Food for the Stomach or Fuel for the Tank: What do Prices Tell Us?

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Abstract

The "food vs. fuel" debate may be difficult to resolve without letting the data 'speak'. We investigate the short and long-run relationships between food and fuel prices. Our analysis spans the period 1989-2013, covering the lead-up to the 2007-08 price spike, the sharp downward movement in the aftermath, as well as the period thereafter. This provides a more complete picture of the interaction between agriculture and fuel markets. Our results indicate the existence of a long-run equilibrium relationship between the prices in these markets. A closer examination of the dynamics between ethanol and corn, soybean, and sugar prices shows that the corn-soybean linkage plays a key role in shaping the long-run relationship between food and fuel prices. Although ethanol prices Granger cause corn prices, no individual agricultural commodity Granger causes ethanol prices. However, corn and soybean as a single group has an impact on the ethanol market.

Key words: *fuel, food, agricultural commodities, cointegration, VECM*
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1 Introduction

Biofuel is produced mainly from corn, soybean, sugarcane, and vegetable oil. In the United States, 94% of the biofuel is produced from corn and the remaining 6% from vegetable oils, animal fat, and waste oils and grease (USDA). In the EU, wheat, barely, corn, and rye respectively account for 70%, 15%, 10%, and 5% of ethanol production, while rapeseed (79%), soybean (18%) and sunflower (3%) contribute to biodiesel production. Since the U.S. government launched the Renewable Fuel Standard (RFS) program under the Energy Policy Act in 2005, the U.S. has emerged as the largest biofuel producer in the world. In 2007, the federal government mandated that 36 billion gallons of biofuel (about 20% of the total fuel consumption) be used by 2022 (Stockus, 2013). Similar mandates are in effect in the European Union (EU) and are proposed elsewhere in the world as well. It has been argued in the literature that increased biofuel demand (and production) has significant impact on prices of agricultural feedstock for biofuel ultimately affecting food prices. The food price crisis of 2005-08 also has been attributed to the expanded biofuel production and higher fuel prices during that span. One explanation is that corn and crude oil prices moved together because higher oil prices contributed to the rapid growth in ethanol production that led to corn price to go up (Tyner, 2010). A report by the International Center for Trade and Development (ICTSD) concluded that market driven expansion of ethanol demand in the U.S. increased corn price by about 21% in 2009, as compared to what it would have been had the ethanol production remained at 2004 level (Babcock, 2012). In 2012, 7.1% of total fuel consumption came from biofuel. More importantly, about 31% of total corn production in the U.S. went to ethanol production, more than double as that of 2005 (15%). The "food vs. fuel" debate intensified following the rise and subsequent fall in global agricultural commodity prices during 2005-08, a period in which fuel markets also exhibited a similar pattern of price movements. Researchers and policy makers acknowledge that diversion of food crops to energy production poses a significant risk for global food security (FAO, 2008; Mitchell, 2008; Abbott, Hurt, and Tyner, 2008; OECD, 2008). However there is no consensus on whether the increased fuel demand caused the food price spike in recent years, how significant the impact is, and how these issues should be addressed.

Empirical studies in the price analysis literature present a mixed picture of whether the food and fuel markets are linked together. Many studies reported that high fuel prices and increased fuel demand are driving agricultural commodity prices. For example, Chen, Kuo, and Chen (2010) used weekly prices for oil, corn, soybean and wheat for the period 1983 - 2010 and found a significant relation between grain prices and oil price. Specifically, they showed that fluctuations in oil prices contributed to the grain price movement during the period of global grain price crisis from 2005 to 2008. Trujillo-Barrera, Mallory, and Garcia (2012) used weekly prices and reported a long-run equilibrium relation between corn and ethanol prices but not in crude oil-corn and crude oil-ethanol price combinations. Mallory, Irwin, and Hayes (2012) also documented a cointegrating relationship between corn, ethanol, and natural gas futures prices.

In contrast, number of other studies (Zhang et al., 2010; Gilbert, 2010; Lombardi, Osbat, and Schnatz, 2012; Zhang and Reed, 2008; Kaltalioglu and Soytas, 2009) have found no causal relation between fuel and food prices in either direction. A recent study by Mueller and colleagues showed increased food prices were cointegrated with biofuel supply and demand in 2007-2008, but no evidence of causality between biofuel production and high grain prices was documented (Mueller, Anderson, and Wallington, 2011). Instead, they concluded that price spikes in 2008 were the result of "a speculative bubble related to high petroleum prices, a weak US dollar, and increased volatility due to commodity index fund investments". Another study by Gilbert (2010) also found no price linkage between food and fuel markets, instead identified the macroeconomic and monetary factors such as Gross Domestic Product (GDP) growth and index based investment in agricultural futures market as the primary cause behind food price rise. In particular, using Granger Causality test, Gilbert did not find any significant relation between crude oil price and vegetable oil price. Some previous studies indicated the fuel-food price relation may depend on research methods being used and data frequency. For example, Nazlioglu (2011) used weekly prices and employed a linear Granger causality test only to find no causal relationship between fuel and food prices. However, employing Diks-Panchenko non-linear Granger causality test on the same data, they documented a persistent unidirectional causality from oil prices to corn and soybean prices. Myers et al. (2014) used common-trend common-cycle decomposition method on monthly price data only to find strong conintergration with a distrinct common trend within both fuel prices (crude oil, gasoline, and ethanol) and prices of agricultural commodities (corn and soybean). But, they did not find any long or short-run cross-market conintegration.

This study aims to provide further evidence to answer the following questions: do the fuel and agricultural commodity prices move together in the short and long-run and do these prices cause each other? To do so we revisit the work by Zhang et al. (2010) (ZLCM hereafter). In a widely cited study, ZLCM used three fuel prices and five agricultural commodity prices for the period 1989-2008 to examine these questions. They find a long-run relation between sugar prices and each of the other four agricultural commodity prices used in their study – corn, soybean, wheat and rice; and a long-run relation between the three fuel prices - crude oil, gasoline and ethanol. No long-run relationships were found between the fuel and commodity prices. This absence of fuel-food linkage was consistent with their VECM analysis and Granger causality tests as well.

The only exception was that sugar was having positive influence on oil prices in short run. They conclude that fuel market could be manifesting its impact on agricultural commodities through sugar market indirectly but no direct relation exists between fuel and agricultural markets. The ZLCM study is noteworthy because it takes in to consideration a wide set of fuel and food market prices.

This paper contributes to the literature in following ways. First, we replicate the ZLCM results using a similar set of prices. Then we apply a similar methodology to an extended sample covering the period 1989-2013. This period covers the lead-up to the 2007-08 price spike, the sharp downward movement in the aftermath, as well as the period thereafter. This extended sample is likely to better capture the long-run dynamics of the food and fuel markets, including the affects of 2007-08 biofuel policy changes. Contrary to the ZLCM results, and results in other recent studies (Myers et al., 2014), we find evidence for long-run equilibrium relationship between food and fuel prices. Furthermore, our vector error correction model (VECM) results from the extended sample (1989-2013), indicate a one-way Granger causality from ethanol to corn markets. None of the individual agricultural commodity prices appear to Granger cause ethanol prices, but we find evidence that corn and soybean together have a significant impact on the ethanol market. These results remain consistent across a variety of tests. The findings from this study have major implications for food and fuel policy. They also indicate the importance of correctly specifying the market interactions in multi-market economic models that are currently employed to investigate the food-fuel market behavior.

The rest of this paper is organized as follows. The next section describes the data used in this study and preliminary tests for the price series data. We then discuss the results of the cointegration analysis. Then we present the results from the vector error correction model and Granger causality tests, followed by the concluding remarks in the final section.

2 Data and preliminary statistics

We use monthly price data for five agricultural commodities: corn (P_m), soybean(P_b), sugarcane(P_s), wheat(P_w), and rice(P_r); and three energy prices, ethanol(P_e), gasoline(P_g), and crude oil(P_o) for the period of March 1989 to August 2013. The details of the price series are provided in Table 1. These price data are similar to those used in previous studies (including the ZLCM study).

–Table 1 here–

Summary statistics for prices in levels, log-transformed, and the first difference in logs, are presented in Table 2 for the extended sample (1989-2013) (a similar table for the shorter sample

(March 1989 - July 2008 is presented in the appendix (Table A.1)). All the price series in levels exhibit relatively high degree of variability. This is relatively lower in case of the log-transformed and log-differenced series. Also, the level series display skewness and kurtosis values far greater than their standard values. Figures 1 and 2 plot the movement of corn and ethanol log-prices, showing the period leading up to, and during the price spike. Other agricultural commodities show a roughly similar pattern to that seen in corn and ethanol prices are similarly (approximately) representative of both gasoline and oil prices.

–Table 2 here–

–Figure 1-2 here

We then test for the presence of a unit root on each of the log-transformed price series using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin(KPSS) tests. We employ the ADF test under various specifications including a constant and trend term (CT), a constant but no trend (CNT), and no constant and no trend (NCNT). The results for the extended sample are presented in Table 3. In each case, the optimal lag length was determined using Akaike's Information Criteria (AIC). The ADF and KPSS tests show that all log-transformed price series, in levels, are non-stationary. The log prices, after first-differencing are found to be stationary. The unit root tests for the ZLCM sample period (not presented here) also yield the same results. Our unit root test results are similar to the results reported by ZLCM, including the results for ethanol and gasoline as well.

–Table 3 here–

Further, we perform the Zivot-Andrews (ZA) unit root test to see if the order of integration remains the same for all the price series when we allow for structural breaks in the data. For the shorter sample, results from the ADF and KPSS tests are consistent with the ZA test (results not shown here) and all price series are I(1) when allowing for structural breaks as well. However, in the extended data (1989-2013) ethanol and soybean prices are found to be stationary if we allow for structural break. As seen in Table 4, the test reveals that ethanol and soybean price series have significant breaks at the 5 per cent level at 06/2005 and 08/1998, respectively. However, these breaks are ignored in this analysis because of two reasons. First, breaks occur in more than one variable and in different periods. It is beyond the scope of this paper to model breaks in multivariate case. The important point, however, is that residuals are clean and estimates are robust even when the structural breaks are ignored. As we will see later the results are robust in a sense that results from smaller sample consistently hold in extended sample as well.

–Table 4 here–

3 Cointegration Analysis

Time series variables are said to be cointegrated if they move together in the long run. For example, having fuel and food price series cointegrated implies that there is a long run relationship among them. Among several methods available, the Engle-Granger (EG) two-step and the JohansenâĂŹs procedures are the most common methods of cointegration analysis. ZLCM, in their paper, apply the Johansen's trace test on 32 different combination of fuel and commodity price series. They find two cointegrating vectors among fuel series, and three vectors among agricultural commodities. In particular, the following price series were cointegrated: (1) oil and gasoline, (2) gasoline and ethanol, and (3) soybeans, sugar, and rice (4) wheat, sugar, and rice, (5) sugar, corn, and rice. Significantly, they detect no cointegrating vectors in any combination of the fuel and agricultural commodity prices indicating no long-run relationship between energy and agricultural commodity prices. We employ both the EG two-step procedure and the Johansen's trace test for the 32 different price combinations that ZLCM use in their study. We test separately for the shorter sample (1989-2008) that ZLCM used, as well as for the extended sample (1989-2013).

The EG two-step procedure on the eight price series did not reveal any significant cointegrating relations between the fuel and the agricultural commodity prices (Table 5) [1]. This is consistent with what ZLCM found using Johansen's trace test. Also, similar to their results, we find that the three fuel price pairs – oil-gasoline, oil-ethanol and gasoline-ethanol are cointegrated. This implies that the world oil and gasoline markets are moving together with the world ethanol market. So, movements in one of these markets may explain fluctuations in other market. Among the agricultural commodity pairs, the EG two-step results indicate cointegration of rice-corn and rice-soybean, albiet at the 10 per cent significance level.

–Table 5 here–

[1] Only the significant results from EG tests in bivariate cases is presented here, other suppressed. No fuel-food price combinations were found to be cointegrated

The results of the Johansen's trace test are presented in Table 6. The table shows the number of cointegrating vectors for each of the price combinations. The first column (*Sample* 1) presents the result for the 1989-2008 sample. The second column (*Full Sample*) is for the extended 1989-2013 sample. Finally the third column presents the corresponding cointegrating vector results from ZLCM's study.

The Johansen test is performed in a step-wise process. First, only the three fuel series were tested revealing two long-run equilibrium relations at the 1 per cent level of significance. This finding is consistent across both the short and the extended sample periods, and in concurrence with ZLCM's results as well. The same test was then repeated with the five commodity price series. For the 1989-2008 sample we find the trace test statistic indicates the presence of at most three cointegrating relations at the 5 per cent level. This is similar to what ZLCM find. For the extended sample however, we find that there are at most four cointegrating vectors.

To find whether the fuel and commodity price series are cointegrated, various combinations of the five agricultural commodity series were sequentially added to the three fuel price series in the order in which these combinations appear in Table 6. In so doing, we find some cointegrating relations between fuel and food prices. In particular, when the information set contains all eight prices, we find evidence for at most four cointegrating vectors in both the short and the extended sample. [2] The four cointegrating vectors that are revealed are the following:

$$lnPo = 16.14lnPm - 28.99lnPb - 9.200lnPs + 21.086lnPw \tag{1a}$$

$$lnPg = 11.17lnPm - 23.27lnPb - 7.79lnPs + 19.14lnPw \tag{1b}$$

$$lnPe = 8.47lnPm - 15.54lnPb - 4.49lnPs + 10.98lnPw \tag{1c}$$

$$lnPr = 7.53lnPm - 5.10lnPb - 0.99lnPs + 0.03lnPw \tag{1d}$$

–Table 6 here–

In the above equations, all coefficients, except for the coefficient on corn in (1b) and the coefficients on sugar and wheat in (1d), are significant at the 5 per cent level. The cointegrating vectors (1a-1d) presented above are our preferred choice among numerous possible vectors of different price combinations. The size of coefficients and number of variables in a cointegrating

[2]For this particular combination of prices, ZLCM found five vectors at 10% significance level. The five long-run relations that they find do not reveal any direct price relations between food and fuel prices. In contrast, the four cointegrating vectors that we find for the 1989-2013 sample indicate long-run relationships between fuel and food prices.

vector largely depend on the way variables are ordered and normalized. In fact, with multiple cointegrating vectors there exist several linear combinations of the cointegrating variables which are cointegrated as well Enders (2008). The results above are the cointegrating vectors identified with the Johansen normalization imposed.

Note that corn, soybean, sugar, and wheat are cointegrated with each of the three fuel prices but rice is not. This could be a result of the fact that all these four commodities are directly used to produce biofuel, while rice is not. Overall, these results imply that the high degree of grain price movements in recent years, particularly in 2007-08, could potentially be related to movements in the fuel market and vice versa. While these cointegration results indicate the presence of a long-run relation between fuel and agricultural commodity prices, the question of whether the fuel and food prices cause each other can not be directly answered just by looking at the cointegrating relations.

To investigate this question, we undertake further analysis on a subset of fuel and food prices. The cointegrating relation (1c) presented above indicates that ethanol, corn, soybean and sugar have a significant long-run equilibrium relationship. Also, corn and sugar are the two major input to ethanol production in the US and Brazil, respectively (Monteiro, Altman, and Lahiri, 2012). Considering the fact that they are the top two ethanol producing countries, it is reasonable to hypothesize that corn and sugar prices are influencing or being influenced by ethanol prices. Also soybean is a major competitor of corn for cropland and other inputs, and soybean oil is increasingly being used to produce biofuel in recent years. For these reasons, we focus on ethanol, corn, soybean, and sugar prices in the remaining analysis.

We undertake the Johansen's trace test with the information set consisting of only the four price series: ethanol, corn, soybean, and sugar, over the short (1989-2008) and the extended period (1989-2013)[3]. Similar to the analysis in the previous section, we employ a step-wise procedure to investigate the long-run relationships between these four prices in greater detail. The Johansen test results are presented in Table 7. The test results for the shorter 1989-2008 sample for each price combination are presented in parenthesis. We perform the trace test with three different specifications (Enders, 2008), and choose the appropriate specification based on the parameter estimates of the corresponding VEC model[4] . The first case (Case 1, the first column in Table 7) includes an intercept within the cointegrating vector. Likewise, Case 2 (the second column) incorporates a drift term in the main equation but not in the cointegrating vector and the third case (Case 3) avoids use of any constants or trends in either equation.

[3]EG two-step procedure on the same four variables did not yield any significant cointegrating vector. So, the results are suppressed.

[4]Results of the VEC model for our preferred specification are discussed in the next section

–Table 7 here–

As seen in Table 7, for most price combinations the number of cointegrating vectors are similar across the sample periods and the various specifications. Notably, whenever corn and soybean prices are in the information set, we find that there exists a significant cointegrating relation. The only exception to this pattern are the cointegration vectors found in the case of corn-sugar, and sugar-soybean under the Case 2 specification for the extended sample period. More importantly, whenever ethanol price is considered in the information set only two price combinations are cointegrated: (1)ethanol, corn, and soybean and (2) ethanol, corn, soybean, and sugar. For the set of prices in (2), the test results indicate a long-run relation across all three specifications when the extended sample is considered. For the shorter sample, there is a long-run relation only under the specification in Case 3.

These results indicate that ethanol and the three commodity prices are moving together in the long-run. This finding is consistent with Trujillo-Barrera, Mallory, and Garcia (2012) who find a significant cointegrating relation between corn and ethanol futures prices. Similarly, Chen, Kuo, and Chen (2010) and Mallory, Irwin, and Hayes (2012) also found the long-run relationship between ethanol (fuel) and agricultural commodity (corn) prices.

To examine the short and long-run dynamics in greater detail, we estimate a Vector Error Correction Model (VECM). We concentrate on the full set of prices, that is when all the four price series are considered in Johansen's procedure. Also, we base our VECM analysis on the specification in case 3 in which we find one cointegrating vector. We find that the Case 1 specification is not appropriate as the estimated coefficient for constant term within the cointegrating vector was not significant. We find Case 2 not appropriate for these two reasons: no drift terms in any of the four price equations are significant, and including a drift term outside of the cointegrating vector involves a deterministic trend in data (Enders, 2008). However, such a trend is not visible in underlying data in this case (Figures 1 and 2).

4 VECM and Granger Causality results

A VECM of the following form was specified and estimated:

$$\Delta P_{jt} = \pi_j EC_{t-1} + \sum_{i=1}^{2} \phi_{ij} \Delta Pe_{t-1} + \sum_{i=1}^{2} \lambda_{ij} \Delta Pm_{t-1} + \sum_{i=1}^{2} \gamma_{ij} \Delta Pb_{t-1} + \sum_{i=1}^{2} \delta_{ij} \Delta Ps_{t-1} + \varepsilon_{jt} \qquad (2)$$

where $j = e, m, b, s$ and e_{jt} is white noise for all j. For all $j = e, m, b, s$, π_j is a coefficient on the error correction term which can be partitioned in to adjustment parameters (α_j) and elements of cointegrating vectors (β_j) such that $\pi_j = \alpha_j \beta_j$. If there are more than one cointegrating vectors then α_j and β_j themselves are vectors. If there are t cointegrating vectors out of n variables, then there are nt elements each in the cointegrating vector and the vector of adjustment parameters.

We choose an optimal lag length of three periods for the VEC model based on Final Prediction Error (FPE) and Akaike's Information Criteria (AIC). AIC and FPE are chosen over several other criteria as they tend to select longer lag lengths which may correct the problem of seasonality and autocorrelation. We estimate separate VECMs for the smaller and the extended sample period. The full results of the estimation are presented in the appendix (Tables A2 and A3). Also, we find that the null hypothesis of no autocorrelation was not rejected in the VECM with 3 lags, and the model was stable in the sense that all characteristic roots are well within the unit circle (results not shown here).

The estimated cointegrating vectors, found by imposing the Johansen normalization restriction, for each sample period are:

$$lnP_e = 31.23 lnP_m - 25.04 lnP_b - 4.78 lnP_s \qquad \text{(Sample period: 1989-2008)} \qquad (3a)$$

$$lnP_e = 7.92 lnP_m - 6.25 lnP_b - 1.38 lnP_s \qquad \text{(Sample period: 1989-2013)} \qquad (3b)$$

In each case we find that the parameters of the cointegrating vector are significant at the 5 per cent level. Also these results are consistent across the two time horizons indicating the robustness of the long-run relation among these prices. The estimated α matrix for each sample is:

$$(\hat{\alpha}_e, \hat{\alpha}_m, \hat{\alpha}_b, \hat{\alpha}_s) = (0.000545, 0.00173, -0.00278, 0.00138) \qquad \text{(Sample period:1989-2008)}$$
$$(\hat{\alpha}_e, \hat{\alpha}_m, \hat{\alpha}_b, \hat{\alpha}_s) = (0.000732, 0.00965, -0.00627, 0.00645) \qquad \text{(Sample period:1989-2013)}$$

We then examine the short run dynamics and role of each variable in the adjustment process. Granger causality tests were conducted by testing a joint hypothesis that coefficients of error correction term and lagged differenced variables in the estimated VECM are zero against the alternative that they are not. For instance, consider in the equation below where $\pi_e = \alpha_e \beta_e$:

$$\Delta Pe_t = \pi_e EC_{t-1} + \sum_{i=1}^{2} \phi_{ie} \Delta Pe_{t-1} + \sum_{i=1}^{2} \lambda_{ie} \Delta Pm_{t-1} + \sum_{i=1}^{2} \gamma_{ie} \Delta Pb_{t-1} + \sum_{i=1}^{2} \delta_{ie} \Delta Ps_{t-1} + \varepsilon_{et}$$

A Granger causality test on ethanol and corn prices, for instance, is conducted by testing the null hypothesis of no Granger causality, i.e. $Ho : \hat{\alpha_e} = \hat{\lambda_{1e}} = \hat{\lambda_{2e}} = 0$ against the alternative that at least one of the coefficients are different from zero. Rejecting the null hypothesis indicates that corn prices Granger cause ethanol or the current ethanol prices are affected by lagged corn prices. Results from the Granger causality tests, for each sample period, are presented in Table 8. We test for all possible directions of causality, and present only those results for which the test statistics were found to be significant. The direction of causality tested for is indicated as follows in the table: $x \leftarrow y$ means y Granger causes x.

–Table 8 here–

The Granger causality tests reveal some interesting relationships between the prices. First we consider the bivariate relations by performing the Granger causality test on pairs of prices. We find that corn and soybean Granger cause each other in both sample periods. Although corn and ethanol did not cause each other until 2008, ethanol prices Granger cause corn price volatility when the extended sample is considered. However, the converse was true in case of soybean and ethanol. We find causality from ethanol to soybean in the 1989-2008 sample, but no such relationship in the 1989-2013 sample. These results indicate that increased demand for ethanol in recent years has a larger impact on corn prices than it did before, but the impact on soybean prices is weakening. This makes sense if one think of increased production of corn-ethanol in recent years and decreasing proportion of ethanol from soybean based products. Instead, soybean oil has been heavily used to produce biodiesel.

In addition, when causality from any two price series to a single series is considered, we find that corn and soybean prices do not cause ethanol prices in the 1989-2008. But we find evidence that ethanol and soybean prices Granger cause corn prices, as well as ethanol and corn Granger cause soybean prices for the same sample period. However, in the extended sample we find that any pair prices, out of ethanol, corn, and soybean, Granger cause the third. Therefore, despite the lack of a significant relation between soybean-ethanol in the 1989-2013 sample, there exists a three way relation between soybean, ethanol, and corn. This indicates that ethanol price is likely to be manifesting its effect on soybean prices through the corn market, even if the ethanol-soybean markets have no direct effect on each other. This might be a reflection of the fact that the U.S. is the largest producer of both corn and soybean, and increased demand of corn for ethanol could be impacting the soybean market.

Interestingly, none of the three prices Granger cause sugar either individually or in a combination. However, both corn and soybean are impacted by sugar price individually, as well as by sugar in combination with ethanol prices. [5] Finally, when all four variables are considered, we find that ethanol, corn, and soybean prices, in each case, are Granger caused by the remaining three prices. But a similar result is not found in the case of sugar prices. These results clearly identify that corn and soybean are playing key role both in short and long-run and ethanol could be manifesting its effect through corn. [6]

We also test for weak exogeneity by testing whether the adjustment parameters obtained from VECM are significant. For example, in the VECM model presented above in equation (4) weak exogeneity of ethanol price is tested in the following manner: A null hypothesis of $Ho : \alpha_e = 0$ is tested against the alternative of $\hat{\alpha}_e \neq 0$. Rejecting the null hypothesis implies that ethanol price is weakly exogenous, implying that it does not contribute to the adjustment process. Since there are four variables and one cointegrating vector, there are four parameters to be tested for each sample period. All four hypotheses and associated test results are listed in Table 9. We find that ethanol and sugar prices appear to be weakly exogenous in both the sample periods, as the null hypotheses can not be rejected even at 10% level. Therefore corn and soybean prices are responsible for the adjustment process that brings all the four prices back to their long-run equilibrium whenever there is a deviation. As listed under the VECM results, estimated value of the adjustment coefficient for corn (α_m) is positive, 0.00965, and for soybean (α_b) is negative, -0.00627. Both of these parameters are significant, and the fact that they have opposite signs is consistent with the dynamic relationship between the prices described above.

–Table 9 here–

We also examine the Forecast Error Variance Decomposition(FEVD) as implied by our VEC model estimates. FEVD explains the proportion of the forecast error variation in a variable that

[5] This is consistent with ZLCM's conclusion that sugar is affecting all the agricultural prices. But ZLCM's finding of significant positive causality between sugar and fuel prices is not evident in our analysis of these four prices.

[6] Again, our results can not support ZLCM‘s conclusion that “sugar plays a key role in the fuel-food linkage”. Instead, corn markets appear to be the key element of fuel-food causality.

is attributable to the variable itself, and that due to the remaining variables in the system. FEVD results for four and twelve steps ahead forecast horizon for the 1989-2013 sample are presented in Table 10. [7]

–Table 10 here–

Table 10 shows the proportion of the forecast error variance explained by shocks in own price, and from shocks in the other prices, for each of the variables. For instance, we find that the shocks in ethanol prices account for only 0.5, 0.2, and 2.7 percent of four step ahead variability in corn, soybean and sugar prices respectively. For the 12 steps ahead forecast, the corresponding estimates are 0.9, 0.3 and 2.8 percent respectively. Corn prices are found to explain about 53 and 65 percent of the variation in soybean prices at one quarter and one year ahead forecast horizon respectively. This reiterates the causality results found above that corn price history impacts (Granger causes) present soybean prices. Also consistent with the causality results, movements in ethanol market are not responsible for any variability in agricultural commodity market at both time horizons, a quarter and a year ahead. In fact, ethanol, corn, and sugar are mostly self explanatory accounting for more than 90 per cent of own variances at 4 months and 87 percent of own variances at 12 months forecast horizon respectively. However, fluctuations in soybean prices are explained more by shocks in corn price than through own price behavior. On the other hand, shocks in corn, soybean, and sugar market each explain only 5.7, 0.9, and 1 percent of the variance in ethanol prices respectively. Interestingly, each price series looses its strength of explaining own variability with increasing time horizon. This means ethanol better explains the exogenous shocks in agricultural prices a year ahead than it does now and vice versa.

5 Conclusions

Cointegration test indicated that prices of gasoline, crude oil, and ethanol are cointegrated. Similar results hold for agricultural commodity prices (corn, wheat, soybean, rice, sugar). For the cross market cointegrations, we used the Johansen's trace test and found four different cointegrating vectors between three fuel and five agricultural commodity prices. Contrary to many previous studies that found no evidence of a long-run fuel-food relationship, our results indicate that the three fuel prices do have long-run equilibrium relations with the five commodity prices. We found that each of the energy prices (crude oil, gasoline, and ethanol) are individually cointegrated with

[7] FEVD results for the 1989-2008 sample are not presented here, but the variance decomposition results are similar to the results seen for the 1989-2013 sample.

all of the agricultural commodities, except for rice. In turn, rice is cointegrated with all four agricultural commodity prices. These results appear to be consistent with previous results in the literature (Chen, Kuo, and Chen, 2010; Mitchell, 2008; Abbott, Hurt, and Tyner, 2008). The cointegration results imply that fuel and commodity markets are entangled and we cannot make a straightforward conclusion of which specific prices are moving together without investigating a particular set of cointegrated prices in greater detail.

To disentangle the fuel-food dilemma, we explore ethanol, corn, soybean, and sugar prices system in greater detail. Again, the Johansen's trace test was used to determine the cointegrating relations in each of the sample periods -1989-2008 and 1989-2013. We find evidence that, in both sample periods, the four prices are cointegrated indicating a long-run equilibrium relation between ethanol, corn, soybean, and sugar markets. The VECM and Granger causality tests for the two sample periods indicate that ethanol does not Granger cause corn price in the 1989-2008 sample, but it does when the extended sample is considered. This is consistent with the previous findings of long and short run relations between corn and ethanol, for example (Mallory, Irwin, and Hayes, 2012). Moreover, soybean and corn Granger cause each other in both samples, sugar caused both corn and soybean, but none of them seemed to be responsible for sugar price fluctuations. Interestingly, when corn and soybean are considered together they are able to account for volatility in ethanol market. Similarly, the Granger causality test indicated that soybean and ethanol prices contributed to corn price movements.

Our results support the hypothesis that the recent expansion in fuel demand has affected agricultural commodity markets both in short and long run. Although the short run price relationship is transitory and may not have lasting impact, existence of long-run price relationships between fuel and food prices is worrisome. Eventually, the food price spikes may have a serious impact on the global poor in that most developing countries are net importers of both food grains and petroleum products. If the fuel-food price relationship, as suggested by our results, persists, it may permanently alter agricultural land distribution (acreage shift) and pose serious threat to global food security. However, commodity price formation involves several other factors and conclusion based on price relationships only does not explain it all. From policy standpoint, however, it is important that policy interventions be designed for counteracting both short and long-run price movements. For example, it would be worthwhile for local and national governments to incentivize second generation biofuel production from inedible plants, wastes, and crop residues, conversion of pasture land to crop production, and land conservation practices.

The results suggest that the food-fuel linkage merits much further investigation. This work can be extended in various ways. First, several other cointegrated price combinations can be used to look at how fuel prices other than ethanol are related with agricultural commodity markets. Second, validity of the results can be checked with econometric models other than cointegration and error correction. Also, one could extend this work to examine price volatility spillovers across the food-fuel markets.

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FIGURES

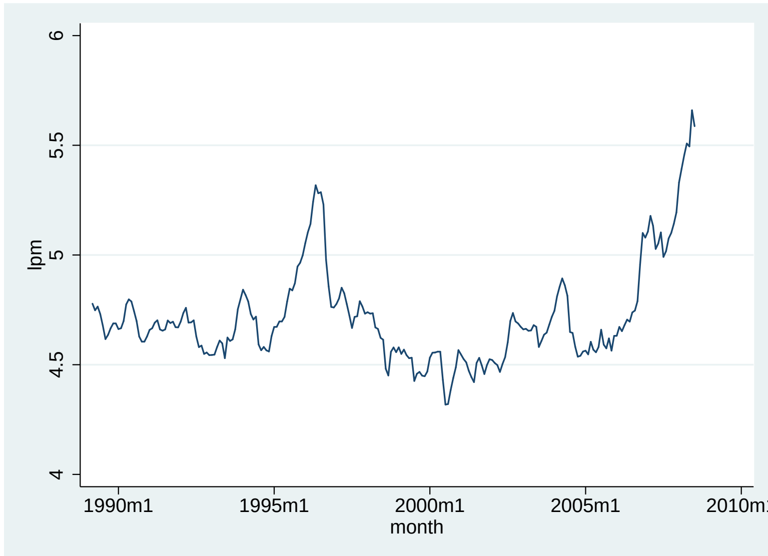

Figure 1: Logged corn price, US$/Mt

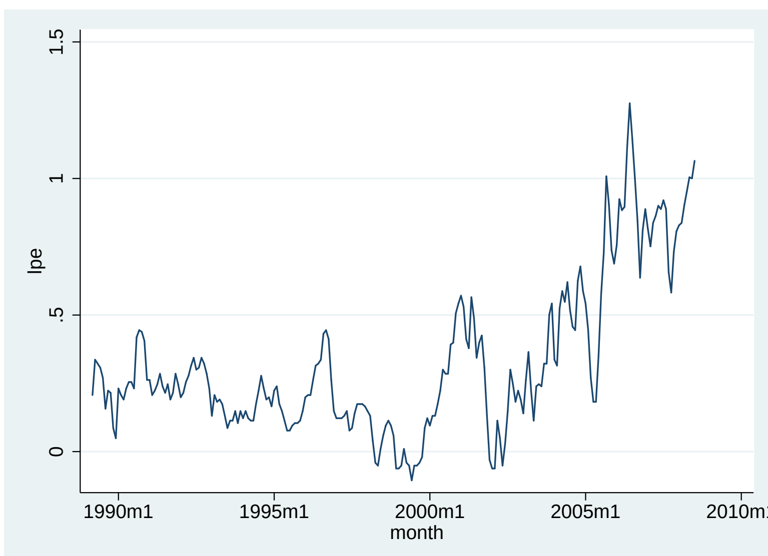

Figure 2: Logged ethanol price, US$/Gal

TABLES

Table 1: Data Description

Commodity Prices	Descriptions	Unit
Ag. Commodities		
Maize	U.S. No.2 Yellow, FOB Gulf of Mexico, U.S. price	US$/MT
Rice	5 percent broken milled white rice, Thailand nominal price quote	US$/MT
Wheat	No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico	US$/MT
Soybeans	U.S. soybeans, Chicago Soybean futures contract (first contract forward) No. 2 yellow and par	US$/MT
Sugar	Free Market, Coffee Sugar and Cocoa Exchange (CSCE) contract no.11 nearest future position	US*c*/lb
Fuels		
Crude-oil	Price index, 2005 = 100, simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh	US$/barrel
Gasoline	U.S. wholesale rack prices, FOB Omaha	*c*/gallon
Ethanol	U.S. wholesale rack prices, FOB Omaha	$/gallon

Table 2: Summary Statistics for 1989-2013 sample

Variable	Mean	Std.dev.	Skewness	Kurtosis	Min.	Max.
Level Price series						
Crude oil	42.68	32.08	1.04	2.72	10.41	132.55
Gasoline	128.97	86.05	0.94	2.48	36	337
Ethanol	1.61	.57	.93	2.75	.90	3.58
Maize	140.97	64.72	1.55	4.23	75.06	332.95
Soybean	280.79	111.77	1.27	3.52	158.31	622.91
Wheat	184.96	71.04	1.28	3.79	102.16	439.72
Sugar	12.17	5.35	1.28	4.25	5.11	29.74
Rice	341.06	149.72	1.45	5.21	162.10	1015.21
Log Price Series(lnP_t)						
Crude Oil	3.49	.69	.47	1.79	2.34	4.88
Gasoline	4.65	.63	.41	1.79	3.58	5.82
Ethanol	.42	.33	.55	2.08	-.10	1.27
Maize	4.86	.38	1.08	3.02	4.32	5.81
Soybean	5.57	.35	.82	2.58	5.06	6.43
Wheat	5.16	.34	.72	2.62	4.62	6.08
Sugar	2.41	.40	.37	2.69	1.63	3.39
Rice	5.75	.38	.61	2.702	5.08	6.92
Log price change series ($ln(Pt/P_{t-1})$)						
Crude oil	.006	.084	-.118	6.564	-.312	.457
Gasoline	.006	.105	-.401	6.002	-.416	.459
Ethanol	.002	.081	.110	4.072	-.266	.280
Maize	.002	.058	-.451	5.876	-.252	.219
Soybean	.002	.057	-.460	5.663	-.256	.165
Wheat	.002	.062	.429	5.077	-.219	.229
Sugar	.001	.076	.085	3.358	-.252	.215
Rice	.002	.064	1.248	11.969	-.281	.412
Observations	294					

Table 3: Unit Root tests for 1989-2008 sample

ADF type	Oil	Gasoline	Ethanol	Corn	Soybean	Wheat	Sugar	Rice
Log Prices$(lnPt)$								
CT	-0.698	-0.891	-1.854	-0.705	-1.371	-1.818	-2.308	-0.216
	(6)	(8)	(7)	(5)	(1)	(1)	(1)	(4)
CNT	0.839	0.376	-1.379	-0.450	-0.848	-1.243	-2.524	-0.680
	(5)	(12)	(3)	(8)	(2)	(2)	(2)	(3)
NCNT	1.763	1.347	-0.399	0.851	0.656	0.473	-0.211	0.680
	(5)	(12)	(3)	(8)	(2)	(2)	(2)	(3)
KPSS	2.73***	1.32***	2.73***	0.47**	0.86***	1.47***	1.21***	0.57**
Diff. Prices$(ln(Pt/P_{t-1})$								
CT	-10.215***	-10.099***	-12.088***	-5.733***	-8.046***	-7.326***	-12.233***	-8.510***
	(1)	(2)	(0)	(7)	(2)	(3)	(0)	(2)
CNT	-10.073***	-3.869***	-9.396***	-5.489***	-9.227***	-9.307***	-9.062***	-8.255***
	(1)	(11)	(2)	(7)	(1)	(1)	(1)	(2)
NCNT	-9.964***	-3.637***	-9.378***	-5.425***	-9.213***	-9.306***	-9.082***	-8.236***
	(1)	(11)	(2)	(7)	(1)	(1)	(1)	(2)
KPSS	0.29	0.27	0.08	0.29	0.44	0.27	0.09	0.30

Note: number in parentheses indicates appropriate lag length where AIC is minimized

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4: Zivot Andrews Test for 1989-2013 sample

Series	Level	Break	First diff.	Break
Gasoline	-4.98	03/1999	-8.90***	02/1999
Crude Oil	-4.73	07/1999	-9.35***	08/2005
Ethanol	-5.12**	06/2005	-9.32***	07/2006
Corn	-4.12	09/1996	-8.36***	07/2010
Soybean	-5.26**	08/1998	-7.87***	07/2008
Wheat	-4.75	05/1997	-13.39***	07/2010
Sugar	-4.20	01/1998	-8.24***	01/2009
Rice	-4.22	02/1999	-11.62***	06/2008

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 5: Engle-Granger Test of Cointegration for 1989-2008 sample

Prices	Oil	Gas	Ethanol	Corn	Soybean	Wheat	Sugar
Gasoline	-6.706***	âĂć	âĂć	âĂć	âĂć	âĂć	âĂć
Ethanol	-3.97***	-4.48***	âĂć	âĂć	âĂć	âĂć	âĂć
Corn	-1.383	-1.92	-2.65	âĂć	âĂć	âĂć	âĂć
Soybean	-1.43	-1.96	-2.59	-2.99	âĂć	âĂć	âĂć
Wheat	-1.46	-2.22	-2.94	-2.99	-2.48	âĂć	âĂć
Sugar	0.53	-0.67	-1.86	-0.43	-0.26	-1.11	âĂć
Rice	-0.85	-1.46	-2.33	-3.21*	-3.12*	-2.89	-2.59

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 6: Johansen Trace Test Results

Price combinations	Cointegrating Vectors			Price combinations	Cointegrating Vectors		
	Sample 1	Full Sample	ZLCM		Sample 1	Full Sample	ZLCM
Fuels only	2***	2***	2***	Fuel , corn , soybean , wheat	3**	3**	3**
Commodities only	3**	4**	3**	Fuel , corn , soybean , sugar	2***	3**	3***
Fuel , corn	2**	2***	2**	Fuel , corn , soybean , rice	3**	2***	3***
Fuel , soybean	2**	2***	2**	Fuel , corn , wheat , sugar	3***	3**	3***
Fuel , wheat	2**	2***	2***	Fuel , corn , wheat , rice	2***	2***	3***
Fuel , sugar	2***	2***	2***	Fuel , corn , sugar , rice	3**	2***	2**
Fuel , rice	2**	2***	2***	Fuel , soybean , wheat , sugar	3***	2***	3***
Fuel , corn , soybean	2***	2***	2**	Fuel , soybean , wheat , rice	4**	4**	2***
Fuel , corn , wheat	2***	3**	3**	Fuel , soybean , sugar , rice	3**	2***	2***
Fuel , corn , sugar	2***	2***	2**	Fuel , wheat , sugar , rice	3**	2***	2***
Fuel , corn , rice	2**	2***	2**	Fuel , corn, soybean , wheat , sugar	3***	3**	4**
Fuel , soybean , wheat	2***	3**	2***	Fuel , corn, soybean , wheat , rice	3**	4**	3**
Fuel , soybean , sugar	2***	2***	2***	Fuel , corn , soybean , sugar , rice	4**	3**	4***
Fuel , soybean , rice	2**	2***	2**	Fuel , corn , wheat , sugar , rice	3***	3**	3**
Fuel , wheat , sugar	2***	2***	2**	Fuel , soybean , wheat , sugar , rice	3***	3**	3***
Fuel , wheat , rice	2**	2***	2***	Fuel , corn , soybean , wheat , sugar , rice	4**	4**	5*
Fuel , sugar , rice	2***	2***	-				

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The tests are based on the specification with an intercept in the cointegrating vector

Table 7: Ethanol vs. Food: Johansen Trace Test Results

Price Combinations	Cointegrating Vectors		
âĂć	Case 1	Case 2	Case 3
Ethanol, corn	0 (0)	0 (0)	0 (0)
Ethanol, soybean	0 (0)	0 (0)	0 (0)
Ethanol,sugar	0 (0)	0 (0)	0 (0)
Corn soybean	1^{**} (1^{**})	1^{**} (1^{**})	1^{**} (1^{**})
Corn, sugar	0 (0)	1^{**} (0)	0 (0)
Soybean, sugar	0 (0)	1^{**} (0)	0 (0)
Ethanol, corn, soybean	1^{**} (1^{**})	1^{**} (1^{**})	1^{**} (1^{**})
Ethanol, corn, sugar	0 (0)	0 (0)	0 (0)
Ethanol, soybean, sugar	0 (0)	0 (0)	0 (0)
Corn, soybean, sugar	1^{***} (1^{**})	2^{**} (1^{**})	1^{***} (1^{***})
Ethanol, corn, soybean, sugar	1^{**} (0)	2^{**} (0)	1^{***} (1^{***})

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Number in parentheses are number of cointegrating vectors in smaller sample, 1989-2008. Case 1 includes intercept term within the cointegration vector. Case 2 is with drift term in the main equation, but not in the cointegrating vector. Case 3 specification has no constants or trend terms in either equation.

Table 8: Granger Causality Results

Direction of causality	1989-2008		1989-2013	
	χ^2	P-value	χ^2	P-value
Ethanol vs. Corn				
Pm←Pe	5.20	0.16	11.21***	0.01
Ethanol vs. Soyeban				
Pb←Pe	9.32**	0.02	4.45	0.22
Corn vs. Soybean				
Pm ←Pb	6.42*	0.09	7.80**	0.05
Pb ←Pm	13.41***	0.004	8.64**	0.03
Corn vs. Sugar				
Pm ←Ps	8.59**	0.03	7.66**	0.05
Soyeban vs. Sugar				
Pb←Ps	19.03***	0.0003	13.06***	0.004
Ethanol, Corn, and Soyeban				
Pe ←Pm Pb	8.10	0.15	12.81**	0.02
Pm ←Pe Pb	9.35*	0.09	12.79**	0.03
Pb ←Pe Pm	15.35***	0.009	9.90*	0.08
Ethanol, Corn, and Sugar				
Pm ←Pe Ps	11.38**	0.04	12.84**	0.02
Ethanol, Soybean, and Sugar				
Pb ←Pe Ps	21.18***	0.001	15.94***	0.007
Corn, Soybean, and Sugar				
Pm ←Pb Ps	11.74**	0.04	8.92	0.11
Pb ←Pm Ps	23.76***	0.00	18.12**	0.003
Ethanol, Corn, Soybean, and Sugar				
Pe ←Pm Pb Ps	10.62	0.16	18.08***	0.01
Pm ←Pe Pb Ps	15.19**	0.03	14.38**	0.04
Pb ←Pe Pm Ps	26.56***	0.00	20.48***	0.005

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Note the left arrow ← indicates direction of causality.

Table 9: Testing for Weak Exogeneity

Ho:	1989 - 2008		1989 - 2013	
âĂć	χ^2	p-value	χ^2	p-value
$\alpha_{eth} = 0$	0.12	0.72	0.02	0.88
$\alpha_{corn} = 0$	2.90^{*}	0.08	6.45^{***}	0.01
$\alpha_{soy} = 0$	7.97^{***}	0.005	2.98^{*}	0.08
$\alpha_{sug} = 0$	0.86	0.35	1.61	0.20

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 10: Forecast Error Variance Decompostion after 4 and 12 months for 1989-2013 sample

Contribution of shocks in:	Forecast error variance decomposition			
âĂć	Ethanol	Corn	Soybean	Sugar
Ethanol	0.92	0.005	0.002	0.027
âĂć	[0.88]	[0.009]	[0.003]	[0.028]
Corn	0.057	0.989	0.535	0.016
âĂć	[0.081]	[0.937]	[0.649]	[0.012]
Soybean	0.009	0.001	0.439	0.043
âĂć	[0.025]	[0.050]	[0.305]	[0.084]
Sugar	0.010	0.005	0.024	0.913
âĂć	[0.016]	[0.003]	[0.043]	[0.875]

number in brackets [.] are FEVD after 12 periods (months)

Table 11: *

Appendix:

Table A1: Summary Statistics for 1989-2008 sample

Variable	Mean	Std.dev.	Skewness	Kurtosis	Min.	Max.
Level Price series						
Crude oil	30.66	22.14	2.19	8.13	10.41	132.55
Gasoline	97.77	61.30	1.781	5.63	36	337
Ethanol	1.45	.482	1.71	5.60	.9	3.58
Maize	115.31	32.68	2.48	10.25	75.06	287.11
Soybean	235.91	65.38	2.43	10.61	158.31	554.15
Wheat	161.52	54.18	2.57	11.01	102.16	439.72
Sugar	10.027	2.755	.343	2.69	5.11	18.05
Rice	282.267	104.40	4.24	27.78	162.1	1015.21
Log price series $(lnPt)$						
Crude oil	3.2	.54	1.036	3.29	2.34	4.89
Gasoline	4.4	.50	.89	2.98	3.58	5.82
Ethanol	.32	.28	1.11	3.57	-.105	1.27
Maize	4.72	.238	1.62	5.91	4.32	5.66
Soybean	5.43	.236	1.34	5.69	5.06	6.32
Wheat	5.04	.27	1.38	5.64	4.63	6.08
Sugar	2.26	.28	-.25	2.43	1.63	2.89
Rice	5.59	.27	1.34	8.53	5.09	6.92
Log price change series $(ln(Pt/P_{t-1})$						
Crude Oil	.008	.081	.388	6.604	-.246	.457
Gasoline	.007	.105	-.098	5.337	-.378	.459
Ethanol	.004	.082	.217	3.8862	-.230	.280
Maize	.003	.053	-.532	5.749	-.252	.167
Soybean	.002	.0531	-.212	5.379	-.249	.165
Wheat	.002	.057	.305	4.493	-.194	.229
Sugar	.0006	.074	.021	3.433	-.252	.215
Rice	.004	.067	1.316	12.029	-.281	.412
Observations	233					

Table 12: *
Table A2: VECM Results for 1989-2008 sample

	D_lpe	D_lpm	D_lpb	D_lps
L._ce1	0.000546	0.00174	-0.00278**	0.00138
	(0.35)	(1.70)	(-2.82)	(0.93)
LD.lpe	0.278***	-0.0633	0.000623	0.0665
	(4.35)	(-1.51)	(0.02)	(1.08)
L2D.lpe	-0.292***	0.0277	-0.0431	-0.00215
	(-4.61)	(0.67)	(-1.07)	(-0.04)
LD.lpm	0.0496	0.306***	0.140	0.0620
	(0.41)	(3.83)	(1.81)	(0.53)
L2D.lpm	0.133	0.125	-0.0993	-0.0598
	(1.06)	(1.52)	(-1.24)	(-0.49)
LD.lpb	0.179	0.0633	0.269***	0.0373
	(1.46)	(0.79)	(3.46)	(0.32)
L2D.lpb	-0.00367	-0.149	-0.0189	0.0279
	(-0.03)	(-1.90)	(-0.25)	(0.24)
LD.lps	0.0259	-0.121*	-0.124**	0.177*
	(0.36)	(-2.56)	(-2.72)	(2.57)
L2D.lps	0.112	0.0398	0.0597	0.0329
	(1.52)	(0.83)	(1.28)	(0.47)
Observations	230			

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: *
Table A3: VECM Results for 1989-2013 sample

	D_lpe	D_lpm	D_lpb	D_lps
L._ce1	0.000733	0.00965*	-0.00627	0.00645
	(0.14)	(2.54)	(-1.73)	(1.27)
LD.lpe	0.253***	-0.0994*	-0.0373	0.0466
	(4.38)	(-2.29)	(-0.90)	(0.80)
L2D.lpe	-0.266***	0.0251	-0.0139	-0.00169
	(-4.67)	(0.59)	(-0.34)	(-0.03)
LD.lpm	0.164	0.303***	0.145*	-0.0373
	(1.64)	(4.03)	(2.02)	(-0.37)
L2D.lpm	0.0691	0.132	-0.00813	-0.00753
	(0.67)	(1.71)	(-0.11)	(-0.07)
LD.lpb	0.0596	0.0232	0.239**	0.0490
	(0.57)	(0.30)	(3.20)	(0.47)
L2D.lpb	0.0907	-0.0960	-0.0145	0.0687
	(0.90)	(-1.27)	(-0.20)	(0.68)
LD.lps	0.0602	-0.0714	-0.122**	0.192**
	(0.98)	(-1.54)	(-2.75)	(3.10)
L2D.lps	0.0867	0.000508	0.0350	0.0179
	(1.38)	(0.01)	(0.78)	(0.28)
Observations	291			

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$