The Evolution of the Ethanol and the Related Markets in the U.S.

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Abstract

This dissertation comprises three substantial chapters that analyse the impact of the U.S. ethanol market on other related markets, specifically the corn and oil markets. Chapter 3 models ethanol price asymmetry changes in demand and supply. We find that both demand and supply are relatively inelastic and both asymmetric and we discuss the policy implications of such results. Chapter 4 approaches the issue of connectedness among ethanol production, corn prices, and oil prices, together with the direct impact that ethanol production has on corn prices. We find in our connectedness analysis for the ethanol boom period that corn's position is improved as the ethanol market matures after the introduction of ethanol-blending mandates. Furthermore, ethanol production shows a dependent position that is due to the relatively small proportion it has on the fuel market. In contrast to apriori expectations, we do not find conclusive evidence to support the claims that ethanol production impacts corn prices. Chapter 5 continues to analyse the potential impact of ethanol prices by addressing the interrelation of price volatilities between corn, ethanol and oil prices in the U.S. ethanol market. We find that there are no statistical significant cross effects from ethanol prices to corn prices. For the pre-ethanol boom period, we find a double-directional significant cross-spillover effect from oil to ethanol which we expect for these two markets given their link through the blending mandates. In the ethanol boom period, however, we find that the own volatility effects are statistically significant only for oil, and a small significant cross-spillover effect from corn to oil, which suggests the position of corn as an energy crop is strengthening in the fuel market.

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Declaration

I hereby declare that this thesis is my own work and effort. The work contained is original except other source of information which have been acknowledged in the customary manner and has never been submitted for any other degree.

Chapter 1

Introduction

Climate change has made the search for cleaner fuel energies a common objective in developed economies. Higher levels of greenhouse gases (GHG) cause the atmosphere to retain more heat than usual and makes the earth warmer, this phenomenon is identified as global warming. Fossil fuel combustion and industrial processes contribute with approximately 80% of the total GHG emission increase from 1970 to 2013 (IPCC, 2014). The effects of these emissions on the environment became evident just recently, with carbon dioxide emissions (CO_2) representing one of the main GHG emissions derived from human activities (since 1970, CO_2 emissions have increased by about 90%).

As one of the largest emitters of CO_2 (second only to China), there is a consensus on the environmental obligations the U.S. must assume. The current U.S. administration has dealt with the Climate Change issue through a general plan to reduce CO_2 emissions, and one of the central elements of this strategy is the promotion of renewable fuels. The principal objective of this scheme is to achieve a cut in CO_2 emissions in the range of 17% below 2005 levels by 2020, 42% below 2005 levels by 2030, and 83% below 2005 levels by 2050 (UN, 2009). Environmental objectives are the keystone of the Climate Change agenda in the U.S., yet there are other supporting reasons behind this. The U.S. consumes a quarter of the world's oil production but has only three percent of the currently found world's oil reserves. Oil's status as a strategic commodity undermines U.S. energy security and weakens the U.S. economy. To achieve energy security, the U.S. aims at reducing the virtual monopoly that oil has over transportation fuel.

The U.S. government has focused on reducing oil demand through the promotion of other fuels, to achieve a competitive market among different transportation fuels in the long run. Corn-based ethanol is one of the fuels currently used for this purpose. Ethanol or ethyl alcohol is produced from starch or sugar-based feedstocks. In the U.S., ethanol is produced from corn,[1] and annual production yields 330-424 gallons per acre (Goettemoeller and Goettemoeller, 2007). With the use of ethanol, the CO_2 emissions reduction range between 10% and 20%.[2]

In 2014, the ethanol industry supported 83,949 direct jobs in the renewable fuel and agriculture industries, and 295,265 indirect jobs across other sectors of the U.S. economy. Overall, there is an underlying national security implication of using a wider and larger quantity of alternative fuels produced domestically. More than 66% of oil consumed in the U.S. is imported. Hence, the replacement of oil-based fuels with ethanol produces a shift from foreign to domestic U.S. energy sources (EIA, 2015).

There is a controversy regarding the reduction of CO_2 emissions in the ethanol distillery process in the U.S. involving the use of coal plants (Searchinger *et al.* 2008). In the U.S., a gallon of ethanol contains two-thirds the energy of a gallon of gasoline.[3] However, for a better engine performance gasoline requires the blending of an oxygenate such as ethanol or methyl tert-butyl ether (MTBE), different from ethanol, which produces less CO_2 emissions as the fuel itself supplies extra oxygen in addition to the one found in the atmosphere. MTBE was used as the main oxygenate in gasoline, but due to environmental and health issues, it was replaced by ethanol in the early 2000s.

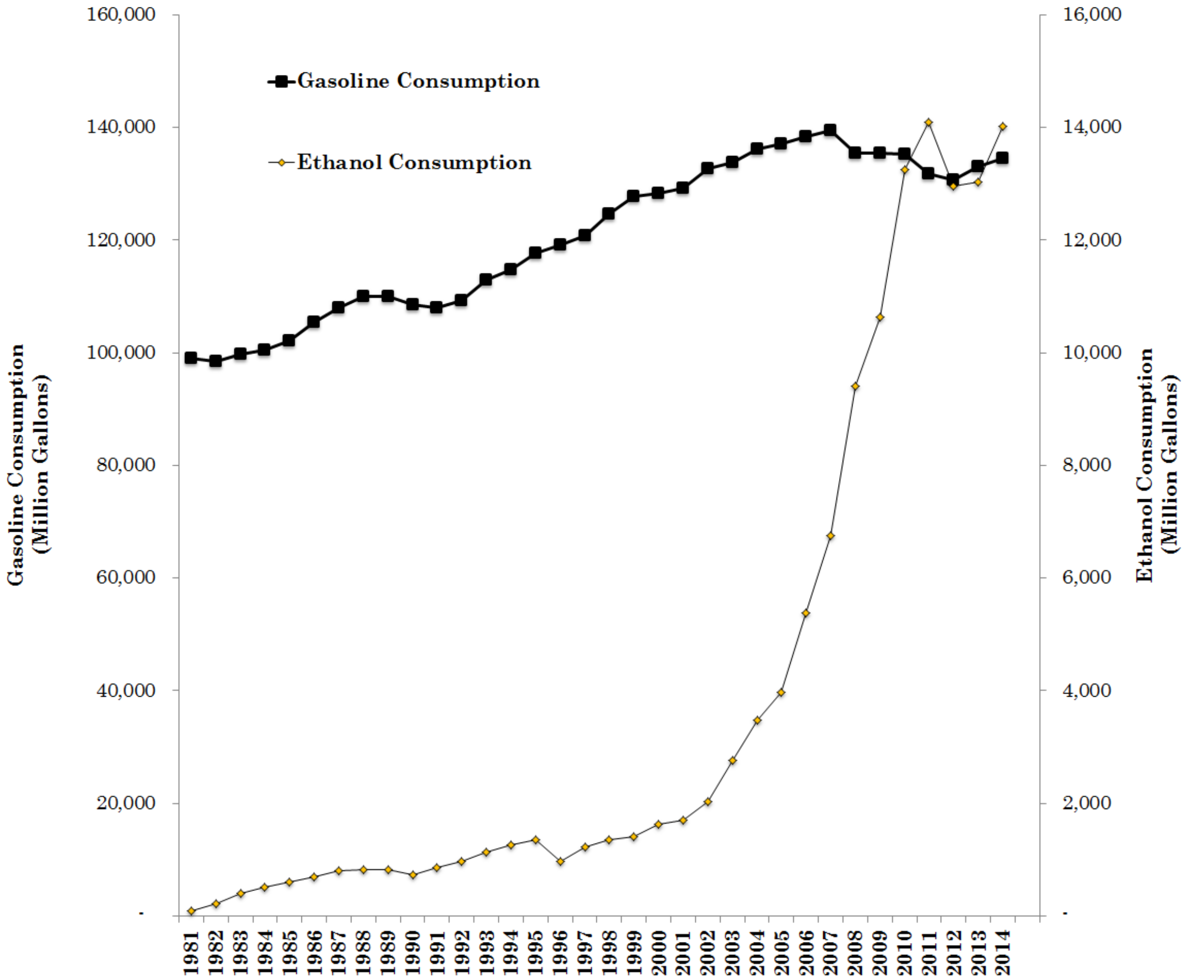
Conventional cars can burn up to 10 % of ethanol in a gasoline-ethanol blend. In January 2011, the U.S. Environmental Protection Agency (EPA) issued a waiver to authorise up to 15% of ethanol blended with gasoline (E15) to be sold only for cars and

[1] In Brazil, ethanol is produced from sugarcane and production reaches 727-870 gallons per acre (Goetemoeller and Goettemoeller, 2007).

[2] The ethanol sugarcane-based industry in Brazil is more efficient than the U.S. corn-based industry because Brazil's cuts in CO_2 emissions range between 87% and 96%; this is due mainly to a higher efficiency in sugarcane as a feedstock (Goettemoeller and Goettemoeller, 2007).

[3] We will refer to petrol as gasoline since its the name used for this fuel in the U.S.

Figure 1.1: Gasoline and Ethanol Consumption in the U.S.

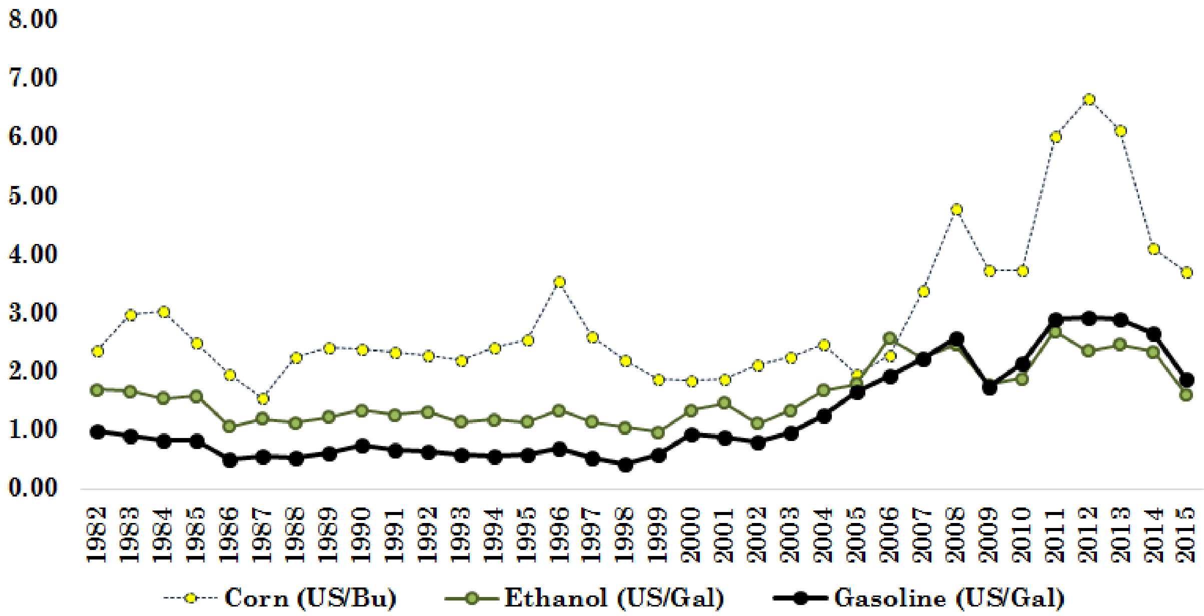


Source: U.S. DOE, Energy Information Administration

light pick-up trucks with a model year of 2001 or more recent. This mixture is becoming increasingly common in the U.S., but not all conventional cars can use this fuel without an engine modification.

In 2014, approximately 136.78 billion U.S. gallon of gasoline were consumed in the U.S. with ethanol accounting 10% of the fuel supply. This close relationship between gasoline and ethanol has been driven by the gradual elimination of MTBE (Methyl tert-butyl ether) as the leading gasoline oxygenate and the subsequent introduction of government mandates requiring an increased use of ethanol in gasoline by the mandated volumes in 2005 and 2007 (Figure 1.1). Since the production of ethanol has an impact on the corn demand in the U.S., these mandated volumes of ethanol production have shifted the use of corn, from a staple grain into a fuel energy source. This premise could lead to assume

Figure 1.2: Evolution of Corn and Fuel prices in the U.S.



Sources: USDA, National Agricultural Statistics Service Administration and U.S. DOE, Energy Information Administration

that corn prices, and other staple grains by association, would increase given the growth in the demand, pushed by the ethanol market (Figure 1.2).

This thesis addresses the U.S. ethanol market from three different empirical approaches. Firstly, in Chapter 2 we discuss the level of government involvement in the ethanol industry, including environmental regulations and subsidies. Secondly, in chapter 3 we identify demand and supply of ethanol and attempt to model asymmetric responses to changes in ethanol prices. Thirdly, in Chapter 4 we address the connectedness among ethanol production, corn prices and oil prices. Fourthly, in Chapter 5 we continue examining the ethanol market by discussing the interrelation of price volatilities between corn, ethanol and oil prices.

Chapter 2 provides an overview of the U.S. ethanol market, identifying the most important legislation bills and events that led to the formation of the U.S. ethanol market.Over the past forty years, environmental concern has been a significant force that has affected the U.S. crude oil and gasoline industry. Much of the Federal Energy legislation was directly or indirectly associated with limiting oil derivatives pollution, reduction of oil imports and promotion of cleaner energies.

Chapter 3 presents our initial empirical analysis with a study that models demand and supply elasticities in the U.S. for the period 1982-2014 considering nonlinearity in ethanol prices. Our findings suggest that the imposition of long-run symmetry, where the underlying relationship is nonlinear, will end in spurious dynamic responses and misleading policy recommendations. In a nonlinear ARDL analysis, we find that both demand and supply are inelastic (less than 1). On (cumulative) positive price changes, supply is relatively more elastic than demand (0.703 vs. -0.055). These results suggest that supply is responsive only to price increases, i.e., more production following price increase but do not change production following price decrease. In the (cumulative) negative price changes demand is relatively more elastic than supply (0.353 vs. 0.025), we have now that demand is responsive only to price decreases, i.e., more consumption following price decrease but do not change consumption following the price increase. In regards to corn prices and its relationship to ethanol production, we find that corn acts as a production cost, i.e., it negatively affects ethanol production, this finding disputes previous results from Luchanksy and Monks (2009) that position corn as a positive relationship to ethanol production that profoundly affects corn prices.

Chapter 4 addresses the issue of how ethanol production influences corn prices using a connectedness approach. Our dynamic analysis of ethanol production, corn and oil prices begins with a Vector Error Correction Model (VECM) and the use of Impulse Response Functions that does not find conclusive evidence of the impact of ethanol production on corn prices before the introduction of the ethanol blending mandates in 2005. Following these results, the connectedness analysis suggests that before the introduction of the ethanol blending mandates oil influenced both ethanol and corn, with the latter being more affected by oil. More importantly, we did not find evidence of ethanol production affecting corn prices. In the second part of the connectedness analysis, we notice that after the introduction of the ethanol blending mandates, our results suggest that ethanol production does not influence corn prices. We also find that corn's position improved as it moved from being affected by oil to having an increasing role as an ethanol component and not just as a food commodity.

Chapter 5 addresses volatility transmission channels between corn, ethanol and oil prices. The evidence from the long-run dynamics suggests that corn, ethanol and oil prices are integrated in the long run, despite the tumultuous period between 2005 and 2008. Before the introduction of the ethanol blending mandates in 2005 we find that volatilities of corn affect volatilities of ethanol, we also find higher persistence in the ethanol market in the presence of external shocks and a double spillover between oil and ethanol volatilities. After the introduction of the ethanol blending mandates, we find that oil persistence is the only significant in the system and that today's oil volatility affects tomorrow's ethanol volatility negatively

Chapter 2

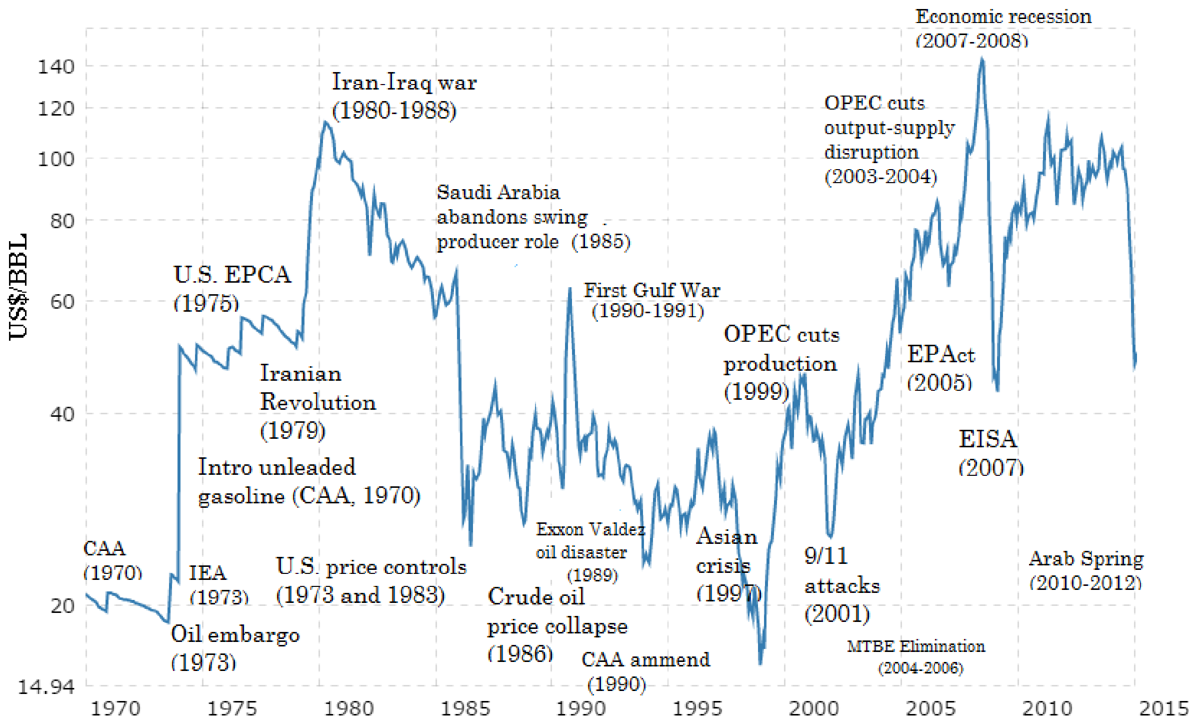
Overview of the Ethanol Market in the U.S.

Ethanol has a long history as a car fuel, and it was used for that purpose even before gasoline became the world's primary fuel. Back in 1826, Samuel Morey developed an engine that ran on ethanol and turpentine, then in 1908 Henry Ford ran his first Ford Model T with ethanol, gasoline or a combination of both. In 1940, the first ethanol plant was built in Omaha, Nebraska; it was used to produce ethanol fuel for the army and to provide ethanol for regional fuel blending. From 1940 to the late 1970s no ethanol was produced commercially in the U.S., due to low gasoline prices.

Over the past forty years, environmental concern has been a significant force that has affected the U.S. crude oil and gasoline industry. Much of the Federal Energy legislation was directly or indirectly associated with limiting oil derivatives pollution and reduction of oil imports. Several political and economic events that occurred between 1970 and 2014 were critical because of the U.S. dependence on oil imports.

According to the Renewable Fuels Association (RFA), the ethanol market share in the U.S. has expanded from just over 1% in 2000 to around 3% in 2006, to 10% in 2011. The production capacity was near 900 million U.S. gallons (gal) in 1990 and increased to 1.63 billion U.S. gal in 2000, afterward, in 2010, this amount rose again to 13.5 billion U.S. gal, as of 2014 this amount was 14.3 billion U.S. gal. In 2011, 209 ethanol distilleries

Figure 2.1: Critical oil related events and U.S. ethanol policies, 1970-2015



Source: U.S. DOE, Energy Information Administration

operated in 29 states, and as of January 2014, 167 under construction or expansion. Most expansion projects focus in updating the technology to improve ethanol production, energy efficiency and the quality of the coproducts they produce to sell as livestock feed (RFA, 2015). Today, researchers agree that ethanol could substantially offset oil use in the U.S. In fact, studies have estimated that ethanol and other alternative fuels could replace over 30% of U.S. gasoline demand by 2030 (AFDC, 2015).

This chapter summarises the main events, changes in technology, and legislations in the development of the ethanol market in the U.S. To discuss the development of this market; we need to turn our attention to the international political climate in the 1970s and the changes in legislation that some of these events posed on environmental regulations. Figure 2.1 presents a comprehensive timeline of the history of oil prices in the U.S. and the main policy events that affected the oil market, and consequently the gasoline and ethanol markets.

The Clean Air Act (CAA) was constituted in 1970 and significantly expanded the role of the Environmental Protection Agency (EPA) in controlling air pollution. It established standards for sulphur dioxide, nitrous oxides, carbon monoxide, oxidants (ozone), non-methane hydrocarbons, and total suspended particulates. A lead standard was adopted in 1978, resulting in an increase in the production of unleaded gasoline, a significant change in refinery output. Lead had been used since the 1920's to boost the gasoline octane, and due to high production costs of other gasoline boosters, its use remained popular until the 1970s. However, due to environmental and health concerns, unleaded gasoline was introduced in the 1970 CAA, and it was implemented in 1974. Production grew, comprising 27 percent of the motor gasoline produced in the United States by 1980. Production increased each year, and by 1992, 98 % of the gasoline produced in the United States was unleaded. The air pollution abatement projects installed during the 1970's resulted in much lower emissions of air pollutants at refineries, per barrel of crude oil run. In 1979, the CAA showed results, the volume of unhealthy emissions decreased considerably. Carbon monoxide (CO) emissions were down by 68 %, emissions of total suspended particulates were halved, sulphur dioxide was 19 % lower and nitrogen oxide emissions dropped 18% (EIA, 2015).

After the implementation of the CAA in 1970, the U.S. was struck with an oil embargo from Arab countries in 1973, a situation that increased oil prices. In 1973, angered by the U.S. support of Israel in the 1973 Yom Kippur war, several Arab nations instituted an oil embargo against the U.S. and the Netherlands. Declining domestic crude oil production, rising demand, and increasing imports turned this embargo into an economic disaster for the U.S. The embargo was accompanied by decreased production from the Organisation of the Petroleum Exporting Countries (OPEC). Following the six-month ban, global oil prices had tripled from the 1973 average of $3 per barrel to about $12 per barrel, and OPEC was firmly in control of the world's oil market. With oil prices reaching their highest peak, energy conservation, and alternative fuels started to receive considerable attention from the U.S. government (Bohi, 1989).

Following the oil shocks from the Arab embargo, the U.S. put legislation in place that had a significant impact on all aspects of the energy industry over the following decades.

The first step was the establishment of an Energy Bureau. In 1974, the U.S. joined other 20 countries to form the International Energy Agency (IEA), to plan for future oil supply disruptions and to establish secure, stable supplies. The following environmental law was known as the Energy Policy and Conservation Act (EPCA) in 1975. This bill set some objectives: increasing oil production through price incentives, establishing a Strategic Petroleum Reserve (SPR), and increasing car fuel efficiency. In 1975, in response to severe pollution concerns, the U.S. replaced lead as its main gasoline additive and introduced the use of methyl tert-butyl ether (MTBE). MTBE was an oxygenate used to raise the engine performance (octane enhancer). Although it slowly replaced lead, its use remained controversial in the U.S., due to water pollution. The elimination of lead as a gasoline booster and the Arab oil embargo paved the way to the reintroduction of ethanol as a fuel. The Department of Energy Organization Act of 1977 allowed the creation of the U.S. Department of Energy (DOE) and the Energy Act of 1978 was passed by the U.S. congress in an attempt to regain its energy destiny. The Act resulted in subsidisation of gasohol (gasoline-ethanol blend) and the introduction of the ethanol blenders' tax credit of $0.45 per gallon. The Iranian Revolution in late 1978 led to a drop in oil production in the years from 1978 to 1981. In 1980, the Iran-Iraq War started, and a reduction in oil production by many Persian Gulf countries was observed, prompting OPEC oil prices to increase to unprecedented levels between 1979 and 1981. These events had an enormous impact on U.S. oil demand, which from 1978 to 1983 fell from 18.8 to 15.2 million barrels per day, the lowest level since 1971, a situation that encouraged fuel-switching and energy conservation (EIA, 2013).

The years between 1980 and 1984 represented an active period for ethanol policies. The extension of the ethanol tax credit; an increase in the ethanol subsidy to 60 cents per gallon; insured loans for small ethanol producers; price guarantees, and purchase agreements for federal agency use of gasohol boosted the ethanol industry (EPA, 2015). During 1986, oil prices faced declining world oil demand and increasing production from non-OPEC countries, to face these changes the OPEC cut production in the first half of the

1980s to defend its official price. Saudi Arabia played a crucial role in the price drop of oil by bearing most of the oil production cuts. At the end of 1985, Saudi Arabia abandoned its swing-producer role, increased production, and aggressively moved to increase its market share.

An initial effort to introduce alternative fuel vehicles (AFVs) was the Alternative Motor Fuels Act (AMFA) of 1988, established to incentive vehicle manufacturer into developing AFVs. The use of vehicles that ran on flex fuel was observed mostly within government bodies, to promote its use. The Act was followed by the Clean Air Act Amendments (CAAA) of November 1990 that mandated the use of cleaner burning fuels in particular regions of the U.S. during the winter months; the use of MTBE and ethanol was mandatory in gasoline.[4] The use of ethanol expanded from octane-enhancer to substitute for lead and MTBE, and to a clean-air additive itself, this was based on its market characteristics, Federal, and State subsidies. After several attempts to introduce cleaner fuels, the Energy Policy Act of 1992 established tougher regulations requiring certain Federal, State, and alternative fuel provider cars to build an inventory of AFVs. It was amended several times in the Energy Conservation and Reauthorization Act of 1998 and again in 2005 through the Energy Policy Act in 2005 (EPAct2005), which emphasised alternative fuel use and infrastructure development (AFDC, 2015).

Two significant events took place between 2000 and 2005. The first was the slow switch from MTBE to ethanol as the definite oxygenate requirement in gasoline. MTBE elimination took around six years; it started in the early 2000s, but it was officially banned in 2004, and the removal was finished in 2006, partly because of groundwater contamination and risks to health. As of October 2003, a total of 18 States had passed legislation that would eventually ban MTBE. California began switching from MTBE to ethanol to make reformulated gasoline, resulting in a significant increase in ethanol demand by mid-year, even though the California MTBE ban did not officially go into effect until 2004. The second event occurred when the Congress passed the Energy Policy Act in

[4]The EPA cleaner fuel mandate was overturned in April 1995 in Federal court. Despite the repeal of this law, ethanol's position in the energy market improved.

2005 (EPAct2005), which instituted a renewable fuel standard. In response, refiners made a wholesale switch removing MTBE and blending fuel with ethanol. President George W. Bush signed EPAct2005, requiring oil companies to add ethanol to their gasoline. This mandate, known as the Renewable Fuels Standard (RFS) did not specify a minimum content, only a minimum amount for all blenders. The RFS, a mandate under yearly revision, began with a level of 4 billion U.S. gal of ethanol to be blended with gasoline in 2006. The Energy Independence and Security Act (EISA) of 2007 expanded the RFS to 36 billion U.S. gal of ethanol and other fuels to be blended into gasoline, diesel and jet fuel by 2022. However, it does not specify the renewable fuels must be produced in the U.S.

The RFS underwent statutory revisions in February 2010 mandating that 15 billions of U.S. gal corn-based ethanol were to be blended into gasoline annually by 2015 (EPA, 2015). During the period from 1982 to 2000 there was a steady increase in ethanol production being led by small tax incentives for corn producers and the blenders' tax credit. The real boost in ethanol production comes from the MTBE elimination and ethanol's use as the oxygenate and the introduction of blending mandates. With the mandates in place, gasoline refiners, wholesalers, and some retailers had no choice but to blend their gasoline with ethanol. Mandated volumes of ethanol to be blended with U.S. gasoline increased from 9 billion U.S. gal in 2008 to approximately 15 billion U.S. gal in 2013. Due to the financial stress of the economic crisis of 2007-08, this was later revised and set at approximately 13 billion U.S. gal.

Table 2.1: Ethanol Fuel Mixtures

Code	**E10**	**E15**	**E85**
Composition	10% ethanol 90% gasoline	15% ethanol 85% gasoline	85% ethanol 15% gasoline
Use	Regular vehicles	Vehicles model year 2001 onwards	Flex Fuel vehicles

Source: Alternative Fuels Data Center.

In 2013, the EPA cited problems with increasing ethanol-gasoline blending above 10%, and this limit is known as the blending wall. The ethanol blending wall is due partly to infrastructure limitations and partly to the 10% ethanol - 90% gasoline blend (known as E10), which is the maximum feasible combination for any car that is not an AFV (Wisner, 2009).

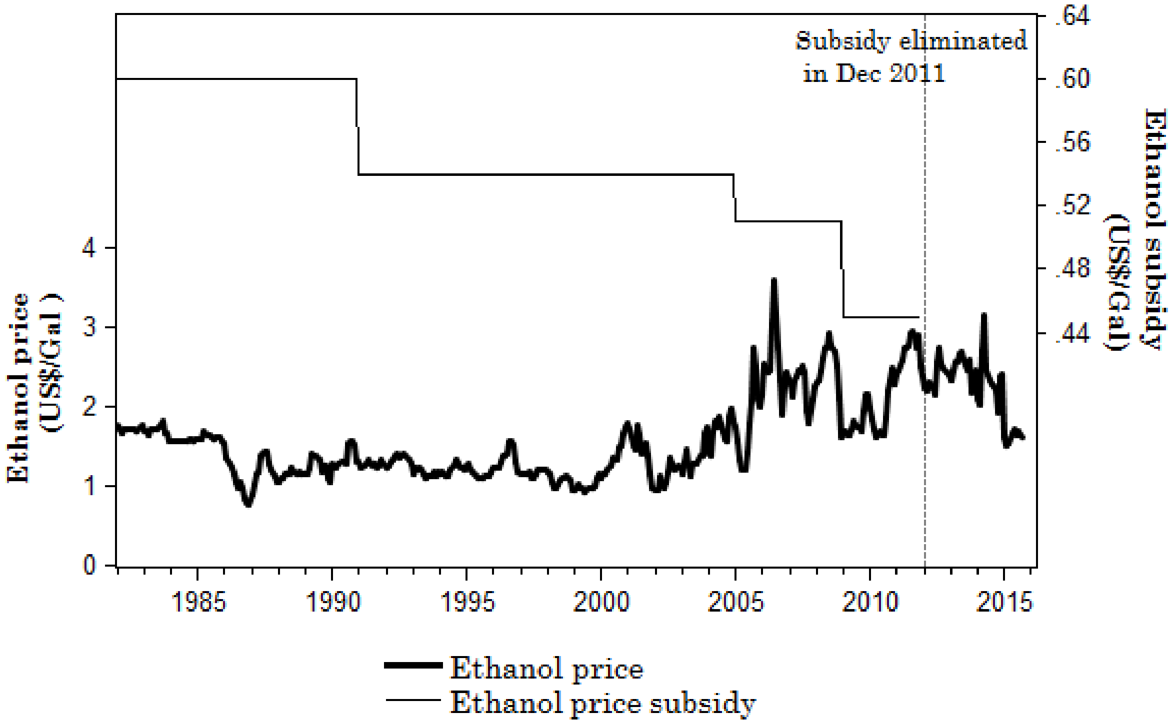
Federally mandated ethanol production levels that increase annually to 2022 started with the late EPAct2005 legislation. Wisner (2010a; 2010b) argues that because of the mandates, there is no need for ethanol blending subsidies. The reasoning is that the fuel industry is required to mix prescribed amounts of ethanol with gasoline and that, if necessary, it can bid up ethanol prices to whatever level is needed to obtain the necessary supply. That process might work better if the ethanol blend wall can be eliminated At this time, the main way of eliminating the blend wall is to expand the E-85 market, but that requires ethanol to be priced at about 34% less (with E-85 priced about 28% less) than gasoline to offset its lower fuel mileage. The E-85 market is common in the Midwest of the U.S., but is limited in size because of the small number of AFVs vehicles (159,533 in 2013), and also the availability of E-85 fuel stations.[5] Table 2.1 presents the current blends allowed by EPA in regular cars and AFVs (Tyner, 2013).

Ethanol tax credits, corn tax credits and ethanol import tariffs, and more recently ethanol blending mandates have been an integral part of the U.S. ethanol policy for several years. Figure 2.2 shows the ethanol subsidy per US/Gal (blenders' ethanol tax credit) in the right axis and the ethanol prices in the left axis. The blenders' ethanol tax credit started at \$0.60 per U.S.gallon from 1978 to 1990, decreased to \$0.54 from 1991 to December 2004, and a further decrease to \$0.51 until 2008. It remained in \$0.45 per U.S. gallon until it was eliminated on December 31, 2011. The cumulative of ethanol subsidies between 2005 and 2009 was approximately USD \$ 17 billion (Cox and Hug, 2010). Despite the elimination of the blenders' tax credit for ethanol, the blending mandates, are still in effect and costly.

One of the primary objectives of the U.S. ethanol market is to achieve energy security by reducing oil imports and promoting alternative domestic energy sources. The policies

[5] In 2014 the U.S. had 2,840 stations (EIA, 2015)

Figure 2.2: Monthly U.S. ethanol prices (USD/gal) and ethanol subsidy (USD/gal)



Source: USDA, National Agricultural Statistics Service Administration

introduced in the past 30 years have helped to establish the use of ethanol as an environmentally friendly alternative to gasoline. Most ethanol in the U.S. uses corn as the primary input; hence, ethanol production growth indicates an extensive use of corn. This scenario calls for research to analyse the impact derived from an increase in corn use in the production of ethanol in the U.S. and corn prices.

Chapter 3

The 2SLS-NARDL Approach to an Analysis of Demand and Supply Elasticities in the U.S. Ethanol Market

3.1 Introduction

Over the past forty years, energy security and environmental concerns have led to increasing the fuel share of ethanol in the U.S. gasoline market. The U.S. ethanol market grew from approximately 500 million U.S. gallons in 1984 to almost 15 billion U.S. gallons in 2014; this represents roughly 10% of the gasoline market (EIA, 2015). These increases in ethanol production have included several clean-air legislation that subsidises the ethanol industry and ultimately has made ethanol relevant. However, the connection of such policies with the increases in ethanol production and the link of it with spikes in agricultural commodity prices calls for a discussion. Therefore, the adequate modelling of the responsiveness of ethanol production (consumption) to changes in ethanol prices (elasticities) is a significant factor in policy implications.

This chapter focuses on the responsiveness of ethanol production (consumption) to the evolution in ethanol prices. The transmission of negative and positive changes in the ethanol price to the corn and gasoline prices is relevant to producers and consumers. Corn is important because it can be used either as food, feed or as a feedstock for ethanol production. On the other hand, fuel consumption represents a sensitive issue to consumers as well. We examine the current relationship between gasoline and ethanol as it grows after the increasing fuel blending mandates that started in 2005. First, we start addressing ethanol price transmission from a static to a dynamic approach applied to ethanol demand and supply. We aim to do this by modelling ethanol demand and ethanol supply using Least Squares, Two-Least Squares in a static form and we continue with the dynamic analyses by using the Autoregressive Distributed Lag (ARDL) to conclude finally with the nonlinear ARDL version.

Bacon (1991) was one of the first researchers attempting to explain the asymmetrical pattern of adjustment in the U.K. gasoline market by analysing the connection with the prices of gasoline and crude oil using the rockets and feathers hypothesis. The rockets and feathers hypothesis is used to explain a (potential) asymmetrical pattern of adjustment in which the asymmetric responses of downstream price changes to changes in upstream prices. In the rockets and feathers hypothesis, given cost increases and decreases, the analysis of an asymmetrical pattern entails the study of the price responses measuring the degree of the price change slow (fast). For example, when the price of crude oil falls, does the price of gasoline fall as quickly as it rises when the crude oil price rises? After the work by Bacon (1991), the literature addressing how downstream prices respond to increases in upstream prices grew considerably (Al-Gudhea *et al.*, 2007; Balke *et al.*, 1998; Bachmeier *et al.*, 2003; Borenstein *et al.*, 1997; Brown and Yücel, 2000; Douglas, 2010; Bastianin *et al.*, 2014; Galeotti *et al.*, 2003; Godby *et al.*, 2000; Grasso and Manera, 2007).

In recent years, the analysis of dynamic asymmetries in the context of nonlinear error correction models has gained further prominence. Many scholars argue that the assumption of linear symmetry remain too restrictive, particularly in the presence of policy interventions or transaction costs (Shin, Yu, Greenwood-Nimmo; 2014). Therefore, the use of a nonlinear dynamic approach seems reasonable. An additional tool to the nonlinear asymmetry study is the use of the cointegrating ARDL models, which allow the inclusion of I(0) and I(1) variables. Thus, at the same time provide positive and negative partial sum decompositions renders a flexible modelling of the dynamic asymmetries between the long- and the short-run of the demand and supply in the U.S. ethanol market.

Early literature on the demand and supply of the U.S. ethanol market has focused on static and dynamics analyses that relegate the importance of asymmetric responses to changes in ethanol prices, given that price changes can split into positive and negative variations. Classic demand and supply theory do not observe asymmetric demand and supply responses to price changes. Demand and supply theory predicts that the reaction of consumers and producers to a small price increase and to a small price decrease is going to be the same. However, researchers have speculated that consumers are more sensitive to price increases than they are to price decreases and for the producers is the opposite situation with the supply. We expect an asymmetric cost pass-through in the ethanol demand and supply because fuel and corn prices are a significant share of the ethanol market costs, it is likely that ethanol demand would show an asymmetric change to ethanol price increases and reductions.

For the present analysis, we study the U.S. ethanol market from a demand and supply perspective, using monthly observations for ethanol production, ethanol, gasoline and corn prices during the period 1982-2014. Our analysis builds upon the research of Rask (1998), and Luchansky and Monks (2009), who estimated symmetric supply and demand curves for this market before the ethanol boom period. We extend previous literature and analyse price elasticities using a 2SLS-NARDL approach, allowing to consider dynamics and asymmetric responses to changes in ethanol prices.

Our results suggest that the imposition of long-run symmetries in demand and supply where the underlying relationship is asymmetric will end in spurious dynamic responses and ultimately misleading policy recommendations, especially in the case of increasing and removing subsidies in the ethanol industry. Rask (1988) recommends gradual elimination of subsidies. However, these suggestions could be misleading due to asymmetric responses to changes in ethanol prices. Moreover, we find evidence of asymmetric responses to changes in ethanol prices in both demand and supply which turned out to be inelastic, with a robust and significant cumulative positive price regime for the supply.

The organisation of this chapter is the following: section 3.2 discusses the literature in the ethanol market; section 3.4.1 describes the data, 3.3 derives the supply and demand schedule and introduces the NARDL model. Section 3.4 discusses the results of the demand and supply estimations using the static, 2SLS-ARDL and 2SLS-NARDL models for comparison of elasticities. Section 3.5 concludes.

3.2 Literature Review

Much of the literature on elasticities in demand and supply from the ethanol market pays particular attention to the Brazilian ethanol industry. Until 2005 Brazil was the biggest ethanol producer in the world, but this situation changed in 2006 when the U.S. took over this position. During the 1990s size of the U.S. ethanol market was almost negligible compared to Brazil, but some of the first serious discussions and empirical analysis of demand and supply in ethanol emerged at that time. In this section, we present a selected analysis of elasticities in the U.S. and the Brazilian ethanol market.

Ahmed, Rask and Baldwin (1989) analysed the potential demand for ethanol as an octane enhancer in the 1980s. With the complete elimination of lead as an octane enhancer, ethanol became one of the main alternatives to lead.[6] A parametric cost minimisation linear programming model was used to estimate the potential demand for ethanol as an octane oxygenate for gasoline. The octane demand study is estimated in two different periods, 1990 and 1995 which constitute the pre- and post- lead scenario. In 1990, lead was eliminated as the gasoline oxygenate, but its influence continues until 1995, due to possible lead stock remains. In 1995, after the use of lead was discontinued from the gaso-

[6]The other options include changes in the refinery process of gasoline; expansion of processing equipment and purchase of higher octane additives. Higher octane additives include two types: aromatics (toluene, benzene and xylene, TBX) and oxygenates (ethanol, MTBE, methanol and the Dupont Waiver).

line market, ethanol, together with other octane enhancers, were introduced as potential lead replacements. Initially, costs for each alternative fuel were estimated using a cost function that takes into account the cost of the octane oxygenate, the cost of gasoline, the octane rating,[7] and the original octane rating of gasoline. The results of Ahmed *et al.* (1989) study suggested that MTBE and ethanol were the best substitutes for lead. However, ethanol production capacity limitations played a significant role in its suitability as the alternative octane enhancer. Ethanol production costs are affected by oil prices, and as oil price rise, gasoline demand drops, causing a decrease in the demand for octane enhancers. In 1989, ethanol had a market subsidy of $0.60 per gallon, and no evidence was available on the potential effects of the use of progressive subsidies in the ethanol market. Ahmed *et al.* (1989) does not address the potential downfalls in the extensive use of subsidies in the U.S. ethanol market.

Almost a decade after Ahmed *et al.* (1989), Rask (1998) used a different approach to analyse both ethanol demand and supply in 50 states for the period from 1984 to 1993. To model the supply, Rask (1998) uses monthly gasohol sales (gasoline-ethanol blend), ethanol prices, corn prices, corn coproduct prices[8] and a time trend that emulates technology changes in the industry. For the demand, the variables used include monthly gasohol sales, ethanol prices, gasoline prices, MTBE prices, annual number of registered cars in the state, transport cost (the distance in miles to the centre of the nearest ethanol producing state), and a dummy variable that represents the Clean Air Act Amendment (CAAA) of 1990. A Tobit model of supply and demand is estimated to analyse the ethanol supply and demand using Instrumental Variables (IV) to account for endogeneity issues in ethanol prices. In addition, a Probit model addresses the following issues: ethanol use in specific regions, state incentives, transportation distance and the CAAA regulations. The author estimates ethanol price elasticities for both supply and demand. His results suggests that on the supply side, the ethanol price elasticity is relatively inelastic. This

[7]The Octane rating or octane number is a measure of the performance of an engine using a given fuel. The higher the Octane number, the more compression the fuel can resist before starting the motor. Gasoline octane relies on the use of other oxygenates to ignite or start an engine (Ahmed *et al.*, 1989).

[8]In ethanol production, other components of the corn kernel not used become coproducts and are mainly sold as cattle food (RFA,2012).

implies that prices, and not quantities of ethanol sold, are impacted by demand shocks. Rask (1998) argues that a gradual elimination of ethanol subsidies will have no impact in the ethanol market due to the unresponsiveness of sales to ethanol price changes. Also, ethanol supply is highly sensitive to corn prices as argued by Ahmed *et al.* (1989), since corn is a fundamental part of ethanol production costs. Despite changes in coproduct prices, ethanol supply shows an inelastic response. These results suggest the growing importance of coproduct sales for the sustainability of the ethanol market.

Regarding demand, results from 1984-1987 show a highly elastic demand curve. Rask (1998), suggests that the estimation results from the period 1984-1993 should be read with caution, ethanol price data published for two states present potential discrepancies. Nevertheless, a low ethanol price elasticity show that for the period 1988-1993 demand is inelastic, which suggests that the U.S. ethanol market is over-subsidised, leading to benefits being received mostly by the ethanol retailers (demand side).

Turning to Brazil, Alves and Bueno (2003) analysed the demand for gasoline in Brazil from 1974 to 1999 using the two-step Engle and Granger procedure (Engle and Granger, 1987). For modelling the demand, the authors used real yearly data from 1974 to 1999, for gasoline consumption; GDP per capita; gasoline and ethanol prices. The results from Alves and Bueno (2003) show that the cross-price elasticity between ethanol and gasoline is positive, confirming that they are substitutes, although imperfect ones. The findings also indicate that any policy trying to replace the use of fossil fuels must begin long before oil reserves are exhausted. Otherwise, gasoline price may increase drastically. Given the share of the ethanol market in Brazil (ethanol comprises roughly 40% of the non-diesel fuels market), an oil-free economy is feasible in this country. Continuing with Brazil, Ferreira *et al.* (2009) enriched the ethanol market scrutiny by concentrating on the Alternative Fuel Vehicles (AFVs) market. Using annual data from 1984 until 1999 they modelled the relationship between ethanol and gasoline prices at time t, based on the values of F_t, G_t and A_t, these terms are the fraction of flex-vehicles, gasoline vehicles and ethanol vehicles in the total stock, respectively. Instead of modelling this dependence in terms of energy prices, Ferreira *et al.* (2009) did it in terms of the distance, price of ethanol and gasoline. As in Alves and Bueno (2003), they tested for cointegration using the Engle and Granger (1987) two-step procedure and added the maximum likelihood tests proposed by Johansen (1991). The authors found that the prices of ethanol are cointegrated with prices of gasoline and causality (in the Granger sense) runs stronger from gasoline to ethanol. Finally, de Freitas and Kaneko (2011) estimate a demand model using a more sophisticated approach. The authors employ a ARDL demand model using monthly dataset from 2003 to 2010. For modelling the demand, de Freitas and Kaneko (2011) used ethanol consumption, income, ethanol prices, gasoline prices and number of car sales. Ferreira *et al.* (2009) also found that ethanol has improved its position as an independent fuel over the years in Brazil and ethanol demand was more sensitive to price variation than the cross price effect of gasohol (gasoline-ethanol blend). The authors also found that rises in income tends to increase the demand for ethanol as a stand-alone fuel.

Roberts (2008) analysed supply and demand elasticities for four staple food commodities: wheat, rice, corn and soybeans, with the estimated elasticities evaluated the impact of the U.S. ethanol market on world food commodity prices. The variables in this study are measured in caloric content of food worldwide, with this in mind, according to the author these four commodities comprise about 75% of the caloric content of food production worldwide. The author uses the weather as an identifier for demand and supply, in this very complex model, the elasticities across the 2SLS and 3SLS vary between 0.08 and 0.13 for supply and -0.05 and -0.08 for demand. The implications of these results suggest that world food prices are predicted to increase by 30% if the ethanol market in the U.S. does not recycle a third of the biofuel calories for animal feed.

In 2009, Luchansky and Monks (2009) updated the study of Rask (1998) in the U.S., by estimating supply and demand curves using two-stage least squares (2SLS) for the period 1997-2006. Similar to Rask (1998), the supply schedule depends on ethanol prices, corn prices, coproduct prices and a trend. The demand schedule is subject to gasoline prices, MTBE prices, nationwide vehicle registrations, the number of U.S states with ethanol plants, and the population of the states banning MTBE. Furthermore, their findings show ethanol supply price response was inelastic to ethanol prices, these are similar results to those of Rask (1998). In contrast with Rask (1998), corn prices were not significantly related to ethanol production. Corn prices were at first treated as exogenous to the model, and then as endogenous following three different specifications with lags. The differences between corn price elasticities between the time periods could be attributed to the gradual ban on MTBE as a gasoline oxygenate and the switch to ethanol. On the other hand, ethanol demand is highly elastic, this suggests a large effect of ethanol prices on quantities sold. These results agree with Rask (1998) estimations for the period of 1984 to 1987.

Recently Anderson (2012), introduced a fuel-switching model to estimate household preferences for ethanol (E85)[9] as a gasoline (E10)[10] substitute in the state of Minnesota. This model analysed ethanol price elasticities from 1996 to 2006, focusing on how demand for ethanol as a gasoline substitute responds to changes in relative fuel prices. Using panel data and instrumental variables to identify demand, with information from of 200 pump stations this behaviour analysis found that demand for E85 is highly responsive to prices, with own price elasticities ranging between -3.2 and -3.8, whereas the gasoline price elasticity is between 2.3 and 3.2. Although not representative at a national level, ethanol price elasticity is similar to Luchansky and Monks results (2009), and gasoline price elasticity are analogous to those of Rask (1998) and Luchansky and Monks (2009). The data used in this model is subject to several selection issues, first, the analysis is not representative for the U.S. since it studies Minnesota, which is one state of the Midwest and part of the Corn Belt region where corn is the predominant crop. The second issue is that the location of pump stations is where preferences for E85 are stronger.

In the past three decades, we find several analyses of the demand and supply of ethanol in the U.S., yet since previous literature attained inconsistent results suggest that further

[9]E85 is an abbreviation for a blend of 85% ethanol and 15% gasoline.

[10] According to the AFDC,(2015) E10 is a low-level blend composed of 10% ethanol and 90% gasoline. Currently, E10 is sold in every state and more than 95% of U.S. gasoline contains up to 10% ethanol to boost octane. However, E10 is not legally recognised as an alternative fuel.

research is needed. Many factors affect ethanol prices, among those we can count ethanol production capacity, the elimination of MTBE and increasing subsidies. We attempt to model demand and supply by introducing dynamics to address accurately short- and long- run implication for demand and supply. Furthermore, we considering asymmetric responses to changes in ethanol prices.

3.3 Methodology

In this section, we analyse demand and supply using static OLS, the ARDL and the nonlinear ARDL (NARDL) methodology. Shin *et al.* 2014 addresses asymmetric cointegrating relationships using among other techniques the bound-testing approach developed Pesaran *et al.*, (2001). We proceed to analyse asymmetric responses to changes in ethanol prices using demand and supply model schedules. We follow the methodology developed by Shin *et al.* 2014.

Demand and supply in the U.S. ethanol market follow the next forms:

$$q_t^D = \beta_0 + \beta_1 t + \beta_2 p_t^E + \beta_3' x_t^D + \varepsilon_t^D \tag{3.1}$$

$$q_t^S = \gamma_0 + \gamma_1 t + \gamma_2 p_t^E + \gamma_3 x_t^S + \varepsilon_t^S \tag{3.2}$$

q_t^D $\left(q_t^S\right)$ denotes the logarithm of ethanol consumption (production), p_t^E is the logarithm of real ethanol prices, x_t^D is the (logged) vector of the demand-shifting factors, and x_t^S is the (logged) vector of the supply-shifting factors. p_t^C is the logarithm of real corn prices.

For $t = 1, ..., T$ captures technological changes in the demand (supply) side, this will mean that the coefficient on t is an estimate of the amount by which the function is shifting in each period. In our case, t acts as a proxy for the increase in ethanol production, which could have a trend component such as productivity growth due to the introduction of new technologies in the ethanol market or the presence of the gasoline-ethanol blending mandates.

Following Rask (1998) and Luchansky and Monks (2009): we have:

$$x_t^D = \left(p_t^G, dum_t^D\right)$$

$$x_t^S = \left(p_t^C, dum_t^S\right)$$

where p_t^G is the logarithm of real gasoline price and p_t^C is the logarithm of real corn prices. Producers (corn farmers) are free to determine their prices, and consumers, (refiners, terminal and gas station owners) are free to use ethanol upon its market characteristics.

Also, we may add a mandate dummy variable, dum_t^D and dum_t^S, which are expected to influence demand and supply schedule significantly. This step dummy takes the value 0 for all periods before the first gasoline-ethanol mandate known as EPAct2005 and then the value 1 for periods after the mandate. By construction $dum_t^D = dum_t^S$.

Given the persistent nature of ethanol production and ethanol price, the static approach of Rask (1998) and Luchansky and Monks (2009) is likely to be either inefficient or biased in the presence of lagged dependent regressors. Therefore, we follow Pesaran and Shin (1998) and Pesaran *et al.* (2001), and consider the fully dynamic Autoregressive-Distributed lag of order p and q (ARDL(p,q) for short) model as follows:

$$q_t^D = \theta_0 + \theta_1 t + \sum_{j=1}^{p} \phi_j q_{t-j}^D + \sum_{j=0}^{q} \theta_{2j} p_{t-j}^E + \sum_{j=0}^{q} \theta_{3j}' x_{t-j}^D + u_t^D \tag{3.3}$$

$$q_t^S = \pi_0 + \pi_1 t + \sum_{j=1}^{p} \psi_j q_{t-j}^S + \sum_{j=0}^{q} \pi_{2j} p_{t-j}^E + \sum_{j=0}^{q} \pi_{3j}' x_{t-j}^S + u_t^S \tag{3.4}$$

To address the simultaneity of ethanol price, p_t^E, we consider the following 2SLS specifications: First, we regress p_t^E against the vector of exogenous variables, $x_t = \left(x_t^{D\prime}, x_t^{S\prime}\right)$:

$$p_t^E = \delta_0 + \delta_1' x_t + e_t$$

and obtain the fitted values:

$$\hat{p}_t^E = \hat{\delta}_0 + \hat{\delta}_1' x_t,$$

where $\hat{\delta}_0$ and $\hat{\delta}_1$ are the OLS estimates of δ_0 and δ_1.

In the second stage, we run the following ARDL regression:

$$q_t^D = \theta_0 + \theta_1 t + \sum_{j=1}^{p} \phi_j q_{t-j}^D + \sum_{j=0}^{q} \theta_{2j} \hat{p}_{t-j}^E + \sum_{j=0}^{q} \theta_{3j}' x_{t-j}^D + u_t^D \tag{3.5}$$

$$q_t^S = \pi_0 + \pi_1 t + \sum_{j=1}^{p} \psi_j q_{t-j}^S + \sum_{j=0}^{q} \pi_{2j} \hat{p}_{t-j}^E + \sum_{j=0}^{q} \pi_{3j}' x_{t-j}^S + u_t^S \tag{3.6}$$

More conveniently, we employ the ECM versions of (3.5) and (3.6) as follows:

$$\Delta q_t^D = \theta_0 + \theta_1 t + \phi q_{t-1}^D + \theta_2 \hat{p}_{t-1}^E + \theta_3' x_{t-1}^D + \sum_{j=1}^{p-1} \tilde{\phi}_j \Delta q_{t-j}^D + \sum_{j=0}^{q-1} \tilde{\theta}_{2j} \Delta \hat{p}_{t-j}^E + \sum_{j=0}^{q-1} \tilde{\theta}_{3j}' \Delta x_{t-j}^D + u_t^D \tag{3.7}$$

$$\Delta q_t^S = \theta_0 + \theta_1 t + \psi q_{t-1}^S + \pi_2 \hat{p}_{t-1}^E + \pi_3' x_{t-1}^S + \sum_{j=1}^{p-1} \tilde{\psi}_j \Delta q_{t-j}^S + \sum_{j=0}^{q-1} \tilde{\pi}_{2j} \Delta \hat{p}_{t-j}^E + \sum_{j=0}^{q-1} \tilde{\pi}_{3j}' \Delta x_{t-j}^S + u_t^S \tag{3.8}$$

From (3.7) and (3.8) we can evaluate the long-run elasticities with respect to p_t^E, x_t^D and x_t^S as

$$\hat{\beta}_2 = -\frac{\hat{\theta}_2}{\hat{\phi}};\ \hat{\beta}_3 = -\frac{\hat{\theta}_3}{\hat{\phi}};\ \hat{\gamma}_2 = -\frac{\hat{\pi}_2}{\hat{\psi}};\ \hat{\gamma}_3 = -\frac{\hat{\pi}_3}{\hat{\psi}}$$

The symmetry condition with respect to prices increases and decreases in own price elasticities of demand and supply is not always met. To address this important issue we consider the following (potentially) asymmetric demand and the supply schedules:

$$q_t^D = \beta_0 + \beta_1 t + \beta_2^+ p_t^{E+} + \beta_2^- p_t^{E-} + \beta_3' x_t^D + \varepsilon_t^D \tag{3.9}$$

$$q_t^S = \gamma_0 + \gamma_1 t + \gamma_2^+ p_t^{E+} + \gamma_2^- p_t^{E-} + \gamma_3 x_t^S + \varepsilon_t^D \tag{3.10}$$

where p_t^E is now decomposed as $p_t^E = p_0^E + p_t^{E+} + p_t^{E-}$, and p_t^{E+} and p_t^{E-} are partial sum processes of positive and negative changes in p_t^E:

$$p_t^{E+} = \sum_{j=1}^{t} \Delta p_j^{E+} = \sum_{j=1}^{t} \max\left(\Delta p_j^E, 0\right),\ p_t^{E-} = \sum_{j=1}^{t} \Delta p_j^{E-} = \sum_{j=1}^{t} \min\left(\Delta p_j^E, 0\right). \tag{3.11}$$

and we make the simplifying assumption that $x_0 = 0$. This simple approach to modelling asymmetric cointegration based on partial sum decompositions has been developed by Shin *et al.* (2014). The leverage news impact may suggest that the demand and supply should react more strongly to price increase (bad news) than to price decrease (good news); that is $\left|\beta_2^+\right| > \left|\beta_2^-\right|$ and $\left|\gamma_2^+\right| > \left|\gamma_2^-\right|$. But such issues may be determined empirically.

The 2SLS-ECM-NARDL versions of (3.9) and (3.10) can be written as follows:

$$\begin{aligned} \Delta q_t^D &= \theta_0 + \theta_1 t + \phi q_{t-1}^D + \theta_2^+ \hat{p}_{t-1}^{E+} + \theta_2^- \hat{p}_{t-1}^{E-} + \theta_3' x_{t-1}^D \\ &+ \sum_{j=1}^{p-1} \tilde{\phi}_j \Delta q_{t-j}^D + \sum_{j=0}^{q-1} \left(\tilde{\theta}_{2j}^+ \Delta \hat{p}_{t-j}^{E+} + \tilde{\theta}_{2j}^- \Delta \hat{p}_{t-j}^{E-} \right) + \sum_{j=0}^{q-1} \tilde{\theta}_{3j}' \Delta x_{t-j}^D + u_t^D \end{aligned} \tag{3.12}$$

$$\begin{aligned} \Delta q_t^S &= \theta_0 + \theta_1 t + \psi q_{t-1}^S + \pi_2^+ \hat{p}_{t-1}^{E+} + \pi_2^- \hat{p}_{t-1}^{E-} + \pi_3' x_{t-1}^S \\ &+ \sum_{j=1}^{p-1} \tilde{\psi}_j \Delta q_{t-j}^S + \sum_{j=0}^{q-1} \left(\tilde{\pi}_{2j}^+ \Delta \hat{p}_{t-j}^{E+} + \tilde{\pi}_{2j}^- \Delta \hat{p}_{t-j}^{E-} \right) + \sum_{j=0}^{q-1} \tilde{\pi}_{3j}' \Delta x_{t-j}^S + u_t^S \end{aligned} \tag{3.13}$$

From (3.12) and (3.13) we can evaluate the long-run elasticities with respect to p_t^{E+}, p_t^{E-}, x_t^D and x_t^S as

$$\hat{\beta}_2^+ = -\frac{\hat{\theta}_2^+}{\hat{\phi}};\ \hat{\beta}_2^- = -\frac{\hat{\theta}_2^-}{\hat{\phi}};\ \hat{\beta}_3 = -\frac{\hat{\theta}_3}{\hat{\phi}};\ \hat{\gamma}_2^+ = -\frac{\hat{\pi}_2^+}{\hat{\psi}};\ \ \hat{\gamma}_2^- = -\frac{\hat{\pi}_2^-}{\hat{\psi}};\ \hat{\gamma}_3 = -\frac{\hat{\pi}_3}{\hat{\psi}}$$

3.3.1 Nonlinear Cointegration Tests

To proceed towards the asymmetric ARDL analysis, we follow the linear cointegration literature and use four different tests to look for the presence of a symmetric or an asymmetric (cointegrating) long-run relationship.

Firstly, the null hypotheses of a symmetric long-run relationship can be tested using the Wald statistic following a χ_k^2 distribution.

Banerjee, Dolado and Mestre (1998) introduced the t-statistic to test the null $H_0 : \phi = 0$ against $H_1 : \phi < 0$ in demand and $H_0 : \psi = 0$ against $H_1 : \psi < 0$ for supply, we refer to this test as the t_{BDM} test. By restricting ϕ and ψ we reduce the ECM equations to a linear regression form allowing only first differences, such restriction implies that there is no long-run relationship between the levels.

The second test developed by Pesaran, *et al.* (2001) proposes to [11] jointly test the null $H_0 : \hat{\phi} = \hat{\theta}_2^+ = \hat{\theta}_2^- = 0$ and $H_0 : \hat{\pi} = \hat{\psi}_2^+ = \hat{\psi}_2^- = 0$, we refer to this test as F_{PSS}. We can find the associated critical values in Pesaran *et al.* 2001 for both tests.

The fourth test is based on Engle and Granger (1987), using a two-step residual-based approach. The first stage involves the estimation of equations by OLS, while in the second stage, the resulting residuals are tested for a unit root. This test is defined as the t-statistic t_{EGDF}.

3.4 Empirical Application

3.4.1 The Data

Our data comprises 396 monthly observations from January 1982 to December 2014 on ethanol production, and gasoline, corn, and ethanol prices. Quantities for ethanol production and prices for ethanol and corn come found in the U.S. Department of Agricultural (USDA), and the gasoline prices were obtained from the U.S. Energy Information Agency (EIA). All data entered in the model are in log-levels and was seasonally adjusted. Furthermore, all prices are put in real terms using the consumer price index (CPI) from the Bureau of Economic Analysis (BEA).

In Figure 3.1 we can observe the upward trend in ethanol production after ethanol replaces MTBE as the main gasoline oxygenate between 2000 and 2006. From mid-2005 through mid-2007 ethanol production capacity was limited, but the industry expanded rapidly during that period due to the recent blending mandates.

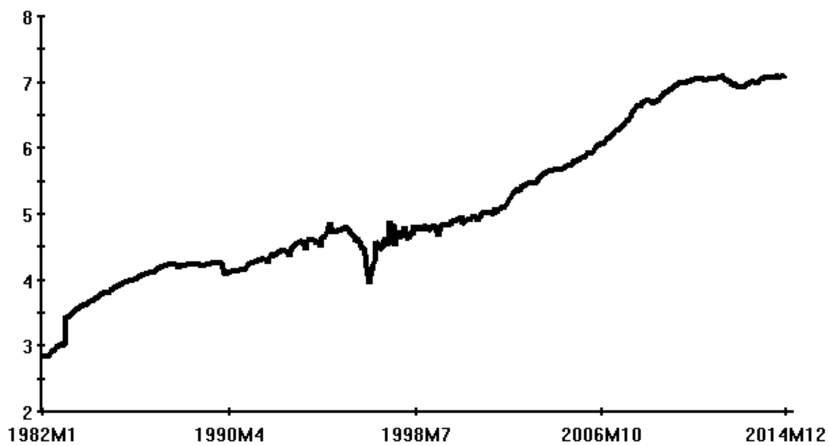
Another important factor in the increase of the ethanol production is the refinery/distillery capacity. In 1990 the ethanol production capacity was near 900 million U.S. gal, this fig-

[11] The bound-test by Pesaran, Shin and Smith (2001) allows to use a mixture of I(0) and I(1) data. Gives an easier interpretation due to the single-equation set-up that it has. Also, the lag-length can vary across different variables (Pesaran and Shin (1999) and Pesaran *et al.* (2001)).

Table 3.1: Descriptive Statistics for Ethanol Production, Ethanol, Gasoline and Corn prices over the Period 1982-2014

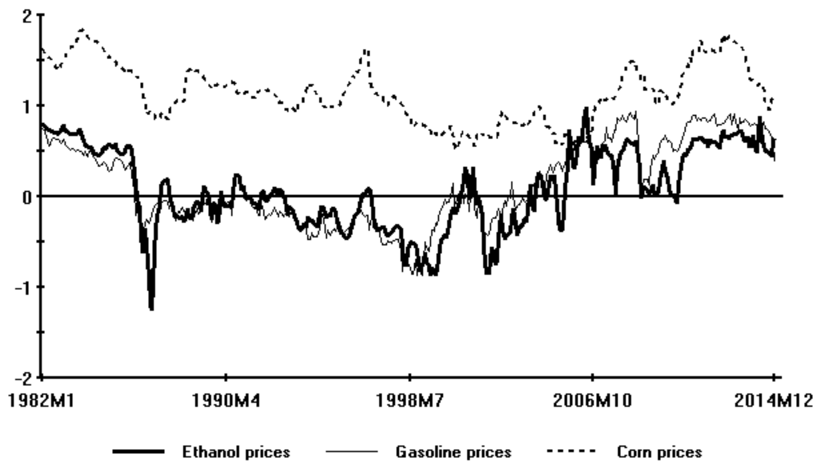
	$q_t = q_t^D = q_t^S$	p_t^E	p_t^G	p_t^C
Mean	330.0110	1.1934	1.2767	3.2866
Median	115.8365	1.0429	1.0059	3.0765
Max	1152.7640	2.6945	2.5443	6.2877
Min	16.9866	0.2816	0.4193	1.6708
S.D	382.9560	0.5093	0.5836	1.0926
Skewness	1.1979	0.4455	0.6026	0.6991
Kurtosis	2.7563	1.9996	2.0593	2.6702

Figure 3.1: U.S. Ethanol Production over the Period 1982-2014 (log-levels)



Source: USDA, National Agricultural Statistics Service Administration

Figure 3.2: U.S. Ethanol, Gasoline and Corn Prices over the Period 1982-2014 (log-levels)



Sources: USDA, National Agricultural Statistics Service Administration (corn prices) and U.S. DOE, Energy Information Administration (fuel prices) ure grew to 1.63 billion U.S. gal in 2000. During the ethanol boom period, this amount increased to 3.6 billion U.S. gal, refineries were forced to produce at overcapacity due to the new blending mandates. In 2010, this number rose again to 13.5 billion U.S. gal, as of 2014 this amount was 14.3 billion U.S. gal. In 2011, 209 ethanol distilleries operated in 29 states, and as of January 2014, 31 states are refining ethanol with 167 ethanol distilleries under construction or expansion.

Figure 3.2 indicates the close co-movement between ethanol and gasoline prices. Ethanol and gasoline prices have co-moved together since the 1980s. Before 1990, the gasoline-ethanol blend was scarce, but the introduction of a federal subsidy in the 1970s boosted local use in Midwest states. During the 1990s ethanol was reintroduced as a national oxygenate for gasoline along with MTBE, this was its direct substitute in that period. By 2006, the gasoline-ethanol relation was stronger with the introduction of EPAct2005 and the complete elimination of its substitute the MTBE. A closer inspection of the data reveals that corn prices started to move closer to gasoline prices during the ethanol industry expansion. Between 1998 and 2004, high corn storage kept low prices, we can observe an increase during the 2007-08 in the staple grain price.

3.4.2 Estimation Results

In this section, we analyse demand and supply using five different estimations. Firstly, we estimate a static OLS and compare it with a linear and nonlinear version of the 2SLS, to account for possible endogeneity and asymmetric responses to changes in ethanol prices. Secondly, we proceed to analyse long- and short-run dynamics using the symmetric 2SLS-ARDL model and thirdly, we attempt to model asymmetric responses to changes in ethanol prices using the simultaneous analysis of both long- and short-run nonlinearities.

A priori we expect the price elasticity of demand to be negative, a decrease in the price of ethanol demand increases. In the case of the gasoline, we anticipate two different effects: a substitution effect and a complement effect. Since ethanol can be a gasoline substitute, an increase in the price of the latter will have a positive impact on ethanol demand. But,

Table 3.2: Selected Elasticities from Rask (1998) and Luchansky and Monks (2009)

Rask (1998)				
	Demand		Supply	
	1984-1987	1988-1993	1984-1987	1988-1993
Ethanol	-2.82	-0.37	0.37	0.75
Gasoline	5.05	-2.13		
Corn			-2.42	-3.03
Luchansky and Monks (2009)				
	Demand		Supply	
	1997-2006			
	Lowest	Highest	Lowest	Highest
Ethanol	-1.605	-2.915	0.224	0.258
Gasoline	-2.08	-3.606		
Corn			-0.126	0.121

Notes: Selected elasticities % change in q for a 1% change in x. In Luchansky and Monks (2009), two elasticities represent the lowest and highest values obtained from the four estimated models. Due to data discrepancies in the period 1984-1987, Rask (1998) considers the results from the period 1998 to 1993 as the main estimations.

if gasoline prices rise, gasoline demand will decrease, and because ethanol is blended with gasoline, its demand will fall too. On the supply side, we expect the own-price effect to be positive, an increase in ethanol price increases ethanol production, regarding corn, a negative relation is expected, as the primary input in ethanol production.

For simplicity, Table 3.2 summarises the most relevant elasticities found in both Rask (1998) and Luchansky and Monks (2009). In the demand side, Rask (1998) finds an inelastic own-price, whereas Luchansky and Monks (2009) estimations suggest the opposite. Gasoline prices are very elastic in both studies. Regarding supply, both studies find an inelastic own-price as expected. Rask (1998) concludes that ethanol production is highly sensitive to corn prices, and Luchansky and Monks (2009) find corn prices very inelastic and not statistically significant on ethanol production. The studies by Rask (1998) and Luchansky and Monks (2009) meet some of the a priori expectations regarding sign, but the statistical insignificance of the supply response to corn from Luchansky and Monks (2009) study and Rask (1998) highly elastic demand suggest possible mis-specification problems.

The static analysis is our reference point for the study; Table 3.3 presents these results.[12] Results indicate that both own-price effects for demand and supply are inelastic, the gasoline price effect and corn price effects are both positives and statistically significant. Moreover, the $EGDF_{MAX}$ test finds evidence of linear cointegration for the demand but not for the supply. The validity of these results is questionable due to evidence of mis-specification problems. We proceed to implement an analysis based on 2SLS in linear and non-linear form.

Table 3.4 addresses endogeneity in demand and supply using instrumental variables (IV) in 3.4 (a) and 3.4 (b), according to the F-statistic of the first stage results the IV are sufficiently strong (Refer to Tables in the Appendices for Chapter 3). In Table 3.4 (a) the results for elasticities and the $EGDF_{MAX}$ are similar to the static estimations in Table 3.3. The nonlinear results for the 2SLS static analysis are presented in Table 3.4 (b). The $EGDF_{MAX}$ test fails to find cointegration in both demand and supply; this highlights the need for a more suitable dynamic specification. Moreover, the Wald tests reject the null hypothesis of symmetry in both demand and supply suggesting the presence of nonlinearity. We conclude that these results are questionable given the evidence of model mis-specification from the diagnostic tests.

Table 3.5 reports estimations results for the 2SLS-ARDL model. The PSS F-test suggest the presence of long-run asymmetry in demand and supply, whereas the BDM t-test finds the opposite for both schedules. In the symmetric ARDL model, the estimated long-run coefficients for the Price elasticity of demand and the price elasticity of supply are -0.78 (inelastic) and 1.97 (elastic) respectively. In the demand, the inelastic own-price effect suggests that quantities sold of ethanol are not sensitive to price change on ethanol. Although we do not follow the same methodology, we can still compare our results to those of Rask (1998) and Luchansky and Monks (2009). Our findings support the results

[12]The static regressions are level equations and the dynamic regressions are error correction models, the dependent variables are not the same. The presence of a low R^2 value in a model in which dependent variable is in first differences (not levels) is an accepted form, especially for ARDL models (Giles, 2013, 2015). Alternatively, we can use the Residual Sum of Square (RSS) to indicate the proportion of the variance in the dependent variable that is predicted by the independent variable. In this sense, we expect the RSS to decrease in the dynamic models when compared to the static ones. Refer to the Diagnostic and Cointegration tests on Tables 3.2 to 3.6 for the RSS.

Table 3.3: Static Estimation of Demand and Supply

	Demand		Supply	
Variable	Coefficient	S.E.	Coefficient	S.E.
p_t^E	-0.361***	0.097	0.345***	0.060
p_t^G	0.205***	0.062		
p_t^C			0.294***	0.051
dum_t	0.820***	0.056		
Constant	3.755***	0.087	2.590***	0.057
Trend	0.007***	0.000	0.010***	0.000
Diagnostics and cointegration tests				
R^2	0.968		0.951	
$\bar{R}^2$	0.968		0.951	
RSS	17.0723		25.9636	
χ^2_{SC}	317.2123[.000]		348.1489[.000]	
χ^H_{SC}	14.5062[.000]		13.7169[.000]	
χ^2_{FF}	10.6147[.001]		55.5532[.000]	
χ^2_N	48.1390[.000]		12.7880[.002]	
$EGDF_{MAX}$	-4.38**		-3.19	

Notes: χ^2_{SC}, χ^2_H, χ^2_{FF} and χ^2_N refer to LM tests for serial correlation, heteroscedasticity, functional form (this test is based in Ramsey's RESET test) and normality respectively. Figures in [ ] are the p-values associated to each diagnostic test. * Significance at the 10% level; ** significance at the 5% level and *** significance at the 1% level respectively. $EGDF_{MAX}$ presents the largest value of the Engle-Granger residual-based ADF test.

Table 3.4: 2SLS Estimation of Demand and Supply

(a) Static 2SLS Regression

	Demand		Supply	
Variable	Coefficient	S.E.	Coefficient	S.E.
$\hat{p}_t^E$	-0.304***	0.105	0.420***	0.063
p_t^G	0.197***	0.065		
p_t^C			0.269***	0.051
dum_t	0.797***	0.056		
Constant	3.719***	0.093	2.582***	0.055
Trend	0.007***	0.0003	0.010***	0.000
R^2	0.968		0.953	
$\bar{R}^2$	0.968		0.952	
RSS	17.0722		25.9635	
χ^2_{SC}	314.4518[.000]		343.4237[.000]	
χ^2_H	9.2649[.002]		12.0979[.001]	
χ^2_{FF}	14.4381[.000]		58.3481[.000]	
χ^2_N	53.5711[.000]		14.4240[.001]	
$EGDF_{MAX}$	-3.49		-2.55	

(b) Asymmetric 2SLS Regression

	Demand		Supply	
Variable	Coefficient	S.E.	Coefficient	S.E.
$\hat{p}_{t-1}^{E+}$	-0.029	0.099	0.138***	0.051
$\hat{p}_{t-1}^{E-}$	-0.404***	0.095	-0.394***	0.070
p_t^G	-0.011	0.063		
p_t^C			-0.031	0.043
dum_t	0.388***	0.067		
Constant	3.600***	0.047	3.715***	0.078
Trend	-0.002	0.001	-0.005***	0.001
R^2	0.9744		0.97219	
$\bar{R}^2$	0.9741		0.9719	
RSS	1.3688		1.3592	
χ^2_{SC}	307.2558[.000]		314.4088[.000]	
χ^2_H	13.6945[.000]		178.9995[.000]	
χ^2_{FF}	2.0263[.155]		2.2963[.130]	
χ^2_N	123.4136[.000]		9.2637[.002]	
$W_{\hat{p}_{t-1}^{E+}=\hat{p}_{t-1}^{E-}}$	83.1048[.000]		266.0095[.000]	
$EGDF_{MAX}$	-3.61		-3.22	

Notes: χ^2_{SC}, χ^2_H, χ^2_{FF} and χ^2_N refer to LM tests for serial correlation, heteroscedasticity, functional form (this test is based in Ramsey's RESET test) and normality respectively. Figures in [ ] are the p-values associated to each diagnostic test. * Significance at the 10% level; ** significance at the 5% level and *** significance at the 1% level respectively. $EGDF_{MAX}$ presents the largest value of the Engle-Granger residual-based ADF test. $W_{\hat{p}_{t-1}^{E+}=\hat{p}_{t-1}^{E-}}$ denotes the Wald test of the equality of the coefficients following the null hypothesis $\hat{\beta}_2^+ = \hat{\beta}_2^-$ for demand and $\hat{\gamma}_2^+ = \hat{\gamma}_2^-$ for supply.

Table 3.5: Dynamic Linear estimation for Demand and Supply

	Demand		Supply	
Variable	Coefficient	S.E.	Coefficient	S.E.
q_{t-1}	-0.097***	0.021	-0.043**	0.016
$\hat{p}^E_{t-1}$	-0.075	0.046	0.084***	0.021
p^G_{t-1}	0.075**	0.029		
p^C_{t-1}			-0.034*	0.016
Δq_{t-1}	-0.470***	0.050	-0.516***	0.050
Δq_{t-2}	-0.151***	0.049	-0.176***	0.050
Δq_{t-11}	0.105**	0.044		
$\Delta \hat{p}^E_{t}$	-0.115	0.059		
$\Delta \hat{p}^E_{t-6}$			-0.106*	0.050
$\Delta \hat{p}^E_{t-8}$	0.104**	0.050		
Constant	0.427***	0.091	0.144***	0.044
Trend	0.00050**	0.00017	0.00043	0.00017*
dum_t	0.067**	0.026		
Long-run elasticities				
$\hat{\beta}_2$	-0.7785	0.472		
$\hat{\beta}_3$	0.7782*	0.2983		
$\hat{\gamma}_2$			1.973**	0.7162
$\hat{\gamma}_3$			-0.809	0.5380
R^2	0.286		0.261	
$\bar{R}^2$	0.267		0.247	
RSS	2.0033		2.0123	
χ^2_{SC}	13.7108[.320]		14.8972[.247]	
χ^2_{H}	38.2704[.000]		45.9707[.000]	
t_{BDM}	-4.5838		-2.02	
F_{PSS}	7.9862***		6.5643***	

Notes: We use the general-to-specific (G2S) approach to select the final ARDL specification, starting with $max\ p = max\ q = 12$, all statistically insignificant stationary regressors are dropped. χ^2_{SC}, χ^2_{H} refer to LM tests for serial correlation and heteroscedasticity diagnostic tests. * Significance at the 10% level; ** significance at the 5% level and *** significance at the 1% level.

Table 3.6: Dynamic Asymmetric estimation for Demand and Supply

	Demand		Supply	
Variable	Coefficient	S.E.	Coefficient	S.E.
q_{t-1}	-0.1167***	0.0251	-0.1154***	0.0240
$\hat{p}_{t-1}^{E+}$	-0.0064	0.0396	0.0811***	0.0206
$\hat{p}_{t-1}^{E-}$	-0.0412	0.0394	0.0029	0.0278
p_t^G	0.0326	0.0256		
p_t^C			-0.0621***	0.0167
Δq_{t-1}	-0.4504***	0.0509	-0.4673***	0.0503
Δq_{t-2}	-0.1455**	0.0494	-0.1560**	0.0487
Δq_{t-11}	0.1080*	0.0442	0.1053**	0.0436
$\Delta \hat{p}_{t-1}^{E-}$	0.1672*	0.0864	0.2144**	0.0864
Constant	0.4490	0.0950		
Trend	-0.0001	0.0004	-0.0010	0.0004
dum_t	0.0426	0.0274		
Long-run Elasticities				
$\hat{\beta}_2^+$	-0.0549	0.34005		
$\hat{\beta}_2^-$	-0.3531	0.32661		
$\hat{\beta}_3$	0.2794	0.22583		
$\hat{\gamma}_2^+$			0.7026***	0.1976
$\hat{\gamma}_2^-$			0.0251	0.2427
$\hat{\gamma}_3$			-0.5384**	0.1763
R^2	0.284		0.303	
$\bar{R}^2$	0.265		0.286	
RSS	1.9865		1.9469	
χ^2_{SC}	18.9935[0.089]		18.5432[0.1002]	
χ^2_H	39.6276[.000]		41.4451[.000]	
t_{BDM}	-4.646**		-4.809***	
F_{PSS}	7.519***		11.346***	
W_{LR}	4.325 [0.0376]		37.312 [0.0000]	

Notes: We use the general-to-specific (G2S) approach to select the final ARDL specification, starting with $max\ p = max\ q = 12$, all non-significant stationary regressors are dropped. χ^2_{SC}, χ^2_H refer to LM tests for serial correlation and heteroscedasticity diagnostic tests. We can test for a symmetric long-run relationship using the Wald statistic following the null hypothesis $\hat{\beta}_2^+ = \hat{\beta}_2^-$ for demand and $\hat{\gamma}_2^+ = \hat{\gamma}_2^-$ for supply. Figures in [ ] are the p-values associated to each diagnostic test. * Significance at the 10% level; ** significance at the 5% level and *** significance at the 1% level respectively.

of Rask (1998) on the demand side during the period 1988-1993. Moreover, the price elasticity of supply is highly elastic, but we find this result misleading given the complex nature of the ethanol market regarding government intervention. As mentioned before in the 2SLS-ARDL model (Table 3.5), the PSS F-test suggests an asymmetric long-run relationship in demand and supply. Moreover, the Wald test supports the previous results by firmly rejecting the null hypothesis of long-run symmetry in both schedules.[13]

Table 3.6 presents the 2SLS-NARDL results. Firstly, we find that both demand and supply are inelastic (less than 1). Previous studies by Rask (1998) and Luchansky and Monks (2009) find inelastic (elastic) results depending on the period analysed. On the supply side, our results are similar to Rask (1998) and Luchansky and Monks (2009) findings, i.e., there is an inelastic response from ethanol production to changes in ethanol prices. Secondly, the analysis of nonlinearity in ethanol price finds that on the (cumulative) positive price changes, supply is relatively more elastic than demand (0.703 vs. -0.055). The previous results suggest that supply is responsive only to price increases, i.e., there is an increase in production following price increases, but in the presence of a prices decrease ethanol production does not change. Thirdly, concerning (cumulative) negative price changes, demand is relatively more elastic than supply (0.353 vs. -0.025). The previous results suggest that demand is responsive only to price decreases, there is more consumption following a price decrease, but consumption does not change following a price increase. Our inelastic results for demand and supply suggest some degree of similarity with those of Rask (1998) and Luchansky and Monks (2009). However, both studies assume linearity in ethanol prices, and due to this linearity assumption, results from Rask (1998) and Luchansky and Monks (2009) could be inconclusive. Our evidence of asymmetric responses to changes in ethanol prices suggests that the reduction in subsidies proposed by Rask (1998) could be misleading.

Additional estimations were performed controlling for other potential supply and demand shift factors in the U.S. ethanol market. On the demand side, we employed GDP, income per capita and the number of vehicles registered in the U.S. For the supply, we

[13]The use of lags R^2.

introduced the price of ethanol production coproducts used for cattle feed. Real GDP and real income were found to be statistically insignificant. On the other hand, adding the number of vehicles registered in the U.S. significantly altered the demand equation estimations due to the high seasonality in car purchases. The coproduct prices altered the supply equation and were found statistically insignificant too. We also used re-estimated demand and supply using nominal prices, but neither demand nor supply exhibited much variation.

3.5 Conclusions

The issue of asymmetric price responsiveness is of significant relevance. Firstly, it may point to significant gaps in economic theory. Secondly, asymmetry can provide important implications for policy. The general assumption is that market power causes asymmetric price responsiveness, empirical evidence of asymmetry can justify intervention. In this chapter, we use asymmetric cointegration with a dynamically flexible ARDL model for demand and supply. Firstly, the estimation of the error correction model allows obtaining both long- and short-run asymmetric cointegrating relationships simultaneously. Moreover, we can test in a straight manner for long-run symmetry restrictions using standard inference.

We start our analysis by using static estimations (OLS) as the reference point; evidence of mis-specification problems in both linear and nonlinear static models is found, there is strong evidence of asymmetric responses to changes in ethanol prices in the 2LS-nonlinear model as well. Afterward, we proceed to analyse the symmetric dynamic ARDL model that provides further proof of asymmetry and the presence of a few significant short-run dynamics. Finally, we proceed to analyse the nonlinear dynamic ARDL model, and our results suggest, the presence of asymmetric long run cointegration in demand and supply. Previous studies by Rask (1998), and Luchansky and Monks (2009) find an extremely low-elasticity for supply and inelastic (elastic) demand in different periods. Our results show that both demand and supply are inelastic (less than 1). Concerning asymmetric responses to changes in ethanol prices, the (cumulative) positive price changes, estimations indicate that supply is relatively more elastic than demand (0.703 vs. -0.055). The cumulative positive price changes suggest that supply is responsive only to price increases (more production following price increase but do not change production following price decrease). Regarding (cumulative) negative price changes, demand is relatively more elastic than supply (0.353 vs. 0.025). The cumulative negative price changes suggest that demand is responsive only to price decreases (more consumption following price decrease but do not change consumption following price increase).

The long-run coefficient for gasoline price is very inelastic but non-significant, which contrast with Rask (1998) and Luchansky and Monks (2009). An interesting result is that ethanol production is affected negatively by corn prices (as expected). Previous claims by Luchansky and Monks (2009), suggest that the close relationship between corn prices and ethanol production produced a positive correlation that ends in ethanol production dictating corn prices. Our results indicate that those claims might be misleading since corn prices behave like a production cost (increases in corn prices lead to a decrease in ethanol production).

Our inelastic results for demand and supply suggest some degree of similarity with those of Rask (1998) and Luchansky and Monks (2009). However, both studies assume linearity in ethanol prices, and due to this linearity assumption, results from Rask (1998) and Luchansky and Monks (2009) could be inconclusive. Our evidence of asymmetric responses to changes in ethanol prices suggests that the reduction in subsidies proposed by Rask (1998) could be misleading.

Chapter 4

Dynamic Interlinkages among the Ethanol Production, Corn and Oil Prices

4.1 Introduction

In his work on climate change, Stern (2006) presents a cost-benefit analysis that called for decisive action to reduce GHG emissions worldwide.[14] The author concludes that a lack of action in the short run would mean that climate change costs by non-intervention are equivalent to losing, at least, 5% of global GDP each year, whereas the costs of taking action now by reducing GHG emissions would be limited to around 1% of global GDP annually. After the Stern review, a consensus was reached regarding Climate Change awareness. However, no agreement on how to approach it in practice was reached. The COP21 U.N. summit held in Paris in December 2015 struck a more defined deal that sets specific goals, including supporting developing countries switch from fossil fuels to greener sources of energy, and for this purpose, the developed world will provide $100 billion a year (UNFCC, 2015). The U.S. is currently the second largest cumulative contributor to

[14]The analysis uses evidence on the economic impact of Climate Change and considers policy challenges involved in managing the transition to a low-carbon economy.

GHG emissions. During COP15, the U.S. announced a target to reduce emissions in the range of 17% below 2005 levels by 2020, 42 % below 2005 levels by 2030, and 83 % below 2005 levels by 2050. These targets are aligned with the energy and climate legislation passed by the House of Representatives. Amongst the mechanisms observed, the U.S. has opted for the use of ethanol to mitigate gas emissions.

Staple grains represent a significant part of household budgets in developing countries and are sensitive goods with economic and political implications (Trostle, 2008; von Braun, 2012). Following the rapid ascent of staple grains prices, between the end of 2005 and 2008.[15] In the U.S. approximately 80 million acres of land are used for corn production and roughly 40 percent of this crop is destined for ethanol production (Nickerson *et al.* 2011). The growth in demand for U.S. corn since the early 2000's has come from the processing of corn into ethanol, which translates into claims of land conversion usage towards corn, preventing the production of other staple grains (Rosegrant *et al.* 2008; Timilsina *et al.* 2011 and Zilberman *et al.* 2013).

For the past decade, a quiet relationship between corn, ethanol production and oil prices has been developing, such link potentially derived from the change of the use of corn for human consumption to a source of fuel production. This relationship has been highly driven by government mandates requiring increased use of ethanol in gasoline. Government support to the ethanol industry currently conceals the issue between staple grains and fuel (Wisner, 2014). The simultaneous use of corn as a staple food and as an energy source poses a threat to corn and other staple grain, a situation that calls for an analysis to explore the connection between corn prices and ethanol production.

The present chapter uses monthly observations for U.S. corn prices, U.S. ethanol production, and oil prices over the years 2000 to 2014, divided into two sub-periods, known as the pre-ethanol period (2000-2005) and ethanol boom periods (2006-2014).[16]

[15] Corn prices nearly quadrupled from about $2 per bushel to almost $8 per bushel, and prices for rice, soybeans, and wheat rose too. These prices briefly dropped in 2009-2010 due to the recession, but corn again broke the $8 per bushel price in 2011 (Rosegrant *et al.*,2008; Timilsina *et a*l., 2011 and Zilberman *et al.*, 2013).

[16] Previous studies have made use of splitting the sample to account for possible structural shifts in the relations among energy variables (Zhang *et al.* 2009; Gardebroek and Hernandez (2013).

We extend the previous literature by examining these relations during and after the 2007-08 financial crisis.

We identify empirically the relationship between corn prices and ethanol production. The dynamic estimation procedure takes into account the following steps: (i) cointegration (ii) Long-run and short-run dynamics in the VECM, (iii) impulse response functions and (iv) connectedness measures. Firstly, we find cointegration using persistence profiles; in the second step weak evidence of a positive impact of ethanol production on corn prices suggests a positive short-run link in the pre-ethanol boom period that is corroborated by the generalised impulse response functions. Finally, the connectedness analysis shows a substantial change in the corn and oil dynamic, where oil prices go from being a dominant market in the system to reduced position in the boom period. Furthermore, overall results suggest that ethanol production does not impact corn prices as mentioned in some of the literature.

This chapter proceeds in the following way: Section 4.2 discusses the literature review. Section 4.3 presents the methodology. Results are presented in Section 4.4 and Section 4.5 concludes. Further details are presented in the Appendix.

4.2 Literature Review

The impact that the ethanol market has over agricultural commodities has sparked the current food versus fuel debate. In the literature, we can find empirical and theoretical papers that evaluate the impact of biofuels on food commodity prices using price level analysis. Zilberman *et al.* (2012) argue that biofuel prices do not affect directly food commodity prices, but food prices are slightly affected by the introduction of the biofuels market. Additionally, they suggest that the type of studies done to the time of their publication could not completely capture the impact of biofuels on food commodity prices.

Time-series analysis has been used to examine price-level dynamics between food and biofuel prices, suggesting that the relationship between these commodities depend on feedstock, biofuels, the model, and data frequency. Zilberman *et al.* (2013) and *Serra et* *al.* (2013), found that the predominant methodological approaches in the energy literature consist of cointegration analysis, Granger causality tests, routinely applied to assess causality, and estimation of Vector Error Correction Models (VECM). In those studies, it is observed the practice of sample splitting as a common technique that allows for time-varying price patterns due to structural changes, such as the new legislation in the biofuels industry.

The error correction models (ECM) employed by Campiche *et al.* (2007), Saghaian (2010), Serra *et al.* (2011), and Wixson and Katchova (2012), provide evidence that energy prices drive feedstock price equilibrium levels in the U.S. Campiche *et al.* (2007) find that soybean and corn prices are cointegrated with oil prices after the ethanol boom period and that crude oil prices drive feedstock prices. Saghaian (2010) analyses monthly prices of corn, soybean, wheat, oil and ethanol. Using Granger causality tests, he finds there is significant evidence of correlation among oil and commodity prices. In the same study, he uses VECM, and those results show there are no causal links between the energy and agricultural markets. Serra *et al.* (2011a) use a smooth transition VECM to identify the relation in prices between gasoline, oil prices, corn and ethanol in the U.S. with monthly data from 1990-2008. They find that the four prices are interrelated in the long run through two cointegrating relationships, the first one representing the gasoline market equilibrium between oil and gasoline prices, and the second representing the ethanol market equilibrium among ethanol, corn and gasoline prices. Wixson and Katchova (2012) also find a long-run cointegrating relationship between soybean prices and crude oil prices. Zhang *et al.* (2010) find no evidence of cointegration between energy and agricultural commodity prices.

Gilbert (2010a) conducts research on food prices in a group of developing countries: Benin, Kenya, Malawi, Nepal, Peru and Vietnam. His paper focuses on rice and corn, particularly in the use of the latter as a biofuel feedstock in the U.S. Rice is the major food staple in Asia whereas corn is in Africa. The first question the author addresses is the relevance of international commodity prices in developing countries. The second question regards how long it takes local prices to adjust to world prices, under the assumption that world prices are relevant in these countries. Gilbert (2010a) concluded that the 2007-08 food price spike did impact grain prices in these six countries, with different effects identified between corn and rice. His evidence shows regional variability within countries was high in Peru but relatively low in Kenya, Malawi and Vietnam.

Gilbert (2010b) uses Granger causality tests, a Capital Asset Pricing Model (CAPM) and the Autorregressive Distributed Lag (ADL) model to identify the main drivers behind the surge in food prices. The variables used for his estimations are indices for agricultural food, grain and vegetable oil prices, world GDP growth, crude oil prices, USD exchange rate, world money supply and futures market open interest, and he uses quarterly data for the period 1971q1-2008q4. The author indicates that monetary factors were an important determinant of food price rises in the 1970s, but monetary transmission channels tend to vary over time. This paper reveals that index futures investment was the principal channel through which monetary and financial activity have jointly affected food prices, especially over recent years. Notice that he does not consider the biofuel data in his study, but through a grain analysis, concludes that recent demand for these crops is directly linked to the use of biofuels.

Monteiro, Altman and Lahiri (2012) aim to investigate the impacts of both U.S. and Brazil ethanol production on world food prices. To avoid the use of nonstationary data, they use a static approach (OLS) in first-differences, using annual data over the period 1980-2007. Cane area in Brazil reallocated for ethanol production is found to influence negatively world food prices whereas, in the U.S. ethanol market, only oil prices and the exchange rate affected food prices. Such different results may reflect the higher productivity in the Brazilian ethanol market relative to the U.S. one. The ethanol market in Brazil is sugarcane-based and is far more efficient than the U.S.'s ethanol market. The energy balance in a U.S. gallon of Brazilian ethanol is 8 to 10 times greater than the than the one in the U.S. Thus, a direct comparison of the U.S. ethanol market with the Brazilian would be misleading since both countries use different measurements.

Despite the many empirical efforts to model food-energy relations, there is no widely-held specification that explains food price changes. The agricultural commodity price boom that took place in the second-half of the 2000s has drawn considerable interest among academics, mainly because the biofuel market is pointed as one of the main reasons for increases in price levels (Meyers and Meyer, 2008; Gilbert, 2010a).

Most studies have researched the linkage between the energy market and surrounding areas to explain food price hikes. Gilbert (2010b) and Monteiro *et al.* (2012) present interesting papers that open the path for further research into the ethanol market and food prices link, by using a connectedness approach this study distances itself from Monteiro *et al.* (2012), and seeks to contribute to the existing literature by analysing whether there is a connection between the ethanol market and agricultural commodities through the use of a VECM, impulse response functions and a connectedness analysis.

4.3 Methodology

4.3.1 The Vector Error Correction Model

In this section we follow a long-run structural VAR modelling developed by Pesaran and Shin (2003). This is a modified and generalised version of Johansen's (1991,1995) that approaches the problem of estimation and hypothesis testing in vector autoregressive error correction models using maximum likelihood (ML).

To start with the analysis we consider a VAR *(p)* with the following form:

$$y_t = c + \Upsilon_1 y_{t-1} + \Upsilon_2 y_{t-2} + ...\Upsilon_p y_{t-p} + \epsilon_t. \tag{4.1}$$

where y_t is an $m \times 1$ vector of variables, Υ_i is an $m \times m$ matrix of unknown coefficients and we also assume that E($\epsilon_t = 0$) where:

$$E(\epsilon_t = 0) = \mathbf{0}; E(\epsilon_t \epsilon_s') = \begin{bmatrix} \sum & \text{for} & t = s \\ \mathbf{0} & \text{for} & t \neq s \end{bmatrix} \tag{4.2}$$

with $\sum$ as an $m \times m$ symmetric positive definitive matrix.

The ML estimation of the VECM follows the finding of the r cointegrating relations among the m-vector of y_t ($\Pi = \alpha\beta'$),[17] we have that:

$$\Delta y_t = c + \alpha\beta' y_{t-1} + \sum_{j=1}^{p-1} \Upsilon_j \Delta y_{t-j} + \epsilon_t. \tag{4.3}$$

The parameters of the VECM are decomposed into the long-run parameters (β) and the short-run parameters (α, Υ_j and $\sum$). Δ is a first difference operator, $\Delta y_t = y_t - y_{t-1}$, denotes the change in the vector y from time $t-1$, ($y_t = y_{(cp)t}, y_{(ep)t}, y_{(op)t}\,'$), that represents corn prices, ethanol production and oil prices respectively; c is a constant, and ϵ_t is the error term.

4.3.2 Persistence Profiles, Impulse Response Functions and Forecast Error Variance Decomposition

In this section, we use a reduced form of a VAR model to illustrate the Persistence Profiles (Pesaran and Shin, 1996). We follow the analysis by introducing the Impulse Response Functions (Pesaran and Shin, 1997), and the connectedness analysis, using Forecast Error Variance Decomposition (FEVD).

We start with a VAR*(p)* model in its structural form:

$$\Psi_0 y_t = \sum_{j=1}^{p} \Psi_j y_{t-j} + \epsilon_t. \tag{4.4}$$

$$y_t = c + \Psi_1 y_{t-1} + \Psi_2 y_{t-2} + \ldots \Psi_p y_{t-p} + \epsilon_t. \tag{4.5}$$

where Ψ_0 is the $m \times m$ contemporaneous matrix, Ψ_j are the VAR parameter matrices, the residuals are $\epsilon_t \sim (0, \sum_\epsilon)$, and where $\sum_\epsilon$ is positive definite. We continue and use for simplicity (Eq. 4.4) in its reduced form:

[17]Please refer to Pesaran and Shin (2003) for the cointegration procedure.

$$y_t = \sum_{j=1}^{p} \Upsilon_j y_{t-j} + \epsilon_t. \tag{4.6}$$

where y_t is an $m \times 1$ vector of variables to consider, Υ_j is an $m \times m$ matrix that contains unknown coefficients and ϵ_t is a vector of errors distributed.

Following Wold's theorem, we transform Eq. 4.6 into an infinite order moving average with the following form:

$$\Delta y_t = c + \sum_{j=0}^{\infty} \Phi_j \epsilon_{t-j}. \tag{4.7}$$

where $\sum_{j=0}^{\infty}$ is a vector of constants, and ϵ_{t-j} are unobserved $m \times 1$ vectors of shocks or innovations that are assumed to be serially uncorrelated with zero means, a non-singular variance-covariance matrix, Ω, and have finite fourth order moments. We also assume that the Φ_j's are evaluated recursively as $\Phi_j = \Upsilon_j \Phi_{j-1} + \Upsilon_2 \Phi_{j-2} + \cdots + \Upsilon_{p-1} \Phi_{j-p+1}$, also the Wold theorem states that Φ_j's must be stable (square summable) and causal ($\Phi_0 = I_m$ and $\Phi_j = 0$ for $j < 0$).[18]

As exposed by Pesaran and Shin (1996), the cointegration analysis must include some estimates of speed that allow to study the position of markets or economies when a shock is applied. In this sense, the Persistence Profiles measure is used as an alternative approach to cointegration, it considers the time profile of the effect of a system-wide shock. Pesaran and Shin (1996) proposed this measure that captures the difference between cointegrated and noncointegrated relations through the effect of shocks to the cointegrated relations.

We assume that the system is cointegrated[19] and we have a matrix $\mathbf{B}$ of order $m \times r$ that allows the $r \times 1$ vector $Z_t = \mathbf{B}' y_t$ to be stationary or I(0), then $\mathbf{B}\Phi(1) = 0$, also $\Phi(1) = \sum_{j=0}^{\infty} \Phi_j$ is known as the long run multiplier matrix with a rank $[\Phi(1) = m - r]$.

The measure of the speed of convergence to equilibrium of cointegrating relations is achieved by focusing on the impact of system-wide shocks, instead of variable-specific

[18]The assumption of causality by the Wold's theorem tends to become unreachable when the dimension of the system increases, therefore this assumption is relaxed when we employ the Generalised Forecast Error Variance Decompositions (GFEVDs).

[19]Please refer to Beveridge and Nelson (1981) for the decomposition estimations.

shocks, in other words we analyse how the equilibrium relation ($Z_t = \mathbf{B}'y_t$) reacts to shocks from the ϵ_t's without orthogonalising the shocks. Lee and Pesaran (1993) extended this idea by deriving the time profile of the response of the variables in 4.7 to system wide shocks at different points in time. They proposed the following variance measure:

$$\Xi_y(n) = V(y_{t+n}|I_{t-1} - V(y_{t+n-1}|I_{t-1}). \tag{4.8}$$

where I_{t-1} is the information available to the period $t-1$, $V(y_{t+n-1})$ is the conditional variance of y_{t+n} given $t-1$. Lee and Pesaran (1993) refer to $\Xi_y(n)$ as the Persistence Profile that characterises the time profiles of the effects of the system-wide shocks on y_t. In the case of 4.7 the persistence profile in Pesaran and Lee (1993) is given by:

$$\Xi_y(n) = \Lambda_n \Omega \Lambda_n' \quad n = 0, 1, 2, .., \tag{4.9}$$

The concept developed by Pesaran and Lee can be extended to the cointegrated systems. Therefore, the Persistence Profile of the cointegrating relation $Z_t = \mathbf{B}'y_t$ can be given by:

$$\Xi_Z(n) = V(Z_{t+n}|I_{t-1} - V(Z_{t+n-1}|I_{t-1}). \tag{4.10}$$

$$\begin{aligned} \Xi_Z(n) &= \beta' \Xi_y(n) \beta. \\ &= \beta' \Lambda_n \Omega \Lambda_n' \beta \qquad \text{for} \qquad \text{n} = 0, 1, 2, .., \end{aligned} \tag{4.11}$$

To proceed with the analyses, the underlying shocks to the VAR model in Eq. 4.6 are generalised, this approach is invariant to the variables order and different from the Cholesky decomposition, originally proposed by Sim (1980), where the shocks are orthogonalised. The time profile of the effects of shocks at a given point in time in a dynamic system to future values (expected) of variables can be measured with impulse response functions.

We follow the approach by Koop, Pesaran and Porter (1996), and proceed to define the (generalised) impulse response function of y_t at horizon h by:

$$\mathbf{GI}_y(h, \delta, \Omega_{t-1}) = E(y_{t+h}|\epsilon_t = \delta, \Omega_{t-1}) - E(y_{t+h}|\Omega_{t-1}) \tag{4.12}$$

In here we shock one element of ϵ_t (jth-element)instead of shocking all elements and integrate out the effects of other shocks by using the historical distribution of errors

We assume that ϵ_t has a multivariate normal distribution[20] we have that:

$$E(\epsilon_t|\epsilon_{jt}) = \delta_j = (\sigma_{1j}, \sigma_{2j}, ..., \sigma_{mj})'\sigma jj^{-1}\delta_j = \sum \mathbf{e}_j \sigma jj^{-1}\delta_j$$

If we set $\delta_j = \sqrt{\sigma jj}$, we obtain the scaled generalised impulse response function is given by:

$$\zeta_j^g(h) = \sigma_{jj}^{-1/2}\Phi_h \sum \mathbf{e}_j, \quad h = 0, 1, 2, ..., \tag{4.13}$$

this measures the effect of one standard error shock to the jth equation's innovation ϵ_{jt} at time t on expected values of y at time $t + h$. The plot of $\zeta_j^g(h)$ against the horizon $h = 0, 1, 2, ...,$ is called the generalised impulse response function.[21]

The above generalised impulse responses can be used in the derivation of the FEVD in our analysis, to some extent this method differs from the impulse response analysis. The FEVD is defined as the proportion of the h-step aheah forecast error variance of variable i which is accounted for by the innovations in variable j in the VAR. In other words, a shock to the i-th variable will affect itself, but it will also be transmitted to the rest of variables through the dynamic structure of the VAR.

[20] For further reference please refer to Koop *et al* (1996)

[21] Pesaran and Shin (1997), proposed this alternative approach to the Cholesky decomposition of the shocks in the impulse response analysis, which overcomes the shortcoming of the orthogonalised impulse responses.

The generalised forecast error variance decompositions, $FEVD^g_{ij,h}$, for $h = 0, 1, 2, ...,$ is given by:

$$FEVD^g_{ij,h} = \frac{\sigma^{-1}_{ii} \sum_{j=1}^{h} (\mathbf{e}'_j \Phi_\ell \sum_u \mathbf{e}_i)^2}{\sum_{j=1}^{h} \mathbf{e}'_i \Phi_\ell \sum_\epsilon \Phi'_\ell \mathbf{e}_i}. \tag{4.14}$$

where $i, j = 1, ..., m$, the forecast horizon is $h = 0, 1, 2, ...,$ the standard deviation of the residual process is σ^{-1}_{ii} of the i-th equation in the VAR system and $\mathbf{e}_i(\mathbf{e}_j)$ is an $m \times 1$ vector identity matrix whose j-th and i-th elements are one and the rest of the elements are zeros.[22]

4.3.3 Connectedness Analysis

Based on Diebold and Yilmaz (2014), Greenwood-Nimmo *et. al.* (2015) used a generalised forecast error decomposition variance (GFEVD) to analyse the system by pairwise based in 4.14. Diebold and Yilmaz (2014) estimated the spillovers firstly in a static way, after that they claimed it can offset some effects during the period of the sample. Therefore, they applied a rolling estimation with time-varying to show how the spillovers have changed along the sample.

Diebold and Yilmaz (2014) measures are defined at the variable level. The interpretation of GFEVDs is complex because the sum of variance shares will exceed 100% if $\sum_{\epsilon_t}$ is non-diagonal. To avoid this issue, Diebold and Yilmaz (2014) employ normalised GFEVDs as follows:

$$\theta^{(h)}_{i \leftarrow j} = \frac{\varrho^{(h)}_{i \leftarrow j}}{\sum_{j=1}^{m} \varrho^{(h)}_{i \leftarrow j}} \tag{4.15}$$

such that $\sum_{j=1}^{m} \varrho^{(h)}_{i \leftarrow j} = 1$ and $\sum_{j=1}^{m} (\varrho^{(h)}_{i \leftarrow j} \theta^{(h)}_{i \leftarrow j}) = m$. Eq. 4.15 provides a percentage interpretation of the GFEVDs. The conceptual framework developed by Diebold and Yilmaz (2014) provides a weighted directed network of $m \times 1$ vector of global variables while it allows to cross-tabulate the h-step ahead NGFEVDs.

[22]For further reference of the generalised forecast error variance decompositions see Pesaran and Pesaran (1997).

The directed network presented by Diebold and Yilmaz (2014) provides $m \times m$ connectedness matrix that is given by:

$$Co^{(h)}_{(m\times m)} = \begin{bmatrix} \theta^{(h)}_{1\leftarrow 1} & \theta^{(h)}_{1\leftarrow 2} & \cdots & \theta^{(h)}_{1\leftarrow m} \\ \theta^{(h)}_{2\leftarrow 1} & \theta^{(h)}_{2\leftarrow 2} & \cdots & \theta^{(h)}_{2\leftarrow m} \\ \vdots & \vdots & \ddots & \vdots \\ \theta^{(h)}_{m\leftarrow 1} & \theta^{(h)}_{m\leftarrow 2} & \cdots & \theta^{(h)}_{m\leftarrow m} \end{bmatrix} \tag{4.16}$$

Each element of the i-th row of $Co^{(h)}$ provides the proportion of the h-step ahead FEV of the i-th variable derivable to each variable in the system. $H^{(h)}_{i\leftarrow i}$ shows the contribution of the shock to the i-th variable itself, this is estimated by the i-th diagonal element of $Co^{(h)}_{(m\times m)}$:

$$H^{(h)}_{i\leftarrow i} = \theta^{(h)}_{i\leftarrow i} \tag{4.17}$$

In Eq. 4.17 the off-diagonal elements of the i-th row of $Co^{(h)}$ capture spillovers from the other variables in the system to variable i. The contribution to the h-step-ahead FEV of variable i from variable $j \neq i$ is represented by the $(i;j)$-th element, $\theta^{(h)}_{i\leftarrow j}$.

The term F (coming from) measures the directional connectedness to the i-th variable $from$ variable j. The total spillover from the system to a variable can be defined by:

$$F^{(h)}_{i\leftarrow \bullet} = \sum_{j=1, j\neq i}^{m} \theta^{(h)}_{i\leftarrow j} \tag{4.18}$$

the subscript $i \leftarrow \bullet$ points out that the directional effect is *coming from* all other variables to variable i.

Spillovers from the i-th variable to the other variables in the system are stored in the i-th column of $Co^{(h)}$. The contribution of variable i to the h-step ahead FEV of the j-th variable in the system is given by $\theta^{(h)}_{j\leftarrow i}$. Therefore, we can estimate the total spillovers from variable i to the system by adding over j (going to), the term is defined as:

$$T^{(h)}_{\bullet\leftarrow i} = \sum_{j=1, j\neq i}^{m} \theta^{(h)}_{j\leftarrow i} \tag{4.19}$$

The net directional connectedness (N) of variable i can be defined now as:

$$N^{(h)}_{\bullet\leftarrow i} = T^{(h)}_{\bullet\leftarrow i} - F^{(h)}_{\bullet\leftarrow i} \tag{4.20}$$

by construction we know that:

$$\sum_{i=1}^{m} N^{(h)}_{\bullet\leftarrow i} = 0$$

After the analysis of connectedness in a variable level, we proceed to introduce two measures for volatility: the heatwave hypothesis and the meteor shower hypothesis. The heatwave hypothesis states that the volatility has variable-specific autocorrelation, whereas the meteor shower hypothesis defines that volatility spillover goes from one variable to the next. In their seminal paper, Engle Ito and Lin (1990) find that the causes of volatility clustering can be due to the heatwave hypothesis and the meteor shower hypothesis.

$$H^{(h)} = \sum_{i=1}^{m} H^{(h)}_{i\leftarrow i} \tag{4.21}$$

$$S^{(h)}_{\bullet\leftarrow i} = \sum_{i=1}^{m} F^{(h)}_{i\leftarrow\bullet} \equiv \sum_{i=1}^{m} T^{(h)}_{\bullet\leftarrow i} \tag{4.22}$$

Engle *et al.* (1990) and Diebold and Yilmaz (2009) referred to $H^{(h)}$ and $S^{(h)}$ as the heatwave and spillover indices, by construction $H^{(h)} + S^{(h)} = m$. We continue our analysis by using the Generalised Connected measures developed by Greenwood-Nimmo *et al.* 2015, these estimations provide a better understanding of the intermediate levels of aggregation in the system.

The elements lying on the prime diagonal of Eq. 4.16 are the within-variable FEV contributions and are given by Eq. 4.17 which transforms into:

$$W_{i\leftarrow i}^{(h)} = \theta_{i\leftarrow i}^{(h)} \tag{4.23}$$

Central to the general connectedness measures suggested by Greenwood-Nimmo *et al.* (2015), we find two indices of particular interes for our study, (i) the level of dependency of the i-th-variable on external conditions and (ii) to what extent the ith-variable is influence or is influenced by the system as a whole. In response to the first query, the authors developed a dependence index $D_i^{(h)}$ to analyse economic blocks in an economy. In our particular case, this index measures the dependence of each price on external market conditions. The $O_i^{(h)}$ index is given by:

$$O_i^{(h)} = \frac{F_{i\leftarrow\bullet}^{(h)}}{W_{i\leftarrow i}^{(h)} + F_{i\leftarrow\bullet}^{(h)}} \tag{4.24}$$

Eq. 4.24 measures the dependence of each price on external market conditions through prices. The relative importance of external shocks for the i-th variable is given by $0 \leq O_i^{(h)} \leq 1$ shows. If $O_i \rightarrow 1$ we have that the conditions in variable i are dominated by external shocks, on the other hand if $O_i^{(h)} \rightarrow 0$ variable i remains unaffected by external shocks.

Similarly to the $O_i^{(h)}$, the influence in the system is measured by the $I_i^{(h)}$ index represented by equation 4.25:

$$I_i^{(h)} = \frac{N_{\bullet\leftarrow i}^{(h)}}{T_{\bullet\leftarrow i}^{(h)} + F_{\bullet\leftarrow i}^{(h)}} \tag{4.25}$$

If in Eq. 4.25 $-1 \leq I_i^{(h)} \leq 1$, for any horizon h, the series is considered a net shock recipient if $-1 \leq I_i^{(h)} < 0$, a net shock transmitter if $0 < I_i^{(h)} \leq 1$ and neither a net transmitter nor recipient if $I_i^{(h)} = 0$. As such, the influence index measures the extent to which the variable influences or is influenced by conditions in the system.

In the connectedness analysis, the coordinate pair $(O_i^{(h)}, I_i^{(h)})$ in the dependence-influence space provide an informative representation of the specific role variable plays in the system. In this manner, an open variable will be located at (1,-1) and a dominant variable would exist in (0,1).

4.4 Empirical Application

4.4.1 The Data

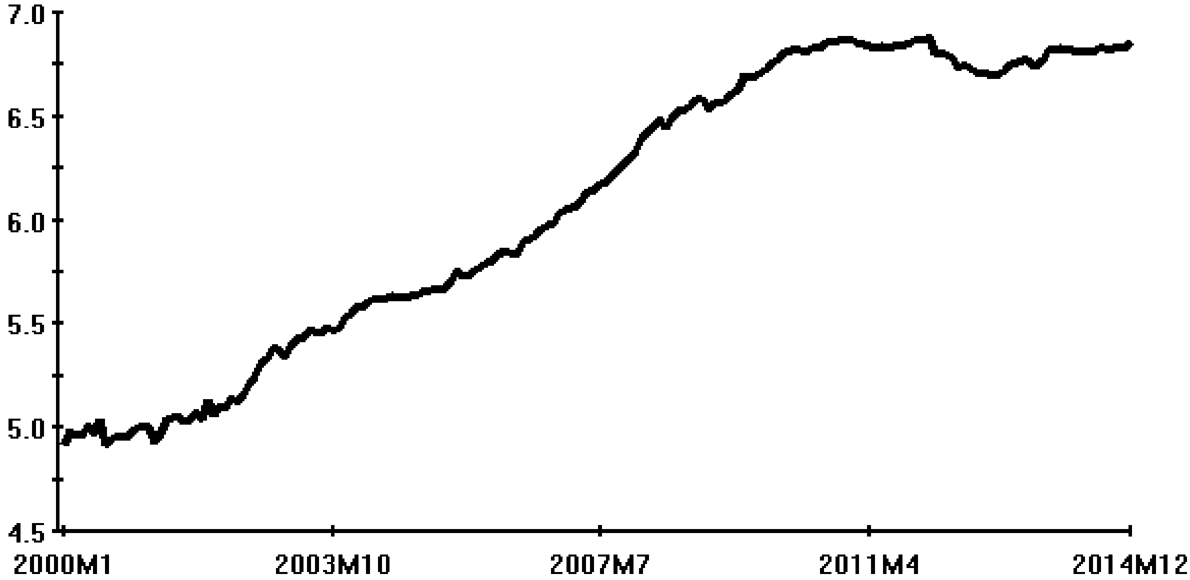
In this chapter, we address the issue of how ethanol production influences corn prices in the U.S. We study the role of ethanol production and corn prices from 2000 to 2014. We start in 2000 because this is the year where ethanol production began increasing more dramatically with the gradual elimination of the MTBE as the gasoline oxygenate and its replacement with ethanol. Therefore, the modest ethanol production in the prior years to 2000 is not relevant for this study.

We consider the tri-variate VECM model for U.S. corn prices, U.S. ethanol production and oil prices. Previous literature (see Gilbert, (2010b) and Monteiro *et al.*, (2012) considered different variations of ethanol production as an ethanol-market related factor; and oil prices as the main macroeconomic factor. In the particular case of corn, the impact of other agricultural food commodities (soy, wheat, sorghum), oil prices, futures market speculation, climate and China's exports of corn can be regarded as important potential corn-market factors. It is important to stress that in 2000 corn started to unfold as a significant energy input in ethanol production which could be affected by other energy commodities (i.e., oil). The further introduction of the gasoline-ethanol blending mandates in 2005 and 2007 further, strengthen its position in the energy market.[23]

Monthly data from January 2000 to December 2014 is split into the pre- and ethanol boom periods. Corn prices are from the Economic Research Bioenergy Statistics division of the United States Department of Agriculture (USDA). Fuel ethanol production data was taken from Datastream 5 (Thomson Reuters) and oil prices are from the United States Energy Information Administration. All the series have been seasonally adjusted

[23]Refer to Appendices for Chapter 4 for further reference to previous analyses that consider different factors that affect these three markets.

Figure 4.1: Ethanol production (log-levels)



U.S. DOE, Energy Information Administration

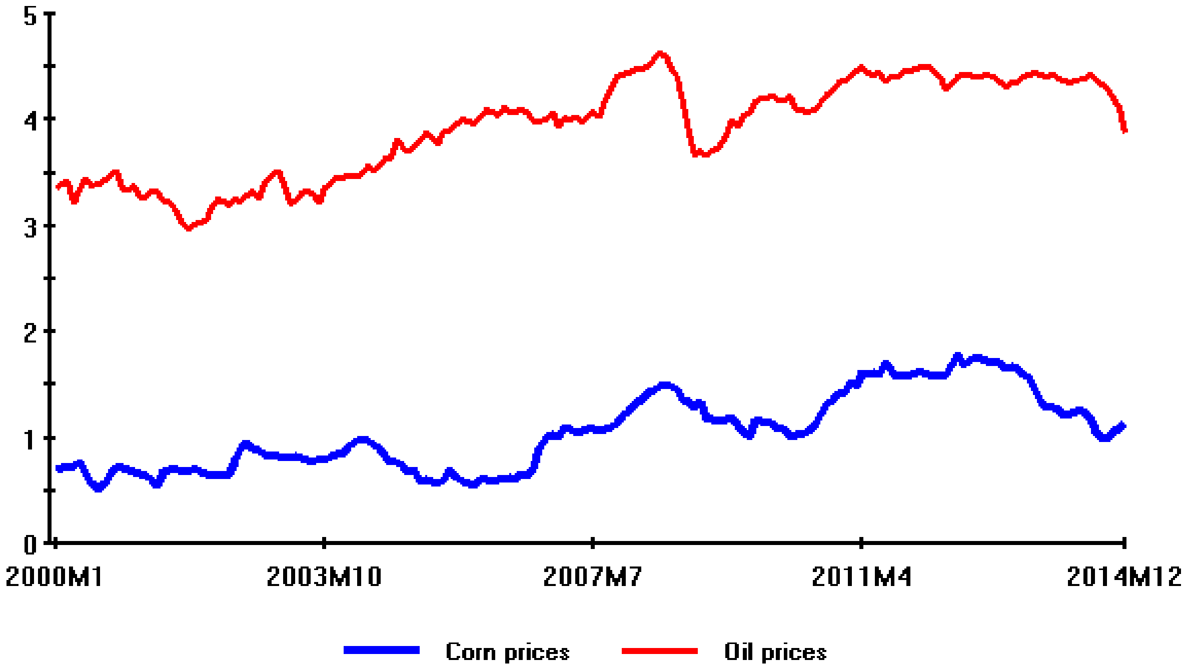
and deflated[24] and transformed with logarithms. The use of real prices is a common practice in the literature since it allows you to know if the series are consistent over time even under sudden changes, as observed in Monteiro *et al.* (2012) and Gilbert (2010a), Fernandez, (2014) among others.

Between 2000 and 2011, global biofuels production increased by more than 500 percent, partially due to the adoption of biofuel mandates in the United States and the European Union and higher oil prices (RFA, 2012). Figure 4.1 shows a steady growth pattern for ethanol production in the U.S. The Energy Policy Act of 2005 (known as EPAct2005) introduced a mandate for four billion U.S. gallons (US/gal) of ethanol to be blended with gasoline. In 2008, the mandated amount was further increased to nine billion US/gal, and it reached to almost sixteen billion US/gal in 2013. It is projected that by 2022 the blend will increase to thirty-six billion US/gal (RFA, 2012).

Corn prices and oil prices are depicted in Figure 4.2. The figure shows price patterns for both commodities in the last 14 years. From 2000 until 2005, corn prices were stable due to surplus. However, after 2006 and throughout the financial crisis corn prices increased.

[24]The U.S. Consumer Price Index (CPI) given by the Bureau of Labour Statistics was used for this purpose.

Figure 4.2: Real Corn and Oil Prices (log-levels)



Source: USDA, National Agricultural Statistics Service Administration

The rapid expansion of ethanol production and the impossibility of corn production to meet the new demands also affected corn prices. Moreover, in 2012, a drought affecting the U.S. fields reduced corn production and in turn increased corn prices (Wisner, 2014).

Figure 4.2 also provides the crude oil prices pattern. In the middle of the financial 2007-08 crisis, oil prices peaked at over \$140 dollars per barrel and gasoline prices reached over \$3 per US/gal, before falling close to \$1 US/gal.

4.4.2 Unit Root and Cointegration Tests

This section presents the unit roots and cointegration test. In the first stage, we test for nonstationarity of the variables employing the Augmented Dickey-Fuller (ADF) unit root test (Tables 4.1, 4.2 and 4.3). The ADF tests results suggest that all three variables contain a unit root in a full sample, the pre- and ethanol boom period. We then determine the optimal lag length for the VAR (Table 4.4).

Table 4.4 presents the Akaike Information Criterion (AIC) for 13 different lag structures (from lags 12 to 0) for the full sample and the pre-ethanol and boom periods. We

Table 4.1: Unit Root Test Results over the period 2000-2014

	Corn prices		Ethanol production		Oil prices	
	C	C & T	C	C & T	C	C & T
	T-stat	T-stat	T-stat	T-stat	T-stat	T-stat
DF	-1.2504	-1.1676	-1.2499	-2.1343	-1.5811	-1.3339
ADF(1)	-1.4721	-1.844	-1.3427	-0.55698	-1.7695	-1.9265
ADF(2)	-1.621	-2.2566	-1.6321	0.18652	-1.8968	-2.3401
ADF(3)	-1.514	-2.0108	-1.5917	0.15365	-1.889	-2.371
ADF(4)	-1.6114	-2.3158	-1.4227	-0.15371	-1.9197	-2.5181
ADF(5)	-1.6104	-2.366	-1.4363	-0.09392	-1.8986	-2.5189
ADF(6)	-1.5769	-2.3359	-1.4303	-0.08122	-1.7656	-2.116

Notes: (i) C stands for the ADF regression with constant only and C & T for the ADF regression with constant and trend. (ii) 5% asymptotic critical values of the ADF statistic are -2.8776 for C and -3.4356 for C & T.

Table 4.2: Unit Root Test Results in pre-ethanol boom period over 2000-2005

	Corn prices		Ethanol production		Oil prices	
	C	C & T	C	C & T	C	C & T
	T-stat	T-stat	T-stat	T-stat	T-stat	T-stat
DF	-1.4778	-1.1905	-1.3233	-5.0479	-0.5918	-1.5765
ADF(1)	-2.5008	-2.4985	-0.3325	-2.8133	-0.5987	-1.5838
ADF(2)	-2.4155	-2.4261	0.1250	-2.0057	-0.2489	-1.2238
ADF(3)	-1.9475	-1.8395	0.2204	-1.8707	-0.1867	-1.1561
ADF(4)	-1.8454	-1.7091	0.1246	-2.0386	-0.1582	-1.1295
ADF(5)	-1.9054	-1.8315	0.1426	-2.0200	-0.4124	-1.4417
ADF(6)	-1.4749	-1.1949	0.2196	-1.9399	-0.4508	-1.5342

Notes: (i) C stands for the ADF regression with constant only and C & T for the ADF regression with constant and trend. (ii) 5% asymptotic critical values of the ADF statistic are -2.9055 for C and -3.4779 for C & T.

Table 4.3: Unit Root Test Results in ethanol boom period over 2006-2014

	Corn prices		Ethanol production		Oil prices	
	C T-stat	C & T T-stat	C T-stat	C & T T-stat	C T-stat	C & T T-stat
DF	-1.8781	-0.6670	-2.7924	-1.4579	-1.9211	-1.5104
ADF(1)	-1.8946	-1.0262	-3.4559	-1.3088	-2.5548	-2.3306
ADF(2)	-1.9924	-1.4355	-3.5400	-1.2886	-3.5238	-3.4635
ADF(3)	-1.9689	-1.3406	-3.2515	-1.3120	-3.4214	-3.3783
ADF(4)	-2.0916	-1.7745	-3.2154	-1.2820	-3.4821	-3.4929
ADF(5)	-2.0981	-1.8127	-3.1585	-1.2568	-3.2387	-3.2266
ADF(6)	-2.1077	-1.8594	-2.9544	-1.3058	-2.7705	-2.6151

Notes: (i) C stands for the ADF regression with constant only and C & T for the ADF regression with constant and trend. (ii) 5% asymptotic critical values of the ADF statistic are -2.8868 for C and -3.444 for C & T.

Table 4.4: Lag Order Selection Results

	2000-2014	Pre ethanol boom period	Ethanol boom period
Order	AIC	AIC	AIC
12	719.8470	253.3397	494.8576
11	719.0181	248.5436	498.4947
10	720.6298	245.0451	498.6776
9	716.7623	245.2373	503.1482
8	719.7477	249.4731	501.9614
7	714.5397	245.6354	505.0714
6	720.1989	250.0833	506.8304
5	724.3309	251.0950	513.8848
4	728.7489	256.6948	516.0618
3	734.7274**	257.0693**	523.4525**
2	721.4295	246.8439	518.1566
1	682.8762	229.9828	509.0802
0	-661.5532	-142.3218	-360.8483

Notes:
AIC=Akaike Information Criterion.
** denotes lag selected.

use the AIC because it is one of the most commonly used statistics in time series analysis (Asteriou and Hall, 2007). In this case, the AIC indicated an optimal lag length of three.

The test for the presence of cointegration between corn prices, ethanol production and crude oil prices is done using Johansen's Max-Eigenvalue and Trace tests (Johansen, 1991). Table 4.5 presents the results for the three samples. We find no cointegrating relationships in the full sample and the pre-ethanol boom period. The ethanol boom period presents at least one cointegrating relationship.

Table 4.5: Johansen Cointegration Test Estimates

A. 2000-2014	Max-Eigenvalue test			Trace test		
Coint rank	Stat	95% C.V.	90% C.V.	Stat	95% C.V.	90% C.V.
None	11.87	21.12	19.02	22.53	31.54	28.78
At most 1	8.66	14.88	12.98	10.66	17.86	15.75
At most 2	2.00	8.07	6.50	2.00	8.07	6.50
Lags	3					
B. Pre ethanol boom period	Max-Eigenvalue test			Trace test		
Coint rank	Stat	95% C.V.	90% C.V.	Stat	95% C.V.	90% C.V.
None	11.07	21.12	19.02	17.21	31.54	28.78
At most 1	6.06	14.88	12.98	6.14	17.86	15.75
At most 2	0.08	8.07	6.50	0.08	8.07	6.50
Lags	3					
C. Ethanol boom period	Max-Eigenvalue test			Trace test		
Coint rank	Stat	95% C.V.	90% C.V.	Stat	95% C.V.	90% C.V.
None	20.92*	21.12	19.02	36.90**	31.54	28.78
At most 1	12.69	14.88	12.98	15.99*	17.86	15.75
At most 2	3.29	8.07	6.50	3.29	8.07	6.50
Lags	3					

Notes:
(i) * denotes significance at 10%.
(ii) ** denotes significance at 5%.

The results in Table 4.5 are not conclusive, the small size of the sample reduces the

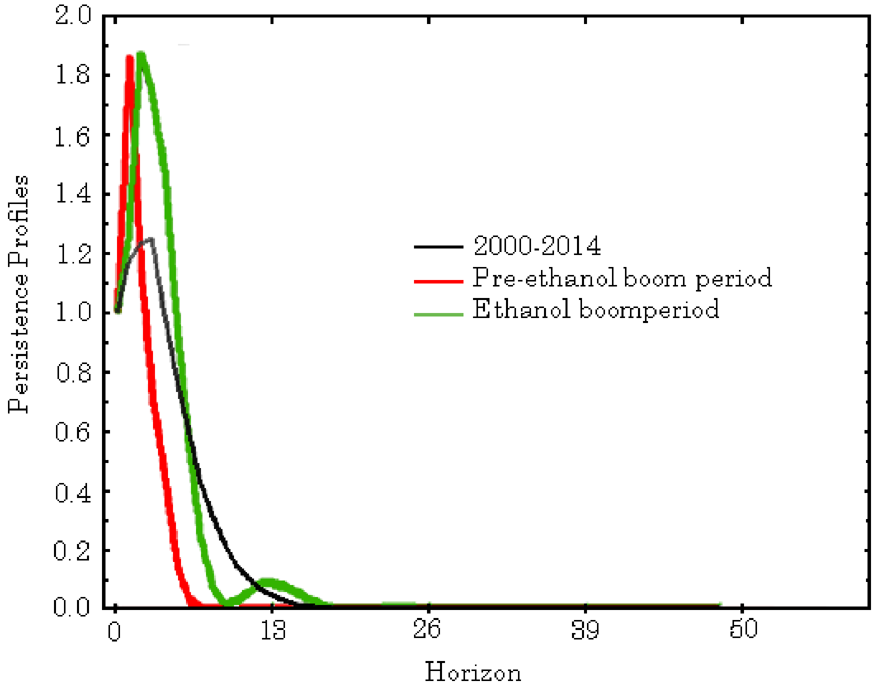


Figure 4.3: Point Estimates of Persistence Profiles based on the VECM Specification

power of the cointegration and may lead to ambiguous results. An informal way to check for cointegration is by using the persistence profile (PP) measure from Pesaran and Shin (1996), this measure provides estimates of the speed with which the system returns to its equilibrium state when shocked. The PP has a value of unity on impact, then tends to zero as the length of the time horizon increases, then we look for the PP to reach stability as fast as possible. Even though this is not a formal cointegration test, PP can be a reliable measure used for this purpose.

Figures 4.3, plot the persistence profiles for the full sample (black line), pre- (red line) and ethanol boom period (green line). The estimates show that the persistence profile of the full sample converges to zero slowly while the persistence profiles for the pre- and ethanol boom periods show a faster rate of convergence. The persistence profiles for the pre- and ethanol boom period increment to its highest peak around 1.9 at the four month and there is a steep decline after, especially for the pre-ethanol boom period.

4.4.3 VECM Estimation Results

The Persistence Profile measures indicate the existence of cointegration in the pre- and ethanol boom period among the corn prices, ethanol production and oil prices. Table 4.6 presents the long-run equilibrium relationships found.[25] We split the sample into pre- and ethanol boom periods, and investigate the time-varying patterns of the long-run relationship as well as the associated short-run dynamic adjustments explained by structural changes, such as the breakthrough of the ethanol industry, financial crises or natural disasters.[26] A priori we expect a bigger impact on corn prices in the ethanol boom period where an increase in mandated amounts of gasoline-ethanol blend, ethanol tax credits and other subsidies are observed.

For the pre- and ethanol boom periods we find the impact on corn prices to be positive although not statistically significant. Signs of corn and oil are expected to be positive, as found in Monteiro *et al.* (2012). In our study, we find weak evidence of ethanol production affecting corn prices. Our results support some of the findings by Monteiro *et al.* (2012), two of the four regressions estimated in their study showed that land used for ethanol production had a positive impact on world food prices, i.e. an increase in ethanol production increased world food prices. However, the results were statistically not significant, providing inconclusive evidence. Furthermore, Monteiro *et al.* (2012) used a rather small dataset with annual data from 1980-2007. Similarly, Gilbert (2010b) finds that recent increases in the demand for grains are because of biofuel production. Monetary incentives given to ethanol productions translate into changes in land use, i.e. a farmer finds more profitable to produce corn for ethanol than wheat or soybean, this creates a closer link between corn and ethanol production.

In our study we use the U.S. ethanol production to measure the impact of the ethanol market on corn prices, for this purpose we employ a VECM and find weak evidence of

[25]Please refer to Chapter 4 Appendix for the VECM diagnostic tests.

[26]Two different dummies were used to account for the 2007-08 financial crisis and the drought of 2012, but because they lacked statistical significance they are not featured in the final VECM specification. Bai and Perron's (1998, 2003) breakpoint test were used to find breaks. Results are available upon request.

ethanol production affecting corn prices in both periods and a further significant impact after the ethanol boom period is not available in VECM results.

On the other hand, the expected relationship between corn prices and oil prices is a positive one. Energy use accounts for a substantial share of the total inputs in the ethanol production, and given the relationship between crude oil and gasoline prices, any changes in crude oil are reflected in corn prices through transportation costs. Our results show that oil prices are positive for a full sample and the ethanol boom period, and in the latter they are significant, i.e.; corn prices are positively affected by oil prices. Monteiro *et al.* (2012) and Gilbert (2010b) find positive results for oil prices, recognising its position as a major agricultural commodity driver.

Table 4.6: Long-Run Cointegrating Relationship

	2000-2014	Pre ethanol boom period	Ethanol boom period
$y_{(cp)t}$	-1.000	-1.000	-1
$y_{(pe)t}$	-1.060	0.241	0.061
	(2.204)	(0.175)	(0.406)
	[-0.481]	[1.379]	[0.151]
$y_{(op)t}$	2.646	-0.288	1.888**
	(4.083)	(0.230)	(0.700)
	[0.648]	[-1.249]	[2.698]
LL	760.317	283.725	546.349

Notes:
(i) Standard errors in ( ) & t-statistics in [ ].
(ii) * denotes significance at the 1%.
(ii) ** denotes significance at the 5% level.
(iii) LL = Log likelihood.

Table 4.7 refers to the short-run estimations of the VECM model when we normalise corn. We find a positive and significant coefficient in the short run for corn, which means that corn prices from this month, depend on its prices from a month ago. In terms of speed after a shock we find that the period 2000-2005 has an statistically significant error correction term. The speed of adjustment in the pre-ethanol boom period is close to five months, this suggest a somewhat fast adjustment towards equilibrium in the event of a shock. On the other hand, we find that in the ethanol boom period it takes around forty-

Table 4.7: Short-Run Dynamics

	2000-2014		2000-2005		2006-2014	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
c	0.064	0.051	-0.117**	0.040	0.003	0.006
$\Delta y_{(cp)t-1}$	0.242**	0.078	0.489**	0.126	0.194	0.100
$\Delta y_{(ep)t-1}$	-0.019	0.065	-0.043	0.059	-0.110	0.159
$\Delta y_{(op)t-1}$	-0.084	0.054	-0.047	0.069	-0.064	0.077
$\Delta y_{(cp)t-2}$	0.114	0.078	0.035	0.137	0.175	0.100
$\Delta y_{(ep)t-2}$	0.043	0.064	0.044	0.057	0.039	0.161
$\Delta y_{(op)t-2}$	0.011	0.055	0.100	0.068	-0.028	0.079
ect	-0.009	0.007	-0.190**	0.066	-0.023	0.017

(ii) * denotes significance at the 1%.

(ii) ** denotes significance at the 5% level.

three months to go back to the long run equilibrium, this shows a very slow adjustment process in the presence of some disturbance in the system.

Our overall results show weak evidence of the ethanol market affecting corn prices, even though we find our predictions consistent with Monteiro *et al.* (2009), we must be cautious in providing definite conclusions for the relationship between corn prices and ethanol production. During the period 2004-2006 MTBE was replaced by ethanol as the main oxygenate in gasoline, our pre-ethanol boom period results suggest that this event had more impact on corn prices rather than the blending mandate that started in 2005.

Next, we conduct the impulse response function analysis to examine the shock propagation mechanism of how the ethanol production shock will influence the future prices of corn and oil.

4.4.4 Impulse Response Functions

In this section, we illustrate the general impulse response method by examining the impulse response of corn prices to a shock in ethanol production, for our analysis we select a forecast horizon of 50 months. Impulse responses are standard tools in VAR analyses, but confidence intervals are often not provided for these measures. For our analysis, we

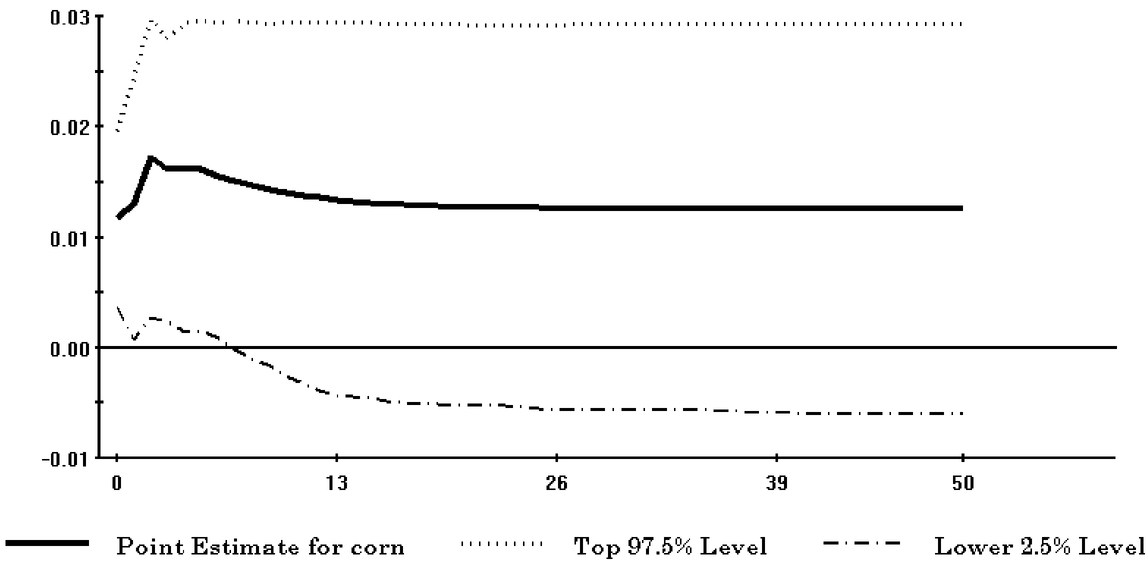


Figure 4.4: Generalised Impulse Responses to One Standard Error Shock in the Ethanol Production Equation over the period 2000-2014

use Confidence Intervals (CIs) based on bootstrap methods.[27]

The results for the generalised impulse response functions for the full sample, pre- and ethanol boom period are presented in Figures 4.4, 4.5, 4.6 respectively. From previous discussions we expect that shocks in ethanol production will have a positive influence in future corn prices, i.e., we anticipate increases in corn prices after a shock in ethanol production. This positive impact is expected especially in the ethanol boom period where higher volumes of ethanol production are observed after 2005.

Figure 4.4 shows that the ethanol production shocks have a small effect on ethanol production, the impact response is around 1.2%, rising to 2.5 % after three months; that dies out after approximately 10 months. We find a faster response in the pre-ethanol boom period (Figure 4.5). The initial impact on corn prices to a shock in the ethanol production equation is positive and significant; this is close to 2% and it increases to 2.8 % after four periods, then it declines to almost zero after 8 months.

A slightly different picture is found in the ethanol boom period, we have a rather small impulse response on corn that starts at 1.5 % in the first month and it rises to less than

[27] Bootstrap methods lead to more reliable results in small sample inference. Please refer to Benkwitz, Lütkepohl and Wolters (2001) for further information.

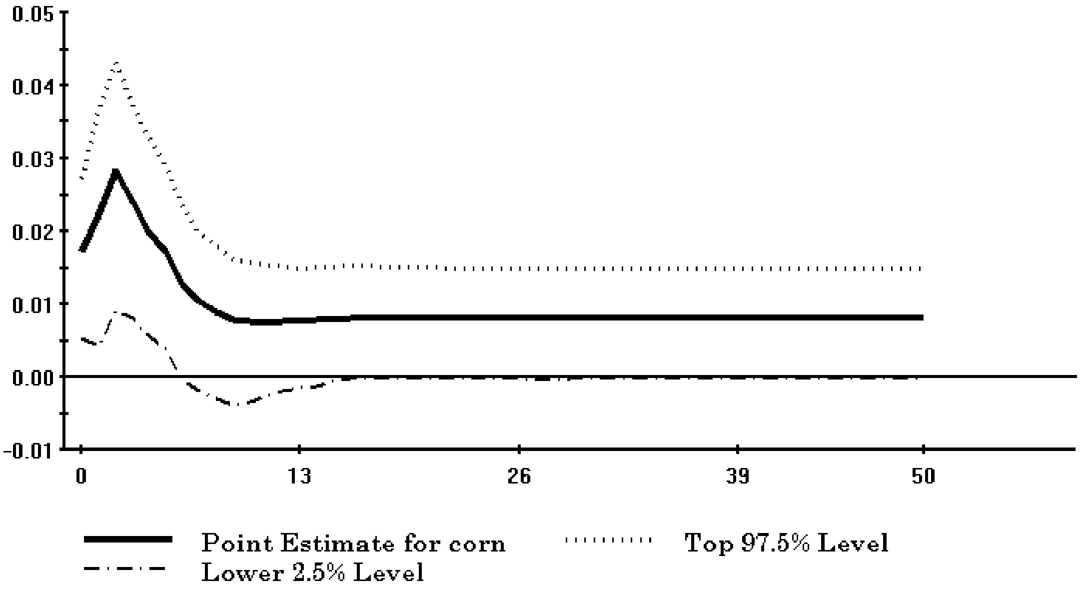


Figure 4.5: Generalised Impulse Responses to One Standard Error Shock in the Ethanol Production Equation over the Pre-Ethanol Boom Period

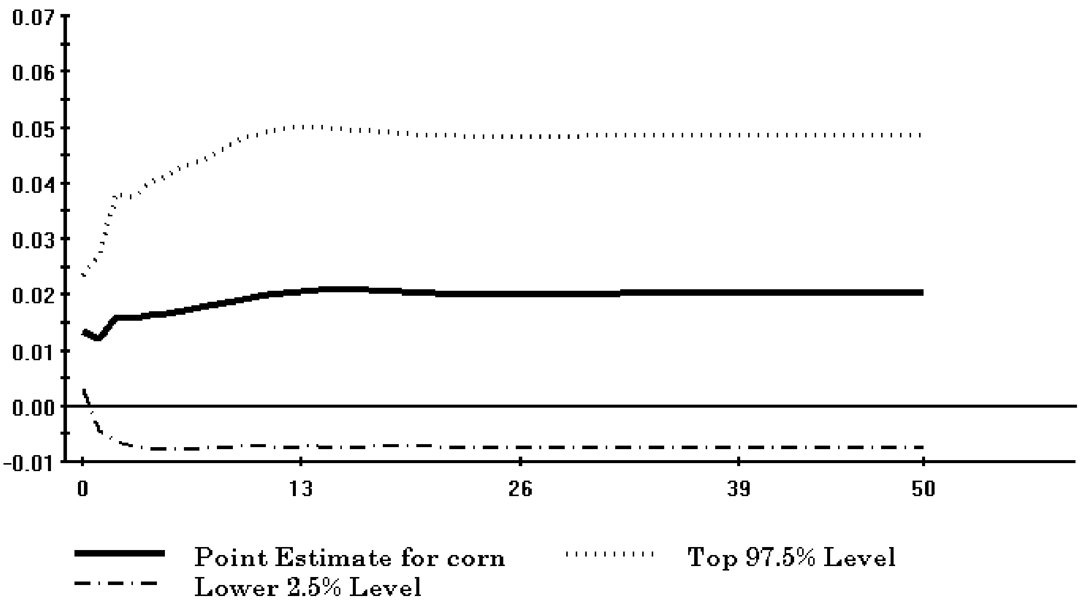


Figure 4.6: Generalised Impulse Responses to One Standard Error Shock in the Ethanol Production Equation over the Ethanol Boom Period

0.5% the following period, this effect dies out almost immediately. Our generalise impulse response results suggest a negligible propagation of the shock to ethanol production in corn prices.

Our generalised impulse response estimates provide similar conclusions to the one found in the VECM analysis. As expected the shock to the ethanol production equation is positive in the three periods, but with a different magnitude in each one of them. The pre-ethanol boom period provides significant evidence of corn prices being affected by the shock in the equation of ethanol production, these results mirror the short-run dynamics from the VECM. However, the findings are subject to great uncertainty, which suggests that the evidence of this analysis is not conclusive.

In the next section, we estimate connectedness measures among corn prices, ethanol production and oil prices to find the dominant market in this tri-variate VECM system.

4.4.5 Connectedness Analysis

A shock in the ethanol production equation to corn prices, suggested weak evidence of a positive impact of corn; following these results, we continue with a connectivity analysis between corn prices, ethanol production and oil prices by using the connectedness technique developed by Diebold and Yilmaz (2014) and Greenwood-Nimmo *et al.* (2015).[28] This analysis of interdependence provides directional connectedness measures and interlinkage indices in the short and the long run in our tri-variate system.

Using the GFEVD results from the VECM, and normalising them (NGFEVD), we construct the 3×3 matrix of connectedness measures across different horizons starting with $h = 1$ (one month) and ending with $h = 24$ (24 months) which we call the short-run and the long-run, respectively.

In Table 4.9 we find that the diagonal elements (own connectedness) are substantially larger than the off-diagonal or cross elements. In the short run own variance shares are 93.8% for corn price, 95.1% for ethanol production and 98.4% for oil price. In the long-run

[28]This analysis can be employed in any model from which FEVDs can be computed (Greenwood-Nimmo *et al.* 2015).

Table 4.8: Connectedness Analysis Estimations over the Period 2000-2014

A. 2000-2014				
$h = 1$	CORN	ETHANOL	OIL	From
CORN	**93.8**	4.7	1.5	6.2
ETHANOL	4.8	**95.1**	0.1	4.9
OIL	1.5	0.1	**98.4**	1.6
To	6.3	4.8	1.5	
Net	0.1	-0.1	-0.1	
Sum	12.5	9.7	3.2	
$h = 24$	CORN	ETHANOL	OIL	From
CORN	**84.1**	2.9	13.0	15.90
ETHANOL	7.2	**74.0**	18.8	25.96
OIL	21.0	3.6	**75.4**	24.63
To	28.21	6.56	31.72	
Net	12.31	-19.41	7.09	
Sum	44.11	32.52	56.35	
Heatwave and spillover effect indices				
H_0	95.8		S_0	4.2
H_{24}	77.8		S_{24}	22.2

Notes: The connectedness measures are computed using the NGFEVD. Values are measured in percentage points such that each row sums 100%. Bold figures show the diagonal elements (own connectedness). Note that Net row is estimated as Net = To - From and the row Sum is given by: Sum = To + From. Heatwave and Spillover effect indices are estimated following equations 4.21 and 4.22.

the heatwave effects (own effects as previously defined in Section 4.3.2) of oil price and ethanol production fall substantially by 23% (from 98.4 to 75.4%) and 21% (from 95.1% to 74%). On the contrary own variance share of corn price decreases by 9.7% only.

Next, we turn to the total directional connectedness (from others or to others) as well as the sum and net contributions to the system. In the short-run they are relatively small, but they rise significantly in the long-run, especially regarding net contributions. In the long-run, we find that both oil and corn price are the positive contributors (7.1% and 12.3%) while ethanol production is the sole recipient (-19.4%). Long-run results are plausible findings, suggesting that both oil and corn price changes are the main driver behind the growth of the ethanol production. The corn price being the larger contributor to ethanol production clearly reflects the trend that corn has become a main input to the ethanol production.

Finally, we find that the aggregate spillover (S^h) rises significantly from 4.2 in the short-run to 22.2 in the long-run, suggesting that a degree of inter-linkage among corn price, ethanol production and oil price is rather modest.

To further investigate how the connectedness pattern among corn price, ethanol production and the oil price has evolved over time, we provide the estimation results for the pre- and the ethanol boom period respectively in Tables 4.10 and 4.11. In the pre-ethanol boom period, we observe that own variance shares dominate (larger than 85 %) in the short run while they decrease in the long-run. Corn prices produce the greatest fall of -47.6% (from 85.2 % to 47.6 %) while ethanol production and oil prices experience substantially smaller decreases at 7.1 % and 2.3 %, respectively. Interestingly, we find that oil price is the only positive contributor (36.2 %), as its contributions to corn price and ethanol production are almost equal, 19.6 % and 18.6 %, and its from contribution is negligible at 2.4 %.

Both corn price and ethanol production are the net recipients with the former being substantially larger at -32.8% than the latter at -3.4%. These results may be plausible since the ethanol demand was rather small and did not represent a big share of the corn

Table 4.9: Connectedness Analysis Estimations in the Pre-ethanol Boom Period

B. Pre ethanol boom period				
$h = 1$	CORN	ETHANOL	OIL	*From*
CORN	**85.2**	14.8	0.0	14.8
ETHANOL	14.8	**85.1**	0.1	14.9
OIL	0.0	0.1	**99.9**	0.1
To	14.8	15.0	0.1	
Net	0.0	0.0	0.0	
Sum	29.7	29.9	0.2	
$h = 24$	CORN	ETHANOL	OIL	*From*
CORN	**47.6**	18.5	33.9	52.4
ETHANOL	17.3	**78.0**	4.7	22.0
OIL	2.3	0.1	**97.6**	2.4
To	19.6	18.6	38.7	
Net	-32.8	-3.4	36.2	
Sum	72.0	40.7	41.1	
Heatwave and spillover effect indices				
H_0	90.0		S_0	10.0
H_{24}	74.4		S_{24}	25.6

Notes: The connectedness measures are computed using the NGFEVD. Values are measured in percentage points such that each row sums 100%. Bold figures show the diagonal elements (own connectedness). Note that Net row is estimated as Net = To - From and the row Sum is given by: Sum = To + From. Heatwave and Spillover effect indices are estimated following equations 4.21 and 4.22.

production before EPAct2005.

Table 4.10: Connectedness Analysis Estimations in the Ethanol Boom Period

C. Ethanol boom period				
$h = 1$	CORN	ETHANOL	OIL	*From*
CORN	**90.3**	5.1	4.6	9.7
ETHANOL	5.3	**94.4**	0.3	5.6
OIL	4.9	0.3	**94.9**	5.1
To	10.2	5.4	4.9	
Net	0.5	-0.2	-0.2	
Sum	19.9	10.9	10.0	
$h = 24$	CORN	ETHANOL	OIL	*From*
CORN	**76.3**	3.9	19.8	23.7
ETHANOL	6.0	**81.9**	12.0	18.1
OIL	46.1	2.9	**51.0**	49.0
To	52.1	6.8	31.9	
Net	28.4	-11.3	-17.1	
Sum	75.9	24.8	80.9	
Heatwave and spillover effect indices				
H_0	93.2		S_0	6.8
H_{24}	69.7		S_{24}	30.3

Notes: The connectedness measures are computed using the NGFEVD. Values are measured in percentage points such that each row sums 100%. Bold figures show the diagonal elements (own connectedness). Note that Net row is estimated as Net = To - From and the row Sum is given by: Sum = To + From. Heatwave and Spillover effect indices are estimated following equations 4.21 and 4.22.

The connectedness results for the ethanol boom period are summarised in Table 4.11; these results provide different patterns compared to the ethanol boom period. In the long-run own variance shares fall significantly for oil prices (-43.9%) while corn price and ethanol production suffer from smaller declines at 14% and 12.5% respectively. Now, corn prices are the only positive net contributor to the system (28.4%) while oil price is the larger recipient (-17.1%) followed by ethanol production (-11.3%). Ethanol boom period results suggest that the role of oil and corn prices switch, corn is now the systemic contributor and oil is the recipient. In the past decade, the use of corn has evolved rapidly from being only a staple food and an animal feedstock to both food and energy feedstock. This slow development that increased corn demand after EPAct2005 suggests a stronger position for corn prices' as it imitates the role of contributor that oil prices had in the pre-ethanol boom period.

Table 4.11: Connectedness Analysis Estimations Among Variables in a Horizon of 24 Months

	Within	From	To	Sum	Net	Open	Infl
A. 2000-2014							
CORN	84.1	15.9	28.2	44.1	12.3	0.16	0.28
ETHANOL	74.0	26.0	6.6	32.5	-19.4	0.26	-0.60
OIL	75.4	24.6	31.7	56.3	7.1	0.25	0.13
Average	77.8	22.2	22.2	44.3	0.0	0.22	-0.06
Average (excl. oil)	79.1	20.9	17.4	38.3	-3.5	0.21	-0.16
B. Pre ethanol boom period							
CORN	47.6	52.4	19.6	72.0	-32.8	0.52	-0.46
ETHANOL	78.0	22.0	18.6	40.7	-3.4	0.22	-0.08
OIL	97.6	2.4	38.7	41.1	36.2	0.02	0.88
Average	74.4	25.6	25.6	51.3	0.0	0.26	0.11
Average (excl. oil)	62.8	37.2	19.1	56.3	-18.1	0.37	-0.27
C. Ethanol boom period							
CORN	76.3	23.7	52.1	75.9	28.4	0.24	0.37
ETHANOL	81.9	18.1	6.8	24.8	-11.3	0.18	-0.45
OIL	51.0	49.0	31.9	80.9	-17.1	0.49	-0.21
Average	69.7	30.3	30.3	60.5	0.0	0.30	-0.10
Average (excl. oil)	79.1	20.9	29.5	50.3	8.6	0.21	-0.04

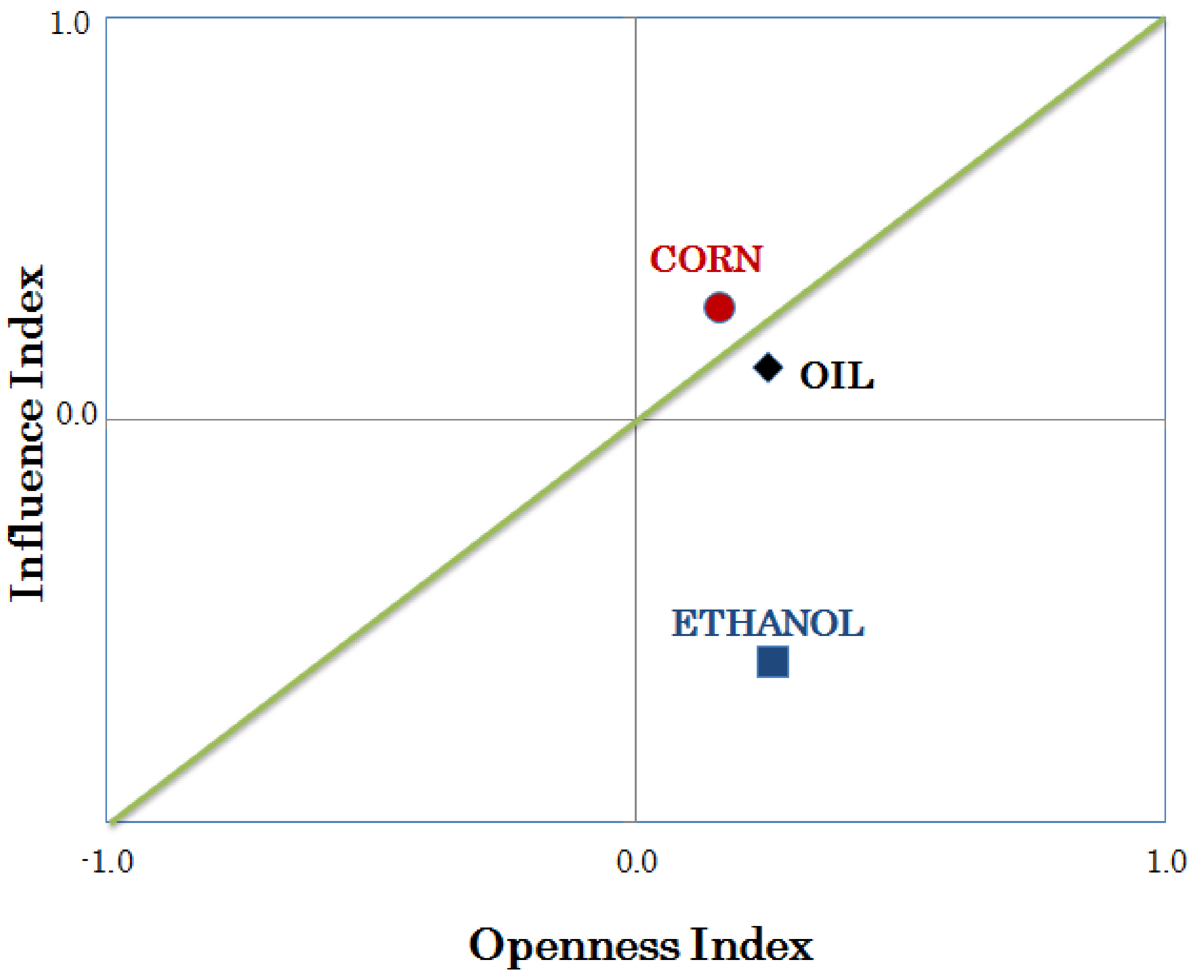
(i) The values of within, from, to and net are computed following equations 4.23, 4.18, 4.19 and 4.20 respectively. The unit of measurement for each of these four quantities is the percentage of the total h-step ahead forecast error variance of the system.
(ii) *Open* denotes the opennesses index and its measured following equation 4.24. As $O_i \to 1$ then conditions are dominated by external shocks while the same variable is unaffected by external shocks if $O_i^{(h)} \to 0$.
(iii) $Infl.$ denotes the influence index and its measured following equation 4.25. The series is considered a net shock recipient if $-1 \leq I_i^{(h)} \leq 0$, a net shock transmitter if $-1 \leq I_i^{(h)} \leq 1$ and neither a net transmitter or recipient if $I_i^{(h)} = 0$. The influence index measures the extent to which the series influences or is influenced by conditions in the system.

To provide a complete picture of the time-varying connectedness structure among corn price, ethanol production and oil price we now construct the within, from, to, sum and net connectedness measures in the long-run with $h = 24$ as a percentage of the system-wide NGFEVD, which are summarised in Table 4.12. We also provide the openness and influence indices at the two rightmost columns. Firstly, the importance of within-market (internal) information provides an indirect indication of relative external dependence with large effects indicative of less dependency. The dependence index provides a more clear picture of the external dependence of each variable in the system as it combines the within and the from connectedness information. In the pre-ethanol boom period, oil price is the least dependent (0.02) while corn price is more dependent on external factors (0.52), followed by ethanol production (0.22). In the boom period, somewhat surprisingly, we find that the external dependency of corn and oil prices has changed dramatically following EPAct2005. The dependence index for corn prices decreases substantially from 0.52 to 0.24 whereas it rises remarkably to 0.49 from 0.02 for oil prices. The ethanol production is shown to be less dependent (0.18), though its value is slightly lower than the pre-boom period.

We now turn to the influence index, which provides a simple means of assessing the risks to the system posed by shocks occurring in different markets. In the pre-ethanol boom period, given its influence (0.88), shocks to the oil price is mostly significant. On the other hand, corn price is the least influential (-0.46) while ethanol production is close to being neutral (-0.08). These results reflect the dominant role of the oil price in the system. Not only does the oil price drive conditions of other variable but also internally, resulting in a strong within effect (97.6%) and a correspondingly negligible from contribution (2.4%). In the boom period, we find that the influence indices of corn and oil prices have also changed dramatically. It becomes significantly positive for corn prices (0.37) while it falls remarkably to -0.21 from 0.88 for oil prices. The ethanol production is found to be more vulnerable to external shocks (-0.45).

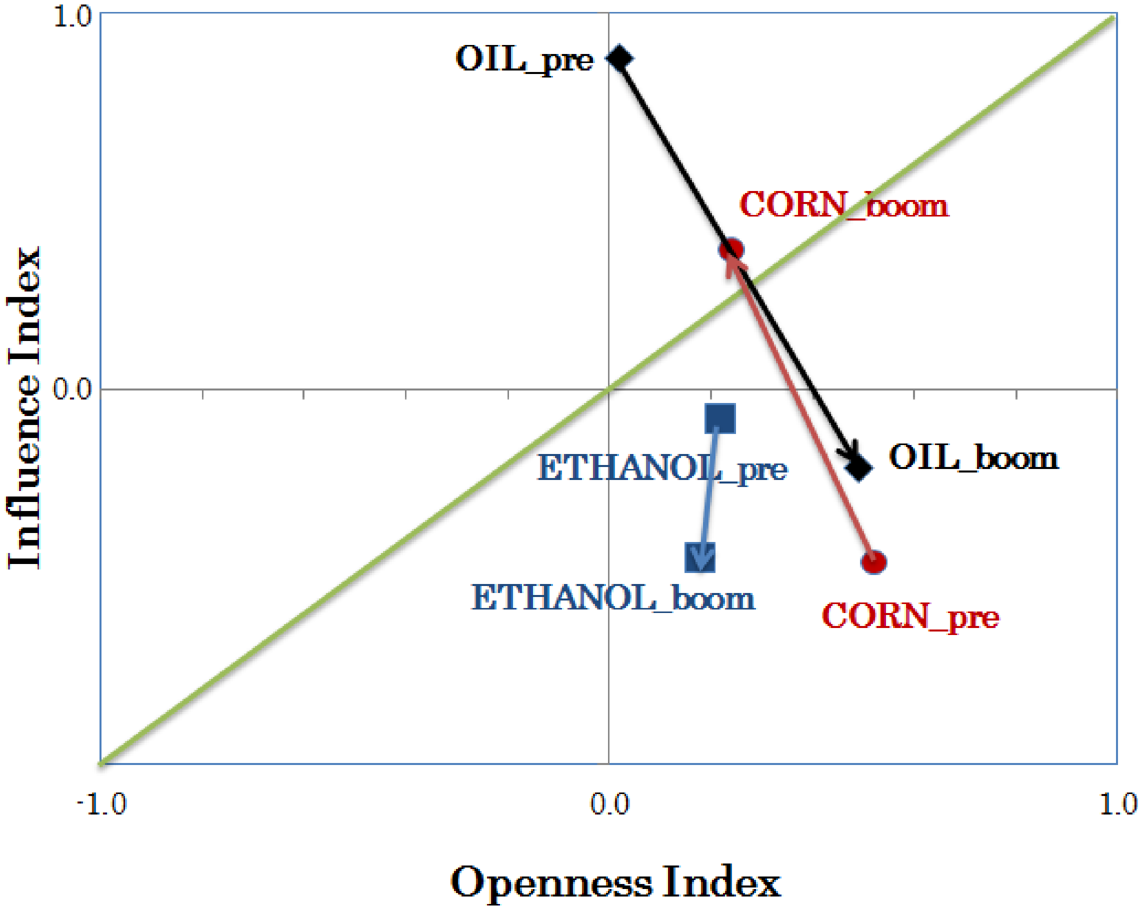
We plot Figure 4.12, displaying the location of each variable in a dependence-influence space, and measuring the extent to which each market can be viewed as dominant and less-dependent (above the 45-degree line) and vice versa. The closer that the series lies to

Figure 4.7: Influence vs. Openness Over the period 2000-2014



Notes: (i) Full-Sample Connectedness Table. (ii) The predictive horizon is 24 months. (iii) Influence and openness are measured following equations 4.25 and 4.24.

Figure 4.8: Influence vs. Openness in the pre- and ethanol boom periods



Notes: The pre-ethanol boom period is followed in each series by the term “pre” and the boom period by “boom”. Influence and openness are measured following equations 4.25 and 4.24.

the limiting point ($O_h = 0$, $I_h = 1$), the more influential it is and less exposed to external conditions. In particular, we record the change in influence and dependence between the pre- and the ethanol boom period samples. Following the EPAct2005 corn prices becomes less dependent and more shock-transmitter to both oil price and ethanol production. On the contrary, the role of oil price moves in an opposite direction with a significant decrease in influence and a marked increase in dependence, simultaneously. Hence, the position of corn and oil price switches and the former lies above the 45-degree line, depicting it as a relatively dominant player in terms of shock-transmission in the system. Such a dramatic change may reflect the fact that the ethanol market has become more mature after the EPAct2005. Finally, the ethanol production remains as a small and dependent market (reflecting its small share in the fuel market, e.g. 10% of the total market share) though it becomes more affected by external shocks. All these results do not provide any direct support for the maintained hypothesis that the ethanol production may exert a negative and volatile effect on the corn market.

We can draw several conclusions from this graphical analysis in the corn, ethanol and oil market. First, the representation of connectedness of the system finds that oil significantly diminishes its dominant influence over external conditions in the ethanol boom period. Second, ethanol position is small and almost negligible, this is due to its small share of the fuel market and also to the small system we used here. Third, corn position improves as the ethanol market matures after the EPAct2005. The latter situation comes as a surprise since a priori we expected a larger impact from ethanol towards corn and we find no evidence of this.

4.5 Conclusions

The connectedness analyses used in this chapter comprehends several methods that help to assess the impact of ethanol production on corn prices. We summarise our analysis in four steps. Firstly, we find cointegration using the persistence profile measure from Pesaran and Shin (1996). The estimates from the persistence profile of the pre- and ethanol boom period converge to the long-run (value of zero) fairly quickly, suggesting cointegration in both periods. Secondly, we estimate a VECM and find weak evidence of a long-run positive cointegrating relationship between ethanol production on corn prices, especially in the pre-ethanol boom period, to further test this result we use generalised impulse response functions. Thirdly, we continue our analysis using generalised impulse response functions giving a shock in the ethanol production equation to observe the impulse response of corn prices. We find a small but positive and significant influence of ethanol production on future corn prices in the pre-ethanol boom period. Also, weak evidence of a positive impact is found in the ethanol boom period. In regards to these weak results, we must be cautious in hypothesising about possible explanations given the high uncertainty in the estimates. Moreover, the significant but still inconclusive result for the impact of ethanol production on corn prices is present in the pre-ethanol boom period. The pre-ethanol boom period is characterised by the slow elimination of MTBE as the main oxygenate on gasoline in the U.S., our results suggest that the MTBE phased-down impacted corn prices more than the introduction of EPAct2005. Fourthly we conclude with the connectedness analysis. Initially, we find that oil prices are the biggest contributor to the system, and corn prices are the biggest recipient in the pre-ethanol boom period, but in the boom period, we find that the roles reverse. Our results suggest that the evolution of corn into a fuel feedstock, and that the increase in corn demand improved corn's position as a feedstock for fuel. On the other hand, the role of oil prices in the fuel market has changed from a monopoly, to have a small but steady decrease in its fuel market share. In a dependence-influence space, we measured the extent to which each market can be dominant and less-dependent. The results of this analysis are similar to the previous connectedness measures regarding the oil and corn price reverse role. Oil significantly reduces its dominant influence in the boom period. Currently, approximately fifteen billion U.S. gallons of ethanol are blended with gasoline; by 2022, this amount is projected to increase to thirty-six billion U.S. gallons. This increase in ethanol production will significantly reduce oil's share in the fuel market and will further decrease oil's position as a dominant influence. We find that corn position is improved as the ethanol market matures during the boom period. Furthermore, ethanol production shows a dependent position that is due to the relatively small proportion it has of the fuel market. Interestingly, in contrast to apriori expectations, we do not find conclusive evidence to support the claims that ethanol production has an impact on corn prices.

Chapter 5

Volatility Spillovers across the Ethanol, Corn and Oil Markets

5.1 Introduction

The growing variability in food commodity prices in the past decade has received considerable interest. Between 2005 and 2008, corn prices had a significant 300% rise and prices for rice, soybeans and wheat, had similar spikes. During the 2009-2010 period, corn prices briefly dropped due to the recession but spiked again a year later. The literature considers several factors as the potential reasons for these price spikes in agricultural markets, droughts, supply shocks, financial speculation and most importantly the growth in demand for biofuels like ethanol. Ethanol production involves the use of corn as the main feedstock; this process has strengthened the link between both corn and ethanol production, especially in the U.S. Currently, the U.S. ethanol industry consumes approximately one-third of the U.S. corn production. The combination of ethanol subsidies, the MTBE ban, high taxes on ethanol imports and rising oil prices accelerated the local ethanol industry to exponential growth (Trujillo-Barrera *et al.*, 2012; Wisner, 2014).

Fluctuations in agricultural and energy commodity prices include macroeconomic factors, monetary policies, speculation in financial markets, climate change and more recently biofuels production. Energy commodities such as oil derivatives have been identified as an important macroeconomic factor, its significant effect on the volatility of agricultural commodity prices, especially in corn, since it is part of a cost production has proved its importance. In the particular case of ethanol prices, oil has a direct effect on ethanol. Other identified reasons are rapid economic growth in developing countries, supply shocks in influential regions, depreciation of the U.S. dollar, fiscal expansion and relaxed monetary policies in influential countries have increased price variability also. However, it is important to understand that diversion of food crops into ethanol production has altered the relationship between agricultural and energy markets substantially (Gilbert, 2010a; 2010b, Tyner, 2010).

In the last decade, the increasing integration of corn and ethanol markets through the current environmental agenda in the U.S. has generated interest in knowing the volatility transmission mechanism volatility across these markets. The recognition of ethanol production as a potential upward driver in agricultural commodity prices, especially corn has questioned the U.S. ethanol agenda. Derimer *et al.* (2012), reports that the U.S. government intervention in the ethanol industry is responsible for the recent volatility in agricultural and fuel prices. Oil is traditionally volatile depending on the prospect for the global economy. Many researchers have addressed this link between agricultural commodity prices and energy prices, but most of these studies focused on price-level analyses (Serra (2011a), Serra *et al.* 2011b; Du and McPhail, 2012; Serra and Gil, 2012a, 2012b). The proliferation of price-level studies between agricultural commodities and energy markets has provided a platform for research on volatility transmission across these markets. However, the volatility studies generated for the U.S. ethanol market are moderate and inconclusive regarding the real impact of ethanol prices on agricultural commodity prices (Zhang *et al.*, 2009; Derimer *et al.*, 2012; Trujillo-Barrera *et al.*, 2012; Gardebroek and Hernandez, 2013; and Algieri, 2014).

We revisit the volatility transmission argument in this chapter, in an attempt to answer the following questions: i) are there any long-run relationships between these prices?; ii) are these price volatilities interrelated?; and iii) are these relationships changing after the entrance of the first ethanol-gasoline mandate in 2005?

The estimation procedure takes into account a two-stage procedure. In the first stage, we use cointegration and the estimation of a Vector Error Correction Model (VECM). In the second stage, we employ volatility modelling using a MGARCH Baba, Engle, Kraft, Kronner (BEKK) model involving corn, ethanol, and oil prices. We analyse the monthly spot prices of corn, ethanol and oil over the period 1982-2014 and consider two sub-sample periods namely the pre-ethanol boom period and the ethanol boom period (Zhang *et al.*, 2009 and Gardebroek and Hernandez (2013) introduced these terms). The pre-ethanol boom period starts in January 1982 and finishes in June 2005; the ethanol boom period begins with the sign of the Energy Policy Act in 2005 (EPAct2005) in July 2005 and finishes in December 2014 which is the end of our sample.

The first stage findings indicate cointegration among corn, ethanol and oil prices in the full sample (1982-2014) and both pre- and ethanol boom periods. Evidence from the VECM shows that oil prices have a substantial influence on ethanol prices, in the three periods. On the other hand, corn prices significantly affect ethanol prices in the boom period. The second stage findings from the MGARCH (BEKK) model present a cross-spillover effect from oil to ethanol and a double-directional spillover between oil and ethanol in the pre-ethanol boom period. In the ethanol boom period, we only find a small cross-spillover effect running from corn prices to oil prices this denotes that after the ethanol-gasoline mandate in 2005; we discover a stronger relationship between corn and oil and not between corn and ethanol as expected.

5.2 Literature Review

An increasing number of studies have investigated the price-level interdependence between renewable energy markets and agricultural commodity prices, see for example Bailis *et al.* 2011; Serra 2011a, Serra *et al.*, 2011b; Du and McPhail, 2012; Serra and Gil, 2012a, 2012b; Trujillo-Barrera *et al.*, 2012; and Zhang *et al.*, 2009. The growing share of the ethanol market in the U.S. transportation system raises attention about the impact of ethanol on the volatility of agricultural commodities (Abdelradi and Serra, 2015). In Table 5.2 we present a selected chronological summary of the literature on volatility across agricultural commodity and energy prices. It provides a description of the data, the models, and the key findings in each article.

Zhang *et al.*, (2009) use a VECM and a BEKK model to address long- and short-run relationships and the volatility transmission channel among oil, gasoline, ethanol, corn, and soybean. The focus of their study was on prices and how price volatility reflects the volatility of current and expected future values. The authors split the data into two periods: 1989-1999 considered as the ethanol pre-boom stage and the ethanol boom period (2000-2007). The findings show no long-run relationships between agricultural and energy price levels. Also, they did not find spillovers from ethanol price volatility to corn and soybean price volatility. This study includes a large number of variables, with soybean driving most of the relationships found. Empirically, a BEKK parameterisation as the one shown in Table 5.2 is a complicated, computational task. Zhang *et al.*, (2009) adopt prices for corn, ethanol, soybean, gasoline and oil, creating a high-dimensional system that provides an excessive amount of computations, which do not allow to capture the relevant cross-equation effects in the system for ethanol and corn prices. The more parameters an MGARCH model has, the flatter the likelihood function becomes, and the harder it is to maximise (Alexander, 2008).

Derimer *et al.* (2012) study the effect of ethanol listing on return and volatility in the corn market. Ethanol began trading in the Chicago Board of Trade (CBOT) in March 2005. Four EGARCH models are estimated for corn prices, each representing different maturities that capture the ethanol listing effect. The results indicate a significant and positive marginal contribution of ethanol listing on corn returns, particularly in the spot market. However, the reported price and volatility effects on the corn market cannot be only attributed to the listing of ethanol in the Chicago Board of Trade (CBOT) as the Energy Policy Act was initiated during the same period in mid-2005. The analysis is incomplete as there are no ethanol future prices before March 2005 and therefore it is not possible to conclude that the ethanol listing is the main contribution for this price volatility.

Wu *et al.* (2011) analyse cross hedging in corn and crude oil futures using weekly data from January 1992 to June 2009. For modelling the spillovers, they use a volatility spillover model following studies of Bekaert and Harvey (1997), Ng (2000), Bekaert *et al.* (2005), Baele (2005), and Christiansen (2007). These studies consider volatility spillover effects on international stock and bond markets. The BEKK model uses oil market shocks as an exogenous influence on the corn spot and futures markets. The authors provide spillover ratios to quantify the strength of the volatility spillovers. The estimation of this asymmetric MGARCH brings a lot of questions. Unlike most other studies, they use three different parametrisations: i) spillovers are constant throughout the entire period; ii) spillovers change after the Energy Policy Act of 2005; iii) spillovers vary on a lagged consumption ratio of ethanol to gasoline that indicates the size of the spillovers between markets. They find evidence of significant spillovers from crude oil prices to the U.S. corn spot and futures prices, particularly after the introduction of the Energy Policy Act of 2005 (EPAct2005). Also, substantial volatility spillovers occur in high periods of ethanol-gasoline consumption ratios. In terms of hedging, the findings of this study suggest that corn market participants can still trust corn future markets to hedge risk and obtain a modest satisfactory performance, even in the presence of significant spillovers from the energy market. The main criticism to this study is the use of volatility spillover ratios that are estimated by residuals and not conditional variance as expected in a GARCH model.

Volatility spillover effects between the U.S. energy and agricultural market in a more recent time period are analysed by Trujillo-Barrera *et al.* (2011). The authors adopt a VECM-BEKK-GARCH model in which exogenous shocks from the oil market are transmitted to the corn and ethanol markets. Their results show strong evidence of linkages from crude oil to corn and ethanol with spillovers between corn and ethanol, but the direction goes mainly from corn to ethanol. These results differ from Zhang *et al.* (2009)

who do not find significant integration between the U.S. agricultural and energy markets in the early 2000s. Additionally, Trujillo-Barrera *et al.* (2011) analysis of the market post 2000s show a strong volatility transmission and spillovers from oil futures to corn and ethanol futures. These results indicate a stronger connection between the above mentioned markets in recent years, especially after the financial crisis of 2007-08.

Although BEKK models are generally flexible enough to allow volatility causality links to flow in any direction, Wu *et al.* (2011) and Trujillo-Barrera *et al.* (2012) force uni-directional spillovers from crude oil to food and biofuel markets. It is important to point out that sensitivity to the squared residuals on oil is not the same as sensitivity to the conditional volatility. In other words, the spillover measurements for oil are price-level estimations rather than volatility ones. Therefore, the results in both studies are misrepresentations of volatilities.

Gardebroek and Hernandez (2013) focus on how energy prices stimulate food price volatility. Their paper examines the level of interdependence and volatility transmission between energy and corn markets in the U.S. from September 1997 to October 2011. This paper follows a MGARCH approach to analyse the dynamics and cross-dynamics of price volatility in oil, ethanol and corn markets. BEKK results for both periods show how the conditional mean returns in oil, ethanol and corn markets are basically only dependent on their own past returns; oil and ethanol show a positive dependence while corn exhibits a negative dependence. Nevertheless, in more recent years corn returns also report mean-spillovers from oil returns, suggesting a stronger role of crude oil as an input in corn production at the mean level. In the case of the conditional variance dynamics, strong GARCH effects are present in both periods.

More recently, Algieri (2014) examines the role of ethanol, biodiesel and oil, financial and macroeconomic factors on daily food commodity futures price returns. The closing futures prices of the main food commodities used to produce the first generation biofuels are the dependent variables. Different models using Maximum Likelihood (ML) estimation are implemented; two traditional GARCH models; three EGARCH specifications, to account for asymmetries; a FIGARCH model, to account for the long-memory in the variance; an ARFIMA FIGARCH model, to account for long-memory properties both in the conditional mean and the conditional variance of the process; and a FIAPARCH model, to combine the properties of asymmetry and long-memory. This array of specifications implies that energy markets can influence price changes, and therefore increase volatility in agricultural markets. Considering all the results from the different GARCH models, they provided evidence of a linkage between the future prices for corn and ethanol.

Study	Model	Data	Key findings
Zhang *et al.* (2009)	VECM and BEKK	• Weekly spot prices • U.S. ethanol, corn, soybean, gasoline and oil • Mar 8, 1989-Dec 8, 2007	No significant links among oil, ethanol, and corn volatilities in either period
Wu *et al.* (2011)	BEKK (oil is used as an exogenous shock)	• Weekly spot and future prices • U.S. oil, ethanol and corn • Jan 2, 1992-Jun 30, 2009	No significant spillover before 2006, after 2006 larger spillover from oil to corn
Derimer *et al.* (2012)	EGARCH	• Daily spot and future prices • U.S. ethanol and corn • Jan 4, 2000-Jan 15, 2010	Ethanol listing leads to greater volatility in the spot and short corn maturity contract market
Trujillo-Barrera *et al.* (2012)	BEKK (oil is used as an exogenous shock) and GJR-GARCH:	• Mid-week closing futures • U.S. oil, ethanol & corn • Jul 30, 2006-Nov 9, 2011	There is strong volatility transmission and spillovers from oil futures to the corn and ethanol futures
Gardebroek and Hernandez (2013)	DCC and BEKK	• Weekly spot prices • U.S. oil, ethanol and corn • Sept 1997-Oct 2011	No significant spillover before 2006, after 2006 larger spillover from oil to corn markets
Algieri (2014)	GARCH, EGARCH, FIGARCH, ARIMA-FIGARCH, FIAPARCH	• Daily futures prices • Multiple agricultural commodities, oil, ethanol and financial factors • May 2005-June 2013	There is a linkage between corn and ethanol futures

Apart from Zhang *et al.* (2009), previous studies find evidence for a level of integration between energy and agricultural markets which has increased in recent years, yet the evidence for an effect of ethanol prices on the level and volatility of agricultural corn prices is limited. Gardebroek and Hernandez (2013) find some volatility spillovers from oil to corn markets and from oil to ethanol markets when they segment the sample to introduce ethanol-related events, but the authors do not regard these as the base results. Derimer *et al.* (2012) and Algieri (2014) regard the introduction of ethanol futures prices and draw possible linkages from this. Nevertheless, these results lack futures prices data prior to 2005, hence the extent of the relationship between corn and energy markets is not clearly determined.

5.3 Methodology

Co-movement and time-varying volatility clustering are typical characteristics of the commodity prices series (Enders, 1995). MGARCH models allow analysing volatility clustering and time-varying dynamic covariances and dynamic correlations. In this sense, we follow a methodology which considers a two-stage procedure estimation. In the first stage, the conditional mean of the variables is modelled by the VECM that allows the price series to co-move. In the second stage, we apply the multivariate GARCH model to analyse volatility transmissions.

5.3.1 The Vector Error Correction Model

Empirical macroeconomic modelling commonly incorporates the concept of cointegration developed by Granger (1981) by using the vector error correction model (VECM). The VECM representation of a dynamic system is obtained by rearranging the traditional Vector Autorregressive (VAR) model, once the variables in the system are cointegrated.

The VECM system can be written as:

$$\Delta x_t = c + \alpha\beta' x_{t-1} + \Sigma_{i=1}^{p-1}\vartheta_i \Delta x_{t-i} + \varepsilon_t. \tag{5.1}$$

The parameters of the VECM are decomposed into the long-run parameters, (β) and the short-run parameters, (α, ϑ_i and Σ). Δ is a first difference operator, $\Delta x_t = x_t - x_{t-1}$, and denotes the change in the vector x from time $t-1$, ($x_t = x_{(c)t}, x_{(e)t}, x_{(o)t}\ '$), that represents the prices of corn, ethanol and oil respectively; c is a constant, and ε_t is the error term.

5.3.2 The BEKK-MGARCH Model

We analyse the level of interdependence and the volatility dynamics between corn, ethanol and oil spot prices to measure volatility spillovers among corn, ethanol and oil markets. This chapter uses the BEKK model to measure own volatility and cross volatility spillovers as well as persistence between markets. To estimate the time-varying conditional covariance matrix of ε_t, extracted from Eq. 5.1, we consider the following trivariate BEKK-MGARCH model(1,1):

$$\varepsilon_t | I_{t-1} \sim N(0, H_t)$$

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon_{t-1}' A' + BH_{t-1}B'. \tag{5.2}$$

The term ε_t, is conditional on the information set I_{t-1} at time $t-1$, normally distributed with zero mean and variance covariance (H_t). The conditional covariance matrix H_t is positive definite by construction. C, A, and B are 3×3 matrices. C is a lower triangular matrix that corresponds to the constant c_{ij}. A, contains the elements a_{ij} and B stores the elements b_{ij}. The elements a_{ii} and b_{ii} in the conditional variance-covariance equation capture the own effects (own-spillovers), i.e. the effect of lagged shocks on the current conditional volatility in corn, ethanol and oil prices respectively. The squared values of a_{ij} (b_{ij}) represents the impact of the squared residual (conditional variance) of row j of ε_{t-1} on the conditional variance of row i of ε_t. In other words, the off-diagonal estimates in $A(B)$ enable the squared residuals (conditional volatilities) from one series to impact the conditional volatilities (H_t) of the other series. Therefore the off-diagonal parameters in matrices A (B) measure the cross-market effects of shock (volatility).

The conditional variance-covariance equations incorporated into the BEKK model effectively capture the volatility dynamics among the variables under consideration. Therefore, useful insights are uncovered by examining the changes in volatility transmission across the corn, ethanol and oil markets. This two-stage procedure is asymptotically consistent and is commonly used because it avoids convergence and local maxima problems (Silvennoinen and Terasvirta, 2009).

In addition, to test for the existence of volatility spillovers, we conduct a likelihood ratio test. First, we estimate the BEKK model in its diagonal form by assuming that $A_{ij}(B_{ij})$ lagged squared residuals (conditional variances) matrices are diagonal.[29]. Then, we conduct a Likelihood Ratio test to check the hypothesis: $H_0 : a_{ij} = b_{ij} = 0, \forall i \neq j)$, no volatility spillover from one market to another. The likelihood test requires nested models, i.e., the first model (full BEKK) can be transformed into the second model (diagonal BEKK) by imposing constraints on the parameters of the first model (Li and Wu, 2013).

5.3.3 The Estimation Procedure

In the previous section, we defined the BEKK-MGARCH model and the specification of its variance and covariance matrices of the model to estimate. In this part, we consider the maximum likelihood (ML) estimation used for MGARCH models (simultaneous estimation) and explain the two-step approach we employed for estimating our BEKK model.

According to Bauwens et al., (2006), the maximum likelihood function is constructed under the assumption of an i.i.d. distribution for the standardised innovations (shocks). However, the i.i.d. assumption can be replaced by the weaker assumption.

Multivariate GARCH models can be estimated simultaneously using ML. However, how this particular estimation is implemented in practice is one of the important is-

[29]The results of the diagonal BEKK are in the Appendix for Chapter 5

sues. The estimation of the parameters simultaneously with the conditional variance increases the efficiency in larger samples, but this is computationally more complicated. If the number of parameters is large, optimisation procedures fail to find the maximum of the likelihood function. The conditional mean parameters may be estimated in a first stage, before the estimation of conditional variance parameters, i.e., a VARMA model, see Bauwens et al., (2006) and Silvennoinen and Tersvirta (2009).

Following the previous studies, Carnero and Eratalay (2012) examine the estimation procedure for a VAR-MGARCH model comparing simultaneous and multiple steps estimation for MGARCH models. By using Monte Carlo experiments through a simulation of time series vectors following the vector autoregressive multivariate GARCH models assume a normal distribution for the innovations (shocks). The results show that multiple step estimation of parameters in MGARCH models is a logical alternative to the maximisation of the full likelihood function in a simultaneous estimation. The results suggest that the differences between volatility and correlation estimates obtained with simultaneous estimation and multiple steps estimations are negligible. Similar to Carnero and Eratalay (2012), Haigh and Holt (2002) apply the VEC-MGARCH framework to study the optimal hedge ratios in crack spread hedging. Error-correction terms are included to capture the cointegrating relationships in a two-step procedure as the residuals are used in the MGARCH model. Lin and Li (2015) estimate spillover effects across natural gas and oil markets using the VEC-MGARCH framework. The use of the two-step approach to estimate the VECM first and then use it in a multivariate GARCH model to specify the autoregressive conditional heteroscedasticity, and examine the volatility spillover between natural gas and oil prices of US.

5.4 Empirical Application

5.4.1 The Data

We collect monthly spot prices for U.S corn, ethanol and crude oil, from January 1982 through December 2014. The domestic corn and ethanol prices are from the U.S. Department of Agriculture (USDA). The oil prices used are the West Texas Intermediate (WTI), also known as Texas light sweet, which is a grade of crude oil used as a benchmark in oil pricing, obtained from the Energy Information Agency (EIA). The series have been seasonally adjusted and transformed through natural logarithms.

Figure 5.1 displays the time-varying evolution of corn, ethanol and crude oil prices. Our sample period covers four recessions, represented by a shaded-grey area and identified by the U.S. National Bureau of Economic Research (NBER): the first from July 1981 to November 1982, the second from July 1990 to March 1991, the third from March 2001 to November 2001, and the final from December 2007 to June 2009. We also highlight the important episodes such as severe droughts (the blue-shaded area) and the important biofuel policies (the dotted vertical grey line).

The replacement of MTBE with ethanol as a gasoline oxygenate started in the early 2000s and finished in 2006. This switch provoked average prices of ethanol and unleaded gasoline to be 43% and 17% higher than those in 2005. Since 2005, we also find that ethanol and oil tend to move more closely. During the 2007-08 global financial crisis period, all prices jumped to higher spikes, especially corn price. These spikes also follow the Energy Independence and Security Act (EISA) enacted in December 2007, that doubled the ethanol-gasoline blend mandate from 4 to 8 U.S. billion gallons. Due to an additional operating capacity for ethanol and additional supply in 2007, ethanol price became lower. On the contrary, higher crude oil prices pushed unleaded gasoline prices higher. In the middle of the crisis oil prices peaked above $140 dollars per barrel and gasoline prices also peaked over $3 per gallon before falling to $1 per gallon. Ethanol prices also became higher than the average in 2007, but still short of the average in 2006. Corn prices

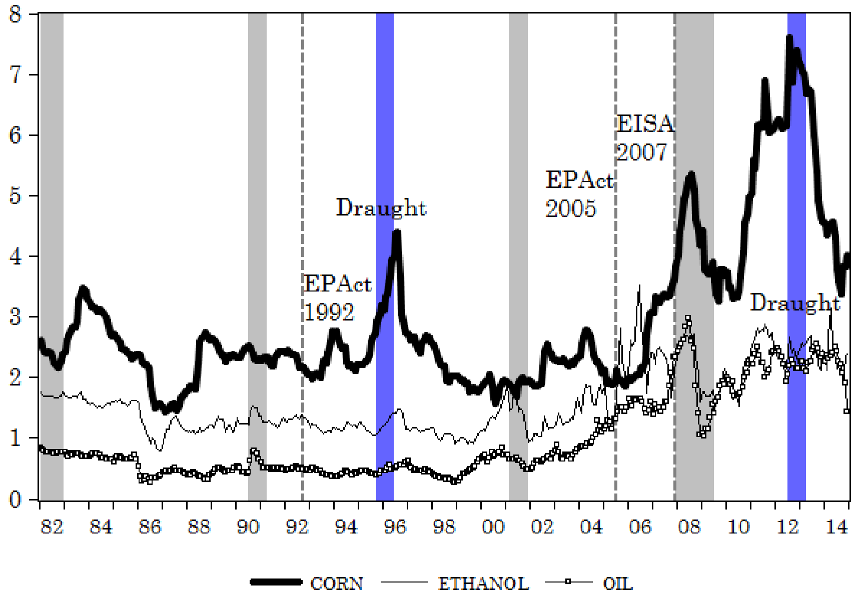


Figure 5.1: U.S. monthly nominal corn, ethanol and oil prices over 1982-2014

increased during the crisis but stabilised afterwards.

5.4.2 Unit Root and Cointegration Test

Firstly, we look for non-stationarity in our variables and perform the cointegration tests required. The Augmented Dickey Fuller GLS (ADF-GLS) test is used to examine for non-stationarity in price levels. The results in Table 5.1 suggest that the prices are non-stationary.[30]

The lag-structure analysis based on the Akaike information criterion (AIC) suggests an optimal lag order of two for a full sample and three for the pre-ethanol and ethanol boom period.[31] According to the results of the Johansen trace test, a single cointegrating relation is found in the full sample and pre-ethanol boom period and two cointegrating relationships in the ethanol boom period. From the full results in Table 5.2 we see that the Trace test suggest the existence of two cointegrating vectors. Table 5.3 presents the results for the first cointegrating vector in the ethanol boom period. Our results suggest

[30] Lags for the ADF-GLS test were chosen by AIC model selection criterion. We also examined the ACF and PACF to ensure the residuals are not serially correlated.

[31] For further reference please see Lütkepohl; 2005.

Table 5.1: Unit root test results

A. 1982-2014		
Constant		Constant and trend
	t-Stat	t-Stat
Ethanol	-1.2394	-1.3272
Corn	-1.9628	-2.5284
Oil	-1.5187	-1.7674
B. Pre-ethanol boom period		
Constant		Constant and trend
	t-Stat	t-Stat
Ethanol	-1.5988	-2.4666
Corn	-2.6028	-3.1441
Oil	-1.2868	-1.2543
C. Ethanol boom period		
Constant		Constant and trend
	t-Stat	t-Stat
Ethanol	-2.0472	-2.9440
Corn	-0.7623	-1.5446
Oil	-2.2568	-3.3520
Notes:		
Test critical values:		
	Constant	Constant and trend
1% level	-2.5710	-3.5644
5% level	-1.9417	-3.0170
10% level	-1.6161	-2.7270

Table 5.2: Johansen cointegration test estimates

	Trace			Max-Eigen		
A. 1982-2014						
Coint rank	Statistic	CV	P-value	Statistic	CV	P-value**
		0.05			0.05	
None	58.19*	29.80	0	44.29*	21.13	0
At most 1	13.90	15.49	0.086	12.41	14.26	0.096
At most 2	1.49	3.84	0.222	1.49	3.84	0.222
Lags	2					
B. Pre- ethanol boom period						
None	30.05*	29.797	0.005	19.899	21.132	0.015
At most 1	10.15	15.49	0.110	8.06	14.26	0.115
At most 2	2.09	3.84	0.263	2.09	3.84	0.263
Lags	3					
C. Ethanol boom period						
None	38.27*	29.797	0.004	21.05	21.132	0.051
At most 1	17.22*	15.495	0.027	12.06	14.265	0.108
At most 2	5.16*	3.841	0.023	5.16	3.841	0.023
Lags	3					

Notes:

* denotes rejection of null hypothesis of no cointegration at the 0.05 level.

**MacKinnon-Haug-Michelis (1999) p-values that there exists a long run relationship between ethanol, corn and oil prices across the three periods.

5.4.3 VECM Estimation Results

Table 5.3 presents the long-run relationships for the full sample, pre- and ethanol boom periods when we normalise oil prices. We find a significant and positive relationship between ethanol and oil prices. This is an expected outcome as ethanol serves as a substitute for gasoline. Hence, as crude oil prices rise, then gasoline price rises and the demand for ethanol increases, which brings an increase in ethanol prices. Such connection will be strengthened through forthcoming blending policies, which currently demand at least 10% of ethanol to be blended with gasoline (AFDC, 2015).

Table 5.3: The long-run cointegrating relationship estimates

	A. 1982-2014	B. Pre-ethanol boom period	C. Ethanol boom period
oil	-1	-1	-1
ethanol	2.033***	2.542***	0.652**
	0.173	0.346	0.226
	[11.726]	[7.355]	[2.886]
corn	0.174	-0.344	0.369**
	0.144	-0.310	0.089
	[1.211]	[-1.110]	[4.124]

Notes:

Standard errors in ( ) & t-statistics in [ ]
* and ** denote significance at the 1% and 5% level, respectively

We split the sample to allow for shifts in price patterns due to structural changes such as breakthrough of the ethanol industry and financial crises. Previously, Gardebroek and Hernandez (2013) used this type of splitting in their study. We split the sample in a pre-ethanol boom period and a boom period. The first period goes from January 1982 to June 2005, before the signing of the EPAct2005, and denoted the pre-ethanol boom period. The boom period starts from July 2005 to December 2014.[32] Gardebroek and

[32]In order to reflect the 2007-08 crisis and the drought of 2012, two different sets of dummies were

Hernandez (2013) split their sample in a similar manner.

The long-run estimation results in the pre-ethanol boom period are qualitatively similar to those in the full sample. In the 1980s and 1990s ethanol was sold as an alternative fuel, but its low performance followed poor sales. Thus, the relationship between oil and ethanol prices was driven mainly by the market condition rather than government policies. In fact, before 2005, the impact of biofuel policies on the ethanol corn-based production was rather small.

Some of the events that characterised the ethanol boom period were the Energy Policy Act in 2005 (EPAct2005), the abolition of MTBE in 2006, the listing of ethanol in the CBOT (Chicago Board of Trade) futures market in 2006, the Energy Independence and Security Act (EISA) in 2007 and finally the financial crisis in 2007-08. These events are likely to render the analysis of dynamic interactions among ethanol, corn and oil prices more complicated. In the boom period, we notice that oil prices have moved in a close relationship with ethanol prices since the beginning of the sample but have run tightly from mid-2007. We find that the long-run relationship between oil and corn prices is positive and statistically significant. During the 2012-13 period, corn prices were driven mainly by drought-reduced supplies, whereas corn faced a chronic surplus before mid-2007.

5.4.4 The BEKK Estimation Results

We estimate the BEKK model in Eq. 5.2 by the maximum likelihood (ML) estimator, which is shown to provide consistent estimation results even in the presence of skewed and leptokurtic errors (Bollerslev and Wooldridge, 1992).

Table 5.4 presents the full sample BEKK estimation results over the period 1982-2014. First, we find that own-volatility effects are significantly higher than cross-spillovers in all three prices. In particular, ethanol return own-volatility is more persistent than those of corn and oil prices. Given that own-volatility effects dominates cross-counterpart, we may

used to account for these events, but because they lacked statistical significance they did not feature in the final VECM specification. Bai and Perron's (2003) breakpoint test was used and we estimated the VECM and BEKK model; results are available upon request.

consider the more parsimonious diagonal BEKK model. Hence, we conduct the likelihood ratio test in order to assess the validity of the diagonal against the full BEKK model. The LR test result reported at the bottom of Table 5.4 follows a χ^2 with 12 degrees of freedom, and it clearly indicates the null hypothesis is strongly rejected. Consequently, we shall focus on the full BEKK model.[33]

In the period 1982-2014, we find several cross-spillover effects, the results show that a_{21}, a_{23}, a_{32} and b_{13} are statistically significant. a_{21} is an uni-directional spillover from corn to ethanol. We find a double-direction spillover, a_{23}, and a_{32}, between oil and ethanol. We found a cross-spillover from oil to corn, b_{13} is a particular conditional volatility on oil leading to a particular conditional volatility on corn in the next period. More importantly, we find that the past ethanol conditional volatility does not affect the future conditional volatility of corn prices.

Table 5.5 presents the BEKK estimation results for the pre- and ethanol boom periods. We find that in the pre-ethanol boom period own-volatility effects are significantly higher for corn, followed by ethanol and in a smaller proportion for oil, also these own volatility effects are larger than the cross-spillovers. On the other hand, we find that in the boom period, the own volatility effects are higher in ethanol, followed by oil and corn. For these two periods, we also conduct the likelihood ratio test, and we find that in both cases the full BEKK is the best fit. The results of this test for each period are reported at the bottom of Table 5.5.[34]

The cross-spillover effects in the pre- and ethanol boom period vary. In the pre-ethanol boom period we find that there is a volatility spillover running from oil to ethanol (b_{23}). Moreover, we find a double-directional cross-spillover effect, a_{23}, and a_{32}, between oil and ethanol, and an uni-directional spillovers running from corn to ethanol in a_{21}. The results for the ethanol boom period summarised in the right side of Table 5.5 indicate that there are no significant cross-volatility effects, apart from a small cross-spillover effect that runs from corn to oil. This result contrasts with the previous findings by Wu *et al.* (2011),

[33]The estimation results obtained using the diagonal model are qualitatively similar, and are presented in the Appendix for Chapter 5.

[34]Both diagonal BEKK models are reported in the Appendix for Chapter 5.

Table 5.4: VECM-BEKK model estimates over the period 1982-2014

	Corn ($j=1$)	Ethanol ($j=2$)	Oil ($j=3$)
c_{1j}	**0.0241****		
	(0.0049)		
c_{2j}	**-0.0104****	-0.0021	
	(0.0052)	(0.0264)	
c_{3j}	**-0.0417****	0.01255	0.00005
	(0.00945)	(0.26100)	(67.11939)
a_{1j}	**0.1159****	-0.0687	-0.0106
	(0.0500)	(0.0461)	(0.0576)
a_{2j}	**0.1181****	**0.2244****	**0.1403****
	(0.0601)	(0.0415)	(0.0558)
a_{3j}	0.1585	**-0.1994****	**0.6206****
	(0.1075)	(0.0661)	(0.0723)
b_{1j}	**0.7870****	0.0352	**0.1409***
	(0.1042)	(0.024351)	(0.0691)
b_{2j}	0.0914	**0.9577****	-0.1236
	(0.1122)	(0.0198)	(0.0858)
b_{3j}	0.3879	0.0013	**0.5076****
	(0.2357)	(0.0508)	(0.1520)
$\chi^2_{L.R.test}$	52.103 [0.0000]		
LL	1726.747		
AIC	-8.694		

Notes: We conduct the Likelihood Ratio test (L.R. test), to test the validity of the diagonal against the full BEKK model, the numm hypothesis states that $H_0 : a_{ij} = b_{ij} = 0, \forall i \neq j$, no volatility spillovers from one market to the other. LL is the log likelihood of the model and AIC is the Aikaike Information Criteria. Figures in [ ] are the p-values. * Significance at the 10% level; ** significance at the 5% level and *** significance at the 1% level respectively.

Table 5.5: VECM-BEKK model estimates for both sub-samples

	Pre-ethanol boom period			Ethanol boom period		
	$Corn_{(j=1)}$	$Ethanol_{(j=2)}$	$Oil_{(j=3)}$	$Corn_{(j=1)}$	$Ethanol_{(j=2)}$	$Oil_{(j=3)}$
c_{1j}	0.0002			0.0171		
	0.1834			0.0313		
c_{2j}	0.0004	0.0000		-0.0336	0.0307	
	1.6156	15.9331		0.0972	0.1173	
c_{3j}	0.0047	-0.0001	0.0189	-0.0059	-0.0378	0.0000
	4.5523	186.6649	0.6173	0.0773	0.2426	3146.85
a_{1j}	-0.0001	0.0005	0.0221	**0.3796***	-0.0659	-0.1228
	0.0619	0.0493	0.0437	0.1623	0.1418	0.1246
a_{2j}	**0.1443****	**0.1611*****	**0.1673*****	0.0069	**0.7173****	0.0194
	0.0664	**0.0525**	**0.0458**	0.2171	0.1901	0.1698
a_{3j}	0.0073	**-0.3279*****	**0.6404*****	**0.4096***	-0.0031	**0.3813***
	0.1180	**0.0744**	**0.0720**	0.2383	0.1716	0.1807
b_{1j}	**0.9981*****	0.0081	-0.0061	0.1184	0.3534	0.3486
	0.0194	0.0158	0.0239	0.3484	0.2227	0.2827
b_{2j}	-0.0244	**0.9730*****	**-0.0561****	-0.3459	0.1279	0.6136
	0.1594	**0.0329**	**0.0249**	0.5602	0.2593	0.4359
b_{3j}	-0.0531	0.0665	**0.7655*****	-0.1279	-0.1890	**0.7083***
	0.4692	0.0822	**0.0469**	0.4913	0.2081	**0.3254**
$\chi^2_{L.R.test}$	33.455 [0008]			24.283 [0.0186]		
LL	1323.226			441.7501		
AIC	-9.39295			-7.61009		

Notes: We conduct the Likelihood Ratio test (L.R. test), to test the validity of the diagonal against the full BEKK model, the numm hypothesis states that $H_0 : a_{ij} = b_{ij} = 0, \forall i \neq j$, no volatility spillovers from one market to the other. LL is the log likelihood of the model and AIC is the Aikaike Information Criteria. Figures in [ ] are the p-values. * Significance at the 10% level; ** significance at the 5% level and *** significance at the 1% level respectively.

Trujillo-Barrera *et al.* (2012), Gardebroek and Hernandez (2013), these authors found cross-spillover effects from oil to corn. The cross-spillover from corn to oil, suggests that the transition of corn into an energy crop has created a stronger relation between corn and oil. Moreover, we do not find cross-spillover effects from ethanol to corn as expected by the increase in ethanol production after EPAct2005.

To investigate in more detail the interactions between corn, ethanol and oil, Figures 5.2 and 5.3 display the time-varying estimates of the conditional correlations.

When comparing the patterns of conditional correlations in the pre- and the boom period, we observe the main difference as follows: First, the conditional correlations between oil and ethanol returns are positive and statistically significant, subject to a small number of fluctuations. On the other hand, the conditional correlations between corn and ethanol returns are slightly positive with an increasing trend since the late 1990's, whereas those between corn and oil returns are slightly negative on average. But, these magnitudes are mostly negligible as compared to those between oil and ethanol returns. So in this period we may argue that only oil and ethanol returns have co-moved. However, we observe all three conditional correlations in the boom period track each other very closely, and even though conditional correlations between oil and ethanol returns are still higher, they are negligible. These correlations have been stronger during the 2007-2011 period, when ethanol and corn prices are also very close to each other. On average these correlations are positive and statistically significant, subject to a number of fluctuations. This may suggest that the policies introduced in the second period render all three returns series to co-move together.

5.5 Conclusions

This chapter examines long-run relationships between corn, ethanol and oil prices, the interrelation among price volatilities and the potential changes after the entrance of the blending mandates in 2005. We use an extended data for the 1982-2014 period that covers the pre- and the ethanol boom periods. This analysis is important because it provides a

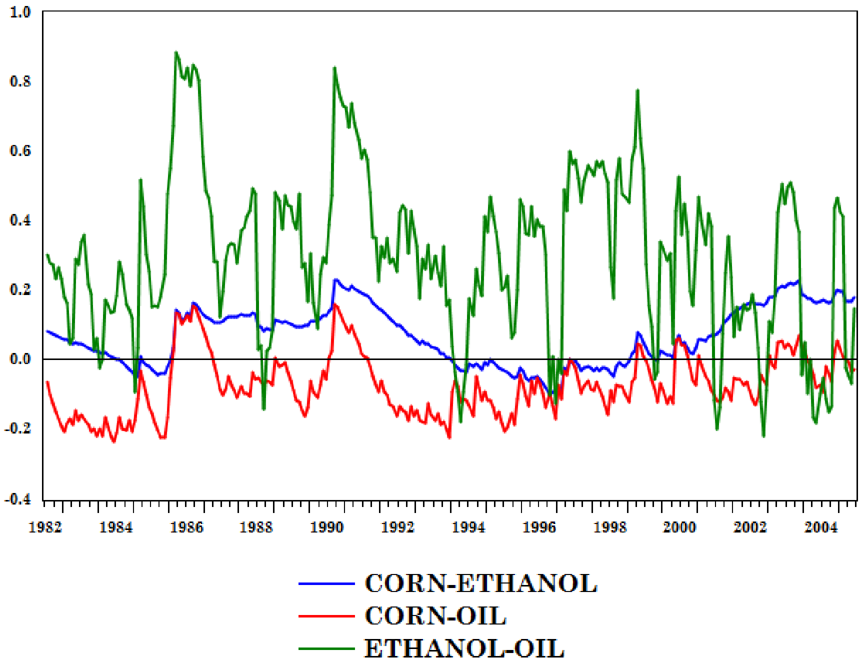


Figure 5.2: Conditional correlations pre-ethanol boom period

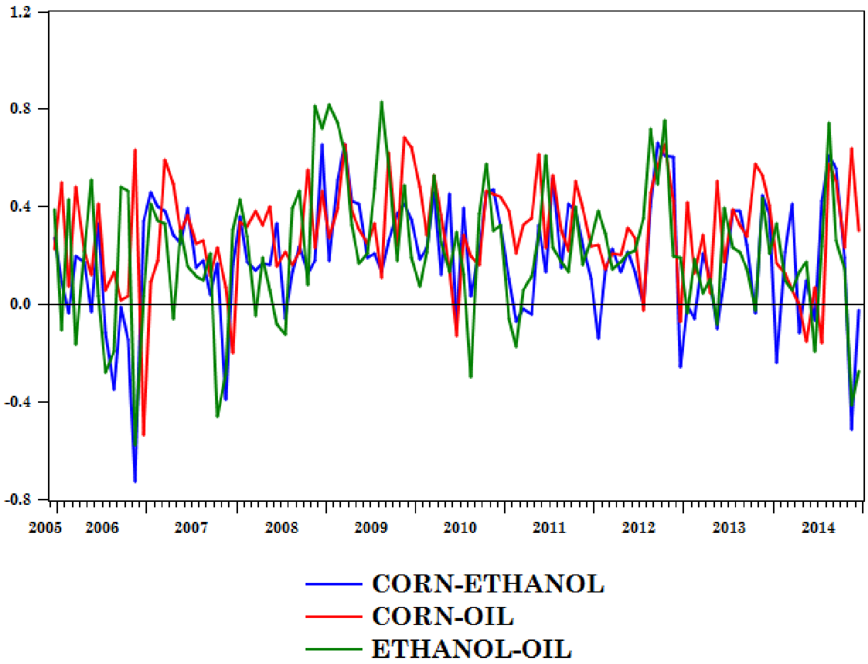


Figure 5.3: Conditional correlations ethanol boom period

framework to study the implementation of ethanol policies in the rapidly growing ethanol market. Using cointegration, a VECM, and a BEKK model, the results from this chapter imply that volatility spillover effects from ethanol prices to corn prices are not an issue, despite the enhanced connection between these two markets.

In the BEKK analysis, we find that the analysis for the full period 1982-2014 includes a bidirectional cross-spillover effect between oil and ethanol, the implication of this result of similar magnitude shows how both ethanol and oil prices are heavily connected and oil cross-spillovers effects of this magnitude have a positive influence on ethanol prices. This result coincides with the findings of Gardebroek and Hernandez (2013) and Trujillo-Barrera (2012).

Similarly, when we split the data into a pre-and ethanol boom period, we observe differences in cross-spillovers conditional volatilities between both periods. In the pre-ethanol boom period, we find a small positive cross-spillover effect from corn to ethanol, suggesting a stronger role of corn as an input in ethanol production, and a comparable small positive cross-spillover effect from oil to ethanol, which represents the influential position of oil prices on ethanol prices as a blending fuel. Between 2005 and 2008 the ethanol industry faced significant changes in environmental policies favoured ethanol, and at the same time, during the period 2007-08 the financial crises strike. The dynamics in the conditional volatilities for the boom period change, and we find a slightly bigger cross-spillover effect from corn to oil which suggests a strengthening position in the corn market.

In the following part of our research, we estimate a second BEKK model to analyse the increasing variability running from oil to corn and ethanol. We proceeded to estimate a modified volatility spillover model allowing oil as an external shock. Our results suggest there is a small volatility spillover running from oil to corn after the ethanol-gasoline mandates, but the impact is negligible.

The implications of these results vary, on the one hand, we find that future corn price volatilities are not affected by ethanol price volatilities, these are good news for the ethanol industry because they suggest that ethanol production does not affect corn prices. On the other hand, current low oil prices represent a decrease input prices in corn production which improves its position as a feedstock in the energy market.

Chapter 6

Conclusions

This dissertation contributes to understanding the dimensions of the U.S. ethanol market and its interaction with corn and oil markets. Nonlinear dynamic models, connectedness measures, and spillover analyses help us comprehend the potential this industry has as renewable energy. Although our results of this market were limited, findings in this dissertation contribute to a better understanding of ethanol price responsiveness, interlinkages between corn, ethanol and oil markets. Chapters 4 and 5 find evidence of the evolution of corn into an important energy crop.

In chapter 3 we use an asymmetric dynamic ARDL model for demand and supply. Our study compiles monthly information from 1982 to 2014 from ethanol production, corn prices, ethanol prices and gasoline prices. We follow previous demand and supply studies by Rask (1998), and Luchansky and Monks (2009). Our study starts by using linear and nonlinear static estimations of demand and supply which serve as the reference point; we find mis-specification problems in both linear and nonlinear static models, and strong evidence of asymmetric responses to changes in ethanol prices in the 2SLS-nonlinear model. Then, we proceed to analyse the symmetric dynamic ARDL model that provides further proof of asymmetry and the presence of a few significant short-run dynamics. Finally, we proceed to examine the nonlinear dynamic ARDL model, and our results suggest the presence of asymmetric long run cointegration in demand and supply. Previous research by Rask (1998) and Luchansky and Monks (2009) find an extremely low-elasticity for supply and inelastic (elastic) for demand, depending on the period. Our results show that both demand and supply are inelastic (less than 1), but the asymmetric price regime shows a positive and negative pattern in the cumulative price changes. Regarding (cumulative) positive price changes, we find that supply is relatively more elastic than demand (0.703 vs.-0.055). The cumulative positive price changes suggest that supply is responsive only to price increases (more production following price increase but do not change production following price decrease). Regarding (cumulative) negative price changes, demand is relatively more elastic than supply (0.353 vs. 0.025). The cumulative negative price changes suggest that demand is responsive only to price decreases (more consumption following price decrease but do not change consumption following price increase). Our findings for the long-run coefficients in the demand are not statistically significant but provide a framework for comparison with supply. Supply and demand are inelastic, but supply relative to demand is less sensitive to price changes. Moreover, when we consider the nonlinear price transmission we find ethanol production is more sensitive to ethanol price increases. Continuing with the long run analysis, we find that the long-run coefficient for gasoline price is very inelastic, which contrast with Rask (1998) and Luchansky and Monks (2009) results. Ethanol production is affected negatively by corn prices. Previous results find a positive relationship by Luchansky and Monks (2009), and suggest that this close relationship between corn prices and ethanol production generated a positive correlation that ended in ethanol production dictating corn prices. Our findings suggest that those claims are misleading since corn prices behave as a production cost, therefore, increases in corn prices lead to a decrease in ethanol production and not the reverse.

Chapter 4 addresses the criticism to the ethanol market regarding the use of corn as fuel feedstock in the period 2000-2014. The literature suggests that the close connection between corn and ethanol increases the demand for this staple grain. Hence, our interest in discussing whether ethanol production affects corn prices. At the beginning of our analysis, we use a Vector Error Correction Model (VECM) to find long-run relationships between corn, ethanol and oil prices. Moreover, the VECM allows us to use impulse responses to investigate further the role of ethanol production on corn prices. We complete our analysis with connectedness measures that allow a more thorough analysis of this dilemma. Initial results from the VECM suggest a long-run relationship between corn prices, ethanol production, and oil prices. We divide our sample into two different periods, the pre-ethanol and ethanol boom periods, with this split in the sample we can identify more clearly any potential changes in the patterns at the time of the most important event affecting the ethanol industry: the introduction of EPAct2005. Our results suggest the analysis cannot provide conclusive evidence of a significant impact of ethanol production on corn prices in the VECM or using impulse response functions. We continue our analysis with the Forecast Error Variance Decomposition (FEVD) connectedness analysis that allows us to study the connectedness among these three markets. In this connectedness analysis, first we reach weak evidence that ethanol production affects corn prices in the ethanol boom period, as such we learn that U.S. ethanol production is highly affected by local factors, such as production costs, corn prices, refineries, technology, and transportation costs. The share of the ethanol in the gasoline market is rather small, hence such results are not unusual. Overall results do not provide a strong support for the headline claims that an increase in the ethanol production has aggravated corn's position as an affordable staple grain. We find that corn's position is improved as the ethanol market matures during the boom period, and corn positions itself as an important energy feedstock.

Oil, corn and ethanol are highly traded global commodities that attract interest among speculators as well as end users. Chapter 5 extends the food-fuel connection analysis in chapter 4 by investigating possible volatility transmission channels between corn, ethanol and oil prices. The price spikes in agricultural markets in the 2007-08 period are associated with various factors, including droughts, supply shocks, speculation and most remarkably with the U.S. ethanol market. In this regard, we analyse volatility spillovers and estimate a VECM, and then we use the VECM residuals to estimate a spillover model (BEKK) and a modified volatility spillover model using oil as an external shock. We follow the previous steps in order to identify volatility transmission channels between corn, ethanol and oil prices. In this regard, volatility spillovers are analysed, and a VECM is estimated, and then the VECM residuals are used to estimate a spillover model (BEKK), and we finalise with a modified volatility spillover model using oil as an external shock. These steps are followed to identify volatility transmission channels between corn, ethanol and oil prices, aiming at identifying if cross-spillover effects are running from ethanol to corn. The VECM analysis shows evidence of a positive relationship in the pre-ethanol boom period and a negative one in the ethanol boom period, this suggests nonlinearity in this market. Our BEKK results suggest there is no statistical significant cross effect from ethanol prices to corn prices. For the pre-ethanol boom period, we find a double-directional significant cross-spillover from oil to ethanol. In the boom period we find that the own-effects are statistically significant and there is a small significant cross-spillover effect from corn to oil, which suggests the position of corn as an energy crop has strengthened. In light of the increasing variability running from oil to ethanol, we proceeded to estimate a modified volatility spillover model allowing oil as an external shock on ethanol and corn prices. Our results suggest there is a small volatility spillover running from oil to corn after the ethanol-gasoline mandates, but the impact is negligible and does not provide conclusive evidence of a significant impact from oil to corn.

The connection between corn and ethanol market calls for further research to be more clearly understood, to continue the analysis of the U.S. ethanol market and to study how this industry evolves over time. The current results from the boom period are not conclusive and it might be too early to appreciate the extent of our estimations. The increasing importance of the corn market as an energy crop raises interest in the study of this market. Furthermore, ethanol legislation in the U.S. keeps evolving; in 2011 the U.S. Congress eliminated an import tariff and a blender tax credit that dated from the early 1970s, the results of such actions are not fully visible yet. Additionally, the ethanol market has reached the 10% blending wall, 14 billion U.S. gallons is the current 10% blending limit for the 140 billion gallons of gasoline that represent the total market share. An increase in such limit would imply a reconversion of the vehicles in the U.S; the conventional car can only run on a 10%, a change that would rise interest in the economic impact on the industry.

Appendices to Chapter 3

Table 1: First Stage Regression for Demand

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	3.718994	0.092818	40.06751	0.0000
$\hat{p}_t^E$	−0.303607	0.105391	−2.880763	0.0042
p_t^G	0.197008	0.064951	3.033172	0.0026
Trend	0.006710	0.000268	25.03559	0.0000
dum_t	0.797452	0.055609	14.34030	0.0000
R^2	0.968428	Mean dependent var		5.139611
$\bar{R}^2$	0.968103	S.D. dependent var		1.152864
S.E.	0.205898	Akaike info criterion		−0.310262
SSR	16.49126	Schwarz criterion		−0.259801
Log-likelihood	66.12167	Hannan-Quinn criter.		−0.290267
F-statistic	2982.987	DW stat		0.226127
Prob(F-statistic)	0.000000			

Table 2: First Stage Regression for Supply

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	2.582327	0.055294	46.70167	0.0000
$\hat{p}_t^E$	0.419621	0.062561	6.707339	0.0000
p_t^C	0.269155	0.050541	5.325468	0.0000
Trend	0.010181	0.000117	87.33361	0.0000
R^2	0.952733	Mean dependent var		5.139611
$\bar{R}^2$	0.952370	S.D. dependent var		1.152864
S.E.	0.251606	Akaike info criterion		0.088193
SSR	24.68910	Schwarz criterion		0.128562
Log-likelihood	-13.37393	Hannan-Quinn criter.		0.104189
F-statistic	2620.342	Durbin-Watson stat		0.135681
Prob(F-statistic)	0.000000			

Appendices to Chapter 4

Table 3: Summary Statistics over the Period 2000-2014

Variables:	Corn	Ethanol production	Oil prices
Maximum:	1.7974	6.8203	0.9096
Minimum:	0.5133	4.7643	-0.7086
Mean:	1.0564	6.0831	0.2017
Std. Deviation:	0.3638	0.6810	0.4183
Skewness:	0.3721	-0.4261	-0.4360
Kurtosis - 3:	-1.0888	-1.3335	-1.0891
Coef of Variation:	0.3444	0.1120	2.0733
Estimated correlation matrix of variables			
	Corn prices	Ethanol production	Oil prices
LRCP	1	0.8111	0.7079
LRQUS	0.8111	1	0.8761
LROP	0.7079	0.8761	1

Table 4: Previous Model Specifications

Dependent variables
US corn prices
World Food Price Index
FPI/US CPI
FPI/US Ethanol prices
FPI/BR CPI
FPI/BR Ethanol prices
Ethanol related factors
QUS/QUS+QBR
QBR/QUS+QBR
US corn prices
Total Corn area
Corn area used to produce ethanol
BR Ethanol consumption
US Ethanol consumption
BR sugarcane prices
Macroeconomic factors
Exchange rate BR/USD
US Money Supply
Chinese Imports of food
US GDP
World Oil price index
Exchange rate BR/USD
BR Money Supply
BR GDP

Table 5: Summary Statistics for the Pre-Ethanol Boom Period

Variables:	Corn	Ethanol production	Oil prices
Maximum:	0.9952	5.7607	0.2119
Minimum:	0.5133	4.7643	-0.7086
Mean:	0.7427	5.2896	-0.2714
Std. Deviation:	0.1145	0.2998	0.2243
Skewness:	0.2665	0.0965	0.4043
Kurtosis - 3:	-0.6560	-1.4841	-0.1819
Coef of Variation:	0.1541	0.0567	0.8263
Estimated correlation matrix of variables			
	Corn prices	Ethanol production	Oil prices
Corn prices	1	0.4331	0.0025
Ethanol production	0.4331	1	0.6964
Oil prices	0.0025	0.6964	1

Table 6: Summary Statistics for the Ethanol Boom Period

Variables:	Corn prices	Ethanol production	Oil prices
Maximum:	1.7974	6.8203	0.9096
Minimum:	0.5483	5.7603	-0.1297
Mean:	1.2380	6.5425	0.4757
Std. Deviation:	0.3338	0.3199	0.2043
Skewness:	-0.3656	-1.1673	-0.5995
Kurtosis - 3:	-0.6105	-0.0087	0.4668
Coef of Variation:	0.2696	0.0489	0.4294
Estimated correlation matrix of variables			
	Corn prices	Ethanol production	Oil prices
Corn prices	1	0.7514	0.4947
Ethanol production	0.7514	1	0.3388
Oil prices	0.4947	0.3388	1

Table 7: Summary Results from the VECMs and Diagnostic Tests

	Full sample	Pre boom period	Boom period
	Corn	Corn	Corn
constant	0.064	-0.117	0.003
	(1.254)	(-2.889)	(0.429)
ecm(-1)	0.009	0.190	0.023
	(1.228)	(2.894)	(1.362)
R2	0.100	0.307	0.096
S.E. of regression	0.053	0.041	0.057
χ^2_{12} S.C.	12.191	12.071	12.741
χ^2_1 Norm.	13.260	7.501	4.331
χ^2_2 Het	0.186	0.803	0.085

Notes:

(i) Rejects null hypothesis at 5% significant level.

(ii) T-stats are given in ().

Appendices to Chapter 5

Table 8: Summary Statistics (log level prices)

A. Full Sample			
	Corn	Ethanol	Oil
Mean	1.00202	0.41936	-0.24025
Median	0.88987	0.35072	-0.40330
Maximum	2.03055	1.25758	1.09128
Minimum	0.36644	-0.23420	-1.28605
Std. Dev.	0.37180	0.31291	0.64157
Skewness	0.94918	0.46693	0.55519
Kurtosis	3.26387	2.23124	1.97664

B. Pre-ethanol boom period			
	Corn	Ethanol	Oil
Mean	0.83359	0.25589	-0.60268
Median	0.84251	0.23324	-0.67145
Maximum	1.48108	0.63795	0.27584
Minimum	0.36644	-0.23420	-1.28605
Std. Dev.	0.19631	0.18110	0.31337
Skewness	0.19924	0.07816	0.34259
Kurtosis	3.60415	2.41351	2.81347

C. Ethanol Boom period			
	Corn	Ethanol	Oil
Mean	1.41865	0.82372	0.65629
Median	1.41969	0.85554	0.72415
Maximum	2.03055	1.25758	1.09128
Minimum	0.62801	0.43363	0.02128
Std. Dev.	0.37613	0.17049	0.23648
Skewness	-0.43168	-0.46105	-0.56339
Kurtosis	2.45876	2.67392	2.57665

Table 9: Log-Level Correlations

A. Full Sample			
	Corn	Ethanol	Oil
Corn	1	0.70823	0.72229
Ethanol	0.70823	1	0.907477
Oil	0.72229	0.90748	1
B. Pre-ethanol boom period			
	Corn	Ethanol	Oil
Corn	1	0.36829	0.11262
Ethanol	0.36829	1	0.73432
Oil	0.11262	0.73432	1
C. Ethanol Boom period			
	Corn	Ethanol	Oil
Corn	1	0.26189	0.62806
Ethanol	0.26189	1	0.48642
Oil	0.62806	0.48642	1

Table 10: VECM Serial Correlation LM Test Results

	χ^2	Prob.	Number of lags
VECM (1982-2014)	2.251	0.987	2
VECM (2005m06-2014m12)	10.961	0.278	3
VECM (2005m07-2014m12)	4.224	0.896	3

Table 11: Summary Statistics ECM residuals

A. Full Sample			
	Corn	Ethanol	Oil
Mean	2.65E-18	4.23E-18	4.66E-18
Median	-0.00280	0.00449	0.00150
Maximum	0.21321	0.30903	0.35166
Minimum	-0.17908	-0.30316	-0.28028
Std. Dev.	0.04535	0.06845	0.07392
Skewness	0.26053	-0.01130	0.02496
Kurtosis	5.97631	5.48589	5.62249
Jarque-Bera	149.50210	101.19990	112.65930
Probability	0	0	0

B. Pre-ethanol boom period			
	Corn	Ethanol	Oil
Mean	-4.08E-06	-0.000196	-4.87E-05
Median	-0.00359	0.00112	0.00117
Maximum	0.21656	0.20251	0.33721
Minimum	-0.17341	-0.17707	-0.28953
Std. Dev.	0.03938	0.05457	0.07134
Skewness	0.39741	0.22163	0.16999
Kurtosis	8.11520	4.11035	5.54477
Jarque-Bera	308.16540	16.43755	75.80168
Probability	0	0.0003	0

C. Ethanol Boom period			
	Corn	Ethanol	Oil
Mean	0.00025	0.00027	0.00065
Median	-0.00015	0.00411	0.00067
Maximum	0.16248	0.20032	0.14828
Minimum	-0.13704	-0.33168	-0.20864
Std. Dev.	0.05563	0.08641	0.07130
Skewness	0.23112	-0.59502	-0.68192
Kurtosis	3.68461	4.24070	3.50356
Jarque-Bera	3.09905	13.42317	9.59949
Probability	0.21235	0.00122	0.00823

Figure 1: ECM Residuals over the period 1982-2014

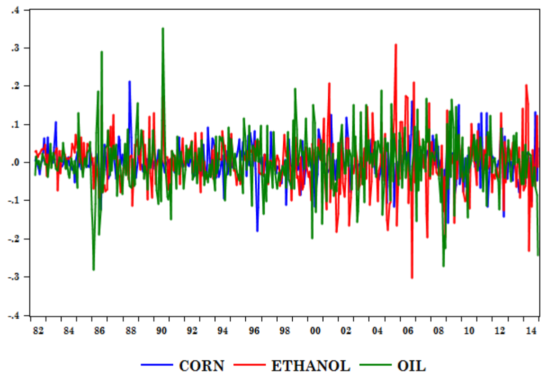


Figure 2: ECM Residuals Pre-Ethanol Boom Period

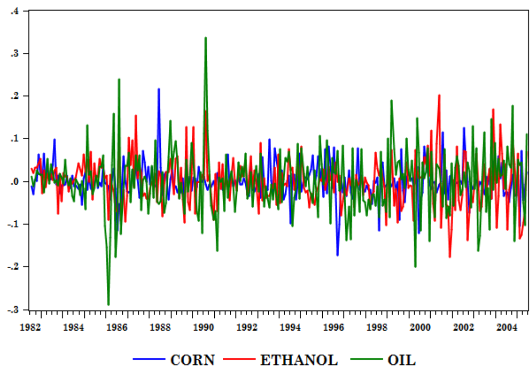


Figure 3: ECM Residuals Ethanol Boom period

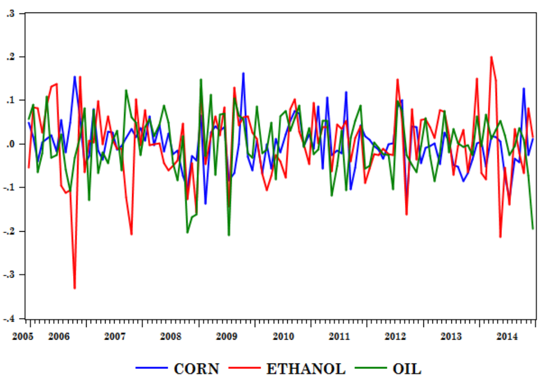


Table 12: Diagonal BEKK Model Estimation Results over the Period 1982-2014

	0.0018		
	(0.0081)		
	0.0065	0.008	
C =	(0.029)	(0.0241)	
	-0.01	0.0335	-0.0000253
	(0.0502)	(0.1704)	(243.2972)
	0.084**		
	(0.0305)		
A =		**0.377****	
		(0.0442)	**0.427****
			(0.0583)
	0.996**		
B =	(0.009)		
		0.924**	
		(0.0187)	**0.768****
			(0.0693)

Notes: Standard errors are given in ().
* and ** denote significance at the 1% and 5% level, respectively.

B. BEKK Diagnostics	
Log likelihood	1700.7
Avg. log likelihood	4.3608
Akaike info criterion	-8.645
Schwarz criterion	-8.492
Hannan-Quinn criter.	-8.584

Table 13: Diagonal BEKK Model Estimation Results for the Pre Ethanol Boom Period

	0.002558		
	0.016234		
	0.005081	0.014284	
C =	0.031702	0.011237	
	-0.02606	0.038104	2.04E-05
	0.173427	0.147249	493.5556
	-0.00386		
	0.078014		
A =		**0.352****	
		0.060074	
			0.4489**
			0.089442
	0.998**		
B =	0.027715		
		0.8972**	
		0.040359	
			0.5649**
			0.15381

Notes: Standard errors are given in ().
* and ** denote significance at the 1% and 5% level, respectively.

B. BEKK Diagnostics	
Log likelihood	1299.615
Avg. log likelihood	4.7956
Akaike info criterion	-9.4806
Schwarz criterion	-9.2812
Hannan-Quinn criter.	-9.4005

Table 14: Diagonal BEKK model Estimation Results for the Ethanol Boom period

A. Variance-covariance equation			
	0.039447		
	0.025078		
	0.019003	0.058366	
C =	0.019826	0.009461	
	0.023193	0.005065	0.060745
	0.040656	0.018398	0.007552
	0.3537**		
	0.138594		
A =		**0.7599****	
		0.11969	
			0.3668**
			0.151927
	0.616772		
B =	0.513134		
		0.017876	
		0.537658	
			0.061239
			2.146042

Notes: Standard errors are given in ().
* and ** denote significance at the 1% and 5% level, respectively.

B. BEKK Diagnostics	
Log likelihood	429.6085
Avg. log likelihood	3.941362
Akaike info criterion	-7.6075
Schwarz criterion	-7.23713
Hannan-Quinn criter.	-7.4573

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