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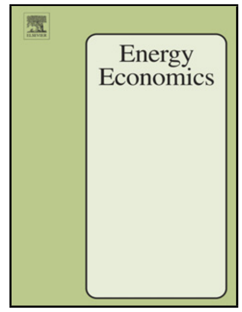

The impact of diesel price on upstream and downstream food prices: Evidence from São Paulo

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Highlights

- Diesel price shocks have a weaker power of predicting downstream prices than upstream prices along the food supply chain.
- Causality from upstream prices to downstream prices is more significant than from downstream to upstream.
- Food prices do not respond to diesel price shocks after 15 months.
- The direction of causality between upstream and downstream prices is market specific.

The impact of diesel price on upstream and downstream food prices: Evidence from São Paulo

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Abstract

The literature on the transmission of oil price shocks to prices along the food supply chain has widely ignored how shocks upstream differ from downstream ones. This article examines this issue by modelling upstream and downstream diesel price shocks along the nutritional high-value food supply chain in São Paulo. Using a Vector Error Correction approach and monthly data from July 2001 to December 2013, we estimate short-run and long-run dynamics in producer and retail prices of meat, eggs, dairy and fats & oil due to changes in the average monthly price of diesel. The results of the Granger causality analysis show that the price of diesel cannot be used to predict the behaviour of producer prices in all the markets under study, and the price of diesel predicts retail price only in the egg market. This result is in line with the nature of price controls in Brazil. As of January 2002, the prices charged by the distributors and the retail have been liberalized, although wholesale prices of the derivatives, including that of diesel, continue to be set by the state oil company with the objective of controlling inflationary pressures. The results of the response of food prices to diesel price shocks show a positive response of both upstream and downstream prices of egg and dairy products both upstream and downstream, while the opposite directions occur in the fat and meat markets albeit the initial positive shock of the producer price of meat. The findings of the study show the important role of public policy in determining the nature of price transmission along the food supply chain.

Keywords: Supply chain, Diesel price, Upstream, Downstream, Nutritional high-value food, Vector error correction
JEL Codes: C01, C22, Q02, Q11, Q13, Q41

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1. Introduction

Research on the relationship between food and energy markets can be traced as far back as 1983, with the analysis of the potential disruptive effect of fuel ethanol on global agricultural commodity prices (Zhang et al., 2010). The increasing attention to the energy-food relationship also emanates from the global energy crises of the 2000s. The general consensus among agricultural economists is that energy price shocks are a potential source of food insecurity, because they may lead to an increase in food prices since producers and retailers may consider these shocks when fixing their prices. For a given income level, household purchasing power on food decreases. In developing countries where food constitutes an integral share of household expenditure (Prakash, 2011; Rapsomanikis and Hallam, 2006), this could be a recipe for worsened living standards. Additionally, volatile energy prices may impede the ability of agents in the food market to correctly predict and plan for future market patterns, a potential source of social unrest (Bellemare, 2015).

A cursory look at the existing literature on the relationship between food and energy prices reveals that the dominant energy markets studied are biofuel, particularly ethanol (Serra et al., 2011a; Serra, 2011) and gasoline (Serra et al., 2011b; Taheripour et al., 2010; Hochman et al., 2008). Dominant food crops examined by these studies include corn, soybeans, wheat and rice. The dominance of these crops in the existing research can be explained by their role in the production of biofuels. Corn is used in the production of ethanol while soybean is used mainly in the production of biodiesel (Fernandez-Perez et al., 2016). For this reason, there exists some competition between producing these crops for livestock feed and producing them for energy.

Despite the dominance of staples and traditional cash crops in the research on food-energy relationship, the nature of nutritional high-value foods coupled with the characteristics of their supply chains underpin the need to analyse the relationship between the prices of these foods and energy prices. These foods are highly perishable, implying that an efficient transport system is required to carry them through the supply chain. But transportation also relies on the energy sector for fuel input. Thus, dynamics in the energy sector may affect both upstream and downstream activities through transportation. Where the shock is negative, players may respond by adjusting prices to cover the associated losses. Given the increasing demand for nutritional high-value foods in developing and emerging countries (Gulati et al., 2007), price dynamics in these markets have relevant ramifications for household food security in these countries. In furtherance, to effectively implement policies that mitigate the negative effects of oil shocks, it is important to assess how energy price shocks affect different sections of the food market chain. This is relevant because different prices exist along the chain due to the presence of agents with different market powers along the supply chain. Despite the importance of this angle of research, the existing studies have generally not looked at this issue.

Against the above background, this study assesses how dynamics in diesel prices determine both the long-run and short-run behaviour of prices in four nutritional high-value food markets (meat, egg, dairy and fat & oil) in São Paulo. More succinctly, we ascertain if the impact of diesel price shocks is higher on upstream prices than downstream prices along the supply chains of these foods. Diesel continues to be the major source of fuel for buses, trucks and agricultural machinery in Brazil. Road transport accounts for 60% of the movement of agricultural cargoes in bulk (Pera and Caixeta-Filho, 2017). For this reason, dynamics in the price of diesel may have significant implications for both producer and retailer welfare. Figure 1 shows the changes in the average price of diesel in the São Paulo region from 2001 to 2013.

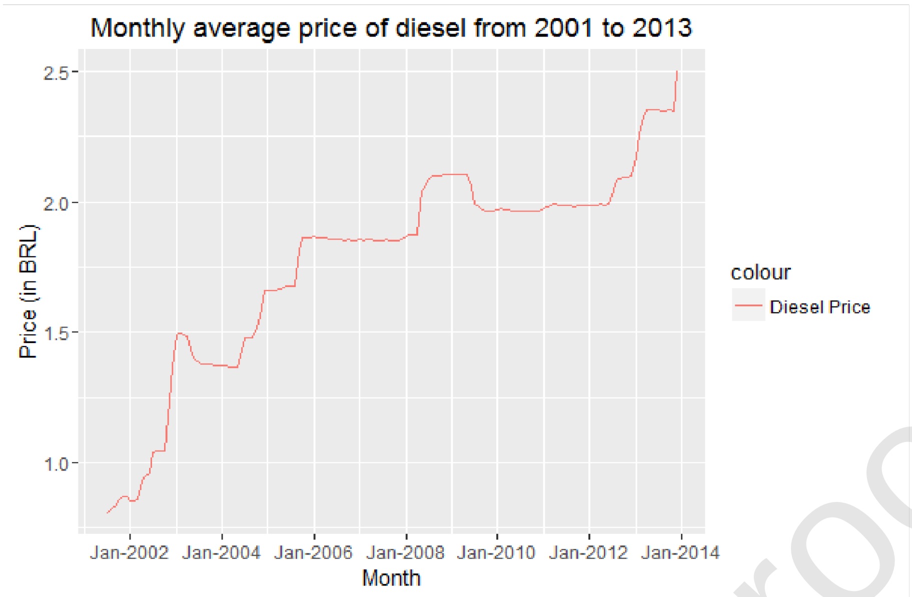

Figure 1: Changes in the average price of diesel from July 2001 to December 2013
Source: Author generated the National Agency of Petroleum's database

Figure 1 shows that the movement of diesel price between 2001 and 2013 is characterised by periods of increasing, decreasing ad constant trends. Between July 2001 and December 2002, the price of diesel has an increasing trend but falls thereafter up to mid-2004. Despite the fuel price deregulation in the beginning of the 2000s, in practice, the government has been indirectly controlling gasoline, diesel and LPG prices through Petrobras, a state owned company that almost monopolizes oil refining in Brazil (Oliveira and Almeida, 2015).

The prices of the nutritional high-value foods under study are presented in Figure 3. We see an increasing trend in the producer and retail prices of meat, although the latter is higher than the former over the entire period. The difference between retail and producer prices is even bigger in the eggs market. Whereas the general trend of the producer price is decreasing, the retail price has a mixed trend, with a decreasing trend between 2003 and 2007 and an increasing trend between 2010 and 2013.

In Figure 2, the change in overall retail sale from July 2001 to December 2013 is presented. The retail sale index, a measure of how much retailers sold their goods, shows an increasing trend throughout the period after a slight dip in 2003. This shows that retailers sold more goods over the period.

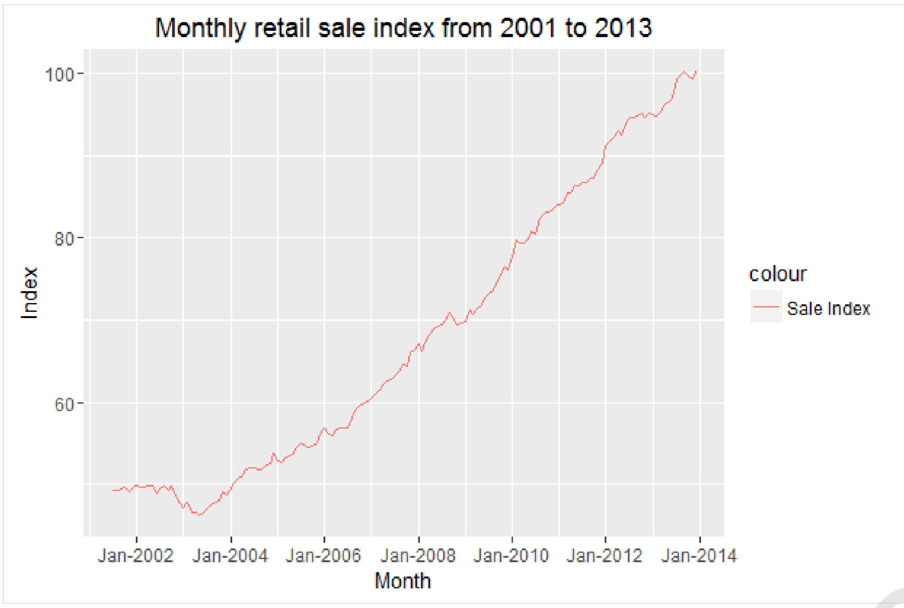

Figure 2: Changes in the retail sale index (July 2001 to December 2013)

The study contributes to the existing research on the relationship between energy shocks and food prices in two respects. Firstly, it focuses on energy price shocks in nutritional high-value food markets. As earlier intimated,the existing studies focus heavily on staples and traditional cash crops because they can be converted to biofuel. Although nutritional high-value foods do not have this characteristic, their high dependence on efficient transportation implies that shocks in the energy market affect these food markets. Secondly, the study contributes to research on the upstream and downstream distribution of external shocks along the food supply chain.

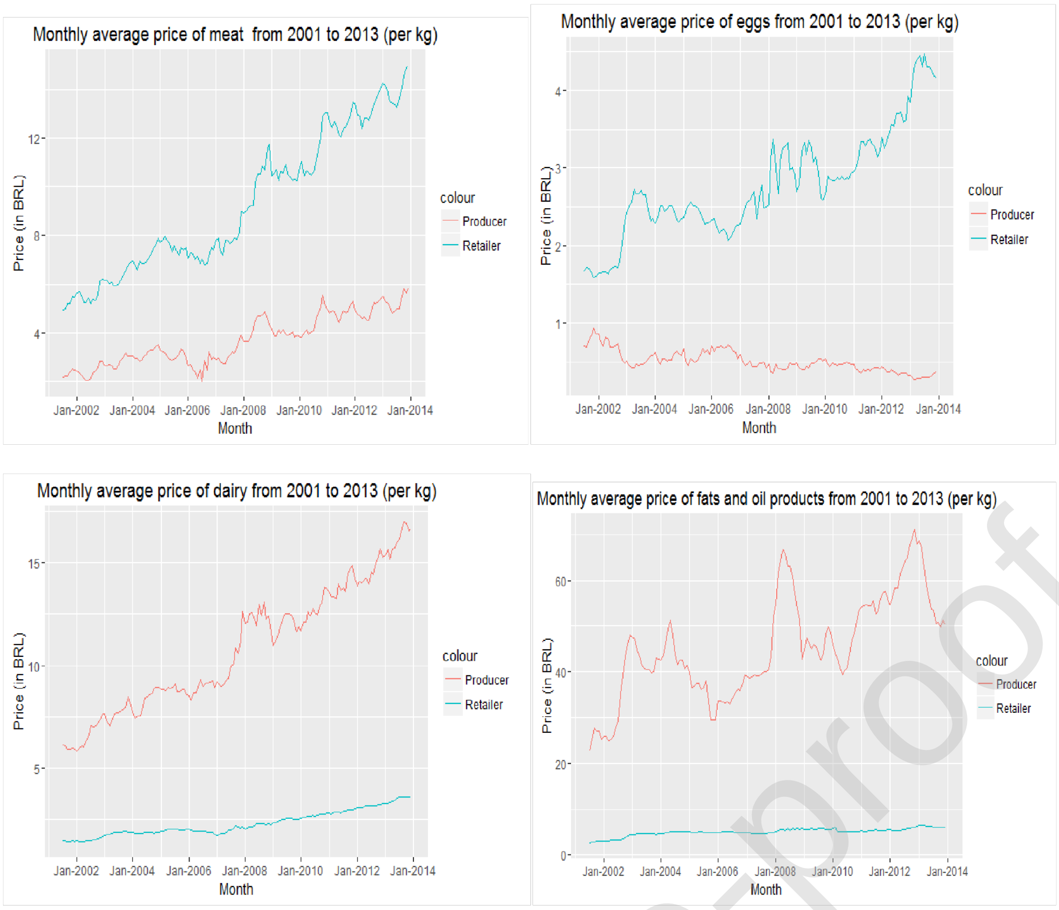

Figure 3: Changes in the average prices of selected foods
Source: Author generated from IEA and FIPE data

2. Literature review

The existing research on fuel-food relationship is anchored on empirically ascertaining if oil prices affect food prices. While some studies focus on analysing the effect of global oil prices on local food prices (Dillon and Barrett, 2015), others examine the relationship at the local market level. Econometric studies have found evidence of causality between oil and agricultural commodity prices. Based on cointegration analysis, Cooke and Robles (2009) find the influence of oil on food prices, while Nazlioglu (2011) provides evidence of a non-linear relationship between oil and food prices and nonlinear causality from oil to corn and soybean prices. Other studies have examined the dynamic relationship between oil prices, agricultural prices and the US dollar, concluding that an increase in oil price and a weak dollar lead to an increase in food prices (Nazlioglu and Soytas, 2012).

More recently, few studies have addressed the issue of price volatility by modelling price volatility spillovers between energy and food markets (Serra, 2011; Zhang et al., 2009; Mensi et al., 2014). Using weekly international crude oil, ethanol and sugar prices, Serra et al. (2011a) examine spillovers in the Brazilian ethanol market. They find a positive relationship between ethanol prices and oil prices at equilibrium, while price dynamics indicate substitution between oil and ethanol. Zhang et al. (2009) analyse volatility in the wholesale prices of corn, ethanol, soybeans, gasoline and oil in the United States. Using a multivariate autoregression model, the authors conclude that the demand for vehicle fuel is a key driver of the demand for ethanol and oil, while the price of gasoline determines the prices of ethanol and oil.

Cabrera and Schulz (2016) investigate dynamics in price and volatility risk associated with linkages between energy and agricultural commodity prices in Germany. The studies on price volatility transmission are based on the assertion that an increased correlation between food and energy prices is bound to result in strong volatility spillovers between these prices. Without accounting for these spillovers, traditional risk management tools are less reliable in mitigating risks. In this wise, a plethora of papers have sought to analyse the effects of price volatility spillovers within the context of how price dynamics in the ethanol market affect economic welfare (Babcock, 2008; de Gorter and Just, 2007; Bruce, 2007) and agricultural land allocation (Fabiosa et al., 2008). Other authors have looked at these effects on land values (Henderson and Gloy, 2009) and agricultural commodity prices both locally and at a more aggregate level (Balcombe and Rapsomanikis, 2008; de Gorter and Just, 2008; Luchansky and Monks, 2009; McNew and Griffith, 2005; McPhail and Babcock, 2008; Serra et al., 2011a; Tyner and Taheripour, 2008).

Findings on the relationship between oil and agricultural commodity prices can be classified under three broad categories. Firstly, many studies find no evidence that oil prices drive agricultural prices. Using monthly price data on five commodities (corn, rice, soybeans, sugar and wheat) and three fuel commodities (ethanol, gasoline and oil), Zhang et al. (2010) assess the relationship between fuel and food prices. Their results show neither short nor long-run relationship between fuel prices and the set of agricultural commodity prices.

The second category of studies extract short-run and long-run relationships from food and fuel price series by dividing the study sample into two periods, with the second often coinciding with the period after the global financial meltdown of 2007/2008. Overall, the studies find neutrality between oil and food prices in the first period and a conclusion that oil prices drive food prices during the second period. Using wheat and corn markets as a case study, Du et al. (2011) investigate the role of speculation in determining volatility in crude oil prices, and how this volatility in turn affects variation in food prices. They find that in the first sub-sample period (November 1998 to October 2006), there is moderate evidence of price variation in crude and wheat markets, while the price of corn behaved differently from that of crude oil prices. A strong and progressively connected variation is, however, found in the second period (October 2006 to January 2009), confirming the hypothesis that higher crude oil prices forecast large corn impact on corn prices and eventually, corn price formation.

In a similar vein, Reboredo (2012) examines co-movements between world oil prices and prices of corn, soybeans and wheat, using weekly data over the period 9 January 1998 to 15 April 2011. Although the results generally showed weak dependence between oil and food prices (in support of the neutrality phenomenon), the last three years of the period witnessed significantly increased dependence between the two markets.

Nazlioglu et al. (2013) study volatility transmission between oil and selected food prices (wheat, corn, soybeans and sugar) over pre and post-crisis periods. The authors use daily data spanning the period 1 Januray 1986 to 21 March 2011, with the pre-crisis period running from 1 January 1986 to 31 December 2005 and the post-crisis period being 1 January 2006 to 21 March 2011. The study concludes that although there is no risk of transmission between oil and food markets in the pre-crisis period, there is significant price spillover from oil to food markets in the post-crisis period, a finding that is confirmed from both variance causality tests and impulse response functions.

Lastly, other studies find that oil prices are significantly related with agricultural commodity prices along the entire period of the study. These studies often deviate from the common methodologies and as a result, differences in the estimates of the impact of oil prices on food prices depend mainly on the nature of the food basket and the underlying assumptions about the interaction between the two markets. Nazlioglu and Soytas (2012) examine the relationship between world oil prices, the US dollar and food prices in twenty-four food markets, using Granger causality and panel cointegration methods. They find strong evidence of transmission from world oil prices to several agricultural commodity prices.

Within the Brazilian context, the existing studies focus heavily on the sugar-ethanol oil nexus. This is because the Brazilian ethanol industry is characterised by its competitiveness and flexibility, with a large number of plants operating on a large scale while using a dual technology that enables producers to switch between ethanol and sugar production, depending on dynamics in market prices. Additionally and depending on the pump price, consumers are able to shift from high to low ethanol-gasoline blends thanks to a strong infrastructural base that facilitates the handling and distribution of fuel ethanol. According to de Almeida et al. (2007), increased demand for ethanol, both internationally and in Brazil, explains the expansion of ethanol production in the country.

Studies on the impact of oil prices on agricultural commodity prices in Brazil have naturally adopted an empirical methodology. Balcombe and Rapsomanikis (2008) assess the sugar-ethanol-oil nexus in Brazil using generalized bivariate error correction models. They find that over the long-run, oil prices are a key driver of ethanol and sugar prices. Sugar prices also Granger-cause ethanol prices. Using weekly data over the period July 2000 to November 2009, Serra (2011) analyses volatility transmission between crude oil, ethanol and sugar prices in Brazil, and find that long-run equilibrium parity exists between ethanol and crude oil, as well as ethanol and sugar price levels. This result implies that an increase in both crude oil and sugar prices signifies an increase in ethanol prices.

The literature on the relationship between oil prices and agricultural commodity prices is methodologically founded on standard supply and demand frameworks and partial or general equilibrium models (Babcock, 2008; Luchansky and Monks, 2009; McPhail and Babcock, 2008). Among these studies, linear regression models such as the Vector Autoregression (VAR), Vector Error Correction (VEC) and corresponding cointegration and causality tests are hugely applied. Other econometric approaches include Threshold Vector Error Correction Modelling (TVECM), Autoregressive Distributed Lag (ARDL) and BEKK-MGARCH. Serra and Zilberman (2013) conduct a thorough analysis of the main methodologies applied in analysing the energy-food relationship. Their findings show that the VECM approach and its variant forms have been the most dominantly used approaches to assess the effect of energy price shocks on the food market. This is in part due to the non-stationary nature of these prices and the presence of cointegration between the prices. Table 1 presents studies that use these approaches as reported by Serra and Zilberman (2013).

Study	Approach	Variables used
Balcombe and Rapsomanikis (2008)	Taylor series expansion of VECM; AVECM; TVECM	Brazilian ethanol and sugar prices, world crude oil prices
Busse et al. (2012)	MS VECM	German diesel, biodiesel, rapeseed oil and soy oil prices
Campiche et al. (2007)	VECM	Corn, sorghum, soybeans, soybean oil, palm oil, world sugar and crude oil prices
Ciaian and Kancs (2011)	VECM	World corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum tea, crude oil
Mallory et al. (2012)	VECM	Nearby and 1-year to expiration futures prices of ethanol, corn and natural gas
Natalenov et al. (2011)	VECM; TVECM	Crude oil, cocoa, coffee, corn, soybeans, soybean oil, wheat, rice, sugar and gold futures prices
Nazlioglu and Soytas (2012)	Panel cointegration; VECM	World prices for 24 agricultural commodities (grains, oils, meats, beverages and other food prices), world crude oil price and USD exchange rates
Peri and Baldi (2010)	TVECM	European sunflower oil, rapeseed oil, soybean oil and diesel prices
Rajcaniova and Pokrivcak (2011)	VECM	EU oil and gasoline prices, German bioethanol, maize, wheat and sugar prices
Rapsomanikis and Hallam (2006)	TVECM	Brazilian ethanol and sugar prices, world crude oil prices
Zhang et al. (2010)	VECM	US prices for ethanol, gasoline, corn, soybeans and wheat; free market sugar price; Thailand rice price; international crude oil price
Serra (2011)	VECM-BEKK-MGARCH	International crude oil, Brazilian ethanol and sugar prices
Serra and Gil (2012)	VECM-BEKK-MGARCH	US corn, US ethanol prices; US corn stocks; US interest rate

AVECM means Assymetric Vector Error Correction Model. TVECM stands for Threshold Vector Error Correction Model. MS VECM means Markov-switching Vector Error Correction Model. MGARCH means Multivariate Generalized Autoregressive Conditional Heteroskedasticity. BEKK stands for the Baba, Engel, Kraft and Kroner model.

Table 1: Dominant methodologies applied in researching the food-oil relationship

Similar to the literature on staples and traditional cash crops, studies on the relationship between oil price and nutritional high-value food prices focus mainly on the dynamic relationship between the two prices. Esmaeili and Shokoohi (2011) use a principal components approach to examine co-movement between food prices and macroeconomic indices (particularly oil prices). They use food prices in seven food markets, including meat, eggs, milk, oilseeds, rice, sugar and wheat. The results of their Granger causality tests show a unidirectional influence of oil prices on the food price index. Nazlioglu and Soytas (2012) use a dynamic panel approach to examine world oil prices and commodity prices, and account for intermarket links by including meat and fresh fruit prices. The authors find that over the long-run, there is a significant and positive transmission of shock from oil prices to food prices. Using a random parameter model, Balcombe and Rapsomanikis (2008) examine price volatility in the meat, dairy and food oils markets, and find a strong evidence of volatility in these price series.

3. Theoretical foundation

Asymmetric Price Transmission (APT), the case where price transmission increases or decreases, has attracted attention from agricultural economists since the turn of the millennium (McCorriston et al., 2001; McCorriston, 2002; Meyer and von Cramon-Taubadel, 2004). The increased attention stems from the conclusion by both theoretical and empirical studies that APT may reveal the weaknesses of traditional economic theory, since if APT is the rule, then it will be difficult to accept an economic theory that treats it as an exception. Secondly, asymmetry in price transmission could spell significant welfare and policy implications, since the presence of asymmetry implies that a group is not benefiting from a price reduction (for buyers) or increase (for sellers).

The theoretical underpinnings of asymmetric food price transmission along the nutritional high-value food supply chain can be found in microeconomic theory, through the structure of agricultural markets and the role food prices play in ensuring the attainment of market goals. The level of prices influences decisions about resource allocation and output mix, thus determining the extent of vertical and/or horizontal integration of markets. From a market organisation perspective, the structure of a market determines the behaviour of firms in respect of the magnitude and speed of transmitting market prices. The structure of the market also determines the differences in market power. In the case of agricultural markets, farmers and consumers often suspect that imperfect competition in processing and retailing grants to middlemen the ability to abuse market power. This results in a positive APT, where retail prices react more quickly or fully to an increase in producer price and less quickly or fully to a decrease.

McCorriston et al. (2001) proffer a theoretical framework that explains the above conjecture by examining how differences in market power from imperfect competition leads to asymmetric price transmission in food markets. They develop a model of farm-retail spread that accounts for imperfect competition. The framework of the model is to have a single intermediate stage, where a food-processing retailer produces a homogeneous good with firms pursuing quantity-setting strategies. The extent of price transmission from the impact of an external shock (such as diesel price shock) occurring at the farm stage (upstream) on retail prices depends, therefore, on the change in aggregate mark-up for firms in this intermediate and oligopolistic stage and any change in cost.

Assuming the initial structure of the food market is competitive, such that the mark-up is zero. Then only changes in costs will explain price transmission. Given a fixed proportion of technology, the level of price transmission will be explained through the competitive industry's share of agricultural raw materials in its cost function. A positive mark-up, however, shows that market power drives price transmission because the mark-up could change based on industry cost. The level of market power and the nature of the demand function also determine how much the aggregate mark-up will change. Under a constant elasticity demand function, even a change in cost will not lead to a positive change in mark-up, implying that the mark-up will not influence price transmission. In situations where the elasticity of demand is not constant, however, the change in mark-up reduces the elasticity of price transmission. This means that retail prices will change less than changes in producer prices, a clear case of negative APT.

McCorriston (2002) expands the above model by examining price transmission when downstream players have market power and operate under non-constant returns to scale. They develop a theoretical model in which agricultural firms produce food by using agricultural inputs together with other variable inputs (such as materials and labour). Based on models of short-run equilibrium with quasi-fixed capital, the authors assume that firms can maximise their profits only by varying the variable inputs and there is potential substitutability between inputs. The authors further assume that the food market cannot exert oligopsonistic power, despite having oligopolistic power.

Given the above assumptions and model set-up, a firm's quantity is a function of agricultural, material and capital inputs that are fixed in the long-run. Its input supply is, therefore, a function of the prices of agricultural inputs, material inputs and an exogenous shift factor that represents the source of external shock after the agricultural sector. Deriving the elasticity of transmission, therefore, involves estimating changes in the endogeneous variables following an external shock.

The authors assert that, the level of this elasticity in the short-run depends on whether a firm's cost function is characterised by constant, increasing or decreasing returns to scale. In the case of constant returns to scale, the level of price transmission when the price of agricultural inputs declines is determined by the change in industry mark-up over the marginal cost required to restore equilibrium. This adjustment in turn depends not only on the level of market power, but also on the nature of the demand curve. With non-constant returns to scale, however, adjustment towards equilibrium is also a function of the cost faced by the firm. When a firm faces increasing returns to scale, the expansion of output required to restore equilibrium exceeds that of constant returns, leading to an increase in price transmission, since the fall in input price is reflected in the corresponding decrease in consumer prices. This implies that although market power may reduce the extent of price transmission when a firm is operating under increasing returns to scale, the level of price transmission is all the same higher than the case of constant returns to scale. Decreasing returns to scale leads to a lower output expansion to equilibrium that is lower than in the constant cost case. Thus, the market power effect is further reinforced, leading to a further relative reduction in consumer prices for a decline in agricultural input prices. In the long-run, capital is variable, implying that the scale parameter can rise leading to increasing returns.

Empirical studies on agricultural markets in developing countries reveal that agricultural markets in these countries are characterised by imperfect competition (Sexton, 2012). This imperfection creates an imbalance in market power along the supply chain, with downstream players (such as retailers) wielding more power in determining prices. An increasing demand for nutritional high-value foods coupled with access to agricultural inputs means that farmers produce more for a given input in order to meet demand from retailers. From the framework of McCorriston et al. (2001), the increased production will require reduced price levels in order to sell produce to retailers. In the case of nutritional high-value foods, these tend to be perishable and require a reduction in producer prices in order to find market. This analysis also applies to retailers who may wish to sell more food procured from producers to meet consumer demand.

We can deduce from the above that in the event of a shock from diesel price, higher retail power means that they are able to reduce price transmission from producers (who may wish to pass on the effect to retailers). Downstream, however, Meyer and von Cramon-Taubadel (2004) argue that retailers selling these foods may be unwilling to raise prices when producer and diesel prices increase for fear of being left with unsold food. Overall, retailers will have higher net welfare losses since they are unable to fully pass the increased cost from producer and diesel prices to consumers.

It is important to note that, the downstream demand-side effect results from the assumption that the elasticity of demand is not constant. With nutritional high-value foods, this assumption is justifiable since the consumption of these foods tends to be income-elastic, with higher incomes meaning higher consumption (Gulati et al., 2007).

From the theoretical framework presented above, we can conclude that in the presence of increasing rate of return, a diesel price shock will have a higher impact on downstream prices than upstream prices in the market of perishable products. Following from this conclusion, the study seeks to ascertain if the impact of a diesel price shock is higher upstream along nutritional high-value food chains, using São Paulo as a case study. The hypothesis to be tested is as follows:

H1: The impact of diesel price shock along the nutritional high-value food supply chain is higher downstream than upstream

4. Econometric methodology

Based on the discussion above and the focus of the study, the empirical strategy adopted is to model agricultural commodity prices based on the interaction between actors along the supply chain and dynamics in diesel prices. This means that the producer price of food depends of the retail price and vice versa, while both prices are determined by the price of diesel. An increase in diesel price may, therefore, result in higher market prices of agricultural commodities. The log-log form of the associated empirical model is as shown in equation (1) below:

$$\begin{cases} lnPRODPRICE_t = \alpha_{0i} + \alpha_{1i} lnRETPRICE_t + \alpha_{2i} lnDIESELP_t + u_t \\ lnRETPRICE_t = \alpha_{3i} + \alpha_{4i} lnPRODPRICE_t + \alpha_{5i} lnDIESELP_t + u_t \end{cases} \tag{1}$$

where $lnPRODPRICE_t$ is the natural log of the average producer price of a nutritional high-value food at month t, $lnRETPRICE_t$ is the natural log of the average retail price and $lnDIESELP_t$ denotes the average diesel price in month t.

Having provided the general framework of the model to be estimated, the next stage entails examining the properties of the time series data. This is relevant in order to avoid spurious results, with the associated empirical strategy involving three steps. Firstly, stationarity properties of the variables are investigated by performing various unit root tests. The presence of a cointegrating relationship is then examined.

If two prices move together in the long-run, they are said to be cointegrated. Although a short-run relationship may exist between the series, cointegration implies that there is a linear relationship that ties them together. Methodologically, the presence of cointegration determines the type of long-run econometric model applied. The overall rank of cointegration is obtained up to when we fail to reject the null hypothesis. To test for the presence of cointegration, the Johansen trace test is applied to all the eight price series. The advantage of the test is that it is able to handle several time series variables.

From the unit root and cointegration analyses, a Vector Error Correction Model (VECM) that specifies the short-run dynamics of each price series in such a way as to capture the dynamics in long-run equilibrium relationships is specified. The VECM is a variant of the Vector Autoregression (VAR) model that enables us to capture short-run causality through differencing and long-run causality through an Error Correction Term (ECT). The general form of the VAR(p) model is as indicated in equation (2):

$$X_t = \mu + A_1 X_{t-1} + ... + A_p X_{t-p} + w_t \tag{2}$$

where μ represents the vector-valued mean of the series, while the coefficient matrix of each lag is shown by A_i. w_t is the noise term and this is assumed to have a mean of zero. The VECM model can be obtained by differencing equation (**??**), giving equation (3) as follows:

$$\Delta X_t = \mu + A_1 X_{t-1} + \Gamma_1 \Delta X_{t-1} + ... + \Gamma_p \Delta X_{t-p} + w_t \tag{3}$$

where $\Delta X_t = X_t - X_{t-1}$, A_1 the coefficient matrix for the first lag and Γ_i the matrices for each differenced lag.

5. Empirical Analysis

5.1. Data

The empirical analysis of this study relies on two sets of data. The first set is monthly average prices of meat, eggs, dairy and fats & oil products sold in São Paulo. The Instituto de Economia Agricola (Institute of Agricultural Economics) of São Paulo and the Institute of Economic Research Foundation (FIPE) are two major institutes that collate this data. The former collates and publishes different food price series covering the prices received by rural producers as well as average wholesale and retail prices in the city, while FIPE surveys retail prices.

The second set of data is average monthly prices of diesel. The National Agency of Petroleum, Natural Gas and Biofuels (ANP) publishes data on average monthly prices of all fuel products on its website [2]. The article uses data on diesel prices published on the site, with the period from July 2001 to December 2013. Using this time frame enables us to capture both pre-crisis and post-crisis periods, while providing sufficient sample size for the study. The prices of the foods under study are expressed per kilogramme while diesel prices are per litre. All prices are in Brazilian Real and with the data being complete, the problem of missing data is not encountered. A weakness the data is that diesel prices in 2013 are recorded twice for each month. The average of the two prices is taken for each month to obtain the monthly average.

Each food price series is adjusted for inflation using price indices published by the Institute of Economic Research Foundation (FIPE). In respect of producer prices, the Food Producer Price Index is used for the adjustment while the Food Consumer Price Index is used to adjust retail prices. Additionally, the Consumer Price Index for Transport, which measures how transport fare change over time, is used to adjust the price of diesel for inflation. Using real prices instead of their norminal values enable us to account for variations in cost of living of families in São Paulo.

The use of monthly data to explore oil price shocks enables us to capture major price changes that may have occurred during the month. This point is relevant because households may plan their food expenditure for a month. Monthly data has also been used by studies in the oil-food literature. Bastianin et al. (2014), Zhang et al. (2010) and Wang et al. (2014) are examples of studies that use monthly data. Table 2 provides the summary statistics of the data. Mean producer price is highest in the fats and oil market, while the producer price of eggs records the lowest mean price. With respect to retail prices, the price of meat has the highest mean while that of dairy has the lowest. The Jarque-Bera test leads to the rejection of the null of normality in all the variables except the retail price of dairy and producer price of fats & oil.

[2] http://www.anp.gov.br/dados-estatisticos

Variable	Name	Observations	Mean	Std. Dev.	Min.	Max	Jarque-Bera	Skewness	Kurtosis
Summary statistics: untransformed data									
meat_producer	Producer price of meat	150	3.662	1.026	2.00	5.789	10.151***	0.252	-1.192
egg_producer	Producer price of eggs	150	0.503	0.134	0.276	0.928	15.847***	0.774	0.258
dairy_producer	Producer price of dairy	150	10.73	3.055	5.793	16.830	8.569**	0.176	-1.141
fat_producer	Producer price of fat & oil	150	45.1	11.017	22.28	71.08	2.625	0.205	-0.532
meat_retailer	Retail price of meat	150	3.74	0.375	2.975	4.575	6.864**	0.052	-1.068
egg_retailer	Retail price of eggs	150	1.141	0.096	0.987	1.415	7.903**	0.529	-0.379
dairy_retailer	Retail price of dairy	150	0.936	0.043	0.819	1.03	1.555	-0.133	-0.454
fat_retailer	Retail price of fat & oil	150	2.104	0.259	1.677	2.51	13.401***	-0.133	-1.459
propensity	Retail sale index	150	67.97	17.108	46.3	100.3	13.707***	0.424	-1.232
diesel_price	Average price of diesel	150	0.436	0.041	0.323	0.511	17.052***	-0.815	0.092
Summary statistics: log-transformed data									
Variable	Name	Observations	Mean	Std. Dev.	Min.	Max	Jarque-Bera	Skewness	Kurtosis
meat_producer	Producer price of meat	150	1.253	0.286	0.693	1.756	8.839***	-0.084	-1.171
egg_producer	Producer price of eggs	150	-0.72	0.259	-1.287	-0.074	1.079	0.144	-0.333
dairy_producer	Producer price of dairy	150	2.331	0.295	1.757	2.823	8.064***	-0.198	-1.089
fat_producer	Producer price of fat & oil	150	3.777	0.256	3.104	4.264	3.937	-0.374	-0.279
meat_retailer	Retail price of meat	150	1.314	0.101	1.09	1.521	6.707**	-0.091	-1.046
egg_retailer	Retail price of eggs	150	0.129	0.083	-0.013	0.347	5.679	0.37	-0.623
dairy_retailer	Retail price of dairy	150	-0.067	0.046	-0.199	0.029	2.171	-0.243	-0.363
fat_retailer	Retail price of fat & oil	150	0.736	0.125	0.517	0.92	14.144***	-0.231	-1.451
propensity	Retail sale index	150	4.188	0.248	3.835	4.608	12.916***	0.208	-1.396
diesel_price	Average price of diesel	150	-0.835	0.098	-1.129	-0.671	30.104***	-1.036	0.613

The subscripts *producer* and *retailer* mean producer and retail prices respectively. Thus, meat_producer means the producer price of meat. diesel_price means the average price of diesel while *propensity* is the propensity of retail sale.*** means significant at the 5% level. Std. Dev. and Min. represent Standard Deviation and Minimum respectively, while Max. shows Maximum values.

Table 2: Summaries Statistics of the Series

The correlation matrix showing the relationship between prices is shown in Table 3. There is a strong correlation between prices of different foods. This is true for producer and retail prices both within markets and across markets. The highest correlation of 95.1% is observed between the producer prices of meat and dairy, while the lowest correlation of 0.5% is recorded between the retails price of eggs and dairy. Generally, producer prices are more correlated than retail prices, an indication of a higher interdependence between upstream markets than their downstream counterparts. With respect to correlation between the price of diesel and food prices, the table shows that food retail prices are more correlated with diesel prices than producer prices. This goes to show that shocks from diesel price dynamics are likely to be higher on retail prices.

	Producer prices				Retail and diesel prices				
	meat	eggs	dairy	fat and oil	meat	eggs	dairy	fat and oil	diesel
meat_producer	1								
egg_producer	-0.769	1							
dairy_producer	0.951	-0.798	1						
fat_producer	0.805	-0.827	0.797	1					
meat_retailer	0.88	-0.561	0.838	0.649	1				
egg_retailer	0.011	-0.437	0.033	0.252	-0.209	1			
dairy_retailer	0.541	-0.406	0.591	0.296	0.395	0.005	1		
fat_retailer	-0.639	0.381	-0.627	-0.383	-0.563	0.315	-0.495	1	
diesel_price	-0.016	-0.232	0.017	0.084	-0.095	0.488	-0.116	0.653	1

The subscripts *producer* and *retailer* mean producer and retail prices respectively. Thus, meat_producer means the producer price of meat. diesel_price means the average price of diesel.

Table 3: Correlation matrix

5.2. Results

5.2.1. Unit root test

Table 4 presents the Augmented Dickey-Fuller unit root test for the time series variables under study. Given that the results depend on the selected lag length, different lag lengths are used to capture how the results vary when the lag length changes. In the case of untransformed data and using the AIC criterion, a lag length of 5 leads to the rejection of the null hypothesis of unit roots only for the producer price of meat and retail price of dairy products. A lag length of 10 with AIC does not reject the null for all the food prices, diesel price and retail sale index. Using the SIC criterion, and a maximum lag length of 5, the null hypothesis is rejected only with the producer price of meat. Increasing the maximum lag length to 10 results in a similar result.

Price series (untransformed data), maximum lag length = 5						
	Using AIC			Using SIC		
Variable	Lag	Statistic	P-value	Lag	Statistic	P-value
meat_producer	4	-3.673	0.032	3	-3.494	0.045
meat_retailer	1	-3.223	0.087	1	-3.223	0.087
egg_producer	3	-3.059	0.135	1	-3.022	0.151
egg_retailer	3	-3.206	0.089	3	-3.206	0.089
dairy_producer	2	-3.358	0.064	1	-3.121	0.109
dairy_retailer	3	-4.031	0.010	1	-2.995	0.162
fat_producer	2	-3.022	0.151	2	-3.022	0.151
fat_retailer	1	-3.218	0.088	1	-3.218	0.088
diesel_price	3	-2.653	0.304	2	-2.864	0.217
propensity	1	-2.735	0.270	1	-2.735	0.270

Price series (untransformed data), maximum lag length = 10						
	Using AIC			Using SIC		
Variable	Lag	Statistic	P-value	Lag	Statistic	P-value
meat_producer	8	-2.067	0.549	3	-3.494	0.045
meat_retailer	7	-2.791	0.247	1	-3.223	0.089
egg_producer	8	-3.078	0.127	1	-3.022	0.151
egg_retailer	3	-3.206	0.089	3	-3.206	0.089
dairy_producer	2	-3.351	0.064	1	-3.121	0.109
dairy_retailer	9	-2.119	0.527	1	-2.995	0.162
fat_producer	2	-3.022	0.151	2	-3.022	0.151
fat_retailer	2	-3.063	0.133	1	-3.218	0.088
diesel_price	3	-2.653	0.304	2	-2.864	0.217
propensity	1	-2.735	0.270	1	-2.735	0.270

Price series (log transformation), maximum lag length = 5						
	AIC			SIC		
Variable	Lag	Statistic	P-value	Lag	Statistic	P-value
meat_producer	4	-3.437	0.051	3	-3.62	0.034
meat_retailer	1	-3.167	0.096	1	-3.167	0.096
egg_producer	1	-3.067	0.132	1	-3.067	0.132
egg_retailer	3	-3.16	0.097	3	-3.16	0.097
dairy_producer	1	-3.2	0.091	1	-3.2	0.091
dairy_retailer	3	-4.041	0.01	1	-2.991	0.164
fat_producer	2	-2.807	0.24	2	-2.807	0.24
fat_retailer	3	-2.994	0.162	1	-3.276	0.078
propensity	1	-3.223	0.087	1	-3.223	0.087
diesel_price	3	-2.722	0.276	2	-3.019	0.152

Price series (log transformation), maximum lag length = 10						
	AIC			SIC		
Variable	Lag	Statistic	P-value	Lag	Statistic	P-value
meat_producer	8	-2.045	0.558	3	-3.62	0.034
meat_retailer	7	-2.813	0.238	1	-3.167	0.096
egg_producer	8	-2.898	0.202	1	-3.167	0.096
egg_retailer	3	-3.16	0.097	3	-3.16	0.097
dairy_producer	1	-3.2	0.091	1	-3.2	0.091
dairy_retailer	9	-2.126	0.524	1	-2.991	0.164
fat_producer	2	-2.807	0.24	2	-2.807	0.24
fat_retailer	2	-3.092	0.121	1	-3.276	0.078
propensity	1	-3.223	0.087	1	-3.223	0.087
diesel_price	2	-3.019	0.152	2	-3.019	0.152

The subscripts $producer$ and $retailer$ mean producer and retail prices respectively. Thus, meat_producer means the producer price of meat. diesel_price means the average price of diesel while $propensity$ is the propensity of retail sale.

Table 4: Unit root tests

Given the presence of unit roots in the data, it is important to examine the degree of integration of the variables. Table 5 presents the unit root tests of the first difference and the log of the first difference of the series. Differencing the series leads to the rejection of the null hypothesis of unit root in all the variables for both the first difference and its log. Since this study uses the log of the series which has been shown to be non-stationary in Table 4, we can confidently conclude that all the series are integrated with an order of I(1).

Price series (differenced transformation), maximum lag length = 5							Price series (differenced transformation), maximum lag length = 10						
	Using AIC			Using SIC				Using AIC			Using SIC		
Variable	Lag	Statistic	P-value	Lag	Statistic	P-value	Variable	Lag	Statistic	P-value	Lag	Statistic	P-value
meat_producer	3	-5.933	0.010	3	-5.933	0.010	meat_producer	7	-6.305	0.010	3	-5.933	0.010
meat_retailer	3	-6.298	0.010	1	-9.633	0.010	meat_retailer	6	-5.583	0.010	1	-9.633	0.010
egg_producer	2	-7.908	0.010	1	-10.009	0.010	egg_producer	7	-4.503	0.010	1	-10.009	0.010
egg_retailer	2	-8.453	0.010	2	-8.453	0.010	egg_retailer	10	-4.595	0.010	2	-8.453	0.010
dairy_producer	1	-8.629	0.010	1	-8.629	0.010	dairy_producer	1	-8.629	0.010	1	-8.629	0.010
dairy_retailer	5	-6.052	0.010	2	-5.712	0.010	dairy_retailer	8	-5.754	0.010	1	-7.077	0.010
fat_producer	1	-6.311	0.010	1	-6.311	0.010	fat_producer	1	-6.311	0.010	1	-6.311	0.010
fat_retailer	1	-9.943	0.010	1	-9.943	0.010	fat_retailer	1	-9.944	0.010	1	-9.944	0.010
diesel_price	2	-6.747	0.010	1	-7.585	0.010	diesel_price	2	-6.474	0.010	1	-7.585	0.010
propensity	1	-8.804	0.010	1	-8.804	0.010	propensity	1	-8.804	0.010	1	-8.804	0.010
Price series (differenced log transformation), maximum lag length = 5							Price series (differenced log transformation), maximum lag length = 10						
	AIC			SIC				AIC			SIC		
Variable	Lag	Statistic	P-value	Lag	Statistic	P-value	Variable	Lag	Statistic	P-value	Lag	Statistic	P-value
meat_producer	3	-6.312	0.010	3	-6.312	0.010	meat_producer	7	-6.389	0.010	2	-6.596	0.010
meat_retailer	1	-9.551	0.010	1	-9.551	0.010	meat_retailer	6	-5.541	0.010	1	-9.551	0.010
egg_producer	2	-7.548	0.010	1	-10.098	0.010	egg_producer	7	-4.587	0.010	1	-10.098	0.010
egg_retailer	2	-8.516	0.010	2	-8.516	0.010	egg_retailer	2	-8.517	0.010	2	-8.517	0.010
dairy_producer	1	-8.698	0.010	1	-8.698	0.010	dairy_producer	1	-8.698	0.010	1	-8.698	0.010
dairy_retailer	5	-6.061	0.010	2	-5.706	0.010	dairy_retailer	8	-5.725	0.010	1	-7.122	0.010
fat_producer	1	-6.724	0.010	1	-6.724	0.010	fat_producer	1	-6.724	0.010	1	-6.724	0.010
fat_retailer	1	-10.113	0.010	1	-10.113	0.010	fat_retailer	1	-10.113	0.010	1	-10.113	0.010
propensity	1	-8.454	0.010	1	-8.454	0.010	propensity	1	-8.454	0.010	1	-8.454	0.010
diesel_price	1	-7.515	0.010	1	-7.515	0.010	diesel_price	1	-7.515	0.010	1	-7.515	0.010

The subscripts *producer* and *retailer* mean producer and retail prices respectively. Thus, meat_producer means the producer price of meat. diesel_price means the average price of diesel while *propensity* is the propensity of retail sale.

Table 5: Unit root tests

5.2.2. *Cointegration test*

Table 6 presents results of the test statistic and critical values of the Johansen trace test. With r denoting the cointegration rank, the test sequentially assesses if r is equal to zero, equal to one and through to $r = n - 1$, where n is the number of price series under study. At the rank of 0, the null hypothesis is $r = 0$ while the null is $r \leq 0$. Subsequent ranks are based on a null of r less than or equal to the rank number while the alternative examines where the rank is greater. From Table 6 and based on the 5% critical value, we reject the null only for $r = 0$, $r \leq 1$, $r \leq 2$ and $r \leq 3$. It can, therefore, be concluded that the price series are cointegrated with a rank of 4.

H0	H1	Test Statistic	10% Critical Value	5% Critical Value	1% Critical Value
r = 0	r > 0	368.62	256.72	263.42	279.07
r ≤ 1	r > 1	271.81	215.17	222.21	234.41
r ≤ 2	r > 2	202.82	176.67	182.22	196.08
r ≤ 3	r > 3	153.76	141.01	146.76	158.49
r ≤ 4	r > 4	111.35	110.42	114.9	124.75
r ≤ 5	r > 5	74.78	83.20	87.31	96.58
r ≤ 6	r > 6	50.65	59.14	62.99	70.05
r ≤ 7	r > 7	30.73	39.06	42.44	48.45
r ≤ 8	r > 8	15.67	22.76	25.32	30.45
r ≤ 9	r > 9	5.57	10.49	12.25	16.26

Table 6: Johansen trace test results

5.2.3. *Vector Error Correction Model*

The results of the VECM model are presented in Table A1 in the Appendix (page 26). All price series are included in the VECM in order to capture any cross-price relationship among the products. This is relevant because the foods under study are highly consumed by middle class households, a great percentage of whom are located in São Paulo given the economic importance of the city (Levy-Costa et al., 2005). Indeed, households are very likely to purchase all these foods together over a month, the time interval of the study. Buying these foods together may, however, signal cross-price effects among them. If bought together, however, there is a high probability that a change in the price of one generates a change in the demand for and price of another, an analogy that can be extended to explain the effect of fuel prices.

It is important to note that the cross-price effects may occur along the entire spectrum of the supply chain. This is because of the interconnected nature of the interaction between agents along the chain, leading to downstream behaviour affecting activities upstream. Including the interaction between retail price of own and other nutritional high-value foods in the same VECM, therefore, enables us to capture both long-run and short-run dynamics not only for a particular food, but other purchased foods as well.

Results of the short-run causality tests are reported in Table 7. The results show a bidirectional relationship between upstream and downstream prices only in the meat and eggs markets, and this relationship is significant at the 5% significance level. Upstream meat prices, however, have a higher predictive power than downstream prices. A unidirectional relationship in which producer prices cause retail prices is seen in the dairy and fats & oil markets.

With respect to causality between diesel and food prices, the price of diesel does not cause producer price in any of the food markets under study. In the downstream segment of the markets, diesel price only causes the retail price of eggs. The result that diesel price does not cause producer and retail prices lends credence to the role of government policy in determining duel prices in Brazil. Until December 2001, all prices in the supply chain were set by the government. As of January 2002, the prices charged by distributors and retailers were liberalized, although wholesale prices of derivatives, including that of diesel, continue to be set by the state oil company with the objective of controlling inflationary pressures. From 2007 onwards the addition of biodiesel to diesel became mandatory, starting with 2% until reaching 5% in 2010. This raised the cost of the state oil company, but the increase was not passed on to the prices of the derivatives. From 2008 to 2011 the nominal prices of wholesale diesel (refinery) remained artificially constant. The losses to the state oil company were offset by contributions from the National Treasury. The analysis above shows that diesel markets are not competitive ones; instead of pure market power, prices of oil derivatives are conditioned by macroeconomic goals.

Granger causality tests (short-run Chi-square tests)					
Log Producer and retail prices		Log Producer and diesel prices		Log Retail and diesel prices	
Meat market					
$Meat_{prod} \to Meat_{ret}$	11.308***	$Meat_{prod} \to$ Diesel	0.697	$Meat_{ret} \to$ Diesel	0.896
$Meat_{ret} \to Meat_{prod}$	1.177	Diesel $\to Meat_{prod}$	1.100	Diesel $\to Meat_{ret}$	0.152
Eggs market					
$Egg_{prod} \to Egg_{ret}$	5.994***	$Egg_{prod} \to$ Diesel	0.039	$Egg_{ret} \to$ Diesel	0.529
$Egg_{ret} \to Egg_{prod}$	5.254***	Diesel $\to Egg_{prod}$	0.286	Diesel $\to Egg_{ret}$	2.935***
Dairy market					
$Dairy_{prod} \to Dairy_{ret}$	3.172***	$Dairy_{prod} \to$ Diesel	0.462	$Dairy_{ret} \to$ Diesel	0.658
$Dairy_{ret} \to Dairy_{prod}$	0.039	Diesel $\to Dairy_{prod}$	0.439	Diesel $\to Dairy_{ret}$	2.152
Fats and oils market					
$Fat_{prod} \to Fat_{ret}$	4.032***	$Fat_{prod} \to$ Diesel	0.685***	$Fat_{ret} \to$ Diesel	1.620
$Fat_{ret} \to Fat_{prod}$	2.244	Diesel $\to Fat_{prod}$	0.368	Diesel $\to Fat_{ret}$	0.872
Granger causality between retail sales index and diesel price					
Propensity $\to$ Diesel	0.582	Diesel$\to$ Propensity	3.436***		

The subscripts *prod* and *ret* mean production and retail prices respectively. Thus, Meat_prod means the producer price of meat. *Diesel* means the average price of diesel while *Propensity* is the retail sale index. *** means significant at the 5% significance level.

Table 7: Short-run Granger causality test

Based on the hypothesis that diesel price shocks are more pronounced on retail prices than producer prices, the results of the Granger causality analysis indicate the non-confirmation of the hypothesis in the meat, dairy and fats & oil markets. The hypothesis is, however, confirmed in the eggs market where the predictive power of the price of diesel on the retail price of eggs is significant although the price of diesel does not cause the price of eggs upstream. Juxtaposing this finding with the conclusion of bidirectional relationship between producer and retail prices in the meat market and a unidirectional relationship in the dairy market indicates the transfer of food prices across markets is determined mainly by internal market forces and not external ones like the price of diesel. Although the price of diesel predicts the retail price of eggs,a finding that corroborates Esmaeili and Shokoohi (2011) on foods including meat, eggs and milk, the predictive power of the producer price of egg exceeds that of diesel, confirming that food prices have a higher predictive power.

The most striking aspect of the VECM is the lack of short-run causality between diesel and food prices at the 5% significance level. This lack of a short-run relationship was already demonstrated by the causality tests indicating a lack of short-run relationships. This finding not withstanding, there is long-run convergence between the two prices.

5.2.4. *Forecast Error Variance Decomposition*

Variance decomposition analysis enables us to obtain information on the relative magnitude of the causal influence of one price on another. More precisely, decomposition provides the share of the variance associated with each price in the VECM caused by shocks to other prices. Table 8 presents the forecast error variance decomposition of upstream food prices, downstream food prices, retail sale index and diesel price. The results show that in the meat market, changes in the price of diesel contributes 0.2% of the variance of the producer price and 0.5% of the variance of the retail price. This finding indicates that retailers could be more motivated to transfer diesel price shocks to meat producers, justifying the need for policy to regulate the transmission of prices along the chain. Similarly, the variance of the producer price of dairy changes by 0.2%, while contribution to the variance of the retail price is 3.2%. A similar scenario is seen in the eggs and fats & oil markets. Comparatively, the contribution of the price of diesel to food price variance is highest in the eggs retail market, a result that confirms the Granger causality findings.

	Forecast error variance of log prices									
	$Meat_{prod}$	$Meat_{ret}$	Egg_{prod}	Egg_{ret}	$Dairy_{prod}$	$Dairy_{ret}$	Fat_{prod}	Fat_{ret}	Propensity	Diesel
$Meat_{prod}$	0.544	0.053	0.137	0.048	0.012	0.038	0.012	0.018	0.024	0.002
$Meat_{ret}$	0.287	0.289	0.057	0.060	0.286	0.007	0.002	0.002	0.005	0.005
Egg_{prod}	0.013	0.098	0.455	0.253	0.277	0.046	0.045	0.023	0.016	0.025
Egg_{ret}	0.024	0.08	0.236	0.259	0.022	0.087	0.106	0.026	0.009	0.149
$Dairy_{prod}$	0.074	0.018	0.091	0.168	0.496	0.009	0.027	0.053	0.062	0.002
$Dairy_{ret}$	0.063	0.004	0.060	0.023	0.079	0.655	0.057	0.022	0.009	0.032
Fat_{prod}	0.042	0.009	0.003	0.033	0.106	0.014	0.687	0.010	0.089	0.006
Fat_{ret}	0.119	0.009	0.059	0.022	0.132	0.030	0.074	0.479	0.045	0.029
Propensity	0.0004	0.006	0.102	0.201	0.075	0.072	0.016	0.089	0.292	0.145
Diesel	0.011	0.007	0.089	0.047	0.069	0.038	0.009	0.103	0.009	0.618

The subscripts *prod* and *ret* mean production and retail prices respectively. For example, Meat_prod means the producer price of meat. *Diesel* means the average price of diesel while *Propensity* is the retail sale index.

Table 8: Forecast error decomposition of prices after 10 periods (months)

5.2.5. *Impulse Response Analysis*

Impulse response analysis enables us to identify dynamics in a variable of interest after an external shock. The analysis indicates the extent to which an unanticipated change in the impulse variable impacts the response variable over the next several periods. The response of producer and retail prices of the foods under study to diesel prices is shown in the Appendix. Figure A1 presents the response of producer and retail prices of meat to diesel prices. In Figure A2 and Figure A3, price responses in the eggs and dairy markets are presented respectively, while Figure A4 shows the response of producer and retail prices of fats and oils to the price of diesel. A period of 36 months, long enough to account for any significant price response, is used for the analysis. Additionally, studies on the behaviour of food prices show that they behave differently during periods of crisis

(Esposti and Listorti, 2012). To examine this conclusion, the analysis controls for the period of the financial crisis and plots the associated impulse response curves. The period June 2006 to December 2013 is used as the crisis period in order to capture both the global meltdown of 2007 and the food price crises of 2010 and 2011.

The impulse response functions show that producer prices in the eggs, dairy and fats & oil markets respond positively to diesel price over the entire 3 months. In the case of the eggs market, an initial fall in price up to the fifth month is followed by a price increase after this period. The price, however, stabilises after the ten months. A similar trend is seen with the producer price of dairy products. With respect to the fats & oil market, shock from diesel price dies out after ten months after a slight increase and fall in the first five months, with the shock nearing zero. Retail prices also respond positively to diesel price shocks in the eggs and dairy markets, although the shock stabilises after ten months and fifteen months respectively. Although the producer price of meat responds positively to the price of diesel, the response is short-lived and decreases after five months and becomes negative after ten months. Although there is an initial negative response of the retail price of meat to diesel price, the response becomes positive and becomes constant from the fifth month.

This results of the impulse response function indicate that the prices of nutritional high-value foods respond weakly to diesel price shocks, a finding that corroborates the conclusion drawn from the short-run Granger causality results. Considering that the price of diesel shows periods of minute changes as shown in Figure 1, this finding shows that food price response follows the direction of movement of diesel prices. Thus, although the analysis took into consideration periods covering the global financial crisis, the fact that diesel prices did not change considerably between 2008 and 2013 implies that the reaction of food prices was minimal.

6. Conclusion

The extent of and asymmetry in price transmission along the food supply chain has important implications for the functioning of the chain. With respect to nutritional high-value foods, the increasing demand for these foods implies that asymmetry in price transmission will hugely affect not only producers and retailers, but also consumers. Although farmers producing these food see the increased demand as a catalyst for increased production and profit (Reardon and Timmer, 2014; Gulati et al., 2007), the inability to transmit higher input prices to wholesalers and/or retailers through higher producer prices indicates that farmers face the risk of recording low profit margins. This has two possible effects. They may be discouraged from investing more to meet demand. Secondly, and in case they increase investment, may leave food on the field, culminating in food loss (Segrè et al., 2014). Downstream, retailers may also suffer a fall in profit margin if they are unable to increase price despite increased demand for fear of throwing food away.

The results of the study have shown that the magnitude and direction of food price transmission along the nutritional high-value food supply chain depends on the food type and time (short-run or long-run). The short-run Granger causality results have shown a significant bidirectional relationship only in the meat market and the producer price of meat has a higher effect than its retail price, an indication that producers are better able to transmit prices to retailers than the latter do.

The positive and significant effect of the producer price of meat on its retail price can also be seen from the high contribution of the latter to the variance of the former. Comparing this finding with the long-run elasticity results of the VECM, it is seen that the producer price of meat converges to equilibrium while the retail price diverges.

Contrary to the results in the meat market, although short-run shocks in the eggs market only move from producer price to retail price, long-run equilibrium convergence is found only in the latter. This shows that although egg producers wield some amount of market power in transmitting prices to retailers, the actions of the latter have a bigger impact in establishing long-run equilibrium. With the fats and oils market, although the producer price influenced retail price in the short-run, there is no long-run convergence.

The results of the relationship between diesel and food prices also reveal differences by type of market price. From the Granger causality findings, it is seen that a change in diesel price significantly affects retail prices in the eggs and dairy markets, but affects producer prices in the fats and oils market. For all these effects, the direction is positive, implying that an increase in diesel price results in an increase in food prices.

It is important to note that, although changes in both the producer and retail prices of eggs significantly lead to an increase in retail price, the effect of the producer price is higher than that of diesel price. This finding confirms the market-power and returns-to-scale conjectures. With increasing returns to scale, retailers in the eggs market get to sell more eggs. But this also reduces their ability to increase the price of eggs when its producer price increases.

A potential source of the diesel price effect in the high-value food market of São Paulo is the development of the ethanol market in Brazil. Rising sugar prices tend to be transitory in that they affect the prices of other agricultural commodities. These transitory effects are caused both by yield and acreage responses, due to the redistribution of land in favour of ethanol production (Zhang et al., 2010).

The results of the study have important implications for policies targeting high-value food markets. Price support policies in developing countries have often targeted farmers, with the goal to help them receive higher producer prices (McCorriston et al., 2001). The study has shown that in the case of diesel price shock, the efficiency of such policies in enhancing the welfare of farmers is specific to the market in which these policies are implemented. In certain markets (such as eggs), the producer price effect is higher than the diesel price effect. In such a case, policy reforms during diesel price changes are necessary to reduce the effect of the differential between retail and producer prices.

7. Appendix

	$\Delta\ln Meat_{prod,t}$	$\Delta\ln Egg_{prod,t}$	$\Delta\ln Dairy_{prod,t}$	$\Delta\ln Fat_{prod,t}$	$\Delta\ln Meat_{ret,t}$	$\Delta\ln Egg_{ret,t}$	$\Delta\ln Dairy_{ret,t}$	$\Delta\ln Fat_{ret,t}$	$\Delta\ln Propensity_{t}$	$\Delta\ln Diesel_{t}$
Error correction terms										
α_1	-0.428(0.089)***	0.101(0.136)	-0.045(0.052)	-0.096(0.078)	0.155(0.045)***	-0.109(0.066)	-0.019(0.027)	-0.058(0.048)	0.020(0.016)	-0.085(0.038)**
α_2	0.185(0.080)**	0.128(0.123)	-0.145(0.047)**	0.082(0.070)	0.177(0.041)***	-0.185(0.059)***	-0.052(0.025)**	0.025(0.044)	0.037(0.014)**	-0.077(0.034)**
α_3	-0.243(0.127)	0.002(0.195)	-0.329(0.075)***	0.128(0.111)	0.166(0.065)**	-0.026(0.095)	-0.064(0.039)	0.179(0.069)**	-0.029(0.023)	0.032(0.054)
α_4	0.030(0.027)	0.212(0.040)***	-0.017(0.016)	0.045(0.023)	-0.007(0.014)	0.116(0.019)***	0.003(0.008)	0.034(0.014)**	-0.004(0.005)	-0.004(0.011)
Meat producer lags										
$\Delta\ln Meat_{prod,t-1}$	0.071(0.089)	0.209(0.138)	0.145(0.053)***	0.105(0.079)	0.105(0.046)**	-0.060(0.067)	0.049(0.028)**	-0.021(0.049)	-0.001(0.016)	0.062(0.038)
$\Delta\ln Meat_{prod,t-2}$	0.538(0.085)***	0.022(0.131)	0.093(0.050)	0.006(0.075)	0.088(0.044)**	-0.078(0.064)	-0.059(0.026)	-0.068(0.046)	0.008(0.015)	-0.007(0.036)
Meat retail lags										
$\Delta\ln Meat_{ret,t-1}$	0.050(0.177)	0.092(0.273)	-0.081(0.104)	0.054(0.156)	-0.266(0.091)**	-0.064(0.133)	-0.051(0.054)	-0.003(0.097)	0.018(0.032)	-0.009(0.075)
$\Delta\ln Meat_{ret,t-2}$	-0.220(0.165)	-0.054(0.254)	-0.107(0.097)	0.038(0.145)	-0.303(0.084)***	0.052(0.124)	-0.013(0.051)	-0.157(0.089)	-0.013(0.029)	0.014(0.070)
Egg producer lags										
$\Delta\ln Egg_{prod,t-1}$	0.137(0.092)	-0.376(0.142)**	0.046(0.054)**	-0.208(0.081)**	-0.113(0.047)**	0.036(0.069)	0.009(0.028)	0.008(0.050)	-0.024(0.016)	0.046(0.039)
$\Delta\ln Egg_{prod,t-2}$	0.119(0.075)	-0.289(0.115)**	0.066(0.044)	-0.177(0.066)**	-0.046(0.038)	0.078(0.056)	0.032(0.023)	0.045(0.041)	-0.004(0.013)	0.00003(0.032)
Egg retail lags										
$\Delta\ln Egg_{ret,t-1}$	0.123(0.132)	-0.418(0.203)**	0.0002(0.078)	-0.147(0.116)	-0.118(0.068)	0.200(0.099)**	-0.028(0.041)	0.094(0.072)	-0.009(0.024)	-0.037(0.056)
$\Delta\ln Egg_{ret,t-2}$	0.043(0.114)	-0.369(0.176)**	0.099(0.067)	0.101(0.101)	-0.059(0.058)	-0.052(0.086)	0.050(0.035)	0.002(0.062)	0.017(0.020)	-0.041(0.049)
Dairy producer lags										
$\Delta\ln Dairy_{prod,t-1}$	-0.338(0.161)**	-0.056(0.247)	0.043(0.095)	-0.160(0.141)	0.002(0.082)	0.021(0.120)	0.031(0.049)**	0.003(0.087)	-0.021(0.029)	-0.071(0.068)
$\Delta\ln Dairy_{prod,t-2}$	-0.101(0.157)	0.430(0.242)	0.092(0.093)	0.026(0.138)	-0.007(0.080)	0.013(0.118)	0.123(0.048)	-0.048(0.086)	0.004(0.019)	0.006(0.067)
Dairy retail lags										
$\Delta\ln Dairy_{ret,t-1}$	-0.422(0.327)	0.466(0.503)	-0.205(0.192)	-0.544(0.287)	0.161(0.167)	0.033(0.245)	-0.068(0.100)	-0.285(0.178)	0.046(0.058)	-0.183(0.139)
$\Delta\ln Dairy_{ret,t-2}$	-0.055(0.296)	0.353(0.456)	-0.047(0.174)	0.105(0.260)	0.123(0.151)	-0.225(0.222)	0.097(0.091)	-0.075(0.161)	-0.030(0.053)	-0.196(0.126)
Fats and oils producer lags										
$\Delta\ln Fat_{prod,t-1}$	-0.182(0.109)	0.272(0.168)	0.095(0.064)	0.272(0.096)**	0.031(0.056)	-0.111(0.082)	-0.061(0.033)	0.052(0.059)	0.008(0.019)	0.027(0.046)
$\Delta\ln Fat_{prod,t-2}$	0.062(0.106)	0.115(0.163)	-0.072(0.062)	-0.139(0.093)	0.069(0.054)	-0.128(0.079)	-0.022(0.033)	0.012(0.058)	-0.004(0.019)	-0.002(0.045)
Fats and oils retail lags										
$\Delta\ln Fat_{ret,t-1}$	0.072(0.179)	-0.686(0.275)**	0.105(0.105)	0.527(0.157)**	0.150(0.091)	0.301(0.134)**	-0.035(0.055)	-0.103(0.097)	-0.012(0.032)	0.064(0.076)
$\Delta\ln Fat_{ret,t-2}$	0.202(0.172)	-0.207(0.264)	0.085(0.101)	0.232(0.151)	0.037(0.088)	-0.137(0.128)	-0.093(0.053)	-0.099(0.093)	-0.001(0.031)	-0.085(0.073)
Consumption propensity lags										
$\Delta\ln Propensity_{t-1}$	0.616(0.488)	-0.997(0.751)	-0.116(0.287)	1.398(0.429)**	-0.085(0.249)	0.309(0.365)	0.005(0.149)	-0.369(0.266)	-0.061(0.087)	-0.183(0.207)
$\Delta\ln Propensity_{t-2}$	1.089(0.503)**	-1.618(0.774)**	0.135(0.296)	-0.099(0.442)	0.011(0.257)	0.694(0.377)	-0.258(0.154)	-0.329(0.274)	-0.070(0.089)	0.080(0.214)
Diesel lags										
$\Delta\ln Diesel_{t-1}$	0.229(0.243)	0.381(0.374)	0.122(0.143)	0.139(0.213)	0.041(0.124)	0.034(0.182)	0.175(0.075)**	0.016(0.132)	0.010(0.043)	0.247(0.103)**
$\Delta\ln Diesel_{t-2}$	-0.222(0.244)	-0.100(0.375)	0.042(0.144)	0.184(0.214)	-0.137(0.125)	-0.216(0.183)	-0.083(0.075)	-0.096(0.133)	-0.018(0.044)	-0.133(0.104)
R^2	0.489	0.346	0.325	0.410	0.382	0.526	0.395	0.29	0.427	0.276
Adjusted R^2	0.379	0.206	0.181	0.284	0.249	0.424	0.265	0.138	0.304	0.121
No. Observations	150	150	150	150	150	150	150	150	150	150
F-statistic	4.444***	2.464***	2.245***	3.239***	2.871***	5.154***	3.039***	1.903**	3.469***	1.775**
Diagnostic tests										
Portmanteau test for serial correlation :										
Chi-squared (P-value): 1391(0.059)										
Breusch-Godfrey LM test:										
Chi-squared (P-value): 1470(0.997)										
Arch-LM test:										
Chi-squared (P-value): 6105(0.306)										
White's test for heteroskedasticity:										
Test statistic (P-value): 3013(0.609)										

$Meat_{prod}$, Egg_{prod}, $Dairy_{prod}$ and Fat_{prod} are the producer prices of meat, eggs, dairy and fat and oil respectively. $Meat_{ret}$, Egg_{ret}, $Dairy_{ret}$ and Fat_{ret} are the retail prices of meat, eggs, dairy and fat & oil respectively. t is time, with t-1 and t-2 being lags of one month and two months respectively. *** and ** mean significant at 1% and 5% respectively. Standard errors are in brackets and are robust to heteroscedasticity and autocorrelation.

Table A1: Vector Error Correction Model Results

7.0.1. Impulse Response Function

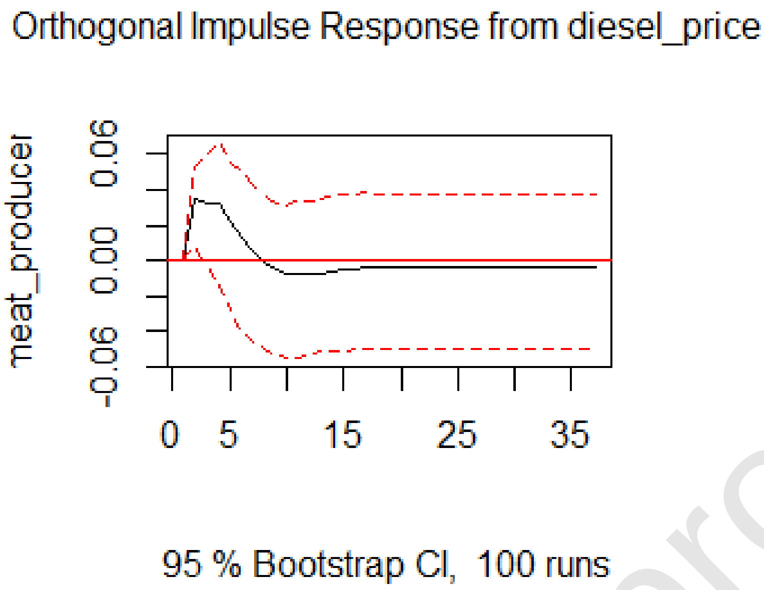

Figure A1a: Response of the producer price of meat

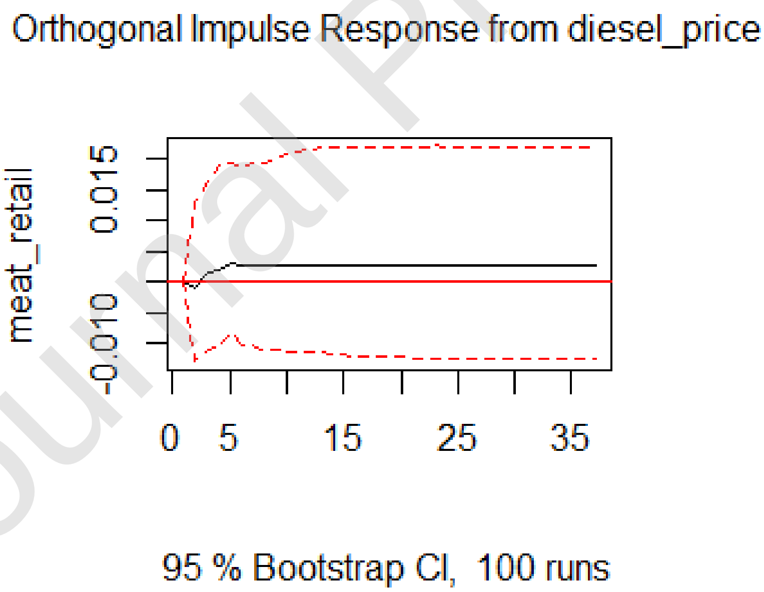

Figure A1b: Response of the retail price of meat

Figure A1: Response of meat prices to diesel price

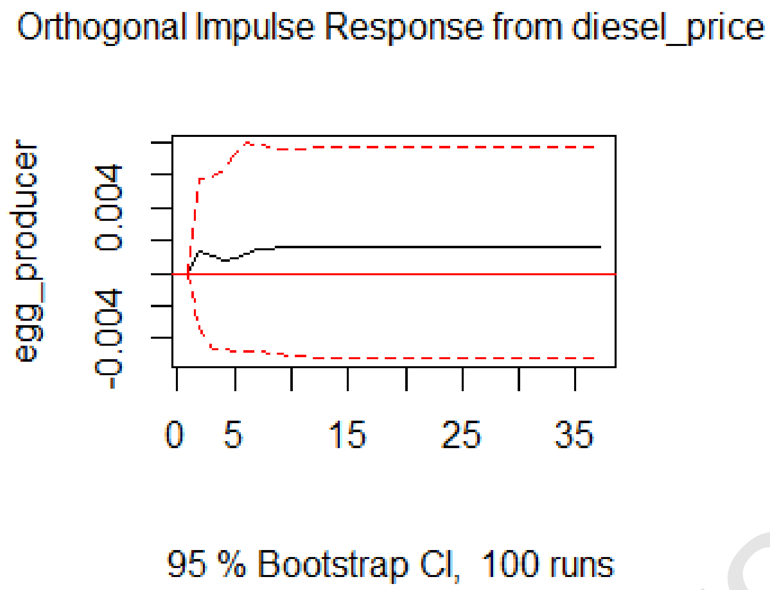

Figure A2a: Response of the producer price of eggs

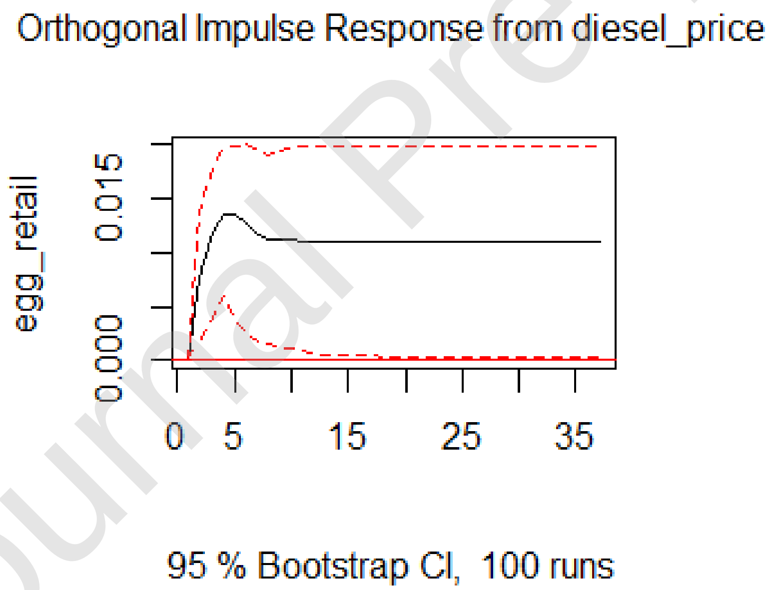

Figure A2b: Response of the retail price of eggs

Figure A2: Response of egg prices to diesel price

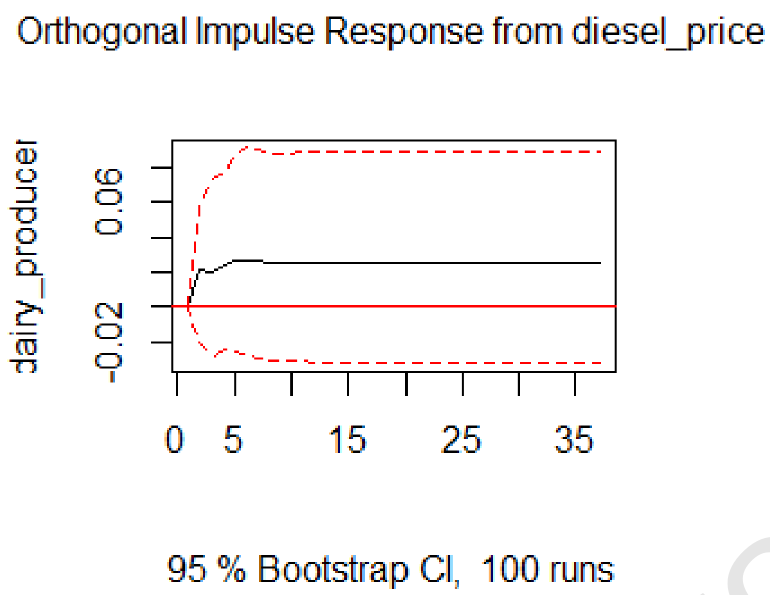

Figure A3a: Response of the producer price of dairy

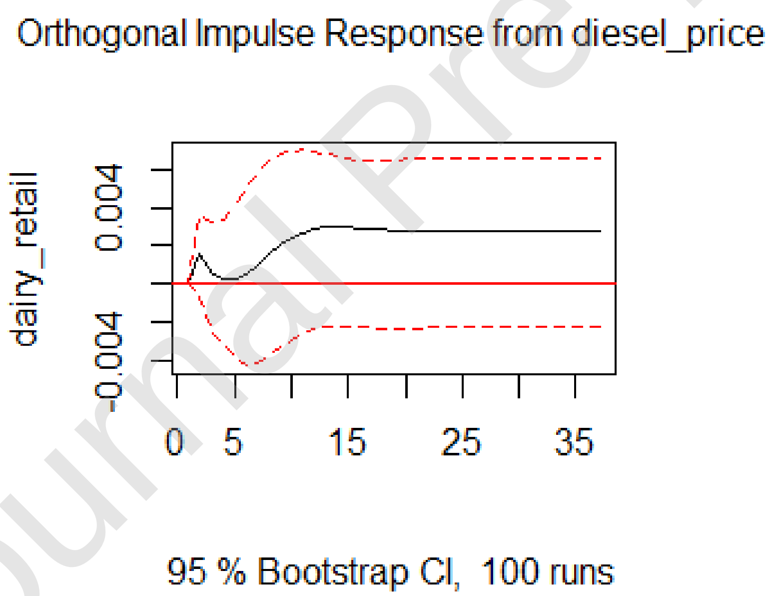

Figure A3b: Response of the retail price of dairy

Figure A3: Response of dairy prices to diesel price

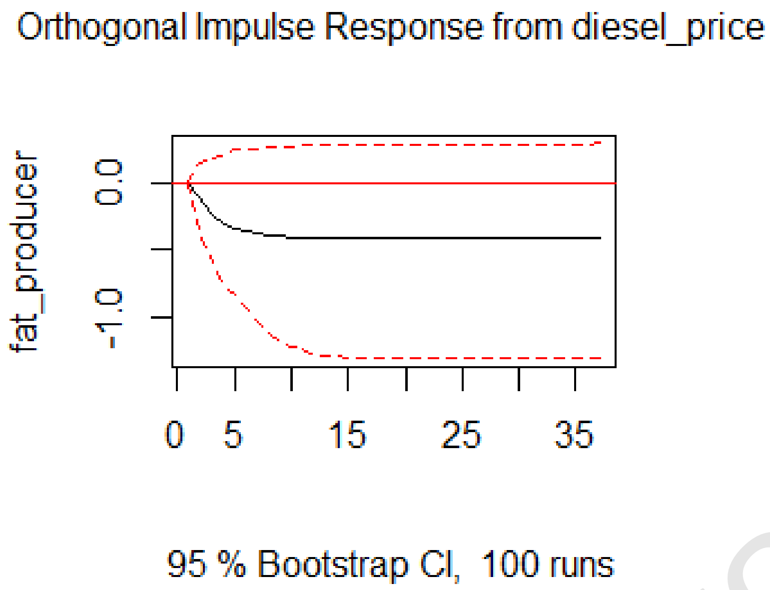

Figure A4a: Response of the producer price of fat & oils

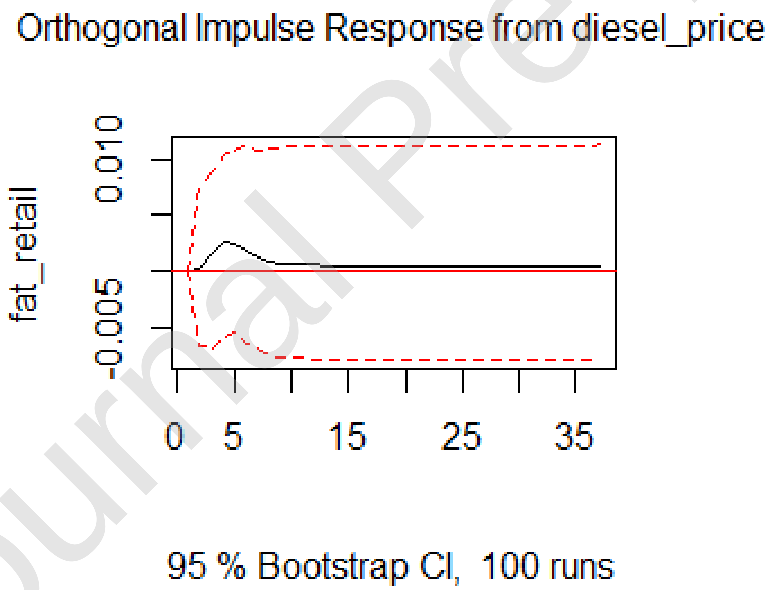

Figure A4b: Response of the retail price of fat & oils

Figure A4: Response of oil prices to diesel price

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References

Babcock, B. A. (2008). Distributional implications of U.S. ethanol policy. *Review Agricultural Economics*, 30:533–542.

Balcombe, K. and Rapsomanikis, G. (2008). Bayesian estimation and selection of nonlinear vector error correction models: The case of the sugar-ethanol-oil nexus in brazil. *American Journal of Agricultural Economics*, 90:658–668.

Bastianin, A., Galeotti, M., and Manera, M. (2014). Causality and predictability in distribution: The ethanol-food price relation revisited. *Energy Economics*, 42:152–160.

Bellemare, M. (2015). Rising food prices, food price volatility and social unrest. *American Journal of Agricultural Economics*, 97(1):1–21.

Bruce, G. (2007). Fuel Ethanol Subsidies and Farm Price Support. *Journal of Agricultural & Food Industrial Organization*, 5(2):1–22.

Busse, S., Brümmer, B., and Ihle, R. (2012). Price formation in the german biodiesel supply chain: a markov-switching vector error correction modeling approach. *Agricultural Economics*, 43:545–560.

Cabrera, L. and Schulz, F. (2016). Volatility linkages between energy and agricultural commodity prices. *Energy Economics*, pages 190–203.

Campiche, J. L., Bryant, H. L., Richardson, J., and Outlaw, J. L. (2007). Examining the evolving correspondence between petroleum prices and agricultural commodity prices. 2007 Annual Meeting, July 29-August 1, 2007, Portland, Oregon TN 9881, American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association).

Ciaian, P. and Kancs, A. (2011). Food, energy and environment: is bioenergy the missing link? *Food Policy*, 36:571–580.

Cooke, B. and Robles, M. (2009). Recent food prices movements: A time series analysis. Discussion paper no. 000942, IFPRI.

de Almeida, E. F., Bomtempo, J. V., and De Souza Silva, C. (2007). The performance of brazilian biofuels: an economic, environmental and social analysis. Discussion paper, Joint Transport Research Centre, Rio de Janeiro, Brazil.

de Gorter, H. and Just, D. R. (2007). The Welfare Economics of an Excise-Tax Exemption for Biofuels. MPRA Paper 5151, University Library of Munich, Germany.

de Gorter, H. and Just, D. R. (2008). "water" in the U.S. ethanol tax credit and mandate: implications for rectangular deadweight costs and the corn-oil price relationship. *Review of Agricultural Economics*, 30:397–410.

Dillon, M. B. and Barrett, B. C. (2015). Global oil prices and local food prices: Evidence from east africa. *American Journal of Agricultural Economics*, 98(1):154–171.

Du, X., Yu, C. L., and Hayes, D. J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis. *Energy Economics*, 33:497–503.

Esmaeili, A. and Shokoohi, Z. (2011). Assessing the effect of oil price on world food prices: Application of principal component analysis. *Energy Policy*, 39:1022–1025.

Esposti, R. and Listorti, G. (2012). Agricultural price transmission across space and commodities during price bubbles. *Agricultural Economics*.

Fabiosa, J. F., Beghin, J. C., Dong, F., Elobeid, A., Tokgoz, S., and Yu, T. H. (2008). Land allocation effects of the global ethanol surge: predictions from the international fapri model. Working Paper 08005, Department of Economics, Iowa State University, Ames, Iowa.

Fernandez-Perez, P., Frijns, B., and Tourani-Rad, A. (2016). Contemporaneous interactions among fuel, biofuel and agricultural commodities. *Energy Economics*, 58:1–10.

Gulati, A., Minot, N., Delgado, C., and Bora, S. (2007). Growth in high-value agriculture in asia and the emergence of vertical links with farmers. Technical report, IFPRI.

Henderson, J. and Gloy, B. A. (2009). The impact of ethanol plants on cropland values in the great plains. *Agricultural Finance Review*, 69:36–48.

Hochman, G., Sexton, S., and Zilberman, D. (2008). The economics of biofuel policy and biotechnology. *Journal of Agricultural and Food Industrial Organization*, 6(2):1–24.

Levy-Costa, B. R., Sichieri, R., dos Santos Pontes, N., and Monteiro, A. C. (2005). Household food availability in brazil : distribution and trends (1974-2003). *Revista Saude Publica*, 39(4):1–10.

Luchansky, M. S. and Monks, J. (2009). Supply and demand elasticities in the U.S. ethanol fuel market. *Energy Economics*, 31:403–410.

Mallory, M., Irwin, S. H., and Hayes, D. J. (2012). How market efficiency and the theory of storage link corn and ethanol markets. *Energy Economics*, 34:2157–2166.

McCorriston, S. (2002). Why should imperfect competition matter to agricultural economists? *European Review of Agricultural Economics*, 29(3):349–371.

McCorriston, S., Morgan, C. W., and Rayner, A. J. (2001). Price transmission: the interaction between market power and returns to scale. *European Review of Agricultural Economics*, 28(2):143–159.

McNew, K. and Griffith, D. (2005). Measuring the impact of ethanol plants on local grain prices. *Review of Agricultural Economics*, 27:164–180.

McPhail, L. L. and Babcock, B. A. (2008). Short-run price and welfare impacts of federal ethanol policies. Working Paper 08-WP468, Center for Agricultural and Rural Development, Iowa State University, Ames, Iowa.

Mensi, W., Hammoudeh, S., Nguyen, K. D., and Yoon, S. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics*, 43:225–243.

Meyer, J. and von Cramon-Taubadel, S. (2004). Asymmetric price transmission: A survey. *Journal of Agricultural Economics*, 55(3):581–611.

Natalenov, V., Alam, M. J., McKenzie, A. M., and Van Huylenbroeck, G. (2011). Is there comovement of agricultural commodities futures prices and crude oil? *Energy Policy*, 39:4971–4984.

Nazlioglu, S. (2011). World oil and agricultural commodity prices: evidence from nonlinear causality. *Energy Policy*, 39:2935–2943.

Nazlioglu, S., Erdem, C., and Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics*, 36:658–665.

Nazlioglu, S. and Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar: a panel cointegration and causality analysis. *Energy Economics*, 34:1098–1104.

Oliveira, P. and Almeida, E. (2015). Determinants of fuel price control in brazil and price policy options. 5th Latin American Energy Economics Meeting.

Pera, T. and Caixeta-Filho, J. (2017). Logística do agronegócio brasileiro: Perfil da infraestrutura de transporte. *Revista Agroanalysis*, 10.

Peri, M. and Baldi, L. (2010). Vegetable oil market and biofuel policy: an asymmetric cointegration approach. *Energy Economics*, 32:687–693.

Prakash, A. (2011). Why volatility matters. In Prakash, A., editor, *Safeguarding Food Security in Volatile Global Markets*, pages 1–24. Rome, FAO.

Rajcaniova, M. and Pokrivcak, J. (2011). The impact of biofuel policies on food prices in the european union. *Journal of Economics (Ekonomicky Casopis)*, 5:459–471.

Rapsomanikis, G. and Hallam, D. (2006). Threshold cointegration in the sugar-ethanol-oil price system in brazil: Evidence from nonlinear vector error correction models. Commodity and trade policy research working paper, FAO, Rome.

Reardon, T. and Timmer, P. C. (2014). Five inter-linked transformations in the asian agrifood economy: Food security implications. *Global Food Security*, 3:108–117.

Reboredo, J. C. (2012). Do food and oil prices co-move? *Energy Policy*, 49:456–467.

Segrè, A., Falasconi, L., Politano, A., and Vittuari, M. (2014). Background paper on the economics of food loss and waste (unedited. working paper). Rome, FAO.

Serra, T. (2011). Volatility spillovers between food and energy markets: A semiparametric approach. *Energy Economics*, 33(6):1155–1164.

Serra, T. and Gil, J. M. (2012). Biodiesel as a motor fuel price stabilization mechanism. *Energy Policy*, 50:689–698.

Serra, T. and Zilberman, D. (2013). Biofuel-related price transmission literature: a review. *Energy Economics*, 37:141–151.

Serra, T., Zilberman, D., and Gil, J. (2011a). Price volatility in ethanol markets. *European Review of Agricultural Economics*, 38:259–280.

Serra, T., Zilberman, D., Gil, J. M., and Goodwin, B. K. (2011b). Nonlinearities in the us corn-ethanol-oil-gasoline price system. *Agricultural Economics*, 42:35–45.

Sexton, J. R. (2012). Market power, misconceptions, and modern agricultural markets. *American Journal of Agricultural Economics*, 95(2):209–219.

Taheripour, F., Hertel, W. T., Tyner, E. W., Beckman, F. J., and Birur, K. D. (2010). Biofuels and their by-products: Global economic and environmental implications. *Biomass and Bioenergy 34*, 34:278–289.

Tyner, W. and Taheripour, F. (2008). Policy options for integrated energy and agricultural markets. *Review of Agricultural Economics*, 30:387–396.

Wang, Y., Wu, C., and Yang, L. (2014). Oil price shocks and agricultural commodity prices. *Energy Economics*, 44:22–35.

Zhang, Z., Lohr, L., Escalante, C., and Wetzstein, M. (2010). Food versus fuel: What do prices tell us? *Energy Policy*, 38:445–51.

Zhang, Z., Lohr, L., Escalante, C. E., and Wetzstein, M. E. (2009). Ethanol, corn and soybean price relations in a volatile vehicle-fuels market. *Energies*, 2:320–339.