Using the estimates from the Dynamic Conditional Correlation (DCC) Multivariate GARCH models specification, it decomposed volatility of food commodities into its main components.

The results obtained in this chapter lead to the following considerations and remarks. Firstly, considering long term volatility, it emerged that commodity prices are less volatile today than they were in the previous decades. Volatility measure in most recent periods however, highlighted that there has been an increase in the volatility for grains, some vegetable oils, and meat prices. This concentration of volatility increases in grains, sunflower oil and beef was consistent with biofuels, having played a major role as these commodities are either directly or indirectly affected by biofuels. Notably, however, there did not appear to be a significant increase over this comparison period in crude oil volatility. This result indicates that increased volatility in food commodity prices may be due to the transmission of price changes from crude oil to the food commodity prices.

Secondly, the results from the MGARCH models showed that even though one cannot directly argue that increased volatility in commodity markets was due to crude oil price volatility, the conditional correlations between the grains and crude oil prices of these price series have moved much more closely than previously with crude oil prices. The increased co-movement between crude oil and grains occurs when biofuel production was on the increase and crude oil prices are on the rise. The results from this analysis confirmed the above trend for commodities that are included in tradable indices such as corn, wheat, and soybeans.

Even though one cannot directly link higher food price volatility to biofuels, there is evidence that higher grains price volatility was at least in part due to greater transmission of oil price shocks to the grains markets. The nature of the “pass through” mechanism from crude oil to commodity markets has changed and may have been determined by biofuels. This chapter provides empirical evidence that increased volatility in grains during the 2008-09 spike was partly due to increased transmission of shocks from the crude oil market to grains. In 2007-08, crude oil prices changes were temporally prior to grains prices. Crude oil prices started to rise in 2007 and this could have prompted the need for alternative energy sources such as biofuels. Biofuels linked crude oil and grains prices over 2007-09 directly through corn as a main feed stock and indirectly to wheat and soybeans - both substituted corn in animal feed and competed for land with corn The results obtained are therefore consistent with the hypothesis of a biofuels-induced link between the crude oil and food markets.

Biofuels production and consumption constraints in the United States became binding after 2008 de-linking crude oil prices with the grains. Biofuels constraints may also have rendered grains more volatile through the idiosyncratic components such as stocks.

CHAPTER 2:
STRUCTURAL CHANGE IN THE RELATIONSHIP BETWEEN ENERGY AND FOOD PRICES

Biofuels have been identified as one of the main drivers of high food prices in the recent decade. This chapter investigates the claim that the advent of biofuels has altered the nature of the relationship between energy and agricultural markets – see Taheripuor and Tyner (2008) and Gilbert and Mugera (2012). In the past, this relationship largely reflected cost factors. Increases in energy prices, the boom in biofuel production and government policy interventions have led to questions in relation to the stability in the long run relationships between food and energy commodity prices. The main hypothesis of this chapter is that recent market and policy events may have induced changes in the relationship between food and energy markets. This chapter asks whether there have been any structural changes in relationships between energy and commodity prices and if so, whether any such breaks may be modelled as shifts in the mean of the food price processes. This chapter tests for the presence of multiple structural breaks in the single price series of crude oil, gasoline, ethanol corn, and wheat without pre-specifying the dates of any such breaks. It also examines the evolution of the price relationships over the recent decade. It conducts an impulse response analysis by examining the pass-through of changes in the crude oil price, to corn and wheat prices at each break date.

The main focus is the United States. This choice is driven by several factors. Firstly, the United States is one of the largest producers and exporters of grains and oilseeds. Secondly, the United States is the world's largest producer and consumer of biofuels. Thirdly, in the recent decade, the United States has experienced a large number of policy and regulatory changes that may have affected both the energy and food commodity markets and their inter-relationship.

1. THE RELATIONSHIP BETWEEN FOOD AND ENERGY COMMODITIES

Evidence on the relationship between food and energy markets is mixed. A number of authors conclude that the linkage is weak or absent (Dillon and Barrett, 2013; Zilberman et al., 2012; Zhang et. al., 2010). Others have argued that there is support for the hypothesis that energy prices are an important driver of long-run world food price levels (Secchi and Babcock, 2007, Tokgoz et al., 2007 Ciaian and Kanks, 2011; Natalenov et al., 2011). Most econometric studies are based around the existence or non-existence of cointegration between grains and energy prices. Cointegration results when it is possible to find a stationary linear combination of two or more series each of which is non-stationary.

The presence of cointegration also indicates that a long-run equilibrium relationship exists between these series which therefore must adjust to ensure the elimination over time of departures from the long run relationship (Engel and Granger, 1987).

Serra et al., (2011b) evaluate price linkages and transmission patterns in the U.S. ethanol industry from 1990 to 2008, a period that saw significant changes in U.S. ethanol and related markets. Their study concentrates on the relationships between ethanol, corn, crude oil and gasoline prices. They found that the four prices are related in the long run through two cointegrating relationships: one between corn and ethanol representing the equilibrium within the ethanol industry and second one between crude, oil and gasoline, representing the equilibrium in the oil-refining industry. The ethanol market provides the link between corn and energy markets, and the price of ethanol increases as the prices of both corn and gasoline increase, with the price of corn being the dominant factor when it is relatively high.

Biofuels production has also been important in Brazil which is currently the leading worldwide producer of ethanol from sugarcane. Strong ethanol demand and less attractive sugar prices have led the Brazilian industry to divert increasing quantities of sugar cane to ethanol production. In the 2007/08 marketing year, the use of sugarcane for alcohol production (55%) slightly exceeded the use for sugar production (45%). Brazilian ethanol production in the 2007/08 marketing year was 22.4 billion litres, while Brazilian ethanol exports were around 3.6 billion litres with the U.S. and Europe being the main destinations (USDA, 2008). In a study on Brazil, Serra (2011c) uses nonparametric corrections to time series estimations to provide support for the presence of a long-run linkage between ethanol and sugar-cane prices. The paper confirms the role of both crude oil and sugarcane prices in as drivers of Brazilian ethanol prices. Balcombe and Rapsomanikis (2008) used ethanol, sugar and crude oil prices to investigate price inter-relationships in the Brazilian ethanol market. They adopt a generalized bivariate error correction models that allow for cointegration between sugar, ethanol, and oil prices, where dynamic adjustments are potentially nonlinear functions of the disequilibrium errors. They find evidence of cointegration between sugar, crude oil and ethanol prices.

Using weekly prices of corn, sorghum, soybeans, soybean oil, palm oil, world sugar and crude oil prices from 2003 to 2007 Campiche et al. (2007) find corn and soybean prices to be cointegrated with crude oil prices in the period subsequent to the boom in biofuels, with crude prices driving feedstock prices. Saghaian (2010) also find evidence for cointegration between crude oil, ethanol, wheat, corn and soybean prices in the US for monthly crude oil, ethanol, wheat, corn, and soybeans prices between December 1996 and December 2008. He finds that crude oil as a driver of corn, soybean, wheat and ethanol prices, while ethanol affects long-run corn prices. Ciaian and Kanks (2011) find cointegration between crude oil and a range of weekly food commodity prices between January 1994 and December 2008. Using weekly German diesel, biodiesel, rapeseed oil and soy oil prices from 2002 to 2007, Busse et al. (2007) conclude that equilibrium feedstock prices of biodiesel are influenced by energy prices (Busse et al., 2009).

A separate strand of research has relied on computable partial and general equilibrium (CGE) models in order to examine the impact of policies on the energy-food commodity relationship (Janda et al., 2012). CGE models focus on equilibrium relationships more than short-run price dynamics. They are well-suited to the examination of the medium and long term impacts of policy changes which can be accurately reflected in the model structure. However, they are less well suited to the explanation of short term price movements in periods of high price volatility where prices may differ substantially from their equilibrium values (Beckman et al., 2011). In that sense, CGE models may be seen as complementing the more data-based models which emerge from the time series econometric approach.

2. U.S. BIOFUELS POLICIES

The United States began subsidizing biofuels in 1978 with the passage of the National Energy Policy Conservation Act of 1978 (Tyner, 2008; U.S. Congress, 1978). However, it is only in the most recent decade that U.S. production of biofuels increased dramatically. In 1983, ethanol production was 375 million gallons, growing to almost three billion gallons by 2000 and by 2010 it had reached 13 billion gallons. Key policy measures aimed at encouraging biofuel production included the Renewable Fuels Standard (RFS), subsidies to ethanol blenders, the blend wall, regulations on gasoline chemistry and import tariffs. Many believe that these interventions helped to create this new, persistent demand for corn and contributed to incentives to create the capacity to produce ethanol and to use corn for fuel rather than food (DeGorter and Just, 2009; Abbot, 2013).

RFS Mandates

2005 saw the enactment of significant changes in the legislation governing ethanol production (Tyner, 2008). The Renewable Fuels Standard (RFS), which mandated minimum production levels for future years for ethanol, was passed (U.S. Congress, 2005). This legislation also included continued subsidization of ethanol production which initiated in 2004. Gasoline blenders were offered a tax credit of $0.51 per gallon referred to as the Volumetric Ethanol Exercise Tax Credit – (VEETC), and import tariffs of $0.45 per gallon plus 2.5% of imported value were imposed on imported ethanol, to insure foreign producers did not get the subsidy. In December 2007, the U.S. Congress passed a major new energy legislation mandating widespread improvements in energy efficiency (U.S. Congress, 2007). The Energy Policy Act (EPA) of 2007 substantially increased RFS mandated minimum ethanol production levels for the future. The VEETC tax credit was later reduced to $0.45 per gallon in 2007-08 food crises, and expired in December 2011. Moreover, the import tariffs on ethanol for fuel were cut in January 2012.

The Blend Wall

EPA regulations also imposed a limit on the amount of ethanol used in reformulated gasoline produced and sold by blenders. This is because ethanol is corrosive and may damage older engines or engines that have not been designed to tolerate high concentrations of ethanol. Modern flex-fuel vehicles use blends including up to 85% ethanol while many vehicles with conventional engines tolerate between 10 and 20 per cent without being damaged. The EPA thus set a limit at 10% (E10) for gasoline not explicitly marketed as E85, and permitted up to 15% of ethanol (E15) to be blended for newer vehicles. Tyner and Viteri (2009) analyse how this affects ethanol and gasoline markets, and refer to this limitation as the "blend wall". This constraint is imposed on gasoline blenders, generating a ceiling on ethanol demand for fuel use. The effects of this ceiling are felt all along the ethanol supply chain. The blend wall restricts ethanol use and therefore reduces demand for corn for ethanol.

The blend wall thus affected the link between crude oil and corn prices. The effect of the blend wall was more influential at high crude oil prices, where ethanol production was limited by the wall level thereby limiting the impact on corn prices. The blend wall was thus an effective constraint on demand, so an increase in the wall limit affected the linkage between crude oil and corn (Tyner, 2010).

MTBE/Oxygenate Substitution

In the early 1990s, the Clean Air Act required additives to reduce carbon monoxide emissions and reduce atmospheric pollution by including either a fuel oxygenator Methyl Tert-Butyl Ether (MTBE) or ethanol. It was subsequently discovered that MTBE was carcinogenic implying a possible threat to drinking water safety (EIA, 2000). Gasoline blenders, who were using MTBE to meet clean air regulations, sought waivers from liability but in 2006 it became clear that such waivers would not be granted. By mid-2006, 25 states had banned the use of MTBE in gasoline. This encouraged blenders to use ethanol rather than face the potential liability costs from MTBE. This contributed to the rapid expansion of ethanol production after 2005 (Hertel and Beckman, 2012).

The timing of the policy changes in regime switches is crucial as they may have led to changes in the relationship between energy and food commodity prices (Abbot, 2013). Key policy intervention dates are reported in the Table7. The econometric analysis which we report in the subsequent section of the chapter has the aim of relating these policy changes to changes in the relationship between grains and energy prices.

Table 7 Policy Interventions	
Date	**Policy Intervention**
June 2002	US Farm Bill-Farm Security and Rural Investment
May2004	VEETC introduced for ethanol blending with gasoline
July 2005	Renewable Fuels Standard (RFS1) - Energy Act
June 2006	MTBE ban became effective - liability waivers not granted
December 2007	Renewable Fuels Standard (RFS2) - Energy Act
May 2008	The Food Conservation and Energy Act
October 2008	The Energy Improvement and Extension Act
January 2009	VEETC credit tax reduced to $0.45 per gallon
February 2010	EPA finalizes RFS Program for 2010 and beyond
December 2011	The VEETC tax credit expired
January 2012	Import tariffs on ethanol for fuel were cut

As discussed previously, CGE analysis is well-suited to the analysis of the impact of policy changes. Adopting the CGE approach, Elobeid and Tokgoz (2008) estimate the effects of a hypothetical removal of federal tax credit and trade liberalization on the U.S. ethanol industry. According to their results, U.S. ethanol prices would have been substantially higher in the absence of these credits. DeGorter and Just (2009a) find that the combined impact of tax credits and the blend mandate effectively subsidize fuel in the U.S. In DeGorter and Just (2009b), the same authors conclude that ethanol would not be commercially viable without government intervention. In DeGorter and Just (2010), they argue that U.S. biofuels mandates have increased the retail prices of gasoline and generate transfers to ethanol producers. Feng and Babcock (2010) analyse land use changes induced by the expansion of ethanol production taking into account acreage allocations. They concluded that elasticities of crop demand are crucial in determining the eventual impacts of yield increases. Hertel and Beckman (2011) argue that the binding U.S. Renewable Fuels Standard has increased the inherent volatility in U.S. coarse grains prices by about one quarter. Jingbo et al., (2011) construct a simplified general equilibrium (multimarket) model of the United States and the rest-of-the-world economies that link the agricultural and energy sectors to each other and to the world markets. Their results show that the largest economic gains to the United States from policy intervention come from the impact of policies on U.S. terms of trade, particularly on the price of oil imports.

This body of literature demonstrates that U.S. biofuels policy has had the potential to substantially raise corn prices and to change the relationship between grains and energy prices. There is less comparable work on the impact of European policy on vegetable oils but the same types of impact may be foreseen. In what follows we show that these changes in U.S. biofuels policy have induced breaks in the time series properties of important grains price series and the relationship of these prices to energy prices.

3. STRUCTRAL BREAK ANALYSIS

As outlined in section 2, there have been major changes in U.S. biofuels policy since the start of the new century. Policy changes have the potential to induce structural breaks both in univariate relationships characterizing the time series property of a price and in multivariate relationships linking different prices. A number of empirical analyses demonstrate that failure to account for structural breaks may lead to incorrect policy implications and predictions. In analysing the U.S. post-war quarterly real GNP series (1947:1-1986:III), Perron (1989) finds that only two policy-driven events had a permanent effect on the macroeconomic variables. First, the 1929 Great Crash generated a dramatic drop in the mean of most aggregate variables. Second, the 1973 oil price shock was followed by a change in the slope of the trend for most aggregates such as a slowdown in growth. Hansen (2001) finds evidence on a structural break in labour productivity in U.S. manufacturing and durables sectors between 1992 and 1996. Analysing the market response of interest rates to discount rates Bai (1997) finds that the response is consistent with the policy interventions by the Federal Reserve Board on its operating procedures. Analysing the long term annual interest and inflation rates of 10 industrialized countries, Haug (2014) implements a Dickey-Fuller unit root test with local generalised least squares. He finds that changes in monetary and fiscal policies are the key drivers of the breaks in real interest rates. Garcia and Perron (1996) examine the time series behaviour of the U.S. real interest rate from 1961 to 1986 by allowing three possible regimes affecting both the mean and variance. They find that the average interest rate value experienced occasional jumps caused by important structural events. One such jump is associated with the sudden rise in the oil price in 1973 while the mid-1981 second jump is more in line with a federal budget deficit explanation than with the change of monetary policy that occurred in the end of 1979.

Defining Structural Breaks

Breaks can be defined as events which change the structure of the econometric model under consideration. A structural break implies non-constancy in either the process generating a variable of interest or in the process linking two or more such variables. Non-constancy may take a variety of forms. We restrict attention to sharp shifts in the values of the parameters in such relationships which nevertheless leave the overall form of the relationship unchanged.

Consider the most simple univariate representation, the first-order autoregression:

$$y_t = \alpha + \rho y_{t-1} + u_t$$
$$E u_t^2 = \sigma^2 \tag{2.1}$$

where u_t is a time series of serially uncorrelated shocks α, $\rho, and\, \sigma^2$ are the parameters with $-1 \leq \rho \leq 1$ and the intercept α may be parameterized in terms of a linear combination of vector of exogenous variables x_t. Stationarity requires that these parameters be constant over time (Hansen, 2001). One can say that a *structural break* has occurred if at least one of parameters α (or β), ρ and σ^2changes at some date - the *break date* - in the sample period.

We further restrict changes to be sharp so that the parameters take one set of values over the sample $(1:\tau_0 T)$ and a second set of values over the sample $(\tau_0 T + 1 : T)$ where T is the sample size. τ_0 is the break point $\tau_0 T$ is the *break date*. In what follows, this chapter focuses in breaks in the mean from in equation(1). Changes in the autoregressive parameter ρ reflect changes in the serial correlation in y_t while the intercept α controls the mean of y_t through the relationship $E(y_t) = \alpha/(1-\rho)$. In the general case, neither the timing nor the magnitude of these breaks will be known.

Over the past fifteen years, there have been important contributions to the structural breaks literature. These include tests for the presence of structural breaks when the break date is unknown and the subsequent estimation of the break dates when any such changes occur. In addition to this, work has been reported on the nature of the breaks. The simplest form of break is that of a sharp jump to new parameter values at the break date (Chow, 1960; Andrews and Ploberger, 1994; Bai and Perron, 1998; Perron, 1989; Bai and Perron, 2003). Sharp breaks may be induced if there is an unanticipated change in government or administration policy is announced. In section 6, we follow this approach in relating breaks in grains price representations to changes in U.S. biofuels policy. The alternative approach is to allow breaks to be smooth or fuzzy (Gallant, 1984; Becker, Enders and Hurn, 2004, 2006; González and Teräsvirta, 2008; Enders and Holt, 2012). In this framework breaks are seen as slowly evolving changes in parameters which take place around a break date.

Moving to a multivariate context, one may be interested in whether related series have common break dates. In that case, we can describe the series as co-breaking. In a subsequent section, this chapter shows that grains prices co-break in that the relationship between the prices is unaffected by breaks in their respective univariate representations.

Consider the equations

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu_y \\ \mu_x \end{pmatrix} + \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix} \tag{2.2}$$

with $$\begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix} \sim NI\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_y{}^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_x{}^2 \end{pmatrix}\right].$$

The implied line of regression linking y_t to x_t is

$$y_t = \alpha + \beta x_t + u_t \tag{2.3}$$

where $\beta = \dfrac{\rho\sigma_y}{\sigma_x}$ and $\alpha = \mu_y - \beta\mu_x$. A change in μ_x to m_x will induce a corresponding change in α to $\mu_y - \beta m_x$. One can say that the series x and y are co-breaking if μ_y also changes, say to m_y such that $\alpha = m_y - \beta m_x$ remains invariant (Hendry and Massman, 2007). In that case, the line of regression (3) continues to hold despite the structural breaks in both the x and y processes. This argument generalizes in a straightforward manner if the relationships (2) become autoregressive or contain exogenous regressors.

Testing for Structural Breaks

One-time structural change when the break-date is known

The classical test for structural change at a known date is due to Chow (1960). This procedure splits the sample into two sub-periods, estimates the parameters for each sub-period, and then uses a Wald F test to ask whether the two sets of parameters are equal. The

Chow test is performed splitting the sample at the known break-date (Chow, 1960; Enders, 2010). In the model

$$y_t = \beta_1' x_t I(t \leq t_0) + \beta_2' x_t I(t > t_0) + u_t$$

(2.4)

where $u_t \sim iid\,\mathcal{N}(0, \sigma^2)$ and $I(x)$ is the indicator function. The Chow test sets the null hypothesis $\mathrm{H}_0\colon \beta_1 = \beta_2$ against the alternative hypothesis $\mathrm{H}_1\colon \beta_1 \neq \beta_2$. This is an *F*-test with *n* and *T*-2*n* degrees of freedom (Teräsvirta, et al., 2010).

The Chow test requires the potential break-date $t_0 = \pi_0 T$ to be known. A researcher who does not know the break date in advance would be obliged either to pick an arbitrary candidate break-date or to choose a break-date based on some feature of the data. In the first case, the Chow test may be uninformative and imprecise, as the true break-date may be missed. In the second case, the Chow test can be misleading, as the candidate break-date is correlated with the data and thus lead to a pre-test selection bias of the data (Hansen, 2001).

Testing for a single structural change when the break date is unknown

In practice, one seldom has precise knowledge on potential break dates. Quandt (1960) suggested taking the largest Chow statistic over all possible break-dates. He proposed to split the sample at a break-date and estimate the model parameters separately on each subsample. If the parameters are constant, the subsample estimates should be the same across candidate break-dates, subject to estimation error. On the other hand, if there is a structural break, then the subsample estimates will vary systematically across candidate break-dates, and this will be reflected in the Chow test sequence. However, the Quandt statistic was seldom implemented because critical values were unavailable. Andrews (1993) and Andrews and Ploberger (1994) proposed a solution to this problem. They derive optimal tests for structural change with an unknown change point. Their procedure involves searching for a break-date by performing the Chow test for every possible date. As in Quandt's (1960) procedure, the break date is identified as the date at which the Chow statistic attains its maximum (or supremum) value.

Consider a model indexed by parameter β_t for $t = 1,2,....,T$, where T is the sample size. The null hypothesis of parameter stability and thus of no structural change is given by:

$$H_0: \beta_t = \beta_0 \text{ for all } t \geq 1 \text{ for some value of } \beta_0.$$

The alternative hypothesis of interest may take a number of different forms. In the case of a one-time structural change alternative with change point $\pi \in (0,1)$ the alternative with change point π is given by

$$H_{1T}(\pi): \beta_t = \beta_1 I(\pi \leq \pi_0) + \beta_2 I(\pi > \pi_0) \tag{2.5}$$

where β_1 and $\beta_2 \neq \beta_1$ are parameters to be estimated, πT is the break date, and $\pi \in (0,1)$ is referred to as the break point. This test procedure falls outside the standard testing framework because the parameter π only appears under the alternative hypothesis and not under the null. Consequently, Wald, LM, and LR-like tests constructed with π treated as a parameter do not possess their standard large sample asymptotic distributions. Critical values are obtained by simulation.

Some restrictions need to be imposed on the break point π to ensure that there is an adequate number of observations in each of the two subsamples. This requires that the break date neither not occurs near the very beginning (t_0) nor near the end of the sample ($T - t_0$). In particular, Andrews (1993) showed that if no restrictions are imposed on π for instance then the test diverges to infinity under the null hypothesis. This indicates that critical values grow and the power of the test decreases as π gets smaller. Hence, the range over which one searches for a maximum must be small enough for the critical values not to be too large and for the test to retain decent power, yet big enough to include potential break dates. Andrews (1993) recommended restriction of the break-date π to an interval such as [0.15, 0.85] and this restriction has now become standard practice.

Testing for multiple unknown break dates

Allowance for multiple breaks at unknown dates is a natural extension of the Andrews (1993) and Andrews and Ploberger (1994) procedures. Bai and Perron (1998; 2003) extended Andrews and Ploberger's (1994) supremum test for a one-time break to allow for $k \geq 1$ possible break dates. In their earlier work Bai and Perron (1998) build a theoretical model on the limiting distribution of estimators and the statistics in linear regression models with structural breaks. In their subsequent research, they proposed a dynamic programming algorithm that enables the investigator to obtain the global minimizers of the sum of squared residuals. They also discuss estimation of the number of break dates and the construction of confidence intervals for the break dates given different conditions on the structure of the data and error terms across subsamples and (Bai and Perron, 2003).

Their procedure is based on sequentially applied least squares. The initial step is to test for a single structural break. If the test rejects the null hypothesis that there is no structural break, the sample is split in two and the test is reapplied to each subsample. This sequence continues until each subsample test fails to find evidence of a break. In the presence of multiple structural breaks, the sum of squared errors, which is a function of the break date, can have a local minimum near each break date. The sample is then split at the break date estimate, and analysis continues on the subsamples. In the context of the regression model with up to *k* breaks.

$$y_t = \beta_j ' x_t + u_t \quad \left(t = \pi_{j-1}T + 1, \ldots, \pi_j T\right) \tag{2.6}$$

Relative to the *k*-partition, $\left(\pi_1, ..., \pi_k\right)$ parameter estimates are obtained by minimizing the sum of squared residuals

$$\sum_{i=1}^{k+1} \sum_{t=\pi_{j-1}T+1}^{\pi_j T} \left(y_t - \beta_j ' x_t\right)^2 \tag{2.7}$$

where $\pi_0 = 0$ and $\pi_{k+1} = 1$.Substituting these estimates in the objective function and denoting the sum of squared residuals as $S_T\left(\pi_1, ..., \pi_k\right)$, the estimated break points $\left(\hat{\pi}_1, \ldots, \hat{\pi}_k\right)$ are such that

$$\left(\hat{\pi}_1, \ldots, \hat{\pi}_k\right) = \arg\min_{\pi_1, \ldots, \pi_k} S_T\left(\pi_1, \ldots, \pi_k\right) \tag{2.8}$$

where the minimization is taken over all partitions $\pi_1, \ldots, \pi_k$.Thus the break-point estimates are global minimizers of the sum of squared residuals of the objective function. Given the sample size *T*, the global sum of squared residuals for the *k*-partition $\left(\tau_1, ..., \tau_k\right)$ for any value of *k* would be a linear combination of the $\frac{1}{2}T\left(T+1\right)$ sums of squared residuals and the estimates of the break points $(\hat{\pi}_1, \ldots, \hat{\pi}_k)$ correspond to the minimum value of this linear combination. The dynamic programming algorithm compares all the combinations corresponding to the *k*-partitions in order to minimize the global sum of squared residuals.[9]

In the application of their model Bai and Perron (2003) consider a number of different cases. In particular, the test statistic for the null hypothesis H_0: k=0 (no structural break) versus the alternative hypothesis H_1: $k=v > 0$ breaks for some fixed number of v breaks defines a *supF* test. The preferred choice for number *k* of breaks can result by reference to the (Schwartz) Bayesian Information Criterion (BIC) or the modified Schwartz criterion proposed by Liu et al. (1997).

Testing for a structural change in cointegrating relationships with unknown break-date

The stability of long-run equilibrium relationships of variables has always been open to question. In particular, there is vast literature on the stability of the money demand equation, some of which include works of Lucas (1988) and Stock and Watson (1993). Perron (1989) argued that if there is a break in the deterministic trend then the conclusion of the presence of a unit root is misleading. Models with constant coefficients have been found to perform poorly in terms of their ability to examine the effects of policy changes or forecasting in the context of oil price shocks and other major regime changes. These issues can be addressed within the cointegration framework.

[9] Becker, Enders and Hurn (2004) model multiple breaks as smooth or fuzzy. They use a trigonometric expansion to approximate the known functional form of the time-varying regression coefficient. González and Teräsvirta (2008) propose a different and simpler specification which can accommodate both sharp and smooth shifts in the mean giving what they term a time-varying autoregressive (TV-AR) process.

Cointegration analysis requires that the price series are non-stationary. This is unclear for ethanol over the relatively short sample for which we have monthly data. Inclusion of ethanol in the cointegration-based analysis is therefore problematic both because it would force use of this shorter sample and because cointegration analysis throws up the ethanol price itself as a trivial cointegrating vector. We therefore, drop the ethanol price from the cointegration analysis, although we subsequently reincorporate it.

We established that the remaining four price time series under consideration are non-stationary and have shown that they experienced structural breaks over the period under consideration. The existence of breaks may make it seem unlikely that the series could be cointegrated, but this is not impossible if the break points are common across series. The results reported in Table 4 indicate that in these data the break points do tend to collect together, in particular in 2004, 2006, 2008 and 2010.

Standard tests for cointegration are either residual-based or VAR-based. Residual-based tests are appropriate if it is known that the variables under investigation are linked by at most a single cointegrating relationship. The Engel and Granger (1987) test consists of application of the ADF test to the residuals from the supposed cointegrating regression estimated by OLS. The critical values are given by Mackinnon (1991). In the more general case in which there may be multiple cointegrating relationships, the Johansen (1988) reduced rank VAR procedure is employed. Consider a VAR(k) in m variables denoted by the vector y which may be written as

$$\Delta y_t = \kappa + \sum_{j=1}^{k-1} \Theta_j \Delta y_{t-j} + \alpha\beta' y_{t-1} + u_t \tag{2.9}$$

The number of independent cointegrating vectors is known as the cointegrating rank and is equal to the rank of the matrix Π. The Π matrix is given by: $\Pi = \alpha\beta'$ where α and β are *m* by *q* matrices where *q* is the cointegrating rank $(0 \leq q < m)$. Each column of β gives the weights of the variables in the relevant cointegrating vector and each column of α gives the reaction of the *n* variables to departures of this vector from its equilibrium value. The number of cointegrating vectors (*q*) can be obtained by verifying the statistical significance of the eigenvalues of Π. If the variables in y_t are not cointegrated then the rank of Π equals zero and the characteristic roots will be equal to zero. The standard (trace) test is based on the sum of the smallest *m*-*q* eigenvalues.

In the context of the grains-energy nexus, the changes in U.S. biofuels policy listed in Table 7 may have resulted in structural breaks which in turn may have affected the cointegration properties of these prices. The stability of long-run relationships can be statistically assessed by testing for structural change of the cointegrating vector between the variables. The standard tests for cointegration are not appropriate, since they suppose that under the alternative hypothesis the cointegrating vector is time-invariant (Gregory and Hansen, 1996). Tests will therefore fail to reject the null hypothesis of no cointegration. They propose a test for cointegration that allows for a single shift in either the intercept alone or the entire coefficient vector with an unknown break date.

4. DATA

This chapter analyzes the logarithms of nominal average weekly cash prices of corn, wheat, crude oil, and gasoline from 2000 to 2012 and ethanol prices from January 2003 to December 2012 giving a total of 678 observations (and 475 observations for ethanol prices observations prior to the construction of lags. We choose spot rather than futures prices since we are keen to represent transactions prices[10] and because we have only a very limited history for ethanol prices, where weekly U.S. ethanol cash prices are only available from November 2003. Data sources are: Corn and wheat (CBOT), cash prices: USDA and Chicago Mercantile Exchange (CME); crude oil (NYMEX, WTI): CME; ethanol cash price: Illinois Department of Agriculture; gasoline cash price: U.S. Energy Information Administration (EIA).[11]

Table 8 reports the non-stationarity tests. The ADF tests fail to reject the null hypothesis of the presence of a unit root at the 5% level for crude oil, gasoline, corn and wheat but not ethanol. We also report the Phillips-Perron (1988) test, which may be more robust to the equation specification. The results are similar but this test now marginally fails to reject non-stationarity for ethanol at then 5% level. In summary, these results clearly demonstrate non-stationarity of the crude oil, gasoline, corn and wheat prices but indicate that it may be problematic to regard the ethanol price appear to be stationary. It is possible the difference in the results for ethanol and the other four commodities is a consequence of the relatively short sample that we have available for ethanol prices.

[10] Irwin et al. (2009) document convergence problems in the U.S, wheat futures market. This may imply additional noise in the wheat cash prices around that time.

[11] Corn, wheat crude oil prices:www.bloomberg.com; *ethanol prices:* www.agr.state.il.us*; gasoline prices:* www.eia.gov.

Table 8 Stationarity tests					
	Lag length	ADF	Phillips-Perron	1% c.v	5% c.v
Crude oil	4	-1.146	-1.290	-3.430	-2.860
Gasoline	1	-1.640	-1.748		
Corn	3	-0.935	-0.899		
Wheat	2	-1.528	-1.592		
Ethanol	3	-3.270	-2.836	-3.442	-2.871

The table reports the ADF and Phillips-Perron test statistics for non-stationarity and the associated critical values. Lag lengths were selected using AIC and SC criteria.
Sample (crude oil, gasoline, corn and wheat) : weekly, 7 January 2000 to 28 December 2012 (678 observations).
Sample: (ethanol): weekly, 28 November 2003 to 28 December 2012 (475 observations)

5. Univariate test results

The discussion in section 2 underlined that there have been a large number of policy changes affecting the U.S. biofuels market. These changes were summarized in Table 7. Other developments may have also affected energy and grains prices in both energy and grains markets. These may include rapid economic growth in China and other Asian emerging economies, depreciation of the U.S. dollar, decades of underinvestment in agriculture, low inventory levels, poor harvests, financialization and speculative forces – see the discussion in section 2. Any of these changes may have resulted in structural breaks in the time series representations of these series. The initial step of our analysis is to look for breaks in the autoregressive representations of these prices.

This chapter implements the Bai and Perron procedure (2003) to test for the presence of multiple breaks in each of these price series setting the maximum of breaks to be five. The *sup-F* test rejects this null hypothesis of no breaks against the alternative of five breaks. We use the BIC to select the preferred number of breaks for each of the prices. The BIC selects five breaks for crude oil gasoline, corn and wheat and four breaks for ethanol. The results, reported in Table 9, confirm that each of the series saw multiple breaks over the sample period.

Table 9
Bai and Perron (date) sup *F* break tests

Crude oil	47.42***	Corn	108.13***
Gasoline	51.83***	Wheat	20.40***
Ethanol	6.11***		

The table reports the Bai and Perron (date) sup F test for structural breaks using a maximum of 5 structural breaks.
Critical values: 1% 4.91; 5% 3.91; 10% 3.4700
*** significant at the 1% level, ** at the 5% level, *at the 10% level
Sample (crude oil, gasoline, corn and wheat) : weekly, 7 January 2000 to 28 December 2012 (678 observations).
Sample: (ethanol): weekly, 28 November 2003 to 28 December 2012 (475 observations)
The BIC selects 5 breaks for crude oil, gasoline, corn and wheat; 4 breaks for ethanol.

Table 10 reports the month and year in which the Bai and Perron (2003) test identify breaks. There is considerable commonality in the break dates.

2002. The first set of breaks occurs in the summer of 2002 with a common break month for corn and wheat. Recall that the U.S. Farm Bill provisions on Farm Security and Rural Investment became effective in May 2002 – see Table 7. This act directed the increase agricultural subsidies by about 16.5 billion dollars resulting in a probable increase in the production of grains such as corn and wheat as well as the oil seeds.

2004. The second set of breaks occurs in the summer of 2004 and appears common across both the two energy commodities and the two grains. Recall that the summer of 2004 saw the introduction of the tax credit given to blenders for each gallon of ethanol mixed with gasoline – see Table 7. The August 2005 break in the ethanol series follows closely after the July 2005 enactment of the RFS1 standard – see Table 7.

2006. The third set of breaks, which occurs in the fall of 2006, and is again common to the two grains as well as crude oil. It comes shortly after the June 2006 MTBE ban and hence may reflect biofuels developments – see section Table 7.

2008. The fourth group of breaks occurs in the fall of 2008. Two important acts that were passed in 2008, the Food, Conservation, and Energy Act, and The Energy Improvement and Extension Act of 2008 – see Table 7. The former was a 288 billion dollar, five-year agricultural policy bill and was a continuation of the 2002 Farm Bill. It included agricultural subsidy as well as pursuing areas such as energy, conservation, nutrition, and rural development. The latter extended existing tax credits for renewable energy initiatives, including cellulosic ethanol and biodiesel development, and wind, solar, geothermal and hydro-electric power. The fall of 2008 also saw the onset of the financial crisis.

2010. The final set of breaks occurs in 2010. These breaks occur after the finalization of the National Renewable Fuel Standard Program (RFS2) for 2010 and beyond in February 2010. The program increased the required renewable fuel volume to be achieved by 2022 see Table 7 and the discussion in section 2.

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Table 10 Estimated break dates						
	Crude Oil	**Gasoline**	**Corn**	**Wheat**	**Ethanol**	**Crude oil - corn**
2002	August	May	June	June	pre-sample	July
2004	July	April	September	July		September
2005					August	
2006	November	March	October	September		September
2007					January	
2008	October	October	October	August	October	
2010	October	November	October	August	September	September

The first five columns of the table reports the month and year in which each of the five breaks identified by the Bai and Perron (2003) procedure occurs. The final column of the table reports the four break dates identified by the Bai and Perron (2003) procedure for the cointegrating vector linking crude oil and corn – see section 7.
Ethanol sample starts in November 2003 precluding of any break prior to this date.

In summary, the univariate structural break analysis shows that the price series under study to have been subject to multiple breaks over the sample period. Inference on the origin of these breaks within a univariate framework is necessarily casual and based on temporal coincidence. However, these estimates do suggest that biofuels-related legislation in 2006 may have been the key event that impacted both the crude oil and the grains markets.

6. Multivariate Test Results

The multivariate methodology requires that the price series are non-stationary. This is unclear for ethanol over the relatively short sample for which we have monthly data. Inclusion of ethanol in the cointegration-based analysis is therefore problematic both because it would force the use of this shorter sample and because cointegration analysis throws up the ethanol price itself as a trivial cointegrating vector. We therefore drop the ethanol price from the remainder of the analysis.

This chapter has established that the remaining four price time series under consideration are non-stationary and have shown that they experienced structural breaks over the period under consideration. We are interested in the long run relationships, if any, between these series. This chapter further poses and addresses three questions:

a) Can we consider the two grains series (corn and wheat) as moving together over the long run? Since they are both non-stationary this requires that they should be cointegrated. Since they experience breaks, these breaks must be common, i.e. they must co-break. If these conditions are satisfied, we can think of a common long run grains price.

b) Can we consider the two energy series (crude oil and gasoline) as moving together over the long run? The same considerations apply as with corn and wheat. If these conditions are satisfied, we can think of a common long run energy price.

c) Supposing an affirmative answer to the first two questions, is there any long run relationship between the grains prices and energy prices? If not, can we identify such a relationship once we allow for structural breaks?

Table 11 **Multivariate Johansen (1988) cointegration tests**		
	χ^2 statistic	p-value
$rank \leq 0$	81.21**	0.000
$rank \leq 1$	28.44*	0.072
$rank \leq 2$	9.709	0.309
$rank \leq 3$	1.452	0.228

The table results of the Johansen (1989) reduced rank tests and the associated tail probabilities for the VAR(4) linking the prices of crude oil, gasoline, corn and wheat. The VAR length was chosen using AIC.
Sample: weekly, 7 January 2000 to 28 December 2012 (678 observations)
** significant at the 5% level, * at the 10% level.

Table 11 reports the Johansen (1989) cointegration tests for the four-vector of prices. We fail to reject the null hypothesis that the $\alpha\beta'$ matrix in equation (2.9) is of rank 1 or less at the 10 per cent level and at rank 0 at the 5 per cent level. This suggests that the four prices are related by one or two stationary combinations of cointegrating vectors.

Table 12 **Bivariate Johansen (1989) cointegration tests**			
	crude oil – gasoline	**corn – wheat**	**crude oil – corn**
VAR length	5	2	4
$rank = 0$	49.56** [0.000]	21.41** [0.005]	8.613 [0.410]
$rank \leq 1$	1.171 [0.297]	1.674 [0.196]	0.660 [0.416]

The table results of three pairs of bivariate Johansen (1989) reduced rank tests. Tail probabilities are given in parentheses. The VAR length was chosen using AIC.
Sample: weekly, 7 January 2000 to 28 December 2012 (678 observations)
** significant at the 5% level, * at the 10% level.

The hypotheses set out at the start of this section indicate that there may be two such vectors, the first linking crude oil and gasoline and the second corn and wheat. The first two columns of Table 12 therefore report the results of two bivariate reduced rank tests which confirm the presence of both energy and a grains cointegrating vector. We conclude that the weaker evidence in Table 11 arises out of the lower power associated with implementation of the test with four price series.

The cointegration of corn and wheat implies that these two series must co-break. Any structural breaks in one of the two series must correspond with breaks in the other series since otherwise cointegration would fail. Taking the grains cointegrating relationship, we can test for co-breaking by imposing the estimated break dates reported for wheat in Table 10 on the corn price series. Regarding these dates as known, we perform a set of Chow tests for each of the five structural breaks. We perform these tests sequentially. If the series co-break, we should fail to reject a break in the corn price series at each of the estimated wheat break dates and similarly with crude oil and gasoline.

Denote the five estimated wheat break dates as $\pi_1 T$, $\pi_2 T$ …, $\pi_5 T$. We first consider the sub-sample [1: $\pi_2 T$] and test for a break at $\pi_1 T$. We then consider the sub-sample [$\pi_1 T$+1: $\pi_3 T$] and test for a break at $\pi_2 T$ and so forth to the sub-sample [$\pi_4 T$+1: T] and test for a break at $\pi_5 T$. Table 13 reports the Chow test for wheat breaks on corn prices. The test statistic shows that we reject the null hypothesis of no structural breaks for all the five break dates. This results confirms that corn and wheat co-break. We run the same procedure for crude oil and gasoline using the estimated gasoline break dates from the Table 10. We again find that imposition of the gasoline breaks dates on crude oil prices implies that also crude oil and gasoline co-break. The results are reported in Table 14.

Table 13
Tests for co-breaking: corn and wheat

Break date	Sample	Statistic	1% c.v.	5% c.v.	10% c.v.
28-Jun-2002	07-Jan-2000 – 16-Jul-2004	4.913***	3.100	2.253	1.873
16-Jul-2004	05-Jul-2002 – 22-Sep-2006	4.486***	3.104	2.256	1.875
22-Sep-2006	23-Jul-2004 – 29-Aug-2008	5.789***	3.107	2.258	1.875
29-Aug-2008	29-Sep-2006 – 06-Aug-2010	10.334***	3.113	2.261	1.878
06-Aug-2010	05-Sep-2008 – 28-Dec-2012	19.344***	3.102	2.255	1.874

The table reports the results of a sequence of Chow tests for corn prices based on the wheat break dates reported in Table 4.
*** significant at the 1% level, ** at the 5% level, *at the 10% level.

Table 14
Test for co-breaking: crude oil and gasoline

Break date	Sample	Statistic	1% c.v.	5% c.v.	10% c.v.
10-May-2002	07-Jan-2000 – 16-Apr-2004	4.902***	3.100	2.254	1.873
16-Apr-2004	17-May-2002 – 24-Mar-2006	6.083***	3.109	2.259	1.876
24-Mar-2006	23-Apr-2004 – 17-Oct-2008	3.523***	3.096	2.252	1.872
17-Oct-2008	31-Mar-2006 – 05-Nov-2010	6.966***	3.094	2.251	1.871
05-Nov-2010	24-Oct-2008 – 28-Dec-2012	5.639***	3.102	2.255	1.874

The table reports the results of a sequence of Chow tests for crude oil prices based on the gasoline break dates reported in Table 4.
*** significant at the 1% level, ** at the 5% level, *at the 10% level.

Returning to Table 12, the final column repeats the Johansen bivariate cointegration exercise for crude oil and corn where we fail to reject the null hypothesis that the $\alpha\beta'$ matrix is of rank zero implying no cointegration. The same conclusion results for the other three possible bivariate combinations (gasoline-corn; gasoline-wheat and crude oil-wheat) since if both the two energy prices and the two grains price are cointegrated but crude oil and corn are not cointegrated, no other energy-grain combination can be cointegrated. These results allow us to take the crude oil – corn relationship as representing the entire energy-grains link for the remainder of this analysis.

The absence of cointegration between the grains and energy prices leads us to the third question posed at the start of this section, namely whether cointegration results if we allow for structural breaks in the cointegrating relationship. Given the presence of multiple breaks in both corn and crude oil, it seems possible that there could be more than one break date in the corn crude oil cointegrating vector. We conduct a Bai and Perron (2003) multiple break date analysis on the corn-crude oil cointegrating vector. As in the corresponding univariate tests, we set a maximum of five breaks and select an actual number using the BIC. The procedure selects four as the preferred number of break dates. The break dates in the cointegrated vector are reported in the final column of Table 10). The 2008 break is therefore the sole instance of co-breaking in that relationship while the remaining four breaks define five energy-grains price regimes. The identified break dates are similar to the ones we identified in the single price series confirming that corn and crude oil do co-break. Moreover, the break dates stay in line with policy interventions in the agricultural and energy markets. The 2006 break date occurs after the RFS1 was enacted and the MTBE band became effective. Both these two factors contributed to the increase in ethanol production which in turn increased the demand for corn and its price thus affecting its relationship with crude oil prices. The VEETC tax credit is reduced and the blend limit becomes eminent in January 2010. The combination of these two factors induced a reduction in biofuel production and this imposes a break in the corn-crude oil price relationship. Importantly, one of the regime changes is coincident with the introduction of the MTBE ban in June 2006 – see section 2.

These results imply that the cointegrating vector linking crude oil and corn should be stationary within each of the five regimes defined by the break points listed in the final column of Table 10. In Table 15, as a robustness check, we report the ADF and Phillips-Perron tests for non-stationarity within these regimes. Both the ADF and PP tests reject the null hypothesis of the presence of a unit root.

Table 15
Piecewise stationarity tests

Regime	Initial date	Final date	Lag length	ADF	PP	5% c.v.	10% c.v.
1	07-Jan-2000	12-Jul-2002	3	-2.878*	-2.702*	-2.888	-2.578
2	19-Jul-2002	17-Sep-2004	10	-2.750*	-2.618*	-2.889	-2.579
3	24-Sep-2004	22-Sep-2006	4	-3.011**	-2.623*	-2.890	-2.580
4	29-Sep 2006	10-Sep-2010	3	-2.621*	-2.723*	-2.883	-2.573
5	17-Sep-2010	28-Dec-2012	3	-3.177**	-3.528**	-2.889	-2.579

The table reports the ADF and Phillips-Perron test statistics for non-stationarity and the associated critical values for the cointegrating vector linking crude oil and corn prices for the five regimes defined in the final column of Table 4. Lag lengths were selected using SC.

The identified break dates moreover, stay in line with policy interventions in the agricultural and energy markets. The 2006 break date occurs after the RFS1 was enacted and the MTBE band became effective. Both these two factors contributed to the increase in ethanol production which in turn increased the demand for corn and its price thus affecting its relationship with crude oil prices. The VEETC tax credit is reduced and the blend limit becomes eminent in January 2010.

The combination of these two factors induced a reduction in biofuel production and this imposes a break in the corn-crude oil price relationship. Importantly, one of the regime changes is coincident with the introduction of the MTBE ban in June 2006 – see table 7. On the basis of these results, we conclude that there has been a relationship between energy and grains prices over the period we have investigated and that this relationship has been subject to regime changes. We can relate one of these changes, that which is identified as having taken place in the fall of 2006, with a prior change in U.S. biofuels policy, namely the June 2006 introduction of the MTBE ban.

The cointegration results reported in Table 12 show that grains prices react to energy prices but not vice versa. The four break dates listed in the final column of Table 10 define a partition of the sample into five sub-samples. We conclude the econometric analysis by looking at the pass-through of changes in the crude oil price, now taken as exogenous, to corn, wheat, ethanol and gasoline prices in each of the five sub-samples defined by the partition. We adopt a common specification for all five sub-samples in order to avoid the possibility that differences in estimated pass-through depend on the specification. Write

$p_t = \begin{pmatrix} p_{corn,t} \\ p_{wheat,t} \\ p_{ethanol,t} \\ p_{gasoline,t} \end{pmatrix}$ and $q_t = p_{crude,t}$. The model and ADL(2) in lnp_t and lnq_t written in error correction format:

$$\Delta \ln p_t = \beta_0 + \beta_1 \Delta \ln p_{t-1} + \beta_{20} \Delta \ln q_t + \beta_{21} \Delta \ln q_{t-1} + \beta_3 \Delta \ln p_{t-2} + \beta_4 \Delta \ln q_{t-2} + u_t \tag{2.10}$$

The model is estimated by FIML subject to the restrictions $\beta_{3jj} \le 0 \quad (j = 1,\ldots,4)$, to guarantee mean reversion, $\beta_{3jk} \ge 0 \quad (j,k = 1,\ldots,4; j \ne k)$, reflecting substitutability between commodities, and $\beta_{4j} \ge 0 \quad (j = 1,\ldots,4)$ to ensure a non-negative equilibrium pass-through from crude oil to grains prices and the ethanol price. The dynamic adjustment β_1 and β_2 coefficients remain unrestricted. The ethanol price is omitted from the system in the estimates for Periods 1 and 2 owing to absence of data.

The pass-through estimates associated with a 1% rise in the crude oil price are reported in Table 16. (Coefficient estimates are available on request). The multipliers and impulse response functions show an important contrast between the responses of corn and wheat prices. Prior to 2004, these two prices moved closely together and more or less independently of energy prices. Since that time, the corn price has become closely linked to crude oil and less closely linked to the wheat price. This may explain why the second cointegrating relationship that between the corn and wheat price, is less well defined than the relationship between crude oil and gasoline prices. Furthermore, the crude oil impacts on the corn price appear to be persistent consistently with these impacts arising out of fundamental markets supply and demand factors and not simply market sentiment. Although wheat prices are also seen as being more affected by energy prices than at the start of the century but the pass-through is lower than in the corn market and the effects are less persistent.

Figure 11 graphs the impulse response functions for a 1% sustained rise in crude oil prices. The five sets of functions are charted on a common scale. The pass-through from the crude oil price to the gasoline price is fairly constant over time in the 0.8-1.0 range, consistently with cointegration of the two prices. This constancy reflects the cracking and distillation technologies which have not been subject to significant change in the period under consideration. Ethanol prices are seen as having been highly sensitive to crude oil prices in the third regime, which follows the introduction of the VEETC tax credit, but less sensitive in the two more recent regimes. We conjecture that this declining sensitivity reflects the impact of the blend wall which will have limited the incentive to produce increased quantities of ethanol even when crude oil prices have been high.

Although we identified four structural breaks in the crude oil-corn price relationship, it is clear from Table 16 that the major qualitative changes took place in the fall of 2004 (between Regimes 2 and 3) and the fall of 2006 (between regimes 3 and 4). The temporal coincidence of these two breaks both took place after major policy developments – the May 2004 introduction the VEETC tax rebate and the June 2006 conformation of the MTBE ban respectively. These results complement CGE results which show the likely impact of these changes.

The results in this chapter contrast with that in Myers et al. (2014). They analyse monthly cash prices for crude oil, gasoline, ethanol, corn and soybeans over the sample 1990-2010. This gives them a longer span than our analysis but with less focus on the most recent years in which biofuels have played an important role. Myers et al. also undertake cointegration analysis but on subsets of variables. They find cointegration between crude oil, gasoline and ethanol prices on the one hand and corn and soybean prices on the other but not between either corn or soybean prices and oil prices.[12] The cointegration results form the basis for their common trend and comovement analysis. This yields the conclusion that there is substantial commonality in the short run comovement of energy and grains prices but, as the consequence of the absence of energy-grains cointegration, this comovement is transitory. Crucially, they suppose a constant structure over their entire sample but substantial and persistent comovement thereafter. If, as our analysis suggests, there have been breaks in the energy-grains relationship over their sample period, their estimates will be averages over the pre- and post-biofuels revolution sub-samples.

[12] The statistical properties of this exercise, involving multiple subsets of variables, are unclear. There is also a danger that, over a period in which there has been substantial inflation, cointegration may appear to result through omission of the general price level from the data universe.

Table 16 Impulse response multipliers										
Regime	Initial date	Final date	Corn		Wheat		Ethanol		Gasoline	
			Impact	Equilibrium	Impact	Equilibrium	Impact	Equilibrium	Impact	Equilibrium
1	01/28/00	07/12/02	0.02%	0.00%	0.06%	0.00%	-	-	0.87%	1.02%
2	07/19/02	09/17/04	0.02%	0.00%	0.13%	0.00%	-	-	0.87%	1.10%
3	09/24/04	09/22/06	0.20%	0.36%	0.09%	0.04%	0.19%	1.63%	1.14%	1.10%
4	09/29/06	09/10/10	0.39%	0.22%	0.33%	0.00%	0.29%	0.22%	0.85%	0.83%
5	09/17/10	12/28/12	0.54%	0.55%	0.30%	0.00%	0.41%	0.06%	0.76%	0.90%

The table reports the impact and equilibrium responses of the corn and wheat prices respectively to a 1% rise in the crude oil price using the model given by equation (8). Coefficient estimates are given in an appendix table. Data unavailability prevents the calculation of impulse response multipliers for ethanol in the first two regimes.

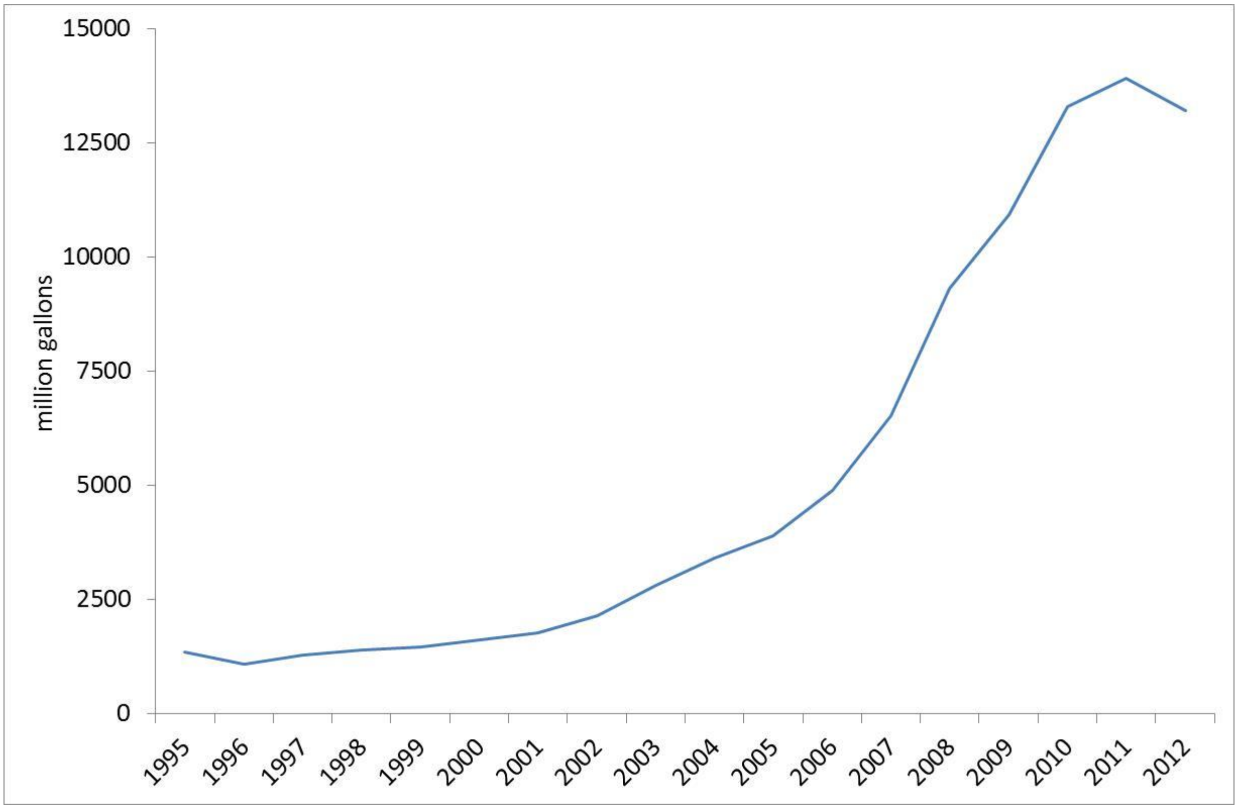

Figure 10: U.S. ethanol production, 1995-2012 (source: EIA)

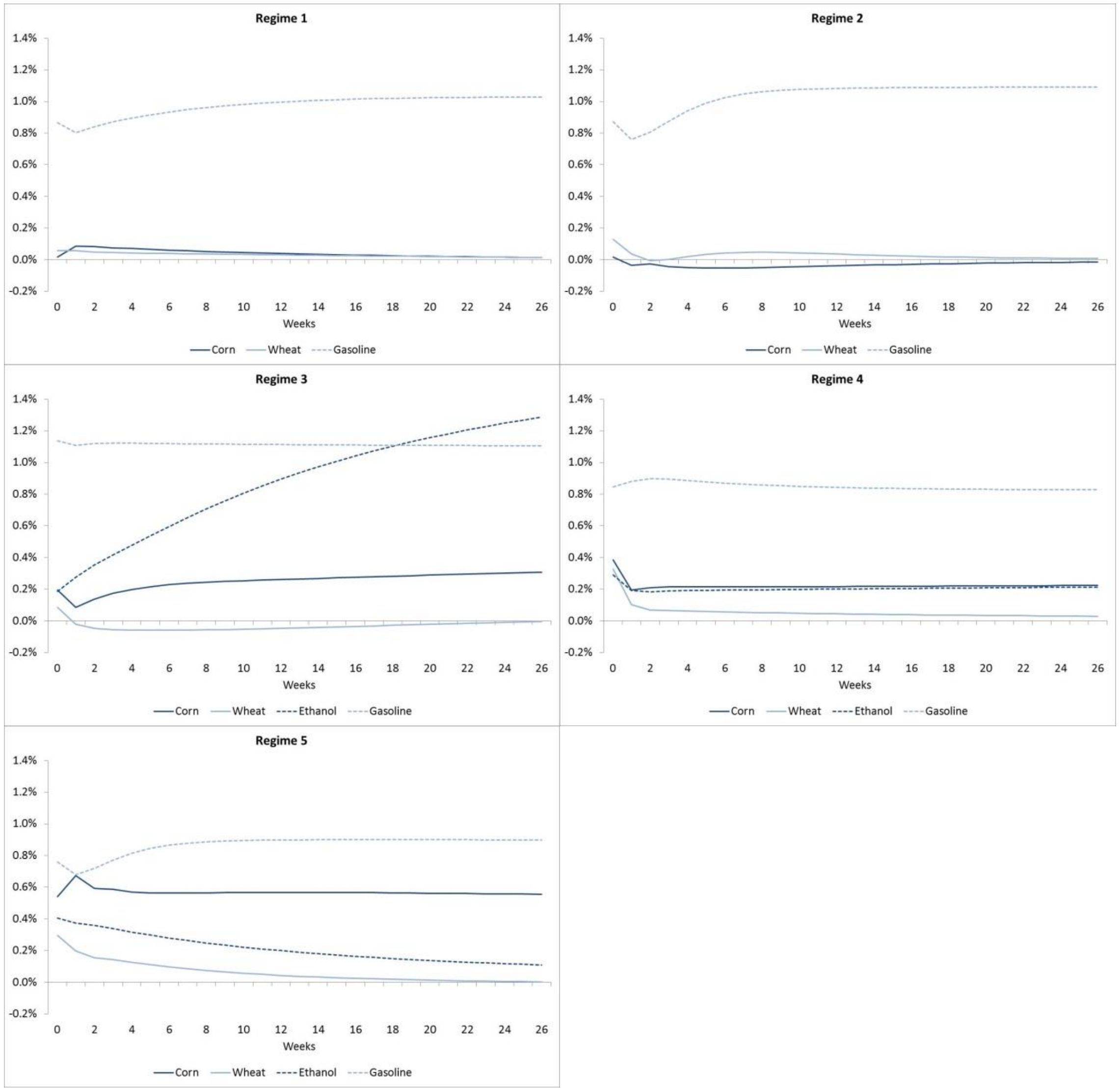

Figure 11: Impulse response functions by regime to a sustained 1% rise in the crude oil price

8. CONCLUSIONS

Food commodities prices increased over the recent decade attracting the attention of market participants and policy makers. Biofuels have been identified as one of the main drivers of high food prices over the most recent decade. High fuel prices combined with legislative policies have been accused of increasing biofuel production causing high food prices and establishing a link between energy and agricultural prices. There has been a huge controversy on the food versus fuel debate and the role of biofuels as well as biofuel policies. The United States has undergone major policy changes over the recent decade, changes that have affected both the energy and agricultural sector. The June 2002 Farm Bill, the two RFS Energy Acts in 2005 and 2007, the 2006 MTBE Ban and the Energy Improvement and Extension Act, are among the policy interventions that the U.S. implemented over that decade.

Responding to an increasing dependence on imported crude oil, the United States has adopted policies to encourage the substitution of locally produced biofuels in commercial gasoline. This resulted in dramatic increases in U.S. ethanol production over the seven years 2004-10. Other countries followed similar policies although generally at a lower scale and with the objective of producing biodiesel. Biodiesel uses vegetable oils as feedstock while ethanol uses corn. In this chapter, we have analysed the impact of the biofuels revolution on the relationship between crude oil and corn prices.

There are two channels through which ethanol production can influence corn prices. The first is that the new feedstock demand for corn moves the corn demand curve to the right and, with less than infinitely elastic supply, this will result in a rise in corn prices.

Mitchell (2008) recorded that the use of corn for ethanol in the U.S. accounted for 70% of additional maize production over 2007-08. He suggested that this was a (perhaps the) major factor which can explain the sharp rise in grains prices over those two years. The second route is that the location of the feedstock demand curve for corn will depend on the crude oil price. Shocks to the oil price are thereby transmitted to the corn market increasing the volatility of corn prices. To the extent that this happens, corn becomes a "petro-commodity".

In this chapter a rigorous econometric analysis is conducted in order to verify whether there has been a structural change in both the prices and price relationships of grains and energy commodities. It is motivated by the fact that prices and price relationships react to both market factors and policy regimes. These factors are not static over time and may change in response to policy and market developments. In addition, the failure to detect and consider breaks induces misspecification which may adversely affect the inference procedure leading to poor forecasting. In particular, ignoring existing breaks in the prices would lead to a biased rejection of the null hypothesis of stationarity in the series. Using the Bai and Perron (1998, 2003) structural break methodology to analyse price relationships between grains and energy prices over the period since 2000 and relate the structural breaks to changes in U.S. biofuel policy.

The multiple structural breaks analysis on both food energy commodity prices shows that the commodities experienced the breaks in line with the policy interventions. In particular, the 2006 break date common in the commodities analysed marks the "ethanol gold rush" which was induced by the 2006 MTBE ban and the 2005 RFS1 Energy Act.

The rise in U.S. ethanol production from corn was driven by U.S. government policies as well as by market forces. Three policy changes were particular important

- the Volumetric Ethanol Exercise Tax Credit (VEETC), introduced in May 2004 ;
- the Renewable Fuels Standard (RFS1) introduced in the July 2005 Energy Act, and
- the MTBE ban which became effective in June 2006.

These three measures coincide with the sharp up-turn in U.S. ethanol production. While it is difficult to assess how ethanol production would have evolved in the absence of these measures, it seems likely that the increases would have been smaller and more gradual. These results show that these policy changes coincide with structural breaks in the relationship between grains and energy prices. Over the period 2000-12, four breaks are identified of which the qualitatively most important are those in the fall of 2004 and the fall of 2006. These breaks reinforce CGE analyses which have looked at the likely impact of these changes.

The structural breaks are present in the marginal processes for the grains and energy prices but are absent from the crude oil – gasoline relationship where the prices co-break. The same is true, but with qualifications, of the corn-wheat relationship. Prior to2004, little relationship is apparent between corn and wheat prices, on the one hand, and energy prices on the other. The corn and wheat prices move together such that (possibly supply-related) divergences decay quite quickly. After 2006, the corn and wheat prices both show a larger responsiveness to changes in crude oil prices with the corn response being both larger and more persistent than the wheat response. As a consequence, corn and wheat prices are less tightly related than previously. It may be reasonable to regard corn as a petro-commodity but this is less clear for wheat.

This chapter also provides evidence of long-run cointegrating relationship between corn and wheat on the one hand and crude and gasoline on the other. Cointegration implies that the series co-break. Corn and wheat do co-break, and crude and gasoline co-break. However find that corn and crude are not cointegrated and thus do not co-break. Given this last result we attempt to verify whether corn and crude are cointegrated if we incorporate structural breaks. We find that corn and crude are cointegrated when breaks are incorporated. Conducting a piece-wise stationarity analysis these break dates appear to be significant.

The results in this chapter show that US biofuel policy and policy changes have both played a major role in defining ethanol production and consumption which in turn affected the relationship between food and energy markets in the recent decade. In particular, it has strengthened the link between energy and grain prices. These results have strong policy considerations as we show that if U.S. agricultural policy is redirected to ensure a return to historical levels of food price volatility it will be necessary to de-link food and energy prices.

CHAPTER 3:

POVERTY AND VULNERBILITY IN TANZANIA

Poverty eradication remains a key and implicit objective of development policy. For more than a decade now, national poverty assessments have been used regularly to inform policy discussions on poverty alleviation in several developing countries. Moreover, exposure to risk and uncertainty about future events and its adverse effects to wellbeing is one of the central views of the basic economic theory of human behaviour, embodied in the assumption that individuals and households are risk averse. As policy makers are mainly interested in applying appropriate forward-looking anti-poverty interventions (i.e., interventions that aim to go beyond the alleviation of current poverty to prevent or reduce future poverty), there is need to go beyond a cataloguing of who is currently poor and who is not, to an assessment of households' vulnerability to poverty. Creating awareness of the potential of such irreversible outcomes may drive individuals and households to engage in risk mitigating strategies to reduce the probability of such events occurring. Moreover, focusing on vulnerability to poverty serves to distinguish ex-ante poverty prevention interventions and ex-post poverty alleviation interventions. Policies directed at reducing vulnerability–both at the micro and macro level– are also instrumental in reducing poverty.

The measurement and analysis of poverty, and vulnerability is fundamental for:

1. Cognitive purposes as it enables one to know what the situation is;
2. Analytical purposes as it enables one to understand the factors determining that particular situation;
3. Policymaking purposes as it enables policy makers to design interventions best adapted to the issues);
4. A Monitoring and evaluation purpose as it enables one to assess the effectiveness of current policies and to determine whether the situation is changing.

The objective of this chapter is to quantitatively assess households' welfare dynamics in the recent years. Tanzania is selected as the country of analysis because maize is the staple food in all households. Maize is also one of the food commodities most severely affected by the recent food spikes. Tanzania has also been recently both economically and politically stable and thus conducive for conducting survey analyses. Tanzania is a relatively big country and also trades on the international markets. Household quantitative and qualitative information have also been well documented for the relative period of analysis. This analysis will be conducted using two waves 2008-09 and 2010-11 household survey panel datasets that have been collected and compiled by the Living Standards Measurement Study (LSMS-ISA, World Bank). To understand poverty, it is essential to examine the economic and social contexts of the households which include the characteristics of local institutions, markets, and communities. Poverty differences cut across gender, ethnicity, age, rural versus urban location, and income source. Rural poverty accounts for nearly 63 percent of poverty worldwide, and is between 65 and 90 percent in sub-Saharan Africa (IMF, 2001). Given the recent international shocks and events, the objective of this study is to quantitatively assess poverty and vulnerability dynamics in Tanzania.

This chapter poses and addresses the following questions:

- What is the nature of poverty at the household level in Tanzania? Who is poor in Tanzania today? What is the share of multi-dimensionally poor people and what is the intensity of poverty? The measure can be broken down into its individual dimensions to identify which deprivations are driving multidimensional poverty in different regions or groups
- What is the dynamics of poverty in Tanzania? Have households become more vulnerable to poverty? What are the key dimensions in which households have become deprived over time?
- What is the nature of vulnerable households in Tanzania? Are they vulnerable to poverty primarily because their consumptions are volatile, which would imply they are mostly vulnerable to transitory poverty, or are they structurally poor?
- How do univariate and multivariate poverty and vulnerability measures differ from one another in measuring household well-being?
- Do shocks matter? If so, what is their nature? Which shocks prevail in rendering households more vulnerable? What has been the role of recent market related shocks (international and domestic) in affecting poverty and vulnerability in Tanzania?
- How can we condense poverty and vulnerability indicators into lean measures that can be easily interpreted and can also be useful to policy makers? Can these measures be a powerful tool for guiding policies to efficiently address deprivations in different groups as well as an effective tool for targeting?

This chapter potentially aims at contributing both theoretically and empirically to the theme of vulnerability and in particular, in relation to recent market-type shocks such as the recent food spike. How international and market shocks are transmitted into domestic economies and their implications at household level is important. The results that will be obtained in this research could act as guidelines for policy makers and in particular the evaluation of the effectiveness of poverty alleviation programs that can be measured by comparing the pre- and post-programs of vulnerability.

1. POVERTY AND VUNERABILITY

Poverty can be defined as an ex-post measure of a household's well-being. It reflects a current state of deprivation in different dimensions such as lack of resources or capabilities to satisfy current needs. Vulnerability, on the other hand, may be broadly considered as an ex-ante measure of well-being, reflecting not so much how well off a household currently is, but what its future prospects are. The main difference between the two phenomena is the presence of risk i.e., the presence of uncertainty in the level of future well-being. The uncertainty that households face about the future stems from multiple sources of risk–harvests may fail, food prices may rise, the main income earner of the household may become ill, etc. The absence of such risks renders poverty and vulnerability synonymous measures of well-being.

Several authors have shown that poverty is a stochastic phenomenon as currently non-poor households who face a high probability of a large adverse shock, may, on experiencing the shock, become poor tomorrow. Moreover, among the currently poor households there may be some who are only transitorily poor while others who will continue to be poor (or poorer) in the future. Thus including vulnerability to poverty in well-being assessments is necessary and desirable.

Poverty

Economists have for a long time used measures of poverty in order to identify and study the welfare of poorer households in a population. Income or consumption expenditures are often regarded as proxies of households' economic welfare and are frequently measured over relatively short periods of time. A household's welfare depends not only on its average income or expenditures, but also on the risk it confronts. This dependence is particularly relevant for households that have few economic resources. To consider an extreme case, a household with low expected consumption expenditures but with a small chance of starving may be considered to be poor, but may prefer not to trade places with a household that has a higher expected consumption but greater consumption risk. Measures of household welfare should thus take into consideration both average expenditures and risks that households confront.

Three elements are required in measuring poverty:

1. Choose the relevant dimension and indicator of well-being;
2. Select a poverty line, that is, a threshold below which a given household or individual will be classified as poor.
3. Select a poverty measure to be used for reporting for the population as a whole or for a population subgroup only.

Topics of risk and poverty have been addressed by estimating expected values of the poverty indices that were introduced by Foster et al. (1984). While useful for measuring poverty, these indices have some limitations especially when one considers the policy applications. For instance, in order measure the impact of risk on welfare, policymakers who minimize the expected value of one of the poverty indices tend to assign too much risk to poorer households.

Income and consumption indicators that reflect material resources have often been used as indicators for multidimensional poverty. These two indicators may however fail to capture other crucial dimensions of poverty especially in developing countries. For instance, people who are consumption poor are nearly the same as those who suffer malnutrition, are ill-educated, or are disempowered. Moreover, monetary poverty indicators often provide insufficient policy guidance regarding deprivations in other dimensions. Coming up with a good poverty measure is indeed a challenging issue. The question remains how to condense social and economic indicators into lean measures that can be easily interpreted and can also be useful to policy makers.

The concept and methodology of multidimensional poverty tackles some of the above mentioned limitations of the Foster et.al. (1984) indices. The Alkire and Foster (2011) multidimensional methodology proposes a dual cut-off at the identification step of poverty measurement. This approach has several desirable properties. Firstly, it can be adopted to different contexts and for different purposes given its different dimensions and indicators. Secondly, the methodology could also be used to examine one particular sector, to represent for example, the quality of education or dimensions of health. Thirdly, ordinal, categorical, and cardinal data can be used. Fourthly, this measure is highly decomposable. The measure can be broken down into its individual dimensions to identify which deprivations are driving multidimensional poverty in different regions or groups. Finally, it is a powerful tool for guiding policies to efficiently address deprivations in different groups. It is also an effective tool for policies that are targeting specific groups.

Unidimensional Poverty Measure.

Amartya Sen (1976) defined two main steps that poverty measurement must address:

1. Identifying the poor among the total population;

   This step dichotomizes the population into *poor a*nd *non-poor*. The main tool is the poverty line, denoted by *z.* An individual or household *i* is poor if $xi < z$ and is non-poor if $xi \geq z$. Poverty lines can be *Absolute Poverty Line*: Does not depend on the size of the entire distribution but based on the cost of a set of goods and services considered necessary for having a satisfactory life.

   Relative Poverty Line: Depends on the size of the entire distribution.

   Hybrid Poverty Line: a combination of absolute and relative poverty lines.

2. Creating a numerical measure of poverty. *How poor is the society?*

   This step construct an index of poverty summarizing the information in the censored achievement vector x*. For each distribution *x* and poverty line z, P(x;z) or P(x*) indicates the level of poverty in the distribution.

Three basic poverty measures can be computed and these are:

1. *The Headcount Ratio (H):* The proportion of the population that is poor;
2. *The poverty gap:* it measures the average depth of poverty across the society as a whole. This provides information regarding how far off households are from the poverty line. This measure captures the mean aggregate income or consumption shortfall relative to the poverty line across the whole population. It is obtained by adding up all the shortfalls of the poor (assuming that the nonpoor have a shortfall of zero) and dividing the total by the population;

3. *The squared gap*, This takes into account not only the distance separating the poor from the poverty line (the poverty gap), but also the inequality among the poor. A higher weight is placed on those households further away from the poverty line.

Unidimensional methods can be applied when one has a well-defined single-dimensional resource variable or monetary dimension to wellbeing, such as income or consumption. Identification in the unidimensional context starts by setting a poverty line corresponding to a minimum level below which one is considered poor.

When estimating poverty using monetary measures, one may have a choice between using income or consumption as the indicator of well-being[13]. Most research has argued that, provided the information on consumption obtained from a household survey is detailed enough, consumption will be a better indicator of poverty measurement than income. This is so for the following reasons:

- *Consumption is a better outcome indicator than income.* Actual consumption is more closely related to a person's well-being i.e., of having enough to meet current basic needs.
- *Consumption may be better measured than income.* In developing countries and in poor agrarian economies, incomes for rural households may fluctuate during the year, according to the harvest cycle. Moreover, in urban economies with large informal sectors, income flows also may be erratic. This implies a potential difficulty for households in correctly recalling their income, in which case the

[13] When both income and consumption are available, the analyst may want to compute poverty measures with both indicators and compare the results

information on income derived from the survey may be of low quality. In addition, large shares of income are not monetized if households consume their own production or exchange it for other goods.

- *Consumption may better reflect a household's actual standard of living and ability to meet basic needs.* Consumption expenditures reflect not only the goods and services that a household can afford based on its current income, but also whether that household can access credit markets or household savings at times when current income is low or even negative, perhaps because of seasonal variation, harvest failure, or other circumstances that cause income to fluctuate widely.

Multi-dimensional Poverty Measure.

Multidimensional poverty is made up of different factors that constitute poor people's experience of deprivation. These factors include poor health, lack of education, inadequate living standard, lack of income, disempowerment, poor quality of work and threat from violence

A multidimensional measure can incorporate a vast range of indicators in order to capture the complexity of poverty and better inform policy makers on how to eradicate poverty. Thus, diverse indicators may be appropriately selected to suit the society and specific situation.

A multidimensional approach to poverty is crucial because of the following reasons:

- Income alone may not capture the various aspects of poverty. The Human Development Report published by the UNDP (1997) highlighted that lack of income only provided part of the picture in terms of the many factors that impact on individuals' level of welfare (longevity, good health, good nutrition, education, being well integrated into society, etc.). It thus called for a new poverty measure that accounted for other welfare indicators, such as a short lifespan, measure which is related to the problem of access to education and communications and a composite index capturing facets of the level of material welfare.

- Poor people themselves when asked, describe their experience of poverty as being multidimensional. Participatory exercises have recently revealed that poor people describe ill-being to include poor health, nutrition, lack of adequate sanitation and clean water, social exclusion, low education, bad housing conditions, violence, shame, disempowerment and much more.
- Multiple dimensions provide policy-relevant information on different aspects of poverty enabling policies makers to be better-equipped to target the affected groups and reduce it.

In recent years, the literature on multidimensional poverty measurement has blossomed in a number of different directions. The 1997 *Human Development Report* and the 2000/1 *World Development Report* introduced poverty as a multidimensional phenomenon, and the Millennium Declaration and MDGs have highlighted multiple dimensions of poverty since 2000.

Bourguignon and Chakravarty (2003), proposed a class of multidimensional poverty measures that extended the Foster Greer and Thorbecke (FGT) class of indices and discussed interrelationships among dimensions. They propose the use of dimension-specific as the basis for determining who is deprived and in which dimension. They then posit the existence of an identification function, which determines whether a person is deprived enough to be called poor, and a poverty measure, which evaluates how much poverty there is overall[14]. Axioms analogous to the ones used in the unidimensional case ensure that the measure properly reflects poverty and that it can be decomposed by subgroup. The axioms also ensure that the poverty measure is consistent with the identification function. Their discussion of identification concerns general forms of identification functions rather than specific examples, and it is clear from the context that trade-offs are being made between continuous dimensional variables (Alkire and Foster, 2011).

Atkinson (2003), linked the emerging axiomatic literature on multidimensional poverty measures to the 'counting' literature that had been implemented in Europe and urged that counting measures be connected more with welfare economics. Two benchmark identification approaches are discussed by Atkinson: the union and intersection approaches. Under union identification, a person who is deprived in any dimension is considered poor. Under intersection identification, only persons who are deprived in all dimensions are considered poor. Both approaches are easy to understand and have useful characteristics, such as being able to be applied to ordinal variables. However, they can be particularly challenging when it comes to separating the poor from the nonpoor.

[14] Axioms analogous to the ones used in the unidimensional case ensure that the measure properly reflects poverty and that it can be decomposed by subgroup. The axioms also ensure that the poverty measure is consistent with the identification function.

This growing literature also includes Alkire and Foster (2011), Chakravarty, Deutsch and Silber (2008), Deutsch and Silber (2005), Duclos, Sahn and Younger (2006) and Maasoumi and Lugo (2008).

Alkire and Foster (AF) Method

This method was first developed in 2007 by Sabina Alkire and James Foster. It is a flexible technique that can incorporate several different 'dimensions' of well-being of household or individuals. Different dimensions and indicators can be selected to create a measure to a particular context.t Alkire and Foster (2011) aimed at constructing poverty measurement method that could be used with discrete and qualitative data as well as continuous and cardinal data. Theoretically, it aimed at re-examine the identification step (addressing the question 'who is poor?'). This poses a much greater challenge when there are multiple dimensions. This measure provides an aggregate poverty measure that reflects the prevalence of poverty and the joint distribution of deprivations.

Poverty measurement can be broken down conceptually into two distinct steps:

1. the identification step defines the cut-offs for distinguishing the poor from the non-poor,
2. the aggregation step brings together the data on the poor into an overall indicator of poverty.

At the identification stage the Alkire and Foster's multidimensional method implements two forms of cut-offs and a counting methodology. The first cut-off is the traditional dimension-specific poverty line or cut-off. This cut-off is set for each dimension and identifies whether a person is deprived with respect to that particular dimension. The second cut-off describes how widely deprived a person must be in order to be considered poor. Weights are attributed to each dimension and if the dimensions are equally weighted, the second cut-off is simply the number of dimensions in which a person must be deprived to be considered poor. Once the cut offs have been identified in terms of who is poor and who is not, the data is then aggregated using a natural extension of the Foster Greer Thorbecke (FGT) poverty measures in wider multidimensional space.

This method captures both the percentage of people who are poor and the overlapping deprivations that each individual or household faces by mapping outcomes for each individual or household against the criteria being measured. This is unique to the Alkire Foster method, and gives it three main advantages:

- Measures created using the technique reflect the intensity of poverty (the average number of deprivations or weighted sum of deprivations that each individual experiences).
- Measures created using the technique are transparent**:** they can be broken down quickly and easily by region or by social group.
- Poverty and Wellbeing Measure: It can be used to create national, regional or international measures of poverty or wellbeing by incorporating dimensions and indicators that are tailored to the context.
- Useful for Policy Makers
    - Effective allocation of resources. Policymakers can identify the poorest people and the aspects in which they are most deprived. This information is vital to investing resources where they are likely to be most effective at reducing poverty.

- Identifying interconnections among deprivations. The Alkire Foster method integrates many different aspects of poverty into a single measure, reflecting interconnections among deprivations and helping to identify poverty traps;
- Showing impacts over time. The method can be quicker to reflect the effects of changes in policies over time. Moreover, this methodology can also be used to monitor the effectiveness of programmes over time.
- Flexibility. Different dimensions, indicators and cut-offs can be used to create measures tailored to specific uses, situations and societies. These can be chosen through participatory processes. The method can be used to create poverty measures, to target poor people as beneficiaries of Conditional Cash Transfers (CCTs) or services, and for the monitoring and evaluation of programmes.

Properties of MPI Measure

There are six basic properties for poverty measures (Foster et al., 2011). These poverty measure properties can be placed in two main categories:

- *Invariance properties:* These are properties that leave poverty measures invariant to certain changes in the sample. Properties in the invariance category include symmetry, normalization, population invariance, scale invariance and focus.

- *Dominance properties:* These are properties that cause a poverty measure to change in a particular direction. Properties in the dominance category include: monotonicity, transfer principle, transfer sensitivity, and subgroup consistency.

Vulnerability

Vulnerability is defined as the probability or risk today of becoming poor or of falling into deeper poverty in the future given the current welfare status of an individual or household. It is a key dimension of welfare, since a risk of large changes in household well-being may constrain households to lower investments in productive assets—when households need to hold some reserves in liquid assets—and in human capital. High risk may also force households to diversify their income sources that may come at the cost of lower returns. Vulnerability may influence household behaviour and coping strategies and is thus an important consideration of poverty reduction policies (Coudouel, Hentschel and Wodon, 2002).

In his definition, Guillaumont (2008) considers two main types of exogenous shocks and thus two main sources of vulnerability; environmental or 'natural' shocks, and climatic shocks; and external shocks, such as fall in external demand, world commodity prices volatility, and international fluctuations of interest rates. Vulnerability can thus be perceived as the result of three components; the size and frequency of the *shocks*; the *exposure* to shocks, that depends on the size, the location, and economic structure; and the ability to react to shocks (Guillaumont, 2008).

The degree of vulnerability depends on the characteristics of the risk involved and the household's ability to respond to risk through risk management strategies. In other words, the extent to which the household can become and/or remain poor depends on the magnitude of the risky event and the ability of the household in managing it. While vulnerability and poverty are conceptually closely related, vulnerability is defined independently of the person's current poverty or welfare status (Christiaensen and Subbarao, 2005).

A household's vulnerability to poverty at any point in time depends on how its livelihood prospects and well-being is likely to evolve over time. This dynamic perspective on household well-being recommends that poverty and vulnerability may be driven by:

- Household exposure to adverse aggregate shocks (e.g. macroeconomic shocks or commodity price shocks) and/or adverse idiosyncratic shocks (e.g., localize crop damage or illness of the main income-earner in the household);
- A low ability to generate income in the long run.

Two main approaches of vulnerability have emerged in the literature. The first associates vulnerability with high expected poverty (Christiaensen and Boisvert, 2000; Christiaensen and Subbarao, 2005; Chaudhuri, 2002); while the second associates it with low expected utility (Ligon and Schechter, 2003). Using an axiomatic approach, Dercon (2005) proposes an additional measure of vulnerability that preserves axioms of expected poverty while accounting for individual risk preferences. Both of these two approaches to vulnerability consider as the object of study household consumption, which is determined by individual characteristics, and is subject to covariate or idiosyncratic risks. An appropriate probability distribution of consumption is constructed. Using the consumption cumulative probability distributions and density functions vulnerability measures related to the Foster, Greer and Thorbecke (FGT) indices (Foster *et al.*, 1984) are constructed for households. Vulnerability can be denoted as

$$V_H(p_h, w_h, z) \tag{3.1}$$

Where V_h is the indicator of the household's vulnerability, w_h is the household's welfare indicator; p_h is the probability that a households welfare indicator will fall below the given poverty line (*z*).

Other vulnerability measures proposed in the literature include vulnerability as the ability to smooth consumption in response to shocks, measured by observed changes in household consumption patterns over time (Glewwe and Hall, 1998; Dercon and Krishnan, 2000). Kamanou and Morduch (2002) estimate the expected distribution of future expenditures for each household and then calculate vulnerability as a function of those distributions in Côte d'Ivoire. They develop an approach built on Monte Carlo and bootstrap predictions of consumption change and apply it on the two-year dataset in Côte d'Ivoire. However their analysis is limited to only two consecutive periods and thus does not take into consideration longer-term issues (Kamanou and Morduch, 2002). These measures have some limitations. Firstly, defining vulnerability uniquely in terms of a household's consumption smoothing ability does not take into consideration the variation across households in levels of exposure to income shocks. A household may have a lower ability to smooth consumption but it may also be exposed to fewer income shocks. Secondly, measures that focus on the ability to smooth consumption ignore the asymmetry in poverty that may be crucial to the notion of vulnerability, particularly the importance of exposure to downside risk.

Measures of Vulnerability

Vulnerability is considered to be a forward-looking or ex-ante welfare measure of a household. This implies that while the poverty status of a household can be contemporarily observable i.e., with the right data one declare the current poverty status of a household is currently poor-the level. This is not the case with vulnerability. One can estimate or make inferences about whether a household is currently vulnerable to future poverty, but cannot directly observe a household's current vulnerability status. It is therefore necessary to make inferences on the future welfare prospects in order to assess vulnerability effectively. In order to do so, one requires a framework that incorporates both the inter-temporal aspects and cross-sectional determinants of consumption patterns at the household level.

Consumption as a welfare measure, (Deaton 1992; Browning and Lusardi 1995) suggests that a household's consumption in any period will, in general, depend on wealth, current and future income as well as shocks. Each of these will in turn depend on a variety of household characteristics as well as a number of features of the aggregate environment (macroeconomic and socio-political) in which the household is based. Thus household *i* consumption in time *t* may be expressed as:

$$c_{it} = c(X_i, \alpha_t, \gamma_i, \varepsilon_{it}) \tag{3.2}$$

Where X_i is a set of household characteristics such as, the educational attainment of the head of the household, presence of a government poverty scheme in the community in which the household resides, as well as interactions between the two to capture potential inequities in the level of access to public programmes. α_t is a vector of parameters describing the state of the economy at time *t*, and γ_i and ε_{it} represent, respectively, an unobserved time-invariant household-level effect, and any idiosyncratic factors (shocks) that create differences in household welfare status.

Vulnerability of a household *i* in time t+1 can be defined as:

$$v_{it+1} = \mathrm{E}\left[p_{\gamma,i,t+1}\left(c_{i,t+1}\right)\mathrm{F}|\left(c_{i,t+1}|X_i, \alpha_t, \gamma_i, \varepsilon_{it}\right)\right] \quad (3.3)$$

From this expression one can deduce that a household's vulnerability level derives from the stochastic properties of the inter-temporal consumption stream it faces, and these in turn depend on a number of household and environmental characteristics in which it operates.

Expected utility approach (Ligon and Schechter, 2002): measures vulnerability as expected utility and takes into account individual risk preferences through the choice of the utility function. Thus vulnerability of household *i* in time *t* can be defined as:

$$V_{i,t=0} = U_i(z) - EU(c_{it}) \quad (3.4)$$

Where U_i is the utility function of an individual household *i*; $EU(c_{it})$ is expected utility which is a function of consumption expenditures. This approach defines vulnerability as low expected utility and is calculated as the difference between the utility derived from a certain level of consumption ($U_i(z)$) is equivalent to the poverty threshold) and the expected utility from each household's consumption. The empirical implementation of this approach requires the specification of the utility function and hence assumptions about risk preferences of households**.** The extent to which individual risk preferences should be explicitly accounted for in analysing vulnerability measures remains debatable. On the one hand, if the vulnerability measures are used to allocate budgets, it would be more efficient to explicitly account for individual risk preferences to discourage moral hazard behaviour. On the other hand, it is acknowledged that individuals are at times be not well informed about their preferences especially those related to risk and uncertainty (Griffin, 1986). Moreover it may be difficult to imagine that human knowledge can be so perfect that tomorrow's hunger could be perceived today. As a result, societies have often developed rules and schemes which override people's individual risk preferences (Shackle, 1965; Kanbur, 1987).

Expected poverty approach (Christiaensen and Boisvert, 2000; Chaudhuri, 2002; Christiaensen and Subbarao, 2005) defines vulnerability as the prospects of an individual or household today of being poor in the future, i.e. the prospects of becoming poor while currently not poor, or the prospects of remaining be poor if currently poor. The level and variability of a household's future consumption behaviour depends on the stochastic nature of the risk factors, the extent to which the household is exposed to these risks and the ability and desire of the household to cope with these shocks. The household consumption can be expressed as:

$$C_{ijt+1} = c\left(X_{ijt}, S_{ijt+1}, \delta_{t+1}, \beta_{ij}, u_{ijt+1}\right) \tag{3.5}$$

where X_{ijt} represents the household's observed and location-specific characteristics *i* in location *j* at time *t*. S_{ijt+1} represent observed local covariate and idiosyncratic shocks experienced by the household between t and t +1. δ_{t+1} is a vector of parameters describing the returns to the locality and household endowments, and the effect of the shocks S_{ijt+1}. It reflects the overall state of the economy at time t[15].

A household adapts its endowments each period based on its previous period's endowments, the shocks it experienced during that period and changes in the economic and political environment.

X_{ijt} can thus also be written as a function of its initial endowment base X_{ij0} and the series of shocks S_{ijt-k} the household experienced between 0 and t, with k =1, …,t

$$X_{ijt} = x\left(X_{ij0}, S_{ijt-k}, \phi_t, e_t\right) \tag{3.6}$$

with ϕ_t the vector of coefficients relating the initial endowments and past shocks to the current asset base. Household consumption can thus also be expressed more generally as a function of initial endowments and past shocks:

$$C_{ijt+1} = c\left(X_{ij0}, S_{ijt-k}, \delta^*_{t+1}, \beta_{ij}, u^*_{ijt+1}\right) \text{ with } k = 0, ..., t \tag{3.7}$$

The household's consumption pattern will follow a stochastic process as the prevailing credit, savings and insurance markets in most developing countries are inefficient (Besley, 1995).

The stochastic properties will depend on the assets owned by the household and its environment as well as the stochastic properties of the risk factors[16].

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[15] Assumptions: δ_{t+1} constant over time. β_{ij} and u_{ijt+1} are unobserved time invariant household and locality effects, and unobserved idiosyncratic shocks respectively, that contribute to differential welfare outcomes for households.

Christiaensen and Subbarao, (2005) specify the demand function as:

$$\ln c_{ijt+1} = X_{ijt}\alpha + S_{ijt+1}\vartheta + S_{ijt+1}\varphi' X_{ijt}' + u_{ijt+1}$$

$$= X_{ijt}\alpha + S_{ijt+1}\vartheta + S_{ijt+1}\varphi' X_{ijt}' + \delta_{ij} + h^{1/2}\left(X_{ijt};\rho\right)\varepsilon_{ijt+1} \qquad (3.8)$$

with $\varepsilon_{ijt+1} \sim N\left(0,\sigma_{\varepsilon}^{2}\right)$

The conditional mean and variance of equation () can then be expressed as:

$$E\left(\ln c_{ijt+1} \mid X_{ijt}\right) = X_{ijt}\alpha + E\left(S_{ijt+1}\right)\left[\vartheta + \varphi' X_{ijt}'\right] + E\left(\delta_{ij}\right) \qquad (3.9)$$

$$V\left(\ln c_{ijt+1} \mid X_{ijt}\right) = \left[\vartheta + \varphi' X_{ijt}'\right]' V\left(S_{ijt+1}\right)\left[\vartheta + \varphi' X_{ijt}'\right] + \sigma_{\delta}^{2} + h\left(X_{ijt};\rho\right)^{*}\sigma_{\varepsilon}^{2} \qquad (3.10)$$

Consequently, the variance of consumption can be decomposed into: (1) the variance resulting from observed covariate shocks; (2) the variance yielded by observed idiosyncratic shocks; and (3) the variance from unobserved idiosyncratic shocks respectively.

$$V\left(\ln c_{ijt+1} \mid X_{ijt+1}\right) = \left[\vartheta_{sc} + \varphi_{sc}' X_{ijt+1}'\right]^{2}\sigma_{sc}^{2} + \left[\vartheta_{si} + \varphi_{si}' X_{ijt+1}'\right]^{2}\sigma_{si}^{2} + h\left(X_{ijt};\rho\right)^{*}\sigma_{\varepsilon}^{2} \qquad (3.11)$$

[16] In their empirical application, Christiaensen and Subbarao (2005) assume that consumption is log normally distributed. This corresponds to what is typically found in the data. In addition, lognormal distributions are completely determined by two parameters: their mean and variance. It thus suffices to estimate the conditional mean and variance of a household's future consumption to obtain an estimate of its ex ante distribution $f(\cdot)$ and its vulnerability or expected poverty (V_{γ}).

2. DATA AND METHODOLOGY

Despite the impressive economic performance in the recent years and the possession raw materials and minerals, Tanzania remains one of the poorest countries. In 2012, its average per capita income stood at US$ 570, placing it in the 176th position out of 191 countries in the world. Even by the most optimistic poverty estimates, there are still approximately 12 million poor people living in Tanzania, which is approximately the same number as in 2001. From a macroeconomic prospective, agriculture remains dominant in the economy, accounting for nearly 45 percent of the GDP and employs around 70 percent of the labour force. Agriculture accounts for three quarters of merchandise exports and represents a source of livelihood to about 80 percent of the population. Agricultural income is the main source of income for the poor, especially in rural areas. Smallholder farmers characterize Tanzanian agriculture. In addition, Tanzania's rank in the United Nations Development Program's (UNDP) Human Development Index has improved since 1995, but its progress toward the Millennium Development Goals (MDGs) has been uneven. The country is expected to reach only three out of seven MDGs by 2015. Tanzania is on track to meet the MDGs related to combating HIV/AIDS and reducing infant and under-five mortality but is lagging in primary school completion, maternal health, poverty eradication, malnutrition, and environmental sustainability. Improving the socio-economic circumstances of this large group of citizens therefore remains a top priority for Tanzanian policy makers. During 2008/09, the Government Budget continued to implement the National Strategy for Growth and Reduction of Poverty (NSGRP), commonly referred to by its Kiswahili acronym MKUKUTA as a means to achieving Millennium Development Goals 2015 and the National Development Vision 2025.

2.1 Data and Data Source

In the 2008-09 survey, the sample size was 3,280 households in 410 Enumeration Areas (2,064 households in rural areas and 1,216 urban areas). The survey was conducted in four different strata: Dar es Salaam, other urban areas on mainland Tanzania, rural mainland Tanzania, and Zanzibar. The sample was constructed based on the National Master Sample frame which is a list of all populated enumeration areas in the country developed from the 2002 Population and Housing Census. The sample includes a partial sub-sample of households interviewed during the 2006/2007 Household Budget Survey. Sample design was done in spring of 2008. . The survey was conducted between October 2008 and October 2009 (Tanzania National Bureau of Statistics, 2009-10).

The sample design for the second wave of the survey revisited all the households interviewed in the first round of the panel, as well as tracking adult split-off household members. The original sample size of 3,265 households was designed to representative at the national, urban/rural, and major agro-ecological zones. The total sample size was 3,265 households in 409 Enumeration Areas (2,063 households in rural areas and 1,202 urban areas). This represented 3168 round-one households, a re-interview rate of over 97 percent. The survey was run between October 2010 and September 2011, with tracking fieldwork continuing until November 2011.

Table 17 below reports the descriptive statistics of the key variables used in this analysis. These include geographical variables, household characteristics, asset ownership as well as shocks.

Table 17: Variables and Statistics

Variable	Mean	Std. Dev.	Min	Max
Rural	.63992	.4800979	0	1
HHsize	5.0341	2.842485	1	46
Education HHhead	16.545	5.138737	1	45
Female HHhead	.24795	.4318891	0	1
Age HHhead	46.046	15.47478	18	102
HH_assets	.38376	.4863786	0	1
Death HH member	.11438	.3183177	0	1
Drought or floods	.24297	.428945	0	1
Hijacking/robbery	.10995	.3128801	0	1
Rise in food prices	.55229	.4973367	0	1
Other shocks	.04044	.1970254	0	1
Water shortage	.32638	.4689631	0	1
Fire	.02496	.1560294	0	1
Fall crop sale prices	.22528	.4178303	0	1
Rise agr. input prices	.21011	.4074513	0	1
Livestock died/ stolen	.18926	.3917749	0	1

Methodology

2.2 Poverty

Unidimensional Poverty Measure

In order to measure poverty using a unidimensional measure, we use household consumption expenditure. The poverty income (or consumption expenditure) measure is used as the baseline for this analysis. We calculate the total annual expenditure of each household. We then determine the income poverty line using the Household Budget Survey (HBS) National Poverty Line which is the 28-day consumption expenditure. The HBS implements a basic needs approach to measure absolute poverty in Tanzania where it defines the absolute minimum resources necessary for long-term physical well-being in terms of consumption of goods. For each survey year the HBS records everything that was purchased and consumed over 28 days in sampled households. This included records on food and non-food items that were purchased as well as food that was grown by the household. It excluded household expenditure that was not for consumption, for example, purchasing inputs for a farm or other businesses operated by the household. Thus the poverty line is then defined as the amount of income required to satisfy those needs. We annualize the HBS poverty line for each of the survey years.

According to 2007/08 and 2011/12 HBS the basic needs poverty lines were calculated as TSH 13998 and 36,482, respectively. Poverty lines are however only provided in the years in which HBS are conducted. Thus we had 2007/08 and 2011/12 HBS Poverty Lines. Given Tanzania's Purchasing Power Parity (PPP) and Consumer Price Index (CPI) we impute the poverty lines for 2008/09 and 2010/11 which are TSH 31,255 and 34,070 respectively. Using the two poverty lines we determine which households are unidimensionally poor.

Multi-dimensional Poverty Indicator

Poverty and vulnerability is acknowledged to be multidimensional. This approach is interesting as the joint distributions of the deprivations contain more information that the marginal distributions of the single dimensions (Ferreira, 2011).

A multidimensional poverty analysis is conducted. This will enable me to identify the key and important dimension of poverty faced by households both at the aggregate level as well as at decomposed level. The multidimensional poverty measure is conducted implementing the Alkire and Foster multidimensional poverty methodology. It is implemented following 12 steps:

Step 1: Choose Unit of Analysis. The unit of analysis is most commonly an individual or household but could also be a community, school, clinic, firm, district, or other unit. In this case we will choose the household as the unit of analysis.

Step 2: Choose Dimensions. The choice of dimensions for which the households may be deprived.

Step 3: Choose Indicators. Indicators are chosen for each dimension on the principles of accuracy (using as many indicators as necessary so that analysis can properly guide policy) and parsimony (using as few indicators as possible to ensure ease of analysis for policy purposes and transparency). Statistical properties are often relevant—for example, when possible and reasonable, it is best to choose indicators that are not highly correlated.

Step 4: Set Poverty Lines. A poverty cut-off is set for each dimension. This step establishes the first cut-off in the methodology. Every person can then be identified as deprived or none deprived with respect to each dimension. Poverty thresholds can be tested for robustness, or multiple sets of thresholds can be used to clarify explicitly different categories of the poor (such as poor and extremely poor).

Step 5: Apply Poverty Lines. This step replaces the person's achievement with his or her status with respect to each cut-off; for example, in the dimension of health, when the indicators are "access to health clinic" and "self-reported morbidity body mass index," people are identified as being deprived or non-deprived for each indicator.

Step 6: Count the Number of Deprivations for Each Person. The total number of deprivations are counted or each individual or household.

Step 7: Set the Second Cut-off. Assuming equal weights for simplicity set a second identification cut-off, *k*, which gives the number of dimensions in which a person must be deprived in order to be considered multidimensionally poor. In practice, it may be useful to calculate the measure for several values of *k*. Robustness checks can be performed across all values of *k*.

Step 8: Apply Cut-off k to obtain the Set of Poor Persons and Censor All Non poor Data. The focus is now on the profile of the poor and the dimensions in which they are deprived. All information on the non poor is replaced with zeroes.

Step 9: Calculate the Headcount, **H**. Divide the number of poor people by the total number of people. It is the proportion of people who are poor in at least *k* of *d* dimensions. The multidimensional headcount is a useful measure, but it does not increase if poor people become more deprived, nor can it be broken down by dimension to analyse how poverty differs among groups. For that reason we need a different set of measures.

Step 10: Calculate the Average Poverty Gap, **A**. *A* is the average number of deprivations a poor person suffers. It is calculated by adding up the proportion of total deprivations each person suffers and dividing by the total number of poor persons.

Step 11: Calculate the Adjusted Headcount, M0. If the data are binary or ordinal, multidimensional poverty is measured by the adjusted headcount, *M*0, which is calculated as *H* times *A*. Headcount poverty is multiplied by the "average" number of dimensions in which all poor people are deprived to reflect the breadth of deprivations.

Step 12: Decompose by Group and Break Down by Dimension. The adjusted headcount *M*0 can be decomposed by population subgroup (such as region, rural/ urban, or ethnicity). After constructing *M*0 for each subgroup of the sample, one can break *M*0 apart to study the contribution of each dimension to overall poverty. To break the group down by dimension, let *Aj* be the contribution of dimension *j* to the average poverty gap

A. A_j could be interpreted as the average deprivation share across the poor in dimension *j*. The dimension-adjusted contribution of dimension *j* to overall poverty, which we call $M0_j$, is then obtained by multiplying *H* by A_j for each dimension.

For this research we select 3 dimensions and 10 indicators which are listed in Table18 below.

Table18: *Dimensions, Indicators and Deprivation Cut-offs*

Dimension	**Indicator**	**Deprivation cut-offs**	**Weight**
Health	Bed net	If at least one member of the of the household did not sleep under a bed net	1/6
	Nutrition	If one member of the household is malnourished	1/6
Education	Years of schooling	No household member has attained 7 years of schooling (primary schooling)	1/6
	School Attendance	If at least one child in the household between 7-15 years of age is not attending school/missed school	1/6
Living Conditions	Water	If the household uses water from unprotected well, rain water, surface water (river/dam/lake/pond/stream) Distance to Water	1/18
	Type of Floor	Households with an earth/sand and dung floor.	1/18
	Access to electricity	Household has no access to electricity	1/18
	Improved sanitation facilities	Household that have no access improved sanitation facilities	1/18
	Cooking Fuel	If the household uses wood/straw/ shrubs/grass /charcoal / none	1/18
	Asset Ownership	If the household owns less than two small assets and no big asset.	1/18

The deprivation cut offs represent the thresholds used in identifying the households that are deprived in that particular indicator. We choose to attribute equal weights to each of the three dimensions. After having selected the dimension and indicators, we construct the achievement matrix which can be defined as:

$$X = \begin{bmatrix} x_{11}\cdots & x_{1d} \\ x_{21}\cdots & x_{2d} \\ & \\ \cdots & \\ & \cdots \\ x_{n1}\cdots & x_{nd} \end{bmatrix}$$

$$z = (z_1, z_2, ..., z_d)$$
$$w = (w_1, w_2, ..., w_d)$$

Where x_{ij} is the achievement of individual *i* of attribute or dimension *j*.

- z_j is the deprivation cut-off of attribute or dimension *j*.
- w_j is the weight of attribute or dimension *j* such that: $\mathrm{w}_1 + \mathrm{w}_2 + ... + \mathrm{w}_\mathrm{d} = \mathrm{d}$

We then derive the deprivation matrix which assigns 1 for households that are deprived in the single indicators and 0 otherwise.

$$g^0 = \begin{bmatrix} g^0{}_{11}\cdots & g^0{}_{1d} \\ g^0{}_{21}\cdots & g^0{}_{2d} \\ & \\ \cdots & \\ & \cdots \\ g^0{}_{n1}\cdots & g^0{}_{nd} \end{bmatrix}$$
$$z = (z_1, z_2, ..., z_d)$$

Where:

$g^0{}_{ij} = 1$ if $x_{ij} < z_j$ (deprived)

$g^0{}_{ij} = 0$ if $x_{ij} \geq z_j$ (non-deprived)

We compute the Raw Dimensional Headcount ratios which are the deprivation rates by dimension, i.e., the proportion of people who are deprived in that dimension. It is the mean of each column of the deprivation matrix:

$$H_j = \left(g^0{}_{1j} + g^0{}_{2j} + ... + g^0{}_{nj}\right)/n \qquad (3.12)$$

Given the weights assigned we compute the weighted deprivation matrix which can be defined as:

$$g^0 = \begin{bmatrix} g^0{}_{11} \cdots & g^0{}_{1d} \\ g^0{}_{21} \cdots & g^0{}_{2d} \\ \cdots & \\ & \cdots \\ g^0{}_{n1} \cdots & g^0{}_{nd} \end{bmatrix}$$

$$z = (z_1, z_2, \ldots\ldots, z_d)$$
$$w = (w_1, w_2, \ldots, w_d)$$

Note that we use the same notation as for the deprivation matrix on purpose.

Where

- $g^0{}_{ij} = w_j$ if $x_{ij} < z_j$ (deprived)
- $g^0{}_{ij} = 0$ if $x_{ij} \geq z_j$ (non-deprived)

Where the 'deprivation count' or score for each household is the sum of the weighted deprivations $c_i = g_{i1} + \ldots + g_{id}$

$$c = \begin{bmatrix} c_1 \\ c_2 \\ \\ \\ c_n \end{bmatrix}$$

Given a poverty cut-off *k*, we compare the deprivation count with the k cut off and then censor the deprivations of those who were not identified as poor.

$\rho_k(x_i; z) = 1$ if $c_i \geq k$ poor

$\rho_k(x_i; z) = 0$ if $c_i < k$ non-poor

Censored Weighted Deprivation Matrix and Deprivation Count Vector

$$g^0(k) = \begin{bmatrix} g^0{}_{11}(k)\ldots & g^0{}_{1d}(k) \\ g^0{}_{21}(k)\ldots & g^0{}_{2d}(k) \\ \ldots & \\ & \ldots \\ g^0{}_{n1}(k)\ldots & g^0{}_{nd}(k) \end{bmatrix} c(k) = \begin{bmatrix} c_1(k) \\ c_2(k) \\ \\ \\ c_n(k) \end{bmatrix}$$

Where

- $g^0{}_{ij}(k) = g_0$ if $c_i \geq k$ (deprived and poor)
- $g^0{}_{ij}(k) = 0$ if $c_i < k$ (deprived or not but non-poor)

Using this matrix (and vector, alternatively) we compute the set of AF indicators for M_0. We first compute the Headcount Ratio of the Multidimensional Poverty Measure. It is defined as the proportion of households who have been identified as poor. It can be defined as:

$$H = \frac{\sum_{i=1}^{n} \rho_k\left(x_i; z\right)}{n} = \frac{q}{n} \qquad (3.13)$$

Where q indicates the number of poor households[17].

Intensity (or breadth) of MD Poverty is the average proportion of deprivations in which the poor are deprived.

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{dq} \qquad (3.14)$$

The Multidimensional Poverty: M_0 (Adjusted Headcount Ratio) is given by the product of incidence and intensity.

$$M_0 = H * A \qquad (3.15)$$

[17] The Headcount Ratio is sometimes referred to as the incidence of poverty, or the poverty rate.

It can also be obtained as the mean of the censored (weighted) deprivation matrix:

$$M_0 = \mu\left(g_0\left(k\right)\right) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{d} g^{0}{}_{ij}}{nd} \tag{3.16}$$

2.3 Vulnerability

Vulnerability, especially in developing countries relates to dimensions such as nutrition and access to food, health, educational opportunities, and mortality (Dercon, 2001). The main concern of this chapter is to measure poverty and vulnerability in a developing-country context. The methodology that is implemented in this research draws on the expected poverty approach (Christiaensen and Subbarao, 2005; Chaudhuri, 2002) and will focus on the model proposed by Dercon (2001 and 2005). The poverty index for a household *i* at time *t*, $p_{it}(z, c_{it})$ is defined over consumption c_{it} and the poverty line *z*.

The level of vulnerability of a household *i* at any initial period $t = 0$ with respect to the households' future consumption $\left(c_{i,t>0}\right)$ will be measured as:

$$\begin{aligned} V_{i,t=0} &= E[p_{it}(z, c_{it})|F(c_{it})] \\ &= \int_{c_t^*}^{z} p_{it}(z, c_{it}) dF(c_{it}) \\ &= F(z) \int_{c_t^*}^{z} p_{it}(z, c_{it}) \frac{f(c_{i,t})}{F(z)}\, dc_{it} \end{aligned} \tag{3.17}$$

with c_t^* the lower bound of future consumption c_t and *F(·)* the cumulative distribution function associated with density function *f(·).*

Households' consumption is derived as:

$$c_{it} = c(X_i, I_i, \beta_t, \alpha_i, \varepsilon_{it}) \qquad (3.18)$$

where X_i is a vector of observable household characteristics, I_i is a vector of observable risk management instruments, β_t is a vector of parameters describing the state of the economy at time *t*, α_i are unobserved but fixed household characteristics and, ε_{it} are stochastic errors.

The household's vulnerability will be measured as the current probability of becoming poor in the future (*F(z)*) multiplied by the conditional expected poverty.

$$p_{it}(z, c_{it}) = \left[\max\left(0, \frac{z - c_{it}}{z}\right)\right]^{\gamma},$$

$$V_{i,t=0,\gamma} = F(z) \int_{c_t^*}^{z} \left[\frac{z - c_{it}}{z}\right]^{\gamma} \frac{f(c_{i,t})}{F(z)}\, dc_{it} \qquad (3.19)$$

A household's vulnerability is measured as the product of the probability that the households consumption level falls below the poverty line ($F(z)$) times the probability weighted function of relative consumption shortfall.

Depending on γ, different aspects of shortfall are emphasized. If $\gamma = 0$, Equation (3.19) simplifies to $F(z)$ and vulnerability is measured as the probability of consumption shortfall. If $\gamma = 1$, vulnerability is measured as the product of probability of shortfall and the conditional expected gap (Christiaensen and Subbarao, 2005). The level of vulnerability is therefore expressed as:

$$V_{i,t=0,y=1} = F(z) \int_{c_t^*}^{z} \left[\frac{z - c_{it}}{z}\right] \frac{f(c_{i,t})}{F(z)} \, dc_{it} \quad (3.20)$$

2.4 Poverty Dynamics - Logit Model

The Logit model implements the logistic function to model binary choices. Models for mutually exclusive binary outcomes focus on the determinants of the probability *p* of the occurrence of one outcome rather than an alternative outcome that occurs with a probability of *1-p*

Suppose the outcome variable, y, takes one of two binary values:

$$y = \begin{cases} 1 \\ 0 \end{cases}$$

Where outcome 1 occurs with probability *p* and outcome 0 occurs with probability *1-p*. The key objective is to measure *p* as a function of regressors *x*. The probability p_i that agent *i* chooses alternative 1 is hypothesized to be:

$$p_i = \frac{1}{1+e^{-\beta' x_i}} \quad (3.21)$$

The logistic transformation maps $\beta' x_i$ from $(-\infty, \infty)$ to $(0,1)$ allowing one to interpret the fitted values as probabilities. If $y_i = 1$ the observation has probability p_i; if y=0 the probability is $1 - p_i$. The probability mass function for the observed outcome, *y* is given by:

$$p_i^{y_i} (1 - p_i)^{(1-y_i)} \quad (3.22)$$

with $E(y) = p$ and $Var(y) = p(1-p)$

The conditional probability has the following form:

$$p_i = \Pr\left(y_i = 1 | x\right) = F\left(x_i^{'}\beta\right) \tag{3.23}$$

where $F\left(\cdot\right)$ is a specified parametric function of $x^{'}\beta$

The density for a single observation can be compactly written as

$p_i^{y_i}\left(1-p_i\right)^{1-y_i}$ where $p_i = F\left(x_i^{'}\beta\right)$

The likelihood function is the joint probability

$$l\left(\beta; y\right) = \prod_{i=1}^{n} p_i^{y_i}\left(1-p_i\right)^{\left(1-y_i\right)} \tag{3.24}$$

and

$$L\left(\beta; y\right) = \sum_{i=1}^{n}\left[y_i \ln p_i + \ln\left(1-p_i\right)\right] = \sum_{i=1}^{n}\left[y_i \ln\left(\frac{p_i}{1-p_i}\right) + \ln\left(1-p_i\right)\right] = \sum_{i=1}^{n}\left[y_i\left(\beta^{'}x_i\right) - \ln\left(1+e^{\beta^{'}x_i}\right)\right] \tag{3.25}$$

The first order condition $\frac{\partial L\left(\beta; y\right)}{\partial \beta} = 0$ yields a set of equations which define the maximum likelihood (ML) estimator $\tilde{\beta}$. The MLE is obtained by iterative methods and is asymptotically normally distributed.

3. RESULTS

3.1 Poverty

Table 19 below reports the raw head count ratios for the consumption expenditure indicator. There is slight decrease in the number of poor households over time. This decrease occurs both in the rural and urban setting. Rural households are poorer compared to the urban ones as they represent a large share of the poor in both survey waves.

Table 19:

Raw Headcounts- Income Poverty Indicator

Poverty Indicator	Year of Survey	
	2008-09	*2010-11*
Total	46%	42%
Rural	60%	54%
Urban	21%	18%

Table 20 reports the raw head count ratios for the MPI poverty measure. Poverty rates have slightly gone down over time and this has been driven by the decrease in rural poor households. Urban poverty has on the contrary slightly increased between the two surveys.

Table 20

Raw Headcounts- Multi-Dimensional Poverty Indicator (MPI)

Poverty Indicator	Year of Survey	
	2008-09	*2010-11*
Total	77%	73%
Rural	91%	87%
Urban	39%	41%

Table 21 reports the raw headcount ratios decomposed by dimensions and indicators. Health dimension reports one of the highest headcounts followed by the living conditions dimension. Over 50 percent of households are deprived in most of the indicators. The analysis over time shows a slight decrease in the headcounts in most of the indicators such as Bednet, Imporved sanitation and Asset ownership. The headcounts however remain above 50 percent in most of the indicators indicating the high level of households deprived.

Table 21:
Raw Headcount Ratio of Households Deprivations by Dimensions

Dimension	Indicator	2008-09	2010-11
Health	Bed net	65%	38%
	Nutrition	73%	75%
Education	Years of schooling	28%	42%
	School Attendance	18%	25%
Living Conditions	Water	75%	73%
	Type of Floor	67%	64%
	Access to electricity	86%	82%
	Improved sanitation facilities	90%	70%
	Cooking Fuel	99%	99%
	Asset Ownership	76%	67%

Censored Headcount Ratios

The Censored headcount ratio of the dimension is the proportion of the population that are poor with respect to a certain cut-off and are deprived in that dimension at the same time. The focus here is to identify the key dimensions and indicators in which the poor households are deprived in.

Table 22 below reports the censored raw headcounts for each dimension and indicator. Poor households are deprived in all indicators. These households are heavily deprived in eight out of ten indicators. Education is the indicator in which poor households are least deprived. However this indicator registered an increase in the number of poor households that are deprived in the second wave of the survey. Poor households are mainly deprived in nutrition, access to water, electricity and improved sanitation facilities. These households lack cooking fuel and are the households that own the least number of assets. This trend is confirmed over time with the second wave results.

Table 22:
Censored Raw Headcount Ratio of Households Deprivations by Dimensions

Dimension	Indicator	2008-09	2010-11
Health	Bed net	61%	34%
	Nutrition	65%	63%
Education	Years of schooling	27%	40%
	School Attendance	17%	25%
Living Conditions	Water	66%	61%
	Type of Floor	62%	59%
	Access to electricity	74%	68%
	Improved sanitation facilities	75%	62%
	Cooking Fuel	77%	73%
	Asset Ownership	66%	56%

MPI components:

Figures 12 and 13 report the MPI break down in its two components in the two respective survey waves. The Raw headcount measures the number of poor people and the average depravation share which measures the intensity of poverty. The first thing to note is that rural households still report highest raw head counts in both survey years classifying over 80 percent of the surveyed population as being poor. There is a slight decrease in the raw headcounts though the intensity remains constant over time. Urban households report relatively lower raw headcounts though these increase over time. The intensity of poverty in urban households increases from 59 percent to 60 percent. At an overall level, though poverty has slightly decreased over time, both the raw headcounts and intensities remain high in both survey waves. In particular, the intensity of poverty, i.e., the depth to which households are deprived in the different dimensions remains over 60 percent with urban intensity increasing over time.

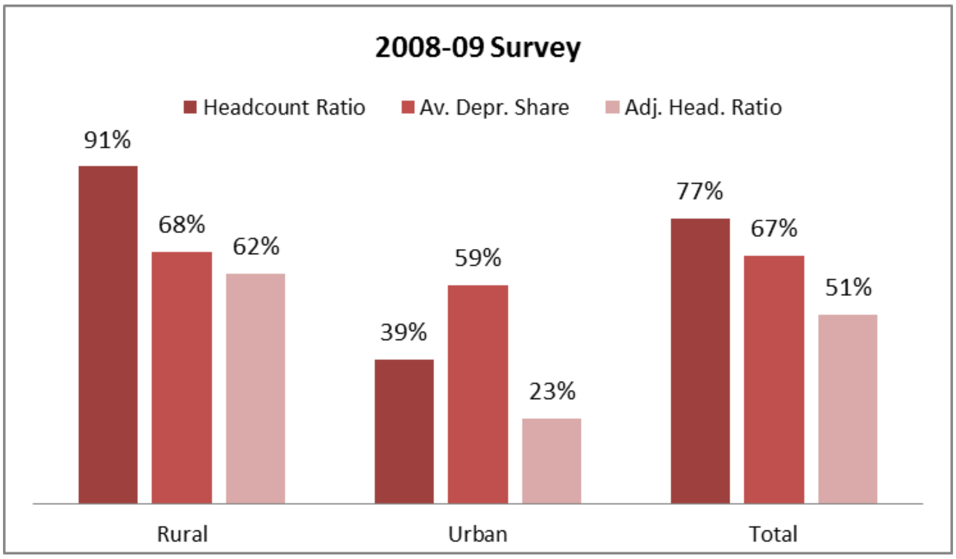

Figure 12: *MPI components 2008-09 Survey*

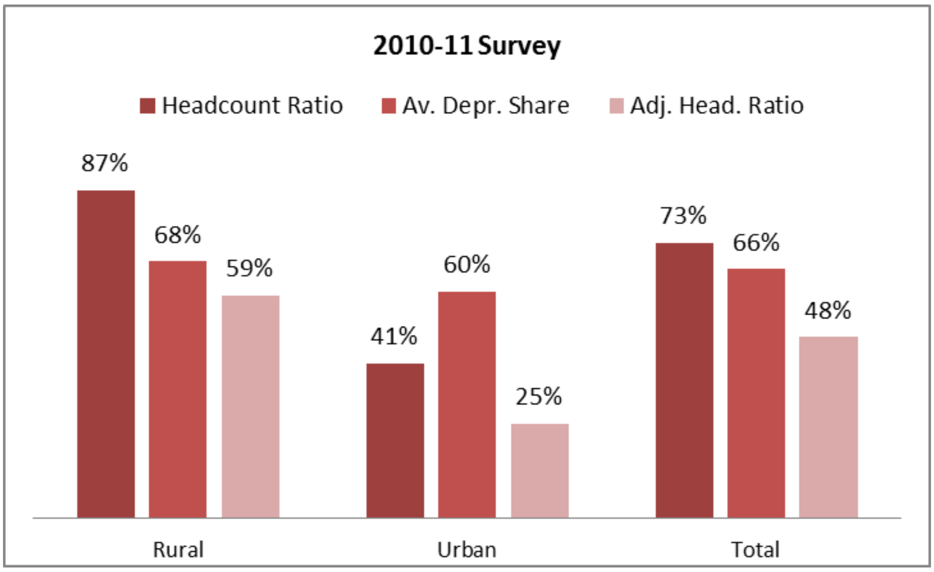

Figure 13: *MPI components 2010-11 Survey*

Contribution to Total Poverty

Figure 14 and 15 represents the contribution of each dimension to poverty and is also decomposed by rural and urban households. These results highlight that at the National level, the health dimension contributes largely to poverty. This is true for both waves of the survey. Another important indicator is cooking fuel which also contributes to poverty in both urban and rural settings. In the rural setting, the living condition indicators such access to electricity as well as acess to imporved sanitation play an important role in explaining poverty in both waves of the survey.

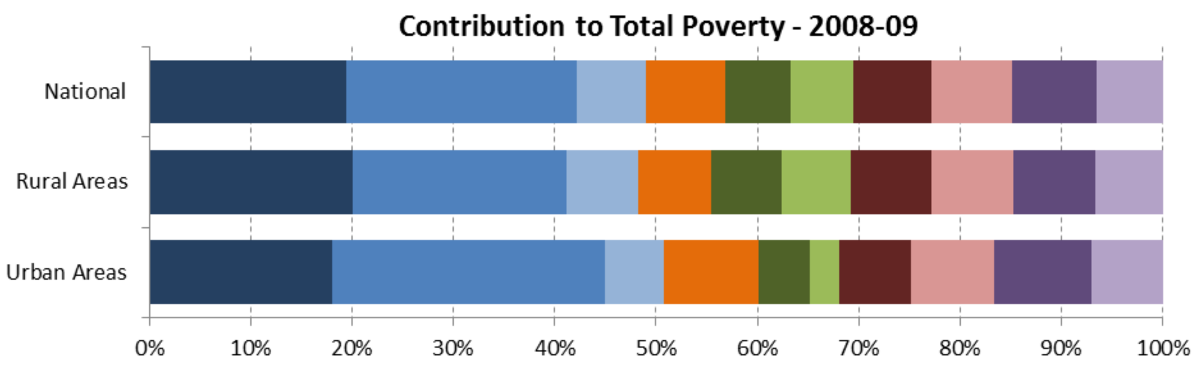

Figure 14: *Contribution to Total Poverty (%)- 2008-09*

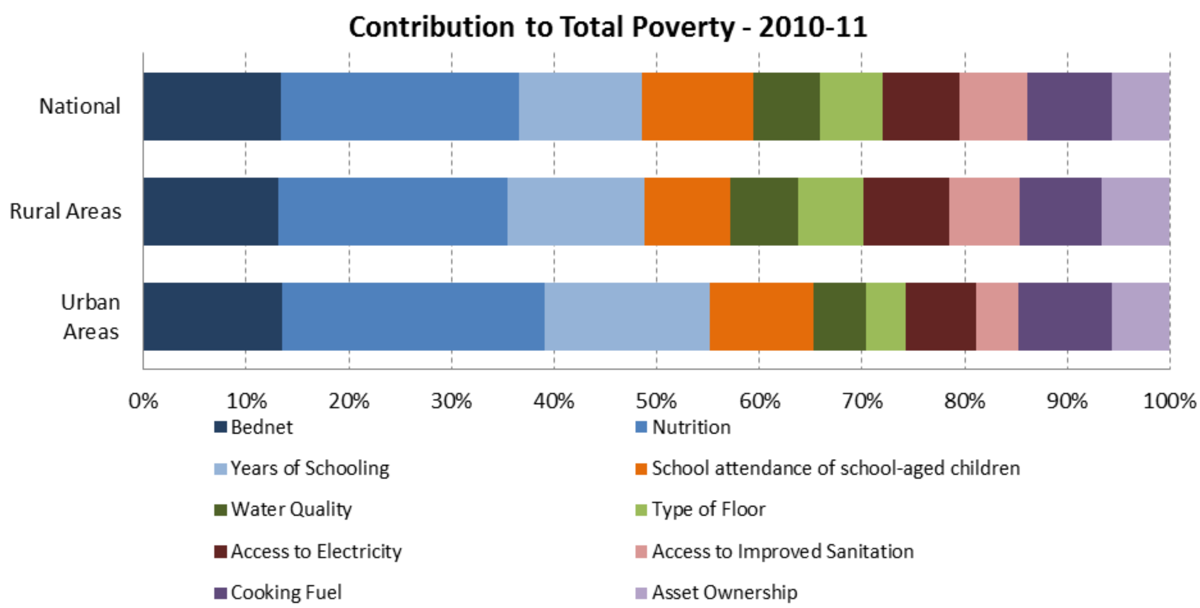

Figure 15: *Contribution to Total Poverty (%)- 2010-11*

3.2 Poverty Dynamics

Transition/Unconditional Poverty Probabilities

For each of the two poverty indicators we calculate the probability of households falling into or out of poverty in time *t+1* (2010-11 wave2). Our dependent binary variable is the poverty status of the household (1 for poor and 0 for non-poor household).

The results are reported in the tables below:

Table 22: ***Transition Probabilities* - MPI *(Mo)***		
	Status 2010-11	
Status 2008-09	non poor	Poor
non poor	73%	27%
Poor	13%	87%

Table 23: ***Transition Probabilities* - Consumption expenditure**		
	Status 2010-11	
Status 2008-09	non poor	Poor
non poor	71%	29%
Poor	20%	80%

Tables 22 and 23 report the unconditional transition probabilities of households. We observe transitions into and out of poverty for the two poverty measures.

In Table 22 transition probabilities for the MPI poverty measure are reported. 87 percent of poor households remain poor while only 13 percent transit and to being non poor. 27 percent of non- poor households in 2008-09 become poor in 2010-11 survey. Table 23 above shows the transition probabilities of the income poverty measure. We can observe that 70 percent of households that were poor in 2008-09 remain poor in 2010-11 while 20 percent transit to becoming non poor. 29 percent of non-poor households in 2008-09 become poor in the second wave of the survey. In both poverty measures the transition probabilities into poverty are higher than those out of poverty highlighting that households have become more vulnerable to poverty over time.

Conditional Probability and Vulnerability

In response to the research questions defined in the previous section we conduct the vulnerability analysis for the two poverty indicators in several steps.

- We run a logit model on the probability of being poor in the first survey period (2008 09) conditioned on the covariates reported at 2008-09.
- We run a logit model on the probability of being poor in the first survey period (2008-09) conditioned on the shocks that hit the households before and at the first year of survey (2008-09).
- We run a logit model on the probability of being poor in the second survey period (2010-11) conditioned on the covariates reported by households in the 2008-09 survey.
- We run a logit model on the probability of being poor in the second survey period (2010-11) given that the household was non poor in the first survey period, conditioned on the covariates and shocks the households reported in the 2008-09 survey.
- We run a logit model on the probability of being poor in the second survey period (2010-11) given that the household was non poor in the first survey period, conditioned upon the shocks that hit the households after the 2008-09 survey year.

We run the logit models for both the 2008-09 and 2010-11 survey conditioned upon covariates of 2008-09 and 2010-11 respectively. The covariates include:

- household characteristics including asset ownership;

- geographical attributes such as location in rural or urban settings;
- shocks.

The models are run using the MPI poverty measure and our baseline measure which is consumption expenditure (income poverty indicator). The results are reported in the Tables below.

Multi-dimensional Poverty Indicator (MPI)

Poverty Dynamics Profiles

Table 24 below reports the results from the logit model that estimates the probability of being poor in 2008-09 given the covariates. Results are also decomposed into rural and urban households. Household size, female headed households and age of the household head positively and significantly affect the poverty probability while household's with highly educated heads as well as those that own assets have a lower probability of becoming poor. Shocks do adversely and significantly affect households' probability of becoming poor. Death of household member, drought or floods, increases in agricultural input prices and death or theft in livestock significantly increase the probability of a household becoming poor. Rise in food prices particularly in rural areas reduces the probability of being poor. This last results may be due to the fact that most households in this setting are rural farming households of food commodities thus increases in prices of these commodities increases their income thus reducing the probability of these households becoming poor.

Table 24: Household's Poverty Profile in 2008-09 wave						
Multi-dimensional Poverty Indicator	Total		Rural		Urban	
	coefficient	Marginal effect	coefficient	Marginal effect	coefficient	Marginal effect
Urban/rural	**-1.9032*****	**-.32525*****	-	-	-	-
HH size	**.31680*****	**.05414*****	**.44090*****	**.02505*****	**.24716*****	**.05156*****
Education HHhead	**-.14910*****	**-.02548*****	**-.18799*****	**-.01068*****	**-.12273*****	**-.0256*****
Female HHhead	**.48261*****	**.07687*****	.25257	.01356	**.59530*****	**.13033*****
Age HHhead	**.01157*****	**.00198*****	**.01971*****	**.00112*****	.00723	.00151
HH assets	**-1.6727*****	**-.31137*****	**-1.8537*****	**-.16127*****	**-1.4930*****	**-.3169*****
Death HH member	**.30507***	**.04869***	.25806	.01347	.36386	.07999
Drought or floods	**.38071*****	**.06149*****	.29099	.01576	**.45034****	**.09963****
Fire	-.00050	-.00009	.02955	.00166	-.03767	-.00780
Fall crop sale prices	.19985	.03310	.05306	.00299	.54417*****	.12268*****
Rise agr. input prices	**.32245***	**.05221****	**.42477****	**.02226****	.19749	.04247
Rise in food prices	**-.37253*****	**-.06296*****	**-.49658*****	**-.02827*****	**-.26662***	**-.05633***
livestock died/ stolen	**.28761***	**.04668***	.23106	.01247	.33573	.07363
Cons	**4.6321*****	-	**2.7439*****	-	.67589	-

Table 25 below reports the results from the logit model that estimates the probability of being poor in the second wave of the survey conducted in 2010-11 conditioned on the 2008-09 covariates. Household size, and the presence of female headed households significantly increase the poverty probability while household's with highly educated heads as well as those that own assets have a lower probability of becoming poor. Shocks do adversely affect households' probability of becoming poor. Drought or floods, incidence of fire and a fall in sales prices significantly increase the probability of a household becoming poor. Rise in food prices particularly in rural areas has a negative and significant effect on the probability of becoming poor. Both the coefficient and the marginal effect of increases in food prices on the probability of becoming poor increases over time highlighting the importance of this shock in defining the poverty profile of households.

Table 25: *Household's Poverty Profile in 2010-11 wave*						
Multi-dimensional Poverty Indicator	Total		Rural		Urban	
	coefficient	Marginal effect	coefficient	Marginal effect	coefficient	Marginal effect
Urban/rural	**-1.8064*** **	**-.34099*** **	-	-	-	-
HH size	**.30677*** **	**.05791*** **	**.42399*** **	**.03394*** **	**.21153*** **	**.04452*** **
Education HHhead	**-.09421*** **	**-.01778*** **	**-.13989*** **	**-.0112*** **	**-.06658*** **	**-.01401*** **
Female HHhead	**.23791***	**.04357***	.21646	.01656	.21079	.04520
Age HHhead	.00180	.00034	-.00217	-.00017	.00980*	.00206*
HH assets	**-1.1864*** **	**-.23478*** **	**-1.1546*** **	**-.1156*** **	**-1.2058*** **	**-.25943*** **
Death HH member	.19079	.03477	.18176	.01380	.21144	.04583
Drought or floods	**.73762*** **	**.12836*** **	**62961*** **	**.04745*** **	**.74956*** **	**.17068*** **
Fire	**.73893***	**.11513** **	.32656	.02310	**1.2922** **	**.30896** **
Fall crop sale prices	**.36974** **	**.06692** **	.18230	.01435	**.80350*** **	**.18592** **
Rise agr. input prices	-.07194	-.01370	-.04755	-.0038	-.33499	-.06677
Rise in food prices	**-.46625*** **	**-.08497*** **	**-.29765***	**-.02324***	**-.58219*** **	**-.12759*** **
livestock died/ stolen	-.08621	-.01646	-.28300	-.02376	.20992	.04553
Cons	**3.8475*** **	-	**2.5157*** **	-	-.12632	-

Vulnerability and Poverty Dynamics Analysis:

In order to determine whether households have become more vulnerable over time we focus on households that were non poor in the 2008-09 survey. Using this subsample, we estimate the probability of these households becoming poor in the 2010-11 wave conditioned on the households' characteristics and other covariates as well as shocks. We run two logit models the first one is on households that were hit by shocks prior 2008-09 while the second model examines those households that were hit by shocks after 2008-09. This enables one to establish whether more vulnerable households are prone to being hit by shocks and whether shocks after 2008-09 played a role in affecting poverty probabilities of households. As reported in Table 26 shocks that hit households after 2008-09 become an important factor in determining the probability of non poor in the 2008-09 households becoming poor in the 20010-11 survey. In particular, shocks that hit households after 2008-09 such as drought or floods, fall in crop sales and rise in food prices become significant in explaining the poverty probability of non poor households becoming poor in the second survey wave.

Table 26:
Vulnerability in 2010-11 conditioned on non poor in 2008-09

Multi-dimensional Poverty Indicator (MPI)	shocks pre-2008-09		shocks post-2008-09	
	coefficient	Marginal effect	Coefficient	Marginal effect
Urban/rural	**-1.2405******	**-.25738******	**-.85871******	**-.15055******
HH size	**.35951******	**.07459******	**.19764******	**.03465******
Education HHhead	.01244	.00258	**-.03622******	**-.00635*****
Female HHhead	-.09942	-.02035	.01098	.00193
Age HHhead	**-.04629******	**-.00961******	.00209	.00037
HH assets	**-.94514******	**-.20590*****	**-.77148******	**-.14532******
Death HH member	-	-	.42889	.08195
Drought or floods	.51720	.11625	**.41842****	**.07889****
Fire	-	-	**1.2734*****	**.28317****
Fall crop sale prices	-1.230	-.18738	**.74910******	**.14968*****
Rise agr. input prices	-		-.19295	-.03259
Rise in food prices	.09546	.01997	**-.40107*****	**-.07349*****
livestock died/ stolen	-	-	-.31627	-.05193
Cons	1.8520***	-	.75090	-

Consumption Expenditure Poverty Indicator

A similar analysis is conducted using the Consumption expenditure poverty line. In both the 2008-09 and 2010-11 surveys, location, household size, education and age of the head of the household, as well as asset ownership in the household determine the poverty probabilities. Shocks such as Hijacking/robbery and water shortage are common in both waves. Loss of employment appears to be relevant in the 2008-09 wave and this shock hits urban households. Drought or floods as well as rise in food prices are relevant in the second wave of the survey. Table 27 reports the vulnerability measure of the non poor households. While the other covariates are significant in both waves, most of the shock that hit households after 2008-09 becomes significant in determining vulnerability of these households.

Table 27: Poverty Profile in 2008-09 wave						
Consumption Expenditure Poverty Indicator	Total		Rural		Urban	
	coefficient	Marginal effect	coefficient	Marginal effect	coefficient	Marginal effect
Urban/rural	**-1.107*** **	**-.2678*** **	-	-	-	-
Hhsize	**.347*** **	**.0841*** **	**.3396*** **	**.06205*** **	**.3436*** **	**.0629*** **
Education HHhead	**-.0799*** **	**-.0193*** **	**-.0857*** **	**-.01566*** **	**-.0733*** **	**-.0134*** **
Female HHhead	.1388	.03335	.09011	.01626	.19455	.03646
Age HHhead	**-.0072** **	**-.0017** **	**-.0126*** **	**-.00230*** **	.00635	.00116
hh_assets	**-1.378*** **	**-.3284*** **	**-1.213*** **	**-.24819*** **	**-1.689*** **	**-.3236*** **
Death HH member	**-.2644*** **	**-.0642*** **	-.16257	-.03009	**-.4162** **	**-.07615*** **
Drought or floods	.03499	.00845	-.11933	-.02206	**.3932* **	**.07719* **
Hijacking/robbery	**-.6561*** **	**-.1621*** **	**-.6131*** **	**-.12598*** **	**-.6701*** **	**-.1083*** **
Rise in food prices	-.1024	-.02475	-.03016	-.00551	-.15673	.02899
Livestock died/ stolen	.19097	.04564	.09742	.01757	.29446	.05717
Loss of employment	**-.6466** **	**-.1601** **	-.36706	-.07295	**-1.110** **	**-.1515*** **
Other	**-.6321*** **	**-.1565*** **	**-.3854** **	-.07694	**.6468* **	**-.1017** **
Water shortage	**-.3431*** **	**-.0836*** **	**-.2652*** **	**-.04977** **	**. 4946*** **	**-.0876*** **
Cons	**2.614*** **	-	1.7996	-	-.07619	-

Table 28:
Poverty Profile in 2010-11 wave

Consumption Expenditure Poverty Indicator	Total		Rural		Urban	
	coefficient	Marginal effect	coefficient	Marginal effect	coefficient	Marginal effect
Urban/rural	**-1.2890*****	**-.31689*****	-	-	-	-
Hhsize	**.25718*****	**.06323*****	**.25541*****	**.04631*****	**.23165*****	**.03730*****
Education HHhead	**-.11813*****	**-.02904*****	**-.14150*****	**-.02566*****	**-.08860*****	**-.01426*****
Female HHhead	-.12943	-.03193	**-.33328****	**-.06308****	.20396	.03379
Age HHhead	**-.00795****	**-.00195****	**-.01495*****	**-.00271*****	.00919	.00148
hh_assets	**-.90272*****	**-.22052*****	**-.75137*****	**-.14707*****	**-1.1647*****	**-.19901*****
Death HH member	**-.48691*****	**-.11922*****	**-.50184*****	**-.09267*****	**-.44030****	**-.07282****
Drought or floods	**.22585****	**.05510****	.18230	.03263	.20008	.03353
Hijacking/robbery	**-.75989*****	**-.18771*****	**-.83115*****	**-.17430*****	**-.70077*****	**-.09912*****
Rise in food prices	**-.18930***	**-.04633***	-.19771	-.03544	-.13458	-.02203
Other	**-.69643*****	**-.17223*****	-.31198	-.06089	**-.87997****	**-.11280*****
Water shortage	**-.35103*****	**-.08646*****	-.09059	-.01653	**-.89418*****	**-.14061*****
Cons	**3.9893*****	-	**3.3402*****	-	.43731	-

Table 29: Vulnerability in 2010-11 conditioned on non poor in 2008-09				
Consumption Expenditure Poverty Indicator	shocks pre-2008-09		shocks post-2008-09	
	Coefficient	Marginal effect	coefficient	Marginal effect
Urban/rural	**-1.0698*** **	**-.22904*** **	**-1.1759*** **	**-.18180*** **
Hhsize	**.21795*** **	**.04666*** **	**.16154*** **	**.02497*** **
Education HHhead	.02275	-.00487	**-.13461*** **	**-.02081*** **
Female HHhead	-.34212	-.07022	-.08712	-.01329
Age HHhead	**.01848** **	**.00396** **	-.00212	-.00033
hh_assets	**-1.3554*** **	**-.28818*** **	**-.63534*** **	**-.10137*** **
Death HH member	-.06264	-.01328	**-.41664*** **	**-.06569** **
Drought or floods	-.17732	-.03678	**.38786** **	**.06384** **
Hijacking/robbery	.18807	.04153	**-.61309*** **	**-.08405*** **
Rise in food prices	.45310	.10096	-.24238	-.03859
Other	-1.6510	-.24272	**-.93722** **	**-.11168*** **
Water shortage	-1.2061	-.20493	**-.30631** **	**-.04693* **
Cons	.47209	-	3.3302***	-

CONCLUSIONS

There has been a huge debate on the role of the recent food spikes on poverty and welfare dynamics in developing countries. In particular, the role of high food prices on developing countries that use commodities that were hit by the food spikes such as corn on households welfare and poverty status. This is relevant for developing countries as most households; especially the poor spend a large share of their income on food consumption expenditure. Despite the importance of this theme the empirical research has been conducted on this theme is still limited and there is insufficient evidence in the current literature to support (or discard) this thesis.

This chapter examined poverty and poverty dynamics in Tanzania over the recent decade using two survey waves. Using both a unidimensional a multidimensional poverty measure, this chapter analysed both poverty and vulnerability in Tanzanian households. We run a logit model for the 2008-09 and 2010-11 survey conditioned upon covariates of 2008-09 and 2010-11 respectively. These included:

- household characteristics including asset ownership;
- geographical attributes such as location in rural or urban settings;
- shocks.

The models were run using the Multi-dimensional Poverty Indicator (MPI) and a baseline measure which is consumption expenditure (income poverty indicator).

Both unidimensional and multidimensional poverty measures highlight the importance of asset ownership in explaining the poverty profile of households. Poor households are deprived in all indicators. These households are heavily deprived in eight out of ten indicators. Education is the indicator in which poor households are least deprived.

Though there is an increase in the number of poor households that are deprived in this indicator over time. Poor households and mainly deprived in nutrition, access to water, electricity and improved sanitation facilities. These households are lack cooking fuel and are the households that own the least assets. In both waves, the raw headcount rations show that rural households are poorer compared to their urban. The MPI measure shows that urban household's poverty intensity has increased over time. The unconditional poverty probabilities show that households have become more vulnerable over time.

Considering the conditional probabilities, the MPI exhibits interesting and robust results. In particular, the poverty profiles in both waves show that the household size, female headed households and age of the household head positively and significantly affect the poverty probability while household's with highly educated heads as well as those that own assets have a lower probability of becoming poor. Shocks do adversely and significantly affect households' probability of becoming poor. Death of household member, drought or floods, increases in agricultural input prices and death or theft in livestock significantly increase the probability of a household becoming poor. Rise in food prices particularly in rural areas reduces the probability of being poor. In order to determine whether households have become more vulnerable over time this chapter focuses on households that were non poor in the 2008-09 survey. Using this subsample, we estimate the probability of these households becoming poor in the 2010-11 wave conditioned on the households' characteristics and other covariates as well as shocks. We run two logit models the first one is on households that were hit by shocks prior 2008-09 while the second model examines those households that were hit by shocks after 2008-09. This enables me to establish whether more vulnerable households are prone to being hit by shocks and whether shocks after 2008-09 played a role in affecting poverty probabilities of households. Shocks that hit households after 2008-09 become an important factor in determining the probability of non poor households becoming poor in the 20010-11 survey. In particular, shocks that hit households after 2008-09 such as drought or floods, fall in crop sales and rise in food prices become significant in explaining the poverty probability of non poor households becoming poor in the second survey wave.

An interesting result obtained both for the poverty profiles as well as vulnerability is the negative coefficient high food prices have on poverty. High food prices seem to reduce the probability of households becoming poor. Two possible explanations exist. Firstly, the sample is made up of both net food buyers as well as net food sellers. Thus an increase in food prices affects the welfare of these two groups of households differently. If the average welfare gain (net sellers) is higher than the welfare loss (net purchasers) then this would imply an overall increase in welfare. Secondly, increases in food prices may have generally increased the welfare of the households (Vu and Glewwem, 2011; Shimeles and Delelegn, 2013; Nigussie, Demeke and Rashid, 2012).

This chapter makes two main contributions. The first one is a methodological one. This chapter implements a multi-dimensional poverty indicator to measure poverty at a household level. This measure enables one to incorporate different aspects of poverty especially for poor and developing countries. This poverty measure enables us to fully assess the poverty profiles and dynamics of households which would have been undermined while using a unidimensional poverty measure such as consumption expenditure. The main consequence of increased food prices is that poor consumers, that devote a larger share of their budgets to food consumption expenditure is on the reduction of other expenditures such as investments in health, education, as well as other non-food items. The negative impact of high food prices is not highly visible in a reduction of food consumption but is likely to be visible in other dimensions such as decreases in schooling rates, health expenditures, and other similar investments, as the need to purchase food at higher prices overwhelms the need to spend on other goods.

The second contribution of this chapter is its empirical contributions. This chapter empirically applies a multidimensional approach to examine both poverty and vulnerability using real household survey data. These results complement the current work on this theme as it empirically examines the nature and the drivers of poverty dynamics at a household level and thus help to better understand the poverty dynamics of Tanzanian households. In particular, the results here show that households have become more vulnerable over time (in the second survey wave compared to the first) and the key driver of vulnerability has been their exposure to shocks. Shocks become particularly relevant in the second wave for households. Market related shocks such as increase in food prices are significant (in the second survey wave) in explaining households poverty profiles ad dynamics. The multidimensional results can be used to compliment results obtained using the income or consumption expenditure poverty measures.

CONCLUSIONS

Agricultural commodities experienced substantial increases in prices over the most recent decade with major surges in both 2007-08 and again in 2010-11. The prices of food commodities such as maize, rice and wheat increased dramatically from late 2006 through to mid-2008, reaching their highest levels in nearly thirty years. In the second half of 2008, the price upswing decelerated and prices of commodities decreased sharply in the midst of the financial and economic crisis. A similar price pattern emerged in early 2009 when the food commodity price index slowly began to climb. After June 2010, prices shot up, and by January 2011, the index of most commodities exceeded the previous 2008 price peak. These price movements coincided with sharp rises in energy prices, in particular crude oil. Sharp increases in agricultural prices were not uncommon, but it is the short period between the recent two price surges that has drawn concerns and raised questions. What were the causes of the increase in world agricultural prices and what are the prospects for future price movements? Were the trend driven by fundamental changes in global agricultural supply and demand relationships that may bring about a different outcome? What are its implication on global food security and sustainability?

Food commodities prices increased and become more volatile in the recent decade attracting the attention of market participants and policy makers. Sharp increases in agricultural prices are not uncommon, but it is rare for two price spikes to occur within 3 years as they normally occur with 6-8 year intervals. The short period between the recent two price surges has therefore drawn concerns and raised questions on the causes and future prospects of commodity markets.

The price spikes were also accompanied by more volatile food commodity prices. There are many competing explanations for the rise in food price volatility over recent years. Biofuels have been identified as one of the main drivers of high and volatile food prices in the recent decade. High fuel prices combined with legislative policies have been accused of increasing biofuel production causing high food prices and potentially established a link between energy and agricultural prices.

There has always been a direct impact of energy prices on food prices through input and transportation costs. However, the intensity of the link between the oil price and food prices has increased over the most recent period and it may have been driven by an increased biofuel production.

Chapter one of this thesis set two main objectives. Firstly, it established whether commodity markets have become more volatile in recent times. Secondly, it analysed the nature of relationship between commodity and crude oil prices. In particular, it studied the evolution of this relationship considering the role played by biofuels. A short and a long term historical volatility measure were calculated for different commodities in order to evaluate whether commodity markets have become more volatile in recent times. It investigated whether the volatility in food commodities is now driven by the transmission of shocks from the crude oil market as a result of increased biofuel production and consumption. This chapter employed Multivariate

General Autoregressive Heteroskedasticity (MGARCH). Conditional correlations were calculated from MGARCH models estimated on daily data over the twelve year sample

2000-2011. Using estimates from the Dynamic Conditional Correlation (DCC) Multivariate GARCH models specification, it decomposes volatility of food commodities into its main components.

The results obtained in this chapter lead to the following considerations and remarks. Firstly, considering long term volatility, it emerged that commodity prices have become less volatile today than they were in the previous decades. Volatility measure in most recent periods however, highlighted that there has been an increase in the volatility for grains, some vegetable oils, and meat prices. This concentration of volatility increases in grains, sunflower oil and beef was consistent with biofuels, having played a major role as these commodities were either directly or indirectly affected by biofuels. Notably, however, there did not appear to be a significant increase over this comparison period in crude oil volatility. This undermined the argument that the increase in grains price volatility may have due to increased crude oil volatility as there was no clear increase in crude oil volatility. This result however prompted the argument that the increased volatility in food commodity prices may have been due to the transmission of price changes from crude oil to the food commodity prices.

Secondly, the results from the MGARCH models showed that even though one cannot directly argue that increased volatility in commodity markets was due to crude oil price volatility, the conditional correlations between the grains and crude oil prices of these price series moved much more closely than previously with crude oil prices. The increased co-movement between crude oil and grains occurred when biofuel production was on the increase and crude oil prices were on the rise. The results from this analysis confirmed the above trend for commodities that are included in tradable indices such as corn, wheat, and soybeans.

Even though one cannot directly link higher food price volatility to biofuels, there is some empirical evidence that higher grains price volatility was at least in part due to greater transmission of oil price shocks to the grains markets. The nature of the “pass through” mechanism from crude oil to commodity markets changed and may have been determined by biofuels. This chapter provides empirical evidence that increased volatility in grains during the 2008-09 spike was partly due to increased transmission of shocks from the crude oil market to grains. In 2007-08, crude oil prices changes were temporally prior to grains prices. Crude oil prices started to rise in 2007 and this could have prompted the need for alternative energy sources such as biofuels. Biofuels linked crude oil and grains prices over 2007-09 directly through corn as a main feed stock and indirectly to wheat and soybeans - both substituted corn in animal feed and competed for land with corn The results obtained are therefore consistent with the hypothesis of a biofuels-induced link between the crude oil and food markets. Biofuels production and consumption constraints in the United States became binding after 2008 de-linking crude oil prices with the grains. Biofuels constraints may also have rendered grains more volatile through the idiosyncratic components such as stocks.

High fuel prices combined with legislative policies have been accused of increasing biofuel production causing high food prices and establishing a link between energy and agricultural prices. There has been a huge controversy on the food versus fuel debate and the role of biofuels as well as biofuel policies. The United States has undergone major policy changes over the recent decade, changes that have affected both the energy and agricultural sector. The June 2002 Farm Bill, the two RFS Energy Acts in 2005 and 2007, the 2006 MTBE Ban and the Energy Improvement and Extension Act are among the policy interventions that the U.S. implemented over that decade.

Responding to an increasing dependence on imported crude oil, the United States has adopted policies to encourage the substitution of locally produced biofuels in commercial gasoline. This resulted in dramatic increases in U.S. ethanol production over the seven years 2004-10. Other countries have followed similar policies although generally at a lower scale and with the objective of producing biodiesel. Biodiesel uses vegetable oils as feedstock while ethanol uses corn. In this chapter, we have analysed the impact of the biofuels revolution on the relationship between crude oil and corn prices.

There are two channels through which ethanol production can influence corn prices. The first is that the new feedstock demand for corn moves the corn demand curve to the right and, with less than infinitely elastic supply; this will result in a rise in corn prices. Mitchell (2008) recorded that the use of corn for ethanol in the U.S. accounted for 70% of additional maize production over 2007-08. He suggested that this was a (perhaps the) major factor which can explain the sharp rise in grains prices over those two years. The second route is that the location of the feedstock demand curve for corn will depend on the crude oil price. Shocks to the oil price are thereby transmitted to the corn market increasing the volatility of corn prices. To the extent that this happens, corn becomes a "petro-commodity".

Chapter two of this thesis conducted a rigorous econometric analysis in order to verify whether there has been a structural change in both the prices and price relationships of grains and energy commodities. It is motivated by the fact that prices and price relationships react to both market factors and policy regimes. These factors are not static over time and may change in response to policy and market developments. In addition, the failure to detect and consider breaks induces misspecification which may adversely affect the inference procedure leading to poor forecasting. In particular, ignoring existing breaks in the prices would lead to a biased rejection of the null hypothesis of stationarity in the series. This chapter implemented the Bai and Perron (1998, 2003) structural break methodology to analyze price relationships between grains and energy prices over the period since 2000 and relate the structural breaks to changes in U.S. biofuel policy.

The multiple structural breaks analysis on both food energy commodity prices showed that the commodities experienced the breaks in line with the policy interventions. In particular, the 2006 break date common in the commodities analysed marks the "ethanol gold rush" which was induced by the 2006 MTBE ban and the 2005 RFS1 Energy Act. The rise in U.S. ethanol production from corn was driven by U.S. government policies as well as by market forces. Three policy changes were particular important. These included:

- the Volumetric Ethanol Exercise Tax Credit (VEETC), introduced in May 2004 ;
- the Renewable Fuels Standard (RFS1) introduced in the July 2005 Energy Act, and
- the MTBE ban which became effective in June 2006.

These three measures coincide with the sharp up-turn in U.S. ethanol production. While it was difficult to assess how ethanol production would have evolved in the absence of these measures, it seems likely that the increases would have been smaller and more gradual. These results show that these policy changes coincided with structural breaks in the relationship between grains and energy prices. Over the period 2000-12, four breaks were identified of which the qualitatively most important are those in the fall of

2004 and the fall of 2006. These breaks reinforced CGE analyses which have looked at the likely impact of these changes.

Prior to 2004, little relationship is apparent between corn and wheat prices, on the one hand, and energy prices on the other. The corn and wheat prices moved together such that (possibly supply-related) divergences decayed quite quickly. After 2006, the corn and wheat prices both showed a larger responsiveness to changes in crude oil prices with the corn response being both larger and more persistent than the wheat response. As a consequence, corn and wheat prices were less tightly related than previously.

This chapter also provided evidence of long-run cointegrating relationship between corn and wheat on the one hand and crude and gasoline on the other. Cointegration implies that the series co-break. Corn and wheat do co-break, and crude and gasoline co-break. However corn and crude were not cointegrated and thus did not co-break. Given this last result we attempted to verify whether corn and crude would become cointegrated if we were to incorporate structural breaks. We found that corn and crude are cointegrated when breaks are incorporated and breaks. Conducting a piece-wise stationarity analysis these break dates appear to be significant.

These results showed that US biofuel policy and policy changes played a major role in defining ethanol production and consumption which in turn affected the relationship between food and energy markets in the recent decade. In particular, it may have strengthened the link between energy and grain prices. These results have strong policy considerations as this chapter shows that if U.S. agricultural policy is redirected to ensure a return to historical levels of food price volatility it will be necessary to de-link food and energy prices.

There has been a huge debate on the role of the recent food spikes on poverty and welfare dynamics in developing countries. In particular, the role of high food prices on developing countries that use commodities that were hit by the food spikes such as corn on households welfare and poverty status. This is relevant for developing countries as most households; especially the poor spend a large share of their income on food consumption expenditure. Despite the importance of this theme the empirical research has been conducted on this theme is still limited and there is insufficient evidence in the current literature to support (or discard) this thesis.

Chapter three examined poverty and poverty dynamics in Tanzania over the recent two survey waves. Using both a unidimensional a multidimensional poverty measure, this chapter analysed both poverty and vulnerability in Tanzanian households. We run a logit model for the 2008-09 and 2010-11 survey conditioned upon covariates of 2008-09 and 2010-11 respectively. These included:

- household characteristics including asset ownership;
- geographical attributes such as location in rural or urban settings;
- shocks.

The models were run using the Multi-dimensional Poverty Indicator (MPI) and a baseline measure which is consumption expenditure (income poverty indicator).

Both unidimensional and multidimensional poverty measures highlight the importance of asset ownership in explaining the poverty profile of households. Poor households are deprived in all indicators. These households are heavily deprived in eight out of ten indicators. Education is the indicator in which poor households are least deprived.

Though there is an increase in the number of poor households that are deprived in this indicator over time. Poor households and mainly deprived in nutrition, access to water, electricity and improved sanitation facilities. These households are lack cooking fuel and are the households that own the least assets. In both waves, the raw headcount rations show that rural households are poorer compared to their urban. The MPI measure shows that urban household's poverty intensity has increased over time. The unconditional poverty probabilities show that households have become more vulnerable over time.

Considering the conditional probabilities, the MPI exhibits interesting and robust results. In particular, the poverty profiles in both waves show that the household size, female headed households and age of the household head positively and significantly affect the poverty probability while household's with highly educated heads as well as those that own assets have a lower probability of becoming poor. Shocks do adversely and significantly affect households' probability of becoming poor. Death of household member, drought or floods, increases in agricultural input prices and death or theft in livestock significantly increase the probability of a household becoming poor. Rise in food prices particularly in rural areas reduces the probability of being poor. This last results may be due to the fact that most households in this setting are rural farming households of food commodities thus increases in prices of these commodities increases their income thus reducing the probability of these households becoming poor.

In order to determine whether households have become more vulnerable over time this chapter focuses on households that were non poor in the 2008-09 survey. Using this subsample, we estimate the probability of these households becoming poor in the 2010-11 wave conditioned on the households' characteristics and other covariates as well as shocks. We run two logit models the first one is on households that were hit by shocks prior 2008-09 while the second model examines those households that were hit by shocks after 2008-09. This enables one to establish whether more vulnerable households are prone to being hit by shocks and whether shocks after 2008-09 played a role in affecting poverty probabilities of households. Shocks that hit households after 2008-09 become an important factor in determining the probability of non poor households becoming poor in the 20010-11 survey. In particular, shocks that hit households after 2008-09 such as drought or floods, fall in crop sales and rise in food prices become significant in explaining the poverty profile and dynamics of non poor households becoming poor in the second survey wave.

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The second contribution of this chapter is its empirical contributions. This chapter empirically applies a multidimensional approach to examine both poverty and vulnerability using real household survey data. These results complement the current work on this theme as it empirically examines the nature and the drivers of poverty dynamics at a household level and thus help to better understand the poverty dynamics of Tanzanian households. In particular, the results here show that households have become more vulnerable over time (in the second survey wave compared to the first) and the key driver of vulnerability has been their exposure to shocks. Shocks become particularly relevant in the second wave for households. Market related shocks such as increase in food prices are significant (in the second survey wave) in explaining households poverty profiles ad dynamics. The multidimensional results can be used to compliment results obtained using the income or consumption expenditure poverty measures.

Further Research

After 2011, increases in crude oil prices and major food commodity prices have exhibited a reduction in prices. Given this trend, there is need for further research on this theme. In particular, it will focus on three main areas:

- This research will examine whether lower crude oil price shocks are transmitted to food commodity prices. It will also evaluate whether there is symmetry in the transmission of the upside (high crude oil prices) and downside (low crude oil prices) mechanisms
- This research will also be extended to evaluate the relationship between energy and food markets given the recent reduction in their prices. In particular, it will examine the role of market forces as well as policy events in shaping the prices and price relationships.
- This research will evaluate whether the reduction in international food commodity prices is transmitted into Tanzanian domestic food commodity prices. It will also evaluate the role it will play on poverty and poverty dynamics of Tanzanian households.
- The third wave of survey data was released by the World Bank earlier this year. With the availability of the latest Tanzania National Panel Survey data 2012-13 released this year by the LSMS it will be possible to conduct a more profound, complete and accurate poverty dynamics analysis.

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