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## Trends, Persistence, and Volatility in Energy Markets

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## ADB Economics Working Paper Series



### Trends, Persistence, and Volatility in Energy Markets

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Atanu Ghoshray

No. 275 | October 2011





**ADB Economics Working Paper Series No. 275**

# **Trends, Persistence, and Volatility in Energy Markets**

**Atanu Ghoshray**

October 2011

Atanu Ghoshray is Senior Lecturer in Economics at the University of Bath. The author would like to thank Maria Socorro Gochoco-Bautista, Shikha Jha, and Emmanuel San Andres for insightful comments on an earlier version of the draft, and Pilipinas Quising for providing the data. The author accepts responsibility for any errors in the paper.

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## **Abstract**

This paper makes a threefold contribution to the underlying dynamic properties and causal effects of energy prices. Firstly, the paper makes a study of the underlying trends to help identify the time series path of nonrenewable energy resources, which can have far reaching consequences for economists and policy makers alike. The analysis is extended to also determine the persistence of oil price shocks. Secondly, the study examines the causal relation between oil prices and the macroeconomy allowing for nonlinear models that have been recently advocated in the literature. Finally, this study describes the relation between oil prices and agricultural commodities. From a policy perspective, these interrelationships of agricultural and oil prices warrant careful consideration in the context of the recent energy crisis, which may very well continue in the future.





# I. Introduction

There exists a significant debate over how the prices of nonrenewable energy resources should be modeled. Despite a large body of empirical work, no pure consensus has been reached as to how to best capture their true dynamics. One objective of this study builds on the existing literature by employing a new data series and recently developed unit root testing procedures. Crude oil, natural gas, and coal prices are examined, aiming to further the knowledge of nonrenewable energy resource time paths in order to inform future research and update the conclusions of past studies, which have not taken into account the potential of structural change. The persistence of shocks and regimes-wise trends is presented, alongside a discussion of the institutional background. While an attempt is made to characterize the nature of the data-generating process, it is not the intention to generate specific models of the underlying mechanics.

## A. Trends in Energy Prices

It is plausible to believe that key macroeconomic variables may inherit the stochastic properties of energy commodities. On the basis of this, Hendry and Juselius (2000) suggest that unit roots should be assumed unless their presence can be soundly rejected. If the series contains a unit root, there are implications for those theories that characterize key macroeconomic variables as mean reverting (Maslyuk and Smyth 2008). As Cochrane (1994) notes, a lack of mean reversion presents a quandary for macroeconomic theory that attempts to model fluctuations as temporary deviations from an underlying trend. Empirical work suggests that oil price rises from 2003 to 2005 have contributed to a 1.5% fall in world economic output (Rogoff 2006). Lee et al. (1995) find a causal relationship of an asymmetric nature between oil price shocks and real gross domestic product (GDP) growth. Cunado and Gracia (2003) analyze the relationship between oil prices, inflation, and economic activity, finding evidence of causality from oil price changes to both of the latter. Carruth et al. (1998) propose a wage model linking input prices, and specifically energy prices, to the equilibrium employment rate. The link between energy prices and their core commodity supply is examined by Kilian (2008), who suggests that oil supply shocks led directly to sharp drops in GDP growth during the 1970s in the United States (US). This touches upon the likelihood of an endogenous system incorporating energy markets and wider macroeconomy, in that there may exist a bidirectional relationship between the two (Bernanke 2004). Rogoff (2006) also heeds caution with relation to security-related disruption. It is clear that understanding the true nature of energy prices should be a key consideration in terms of management of the global economy.

## **B. Oil Price Shocks and the Macroeconomy**

It has generally been argued that oil price shocks are one of the most severe supply-side shocks that can affect macroeconomic variables. From a theoretical point of view there are different reasons why an oil shock can affect macroeconomic variables. Recent studies (Hamilton 2003, Lee et al. 1995, Kilian and Vigfusson 2009, Hamilton 2010) have called for tests that allow a nonlinear specification of the oil price–macroeconomy relationship. There are various channels in which oil price shocks affect the macroeconomy. Firstly, an oil price shock can cause aggregate demand to be lowered since the price rise redistributes income between the net oil import and export countries. Secondly, an oil price increase would mean the productivity of a given amount of capital or labor would decline as firms would buy less energy, leading to a fall in output. This decline in the productivity of capital and labor causes real wages to be lower, leading to further lowering of factor productivity. This can have a nonlinear effect if the oil price shocks affect macroeconomic variables through sectoral reallocations of resources or depressing irreversible investment through their effects on uncertainty (Ferderer 1996). Another objective of this study is to investigate whether there is any evidence of oil price volatility on the macroeconomy of Asian countries.

## **C. Relation between Energy and Agricultural Prices**

In recent years the interest in the relation between energy and agricultural commodity markets has increased significantly given the expansion of bioenergy production. The sharp spike that occurred in food prices over the period 2006–2008 more or less coincided with the relatively sharper price spike that occurred in oil prices. This may lead one to believe that oil market dynamics had a significant impact on agricultural markets (Gilbert 2010). Oil prices are expected to affect agricultural commodity prices through various channels. Baffes (2007) provides reasons as to why this may be the case. An increase in energy prices may affect agricultural prices as the cost of production of agricultural commodities would be expected to increase. Oil enters the production function of agricultural commodities as energy-intensive inputs, such as fertilizer and transportation. Some agricultural commodities such as corn and sugar can be used to produce biofuels; other commodities such as soybeans and palm oil produce biodiesel, which are substitutes for crude oil. Besides, when the price of oil increases, the income of oil-exporting countries may increase, which in turn can lead to an increase in the demand for agricultural commodities. On the other hand, increases in crude oil prices reduce disposable income for countries that import oil. This in turn may slow down industrial production. While one may argue that the lower income may have a negative impact on food consumption, the effect is likely to be small as food is expected to have a low income elasticity. The lower industrial production on the other hand is likely to create a negative impact on the demand for raw materials, exerting a downward pressure on agricultural prices. Overall, a spike in oil prices can increase agricultural prices through increased cost of production, which in turn can be dampened by the fall in global

consumption. On the other hand, Ciaian and Kanacs (2010) argue that since the demand for food is price-inelastic, and supply of land is fixed, the impact of an energy price increase on agricultural production can be substantial. The impact of price changes on agricultural commodity prices raises questions about the linkages between the two markets. The objective of this paper is to estimate the impact of oil prices on agricultural prices.

## II. Literature Review

A body of literature exists examining the stochastic properties of nonrenewable energy commodity price series. These may address the topic exclusively or as a prerequisite to further econometric estimation. A review of the literature is not only informative in terms of the subject matter but also serves as a useful chronology of developments in unit root testing since the seminal work of Dickey and Fuller (1979 and 1981). Although many of the studies below test a range of series, only the finding relating to coal, gas, and oil will draw comment.

### A. Trends and Persistence in Energy Prices

Considering conventional unit root tests with constant coefficients such as those of Dickey and Fuller (1981), Kwiatkowski et al. (1992), and Phillips and Perron (1988). Berck and Roberts (1996) examine eight price series including coal, petroleum, and natural gas using annual data from 1870 to 1991. All series were found to be nonstationary when applying the augmented Dickey–Fuller (ADF) and Schmidt and Phillips (1992) tests. Pindyck (1999) attempts to model nonrenewable energy resources prices using a Kalman filter. Using data similar to that of Berck and Roberts (1996) spanning 1870–1996, Pindyck rejects stationarity for annual averages of producer prices for crude oil, bituminous coal, and natural gas using the ADF test. Krichene (2004) analyzes demand and supply elasticities in oil and gas markets using annual data over the period 1918–1999, and subsamples pre-1973 and post-1973 oil price shocks. Using the ADF test on both real and nominal prices, oil and gas series were found to be nonstationary across the entire sample period. Over the period 1918–1973, oil was found to be stationary and gas nonstationary, with both being deemed stationary over the period 1973–1999.

A more recent body of work exists, characterized by shorter sample periods with higher-frequency data. Coimbra and Estevez (2004) use end of week, month, and quarter observations on Brent crude spot prices in an assessment of the validity of the carry-over and market efficiency assumptions in macroeconomic forecasting. Using the ADF test they are unable to reject nonstationarity for the period January 1989 to December 2003, and for a partial sample from 1992 to 2003, excluding the Gulf War period from January

1992 to December 2003. However, nonstationarity is rejected using daily and monthly observations. Ewing and Harter (2000) examine monthly observations of Brent and Alaskan North Slope crude oil over the period 1974–1996 in order to study intermarket price convergence. Using the Dickey–Fuller and Kwiatkowski et al. (1992) tests, they find both series nonstationary. Sivapulle and Moosa (1999) employ daily data reported by the New York Mercantile Exchange (NYMEX) of Brent and West Texas Intermediate (WTI) crude oil to examine the lead-lag effects in spot and future oil markets. They are unable to reject nonstationarity for both price series using either the Dickey and Fuller and Kwiatkowski et al. tests. Alizadeh and Nomikos (2002) use the same unit root tests on weekly observations of Brent, WTI, and Nigerian Bonny Crude futures in assessing the relationship between prices and tanker freight rates. They find all series to be nonstationary over the period 1993–2001. Serletis and Rangel-Ruiz (2004) perform ADF and PP tests on US Henry Hub, AECO Alberta Natural Gas, and WTI crude oil price series in their study on the interconnectedness of the North American energy markets. Using daily observations over the period 1991–2001, they find all series to be nonstationary.

These studies all find evidence of nonstationarity in oil, gas, and coal prices with only two of the eight studies finding evidence of stationarity. In one case this was achieved using high-frequency data, and in another, by utilizing shorter subsamples to take into account the possibility of a significant event. The latter point turns our attention to studies that have employed tests that allow for either single or multiple structural breaks, i.e., Perron (1989), Lumsdaine and Papell (1997), Zivot and Andrews (1992), Leybourne and McCabe (1994), and Lee and Strazicich (2003 and 2004).

Gulen (1997) examines fragmentation in the world oil markets using monthly price series of 13 branded crude spot and longer-term contract price spanning periods from 8 to 15 years. Using the Perron (1989) test with a break specified *a priori* to take into account the 1986 oil price crash, nonstationarity can be rejected for four of the 15 series using spot prices. Using contract prices, rejection rises to five of the 15 series, two of which can only be rejected at the 5% level. An extension of this study, Gulen (1999) employs weekly data for 1991–1996. The Perron (1989) test is applied with a break in early 1994 and finds nonstationarity cannot be rejected for any series. Ahrens and Sharma (1997), using an extension of the data used by Berck and Roberts (1996), examine 11 commodity price series including coal, petroleum, and natural gas using annual data for 1870–1990. Those series found to be nonstationary under the Leybourne and McCabe (1994) tests are then retested using the Perron (1989) and Ouliaris, Park, and Phillips (1989) tests to allow for the possibility of structural breaks. Ahrens and Sharma (1997) find petroleum stationary under the Ouliaris et al. (1989) test with a quadratic trend and Perron (1989) regardless of specified break date. Natural gas was found to be nonstationary under the Ouliaris et al. (1989) and Perron (1989) tests, with stationarity of petroleum, gas, and coal rejected by the Leybourne and McCabe (1994) test.

Serletis (1992) published the first study on the temporal properties of oil prices with an endogenously specified structural break. Daily observations of crude oil, heating oil, and unleaded gasoline are tested over the sample period 1983–1990. Both ADF and Zivot and Andrews (1992) are applied to the series. When accounting for a single endogenously specified break, the unit root hypothesis is rejected for all three series. Sadorsky (1999) tests for a unit root in the US producer price index of real crude oil prices as part of a study to determine the effect of oil shock on real stock returns. Using monthly data over the period 1947–1996, the series is found to be nonstationary using both Phillips–Perron and Zivot–Andrews tests. Although the use of an aggregated price index may be appropriate in the context of the wider empirical question, it is possible that comovements of components of the index might mask the true nature of the underlying series.

Lee et al. (2006) employ the Lee and Strazicich (2003 and 2004) test with up to two breaks employing the same series as Ahrens and Sharma (1997). Their results largely strengthen those of Ahrens and Sharma (1997). The conclusion of unit roots in the study of Berck and Roberts (1996) is also reversed in the case of gas and coal.<sup>1</sup> Postali and Picchetti (2006) use the Lee–Strazicich test to find evidence of trend stationarity in crude oil prices. Using an annual series of US average crude oil prices from 1861 to 1944 and extended to using price data for Arabian Light and Brent up to 1999, they reject the null of a unit root for the full sample and a range of subsamples spanning over 100 years when allowing trend and intercept breaks. In contrast, Maslyuk and Smyth (2008), employing weekly data spanning 1991–2004, are unable to reject the random walk hypothesis for spot and future prices series of Brent and WTI using the Lee–Strazicich tests.

In summary, the empirical evidence is mixed, but remains weighted in favor of nonstationarity in oil, gas, and coal prices despite an increasing amount of studies finding evidence to the contrary. It is perhaps natural that examination of oil prices has taken a front seat over those of natural gas and coal. Both Pindyck (1999) and Postali and Pichetti (2006) highlight that sample sizes in excess of 100 years using annual data would be required to reject the null when the autoregressive parameter is close to 1. It might be expected that studies employing higher frequency data over a shorter sample period have been less able to reject the null given persistence of shocks to such commodities. However the drive for statistical results should not dominate the choice of appropriate data with respect to the question that is being posed.

## **B. Oil Prices and the Macroeconomy**

Hamilton (1983) provides one of the most influential studies that documents the effect oil prices have on the US macroeconomy. He establishes that a negative and significant relationship exists between oil prices and GDP growth. Further studies by Burbridge

<sup>1</sup> This might explain Berck and Roberts' (1996) finding of inferior predictive performance of ARIMA models over ARMA models despite the later representing a misspecification in the context of their results.

and Harrison (1984) and Gisser and Goodwin (1986) provided support to this finding. While Gisser and Goodwin (1986) reinforced the findings of Hamilton (1983), Burbridge and Harrison (1984) obtain mixed results using data from Japan, the UK, and the US. However, in general, the results of Burbridge and Harrison (1984) added support to the findings of Hamilton (1983). Several different mechanisms were proposed to explain the inverse relationship between oil price movements and aggregate economic activity in the US. One such mechanism is through the supply side, in which oil price increases lead to reduced availability of input in the production process. As a result the productivity of a given amount of labor and capital declines, leading to a potential fall in output. Other explanations that have been offered are income transfers from oil-importing to oil-exporting countries, monetary policy, and a real balance effect. However, by the mid-1980s, the estimated linear relationship that was documented by the above studies started to break down. The declines in oil prices that occurred over the second half of the 1980s seemed to have a smaller effect on the macroeconomy than expected. Studies made by Mork (1989), Mory (1993), and Ferderer (1996) found evidence that the link between oil prices and the macroeconomy were characterized by an asymmetric rather than linear relationship.

The study by Mork (1989) revealed the apparent breakdown in the relationship between oil and the macroeconomy. When Mork did not find the alleged significant relationship, he divided oil price changes into negative and positive changes and reestablished the link between oil price changes and GDP. The motivation for dividing the oil price changes into positive and negative changes was that while price increases and decreases have opposite and symmetric effects on the production possibility frontier, any oil price shock causes a certain costly resource allocation. Mork argues that these two effects work in opposite directions and could offset each other when prices of oil fell, but when prices increased, the two effects worked in the same direction. This asymmetric effect of oil price shocks seemed to provide a better statistical fit after the mid-1980s and provided avenues for further empirical studies. Mory (1993) followed the study by Mork (1989) and found positive oil price shocks to have an impact on the macroeconomy but negative shocks to have no impact. Lee et al. (1995) also found asymmetry between positive and negative shocks. A further study by Ferderer (1996) added further support to the asymmetric relationship between oil prices and industrial production. The upshot of these studies was that rising oil prices appear to lower aggregate economic activity more than falling prices raise it.

The breakdown of the linear symmetric relationship proposed by Hamilton (1983) is a result that does not capture the transmission channel where oil shocks exert an asymmetric influence on economic activity. For example, an oil price decrease may actually retard economic growth (Guo and Kliesen 2005). An oil price shock increases the uncertainty about future oil prices causing delays in investment (Bernanke 1983). Besides, an oil price shock induces allocation of resources from more adversely influenced sectors to less adversely influenced sectors that can prove to be costly

(Hamilton 1983). Thus, while an increase in oil prices have a negative influence on the macroeconomy, a decrease in oil prices is ambiguous (Guo and Kliesen 2005). Most oil price changes were positive prior to 1986, whereas after 1986 oil prices have experienced sharp changes in both directions. Various studies (Lee et al. 1995, Hamilton 1996) conclude that linear specification due to Hamilton (1983) is a good approximation of the data before 1986, but not after 1986 due to the nonlinearity induced by large negative changes in oil prices.

Recognizing the asymmetric effect, a series of specifications of oil price shocks was investigated. These price shocks comprised specifications that distinguished oil price increases from decreases, relative magnitudes of price increases, and unanticipated shocks at different points of time attributable to oil price volatility. Lee et al. (1995) propose a function described as scaled oil price increases, where they focus on the concept of volatility by suggesting that an oil price shock is likely to have a greater impact on the macroeconomy when oil prices have been relatively tranquil compared to the impact that an oil price shock would have on the macroeconomy when oil prices have been experiencing volatility. Hamilton (1996 and 2003) propose a nonlinear function of price changes. Hamilton (2003) defines an oil price shock to be equal to the difference between the current oil price and the maximum oil price in the past three years. Using this measure, Hamilton (2003) finds that the proposed measure of the oil price shock exerts a significant negative influence on GDP growth. Kilian and Vigfusson (2009) explore nonlinear functions of oil price shocks in the spirit of Mork (1989) where they explore the hypothesis that oil price increases have different effects on the economy from oil price decreases. Kilian and Vigfusson (2009) find little evidence of nonlinearity in the relation between oil prices and GDP growth in the US. However, in a recent paper, Hamilton (2010) reinforces the view that oil prices and GDP growth are nonlinearly related and provides possible explanations for the results obtained by Kilian and Vigfusson (2009).

### **C. Energy Prices and Agricultural Commodities**

There have been a number of recent studies that have attempted to investigate the potential contribution of biofuels to food price increases. Mitchell (2008) argues that biofuels played an important role behind the surge in food prices. The most important reason for the food price increase was the large increase in biofuels production from grains. Without these increases in biofuel production, global corn stocks would not have declined and a price spike would not have occurred. This view is backed by separate studies made by the Organisation for Economic Co-operation and Development (OECD 2009) and the Food and Agriculture Organization (FAO 2008). However, the role played by biofuels has been undermined by the US Department of Agriculture (USDA) (Reuters 2008) and the European Commission (European Commission 2008). The USDA argues that oil price increases are not a major factor behind the increase in agricultural commodity prices. The USDA states that only 3% of the 40% increase in food prices can



be linked to the production of biofuel (Reuters 2008). The European Commission echoes the view of the USDA. According to the European Commission, the European Union uses less than 1% of its cereal production toward the production of ethanol. Thus, their conclusion is that biofuel production is unlikely to affect agricultural markets (European Commission 2008).

Do energy markets have a relation on agricultural commodity prices? The exact relation between the two is not yet fully understood (IMF 2008, von Braun 2008, World Bank 2008). Theoretical models have been developed to understand the relation between energy and agricultural markets. These studies are very new and only a handful of models have been proposed so far. Gardner (2007) constructs a model that allows for vertical integration of ethanol and corn markets to understand the welfare effects of corn and ethanol subsidies. However, Ciaian and Kancs (2010) point out a major shortcoming of his model stating that the ethanol market cannot be modeled separately from the fuel market as price transmission between fuel and corn depends crucially on the assumption about the cross-price elasticity between fuel and ethanol. de Gorter and Just (2008 and 2009) build upon the Gardner (2007) model and analyze the price transmission between fuel and corn. In their model the price transmission from fuel to corn is established through the demand for corn in ethanol production. They argue that the price transmission is likely to occur when price of fuel is sufficiently higher and/or corn price is considerably lower so that the production of biofuel is profitable rather than allowing corn to be produced for food or feed. In another study, Saitone et al. (2008) examine how market power in the corn market affects the impact of the ethanol subsidy. Their study shows that price transmission between ethanol and corn can be suppressed if market power exists in the upstream input market and downstream in the corn processing sector. Ciaian and Kancs (2010) extend the work of Gardner (2007) and de Gorter and Just (2008 and 2009) by taking into account cross-commodity effects. This is made possible by allowing for two agricultural commodities in the model, one commodity being suitable for biofuel production and the other unsuitable. Further, they explicitly include the agricultural input market for price transmission to take place.

A number of recent empirical studies have been made to study the impact of energy prices on agricultural commodity prices. Yu et al. (2006) study the causal link between crude oil and vegetable oil prices, which can be used for producing biodiesel. In light of the recent oil price shock and growing environmental concerns, Yu et al. (2006) emphasize the importance of biodiesel as an important alternative fuel. Biodiesel is the mono alky esters made from soybean or palm oil. They argue that the rise in oil prices stimulated the demand for biodiesel, which in turn had an impact on vegetable oils. Their paper makes use of time-series methods and directed acyclic graphs to four major traded edible oils prices, including soybean, sunflower, rapeseed, and palm oils, along with one weighted average world crude oil price. The empirical results find a single, long-run cointegration relationship among those five oil prices. They do not find that shocks in crude oil prices have a significant influence on the variation of vegetable oil prices. Yu et

al. (2006) argue that maybe the influence of crude oil price on vegetable oils will grow if oil prices remain persistently high and vegetable oils become an increasing source of biodiesel.

Campiche et al. (2007) examine whether a long-run relationship holds between crude oil prices and various agricultural commodities, such as corn, sorghum, sugar, soybeans, soybean oil, and palm oil prices during the 2003–2007 time period. The objective of their study was to determine whether or not there is an increasing tendency for price changes in oil to track price changes in selected agricultural commodities. The degree of comovement between crude oil prices and the prices of corn, sorghum, soybeans, and soybean oil was expected to be higher in 2006–2007 than in 2003–2005. Even though both ethanol and biodiesel were produced prior to 2006, Campiche et al. (2007) made a priori expectations that agricultural feedstock prices did not become significantly associated with crude oil prices until the 2006–2007 time period. They argue that during the 2005–2006 time period, crude oil prices increased, significantly allowing biofuels to be economic alternatives to fossil fuels. Therefore, the degree of comovement was expected to be higher for the 2006–2007 time period than for the 2003–2005 time period. Campiche et al. (2007) employ the multivariate cointegration test due to Johansen (1988) and find no cointegrating relationships during the 2003–2005 time period. However, when considering the 2006–2007 time period, they find that corn prices and soybean prices were cointegrated with crude oil prices.

Hameed and Arshad (2008) make use of cointegration methods to test whether increasing oil prices are to be taken as one of the factors that may contribute to the rise in agricultural commodity prices. Their study investigates the long-run relationship between the prices of oil and vegetable oil. They choose palm, soybean, sunflower and rapeseed oil prices to represent those vegetable oils that may be used for the production of biodiesel. They employ the bivariate cointegration approach using Engle and Granger (1987) two-stage estimation procedure. Their results provide a strong evidence of long-run equilibrium relation between the prices of oil and vegetable oils. The estimates of the error correction models reveal a unidirectional long-run causality flowing from crude oil to each of the vegetable oil prices chosen in their under study.

Harri et al. (2009) employ a multivariate cointegration approach to analyze the relationship between oil, exchange rates, and agricultural commodity prices. They argue that energy impacts agricultural commodity production through the use of energy-derived inputs that are increasingly being employed in agriculture. On the other hand, agricultural commodities are used to produce energy, allowing for price interdependencies in both energy and agricultural markets. Harri et al. find that corn, cotton, and soybeans form a long-run relationship with oil.

Tyner (2009) notes that since 2006, the ethanol market has established a link between crude oil and corn prices that did not exist historically. He finds that the correlation

between annual crude oil and corn prices was negative ( $-0.26$ ) in 1988–2005; in contrast, it reached a value of 0.80 during 2006–2008. Du et al. (2009) investigate the spillover of crude oil price volatility to agricultural markets (specifically corn and wheat). They find that the spillover effects are not statistically significant from zero over the period from November 1998 to October 2006. However, for the period October 2006 to January 2009, the results indicate significant volatility spillover from the crude oil market to the corn market. Based on these recent studies, it is clear that the strong link between crude oil prices and corn prices is a recent phenomenon; hence, econometric investigations of price transmission with annual or monthly data would result in small samples that would not provide reliable estimates (Hertel and Beckman 2010).

### III. Econometric Methodology

In order to ensure a full account of the temporal properties of the series in question a battery of unit root tests are conducted. These tests are presented in such a way as to assist the reader to draw equivalence with the empirical findings presented in the literature review. It begins with a brief overview of conventional tests that do not take into account structural breaks and then move on to a fuller examination of those that do.

#### A. Measuring Trends

The Dickey–Fuller test is based on the hypothesis that the series follows a unit root process against the alternative of a stationary process. However the inclusion of the deterministic terms imply a loss of power, which biases the test in favor of the null that the series contains a unit root. The Phillips and Perron (1988) test specifies a modified ADF style test in which the error terms are not required to satisfy the classical assumptions. The correction is made in the test statistics themselves and, as such, the test has advantages over the ADF test that it does not rely upon lag length specifications and is robust to general heteroskedasticity. Both the ADF and PP test suffer from size distortions in the presence of a large negative moving average component and low power with a near unit root process. Elliot, Rothenberg, and Stock (1996) and Ng and Perron (2001) offer alternative tests that improve finite sample performance in comparison to their respective counterparts. Elliot, Rothenberg, and Stock (1996) derive tests based on a feasible point optimal test methodology and a process of generalized least squares detrending to derive an efficient ADF  $t$ -statistic. Ng and Perron (2001) use modified information criteria and a modification of the Phillips–Perron test, which displays superior size and power properties.

Perron (1989) showed that if a structural break is ignored the power of the unit root test is lowered. His paper however, was criticized for the fact that he assumed that the date

of the structural break is known. Zivot and Andrews (1992) developed a unit root test that allowed for the break to be unknown and determined endogenously from the data. Since the unit root test suffers from low power by ignoring a single structural break, it was argued by Lumsdaine and Papell (1997) that the loss of power is greater if there are two structural breaks. They formulated a method that is an extension of Zivot–Andrews, which tests for a unit root under the null hypothesis against the alternative of two structural breaks determined endogenously from the data.

When considering unit root tests that allow for structural breaks, there may be a case of size distortion that leads to spurious rejection of the null hypothesis of a unit root when the actual time series process contains a unit root with a structural break (Nunes et al. 1997). The test developed by Lumsdaine and Papell (1997) suffer from the same size distortion problems and consequent spurious rejection of the null hypothesis (Lee and Strazicich 2003). The minimum two-break Lagrange multiplier test developed by Lee and Strazicich (2003) allows for structural break under the null hypothesis and does not suffer from the spurious rejection of the null hypothesis. Besides, the minimum LM test possesses greater power than the Lumsdaine–Papell test. The upshot is that under the LM test setting, rejection of the null hypothesis can be considered as genuine evidence of stationarity. A further disadvantage of the Zivot–Andrews test and the Lumsdaine–Papell test is that the tests tend to estimate the breakpoint incorrectly where bias in estimating the unit root test is the greatest (Lee et al. 2006). This leads to size distortion, which increases with the magnitude of the break. This size distortion does not occur when using the LM test as it employs a different detrending method (Lee et al. 2006).

The energy price series under consideration may be trend stationary. If the underlying commodity price series were to be trend stationary, then to test the nature of the underlying trends, one typically estimates the following log-linear time trend model:

$$P_t = \alpha + \beta t + \varepsilon_t \quad (1)$$

where  $P_t$  is the log energy price, and the errors denoted by  $\varepsilon_t$  is a process integrated of order zero, or  $I(0)$  and is assumed to follow an autoregressive moving average process to allow for cyclical fluctuations of prices around their long-run trend. If the price series  $P_t$  were to contain a unit root, or in other words were to be integrated of order one, i.e.,  $I(1)$ , then estimating the trend stationary model given by (1) will generate spurious estimates of the trend, by concluding that the trend is significant when it is actually not. A negative estimate of  $\beta$  that is statistically significant implies that the underlying price series follows a negative trend. An appropriate strategy for estimating the trend is to adopt the following difference stationary model:

$$\Delta P_t = \beta + \eta_t \quad (2)$$

where  $\eta_t$  is a stationary error process. In the difference stationary model, if a negative estimate of  $\beta$  is statistically significant, it can be concluded that the underlying price series follows a negative trend. An important point to note is that if the price series is a trend stationary process but is treated as a difference stationary process, then tests based on equation (2) are inefficient, lacking power relative to those based on equation (1).

If structural break(s) are ignored the power of the unit root test is lowered. This paper considers the unit root test subject to two endogenously determined structural breaks (Lee and Strazicich 2003) and a single structural break (Lee and Strazicich 2004). The Lee–Strazicich unit root test determines the break points endogenously by utilizing a grid search (details of the test can be found in the Appendix).

If up to two structural breaks in any price series can be identified, the next step is to determine whether the sign of the trend is negative or positive and whether it is significant or not. Besides, it would be of interest to observe whether the trend changes signs in the different regimes that are outlined by the structural breaks. In order to determine how the trend has shifted over time, the data generating process is modeled in the manner conducted by Kellard and Wohar (2006). For the trend-stationary process the logarithm of the commodity price series is regressed against a constant and a time trend and one or two intercept and slope dummy variables corresponding to the results of the structural break tests. The error structure is modeled as an ARMA(p,q) process (details provided in the Appendix).

Following Kellard and Wohar (2006) and Ghoshray and Johnson (2010), the trend function for price is reparameterized to facilitate the estimation of the trend coefficient for up to three different regimes. For the three-regime model,  $P_t^*$  is defined as:

$$P_t^* = \begin{cases} P_t & \text{if } 1 \leq t \leq TB1 \\ P_t - \delta_1(TB1 - TB0) & \text{if } TB1 + 1 \leq t \leq TB2 \\ P_t - \delta_1(TB1 - TB0) - \delta_3(TB2 - TB1) & \text{if } t > TB2 \end{cases} \quad (3)$$

In the model in equation (3),  $\delta_1$  and  $\delta_3$  denote the slope coefficients of price in different regimes.  $TB0$  denotes the starting point of the data, whereas  $TB1$  and  $TB2$  denote the break points selected by the Lee–Strazicich test. The estimation was conducted by exact maximum likelihood and the ARMA order (p,q) was selected through the SBC allowing all possible models with  $p + q \leq 6$ .

## B. Measuring Persistence

To provide an alternative assessment of the autoregressive process of the series, the Andrews (1993) exactly median unbiased estimator is used. This allows examination of the persistence of shock to the series via a number of summary measures of persistence. Given the issues of low power of unit roots test in the near unit root case, one cannot imply acceptance of the null by an inability to reject it, thus exact point estimators allow an apportioning of the nonrejection as being due to either statistical uncertainty or the null in fact being true. In such case, least square estimators suffer from significant downward median-bias when an intercept and trend are present. Thus by calculating an exact least squares bias correction one can pick an estimate of the autoregressive parameter that would result in the LSE having a median of the estimated least squares parameter, and as such be exactly median unbiased, as in the case of an AR(1) process.<sup>2</sup>

In econometric terms this would imply that prices can be described by a stationary autoregressive I(0) model or a nonstationary unit root I(1) model. While a lot of emphasis is placed on unit root tests, there exists a problem of bias. Standard estimators such as least squares are significantly downward biased especially when the autoregressive coefficient is close to unity. To deal with this problem, Andrews (1993) devised an approach, the median unbiased model, which determines whether an autoregressive (AR) or unit root (UR) model best fits the data. The model has the advantage of correcting any bias in the autoregressive parameter in the AR model when estimated by least squares. To derive persistence measures such as half lives at different regimes, the median unbiased estimates of the autoregressive parameter is calculated using Hansen's (1999) grid bootstrap method, which is an improvement over the Andrews (1993) method.

Three measures are employed to measure the persistence of shocks to the agents' expectations. These measures include the impulse response functions (IRF), the cumulative impulse response function (CIR), and the half life of a unit shock (HLS). These measures are defined as follows:

$$\begin{aligned} \text{IRF}[t] &= \phi^t \quad \forall \quad t = 0, 1, 2, \dots \\ \text{CIR} &= \sum_{t=0}^{\infty} \text{IRF}[t] = [1 - \phi]^{-1} \\ \text{HLS} &= \text{ABS} \frac{\log[0.5]}{\log \phi} \end{aligned} \tag{4}$$

where  $\phi$  denotes the estimate of the autoregressive coefficient. The relative magnitude of the IRF across different time horizons gives an indication of the extent of the persistence

<sup>2</sup> Andrews and Chen (1994) consider a AR(p) process to specify an approximately median-unbiased estimator for the more general case.

of shocks to the agents' expectations. In the case where the expectations are found to be stationary  $I(0)$ , the IRF dies out with time, and if the expectations contain a unit root then the IRF does not die out. The CIR gives the sum of the IRF over infinite time horizons and the HLS indicates the time taken for the IRF reaches half its original magnitude.

### C. Estimating Oil Price Volatility on the Macroeconomy

To assess whether there is any evidence of oil price volatility on the macroeconomy of Asian countries, Granger causality tests are carried out in the spirit of Mork (1989), Lee et al. (1995), Kilian and Vigfusson (2009), and Hamilton (2003 and 2010). This involves estimating the following model:

$$\Delta Y_t = \alpha + \sum_{i=1}^p \psi_i \Delta Y_{t-i} + \sum_{i=1}^p \phi_i \Delta \tilde{P}_{t-i} + \varepsilon_t \quad (5)$$

where  $Y_t$  denotes the macroeconomic variable of interest, being industrial production or inflation. Mork (1989) and Kilian and Vigfusson (2009) propose the nonlinear function of oil prices to be given by the following function:  $\tilde{P}_t = \max\{0, P_t\}$ . In this case, oil price increases are treated in a different way to oil price decreases. Hamilton (2003 and 2010) propose that the nonlinearities can be captured with a specification in which what matters is whether oil prices reach a 3-year high, which can be given by the following function:

$$\tilde{P}_t = \max\{0, P_t - \max(P_{t-1}, \dots, P_{t-36})\}.$$

Hamilton argues that to measure how unsettling oil price changes are for spending decisions made by households, it is more appropriate to compare the current price of oil with the most recent years rather than the previous month. Under this specification, if oil prices have been lower than they have been at some point during the most recent years, then no oil price shock would have occurred. A further approach is due to Lee et al. (1995) who propose an oil shock variable based on the ratio of oil shocks to their conditional volatility, which can be given by the following function:

$$\tilde{P}_t = \max\left[0, \hat{e}_t / \sqrt{\hat{h}_t}\right], \text{ where} \quad (6)$$

$$\Delta P_t = \eta + \sum_{i=1}^k \eta_i \Delta P_{t-i} + e_t, \quad e_t | I_{t-1} \sim N(0, h_t)$$

$$h_t = \pi_0 + \pi_1 e_{t-1}^2 + \pi_2 h_{t-1} \quad (7)$$

Lee et al. (1995) argue that an oil price shock is likely to have a greater impact on industrial production in an environment when oil prices have been stable than in an environment where changes in oil prices have been erratic. Their reasoning is that price changes in a volatile environment are likely to be reversed. For example, a significant relationship between  $\tilde{P}_t$  and industrial production implies that a oil price shock will cause a decrease in industrial production, while in a period of high volatility a price increase is less likely to cause a decrease in industrial production. The causation can be tested by the joint hypothesis  $H_0 : (\phi_i = 0)$  for all  $i$  using an F-test.

## D. Estimating the Relationship between Oil Prices and Agricultural Commodity Prices

Two methods of estimating the long-run relationship between oil prices and agricultural commodity prices are employed. One of the methods is the linear cointegration approach of Johansen (1988) that allows to test for cointegration within a vector autoregressive (VAR) framework. The other method developed by Hansen and Seo (2002) is an extension of the vector error correction model (VECM) to allow for a nonlinear threshold cointegration approach. A brief description of the two methods is provided below (more details can be found in the Appendix).

The Johansen (1998) method involves estimating the following VECM:

$$\Delta P_t = \mu + \Pi P_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_{t-i} + \varepsilon_t \quad (8)$$

where  $\Delta P_t$  is a vector of first differenced price series. This way of specifying the system contains information on both the short- and long-run adjustment to changes in  $P_t$  via the estimates of  $\Gamma_i$  (short-run coefficient matrix) and  $\Pi$  (long-run matrix), respectively.

Hansen and Seo (2002) formulate a two-regime threshold VECM as follows:

$$\Delta P_t = \begin{cases} \Pi_1 Z_{t-1}(\beta) + \varepsilon_t & \text{if } \omega_{t-1}(\beta) \leq \gamma \\ \Pi_2 Z_{t-1}(\beta) + \varepsilon_t & \text{if } \omega_{t-1}(\beta) > \gamma \end{cases} \quad (9)$$

where  $\omega_{t-1}$  is the  $I(0)$  error correction term (equivalent to the  $\beta' P_{t-1}$  term in the Johansen model described above),  $\Pi_1$  and  $\Pi_2$  are the coefficient matrices that describe the dynamics in the two regimes, and  $\gamma$  denotes the threshold parameter.

## IV. Data and Institutional Background

The price series examined are oil, gas, and coal using monthly observations over the period January 1975 to December 2009 with gas beginning in January 1976, coal starting in February 1979, and oil spanning the entire sample.<sup>3</sup> These series build on previous studies by extending the sample period for those studies that have employed higher than annual frequency data. All prices are deflated to June 1985 prices using the US producer price index provided by the US Bureau of Labor Statistics and expressed as natural logs. The use of monthly data, presumably limited somewhat by the availability of a sufficient number of observations until this time has been limited. It is noted that a structural break is likely to have occurred due to the energy crisis of 1973. Thus a time span of 1975 to 2009 allows an examination of the evolution of energy prices and the period of volatility that followed the 1973 energy crisis.

<sup>3</sup> Further details of all the data used in this study can be found in the Appendix.



## A. Data Selection

The data source for Brent, WTI, Dubai, and Australian thermal coal is the International Financial Statistics Database published by the International Monetary Fund. Gas is taken from the Energy Information Administration. Brent, Dubai, and WTI are free on board price measured in US dollars per barrel, gas the US wellhead price in US dollars per thousand cubic feet, and coal in US dollars per metric ton.

Brent is a high API gravity (light) sweet crude, meaning its recoverable hydrocarbon content is higher, making it ideal for the production of gasoline, liquefied petroleum gas, and middle distillates such as jet fuel and kerosene. Typically Brent is refined and consumed in Northwestern Europe. Similar to Brent, WTI is a high API gravity sweet crude and is typically refined for use in the midwestern part of the US for national consumption. Brent and WTI represent benchmarks for pricing of crudes in Africa, the Americas, and Europe. Given the availability of data and the level of interest in crude oil there seemed no reason to exclude either of these benchmark crudes. The US wellhead price of gas is the value of all transactions relating to natural gas liquids as it leaves the well. Since no real-time wellhead price for natural gas is available, prices from Henry Hub, the largest trading point for gas in the US, are taken as a surrogate for wellhead prices, which has been shown to largely define North American natural gas prices (Serletis and Rangel-Ruiz 2004). Australia was estimated to be the world's fourth largest coal producer and the world's largest coal exporter, exporting over 75% of its total production (World Coal Institute 2008). Australian bituminous thermal coal is typically used in power generation. Australian thermal coal is largely traded in the Pacific market, primarily exporting to Japan; the Republic of Korea; and Taipei, China, with the Southeast Asian market accounting for 47% of world consumption in 1997 growing to 60% in 2007, and the Pacific market accounting for 57% worldwide of seaborne trade in thermal coal (BP p.l.c. 2008).

## B. Descriptive Statistics

An analysis of the descriptive statistics of the energy prices used in this study can be found in Table 1. From Table 1, the average prices are generally close for the three major oil prices. The coefficient of variation suggests that there is substantial month-to-month variation in all of the prices, with coal showing a relatively lower variation. However, apart from coal all the other energy prices show that the variation appears to be consistent, ranging between 67.2%–71.3%. Finally, the last two columns measure skewness and kurtosis. All energy prices demonstrate positive skewness, implying that there are a few downward spikes to match the upward spikes. However, the upward spikes do not seem to be significantly more pronounced than the downward spikes given the estimates of skewness. All wheat prices display significant kurtosis, implying that the distribution of wheat prices have tails that are thicker than that of the normal distribution. Overall, all five price series display high variability and significant positive skewness and negative excess kurtosis giving each series fat tails and a long right tail. This suggests the commodities exhibit high price volatility that is downwardly rigid.

**Table 1: Descriptive Statistics**

	Mean	Coefficient of Variation	Skewness	Kurtosis
WTI	30.01	148.63	2.29	6.32
Brent	29.29	145.28	2.25	6.14
Dubai	27.26	140.15	2.30	6.46
Coal	42.79	193.44	3.49	15.73
Gas	2.82	145.36	1.68	2.76

Source: Author's calculations.

### C. Price Series History, Structural Breaks, and Trends

This section provides a brief discussion of the major events that are likely to have impacted on the world energy markets. There are three key points to note. First is the Iranian revolution, which caused a sharp price rise in the latter part of 1979. Second, following a number of warnings to OPEC and non-OPEC producers to cut production in the face of a continuing loss of market share due to quota violations, Saudi Arabia abandoned its position as swing producer, causing an oil price crash at the beginning of 1986. Finally, the late 1990s saw a combination of the East Asian economic crisis and a series of large output cuts by OPEC and non-OPEC countries, causing a sharp decline in oil and gas prices followed by a sharp increase throughout the 2000s, interrupted only by the 2001 9/11 terrorist attacks on the US. This chronology by no means covers all the events that characterize the sample, but highlights the areas likely to be of greatest significance to this paper with respect to long-term structural change.

Innovational outliers suggest that until the late 1980s, the oil series appear far more responsive to shocks relative to gas. After the oil price crash of 1986 gas prices became increasingly volatile; following the Natural Gas Wellhead Decontrol Act of 1989 they become more responsive to shocks than oil prices. Both gas and oil series appear to follow a similar general trend, rising in the later part of the 1970s and then falling throughout the early 1980s, then appearing to lose any trend until the mid-1990s to late 1990s when prices began to rise again. Innovational outliers in gas prices tend to lag those in oil until the mid-1980s; this lag decreases later in the sample. Maslyuk and Smyth (2008) note this increased speed in reaction to news and expected news to be consistent with the efficiency generated by gradual deregulation in the North American energy markets, which further resulted in a decoupling of US and oil and gas market cycles (Serletis and Rangel-Ruiz 2004). In contrast, coal displays a sharp upward spike in 1975, a result of the OPEC oil embargo that stimulated modernization and expansion of the coal industry. This was followed by a decline in prices throughout the 1980s and 1990s as oil prices fell and advances in technology driven by the coal boom of the 1970s lowered the need for mine workers (Black et al. 2005). The sharp rise in oil and gas prices of the late 1990s and early 2000s coincides with a fall in coal prices. Coal appears countercyclical with respect to gas and oil, which could be due in part to a substitution effect, but also an asymmetric reaction to a shock between the North American/European and the Pacific/Asian market energy markets.

## V. Empirical Analysis

The results of the LM unit root test procedure that allows for structural breaks are presented in Table 2. Lags to induce white noise errors were specified using the general to specific methodology. If break points appeared in the first or last 10% of the series the tests were rerun using a 10% trimming zone; however, in no case did this change the conclusions of the tests. More test-specific details are presented in the Appendix.

**Table 2: Test for Stochastic Trends Allowing for Breaks**

	LM Test with 2 Breaks			LM Test with 1 Break		Concl.
	LM	TB1	TB2	LM	TB	DS/TS(B)
WTI	-5.02 (1)			-3.25 (1)	December 1986	DS(B)
Brent	-4.89 (10)			-3.23 (10)	January 1999	DS(B)
Dubai	-4.68 (10)			-3.06 (10)		DS
Coal	-5.61 (11)*	June 1983	September 2003			TS(B)
Gas	-5.17 (11)	September 1985	November 1999	-2.89 (11)		DS(B)

\*Denotes significance at the 10% level.

Note: Numbers in parentheses denote the lag length. TB1 and TB2 denote the first and second break points/dates. DS and TS denote difference stationary and trend stationary processes, respectively. DS(B) and TS(B) denote difference stationary with structural breaks(s) and trend stationary with structural break, respectively.

Source: Author's calculations.

### A. Trends and Persistence

The results of the LM test are presented in Table 2. In the case of WTI, the null hypothesis of a unit root allowing for structural breaks cannot be rejected at the standard conventional levels. Under the null, there was no significant structural break. The same results hold for the other oil prices in this study, being Dubai and Brent. For coal, the null hypothesis of a unit root can be rejected, hence it can be concluded that the process is stationary with two structural breaks. Given that the null is rejected only for coal, the test is repeated, this time allowing for a single break in the null and alternative hypothesis. For all prices the null hypothesis cannot be rejected, thereby leading one to conclude that the prices are difference stationary and shocks that occur to these prices are likely to be permanent in nature. Upon considering the structural breaks, a significant structural break is found to occur for WTI (being December 1986) and Brent (being January 1999). The overall conclusion is that except for coal, which is found to be a trend-stationary process with breaks, all the other prices (WTI, Brent, Dubai, and gas) are difference-stationary processes. Further, gas is found to contain two significant break points, WTI and Brent one break point and no breaks for Dubai prices.

For WTI, a single structural break occurs around December 1986. The breaks coincide with the period of the oil price crash. This was the time when Saudi Arabia abandoned

the swing price producer role, and average prices of oil plummeted by over 50%. For Brent, the structural break is at January 1999, which may have resulted from a series of significant oil output cuts by OPEC and non-OPEC countries. In the case of Dubai, there is no evidence of structural breaks and the conclusion is that prices follow a driftless random walk. The first structural break for coal is recorded on June 1983, most likely a result of structural changes in OPEC. The second break for coal on September 2003 is a time when coal prices rose rapidly due to growth in demand from Asian markets that supply was not able to meet, and increasing shipping congestion in Australian ports resulted in cutbacks in export volume. Gas has a significant trend break in September 1985, which coincides with regulatory reforms by Canada that led to long-term increases in gas sales to the US in 1985. A second significant trend break is observed in November 1999, possibly due to linkages with the oil markets.

Table 3 presents the estimation results of the prevalence of trends following the study on commodity prices by Kellard and Wohar (2006) and adopted for further analysis on energy prices by Ghoshray and Johnson (2010). The coefficient on each slope dummy gives an idea of the underlying trend in each regime that is identified. For example, given that coal and gas have been found to contain two structural breaks, the sample period chosen can be divided into three regimes. In the first two regimes, coal has a trend coefficient of 0.33 suggesting it is positive; however, the absolute value of the t-statistic given in parentheses is found to be less than the critical value, therefore the trend in this regime is rendered insignificant. In the second regime, the coefficient is negative but insignificant, and the conclusion is that although a significant structural break can be observed to warrant a different regime, there is no significant change in the trend across these regimes. In the final regime the trend coefficient is found to be positive and significant. The coefficient is large in magnitude suggesting that since September 2003, coal prices have an underlying trend growth of 1.63%. A similar situation arises when considering the underlying trends of gas. The first two regimes are found to contain insignificant trends; however, in the last regime, from November 1999, gas prices seem to contain an underlying trend growth of 0.95%. Dubai oil prices do not display any significant trends in its underlying time path and over the sample period considered is modeled as a random walk with drift process. However, the drift is found to be insignificant, which implies the most current price is likely to be the best forecast. WTI and Brent are modeled over two regimes given the finding of a single structural break. Both prices are found to contain no significant trends in the first regime, but significant trends are observed in the second regime. In both cases they are found to be positive and significant. While WTI is found to contain a trend growth of 0.41%, Brent shows a relatively sharper trend growth of 1.27%.

**Table 3: Coefficient Estimates for Stochastic/Deterministic Trends**

	TB1	TB2	Regime 1	Regime 2	Regime 3	ARMA
WTI	December 1986		0.12 (0.31)	0.41 (1.79)	NA	[1,0]
Brent	January 1999		0.01 (0.09)	1.27 (4.48)	NA	[1,1]
Dubai			0.46 (0.79)	NA	NA	[1,0]
Coal	June 1983	September 2003	0.33 (0.77)	-0.05 (0.62)	1.63 (5.47)	[2,0]
Gas	September 1985	November 1999	0.99 (2.76)	0.14 (0.60)	0.95 (2.62)	[1,2]

NA = not available.

Note: Numbers in parentheses denote t-ratios. TB1 and TB2 denote the first and second break points/dates. Numbers in square brackets denote the autoregressive moving average process.

Source: Author's calculations.

To derive persistence measures such as half lives at different regimes, the median unbiased estimates of the autoregressive parameter are calculated using Hansen's (1999) grid bootstrap method. The median-unbiased estimate along with the 90% confidence intervals are calculated using the grid-bootstrap method of Hansen (1999) by employing 200 grid-points and 1,000 bootstrap replications at each grid-point. This method is used to correct for the bias to the autoregressive estimates, a sentiment explained in Andrews (1993). Three different measures of the persistence of shocks to the energy price series are used. Table 4 sets out the result of the Hansen (1999) parametric bootstrap.

**Table 4: Results of the Median Unbiased Measure of Persistence**

		Regime 1	Regime 2	Regime 3
WTI	Est. (Conf. Int.)	0.981 (0.972,1.01)	0.987 (0.979,1.009)	NA
	HLS	36.14	52.97	NA
	IRF (12)	0.794	0.854	NA
	CIR	52.63	76.92	NA
BRENT	Est. (Conf. Int.)	0.968 (0.955,1.003)	0.974 (0.959,1.039)	NA
	HLS	21.31	26.31	NA
	IRF (12)	0.676	0.729	NA
	CIR	31.25	38.46	NA
DUBAI	Est. (Conf. Int.)	0.981 (0.975,1.007)	NA	NA
	HLS	36.14	NA	NA
	IRF (12)	0.794	NA	NA
	CIR	52.63	NA	NA
GAS	Est. (Conf. Int.)	0.987 (0.982,0.995)	0.789 (0.735,0.868)	0.926 (0.892,1.02)
	HLS	52.97	2.92	9.015
	IRF (12)	0.854	0.058	0.397
	CIR	76.92	4.74	13.51
COAL	Est. (Conf. Int.)	0.961 (0.891,0.973)	0.977(0.964, 1.014)	0.917(0.895, 1.034)
	HLS	17.45	29.87	8.00
	IRF (12)	0.620	0.756	0.353
	CIR	25.46	43.47	12.05

NA = not available.

Note: Conf. Int. refers to the 90% confidence interval. HLS denotes the half life shock, IRF(12) denotes the impulse response function over a 12-month horizon, and CIR denotes the cumulative impulse response.

Source: Author's calculations.

In the case of WTI where two regimes have been identified, the estimated coefficient is high (near unity) in both regimes, but is relatively higher in the second regime than the first. The confidence interval shows a relatively wider interval, implying that the variability has increased in the second regime. A similar story emerges when one examines the half life shocks, impulse responses over a 12-month horizon, and the cumulative impulse responses. The second regime shows that the persistence of shocks is relatively higher in the second regime compared to the first. In the case of WTI, the impulse response function shows an approximately 19% reduction in the level of persistence after 12 months and a 13% reduction in the level of persistence after 12 months in the second regime. For WTI, in the first regime, it would take approximately 3 years for half of the shock to die out and over 4 years for the remaining shocks to die out. In the second regime the shocks are more persistent, where it takes a over 4 years for half the shock to dissipate and over 6 years for any shock to die out. Brent prices seem to suggest a similar degree of persistence to shocks across the two identified regimes. However, the duration of time for the shocks to dissipate or die out is relatively short-lived compared to WTI. For Brent, the impulse response function shows an approximately 30% reduction in the level of persistence after 12 months in the first regime and a 25% reduction in the level of persistence after 12 months in the second regime. For Dubai prices, there is no regime-changing behavior and the degree of persistence mirrors that of WTI in the first regime. For other energy prices such as gas and coal, there are three regimes over which the degree of persistence in prices changes over time. In the case of gas there is evidence that the persistence falls in the second regime compared to the first, and then increases in the third and final regime. However, in the final regime it can be observed that the variability in gas prices has noticeably increased. In the case of coal, the persistence increases from the first to the second regime, and then falls in the final regime. However, the associated variability of coal prices increases across the regimes.

The persistence in oil prices may reflect oil's position as the world's most actively traded commodity. Thus pressure to develop markets to allow international arbitrage has resulted in more efficient markets than those of coal and gas. The key finding to note is that all prices display a significant level of persistence, thus for the policy maker, price shocks are likely to be long-lasting rather than short-term, transitory ones. Given the prevalence of multiple breaks, Pindyck's (1999) proposition of prices with fluctuating trends or large discrete changes combined with nonstationary or near unit root processes might make these energy commodities less amenable to stabilization policies than those for whom shocks will be transitory. Considering the approximate investment horizon of 30 years in oil and gas fields, such persistence would imply that ignoring the mean reverting component is of little consequence.

## **B. Oil Price Volatility and the Macroeconomy**

The results of the causation between oil price variability and industrial production of Asian countries are reported in Table 5. The first considers the WTI oil price, reported in the

upper panel of Table 5. Using the oil price shock specification proposed by Mork (1989) and Kilian and Vigfusson (2009), the oil price shocks affect Indonesia, Malaysia, and the Philippines at the 10% significance level. For these countries the F-statistic is higher than the 10% critical value, thereby rejecting the null hypothesis that oil price shocks do not cause a change in industrial production. For the other countries, namely, the PRC, India, Thailand, and an index measure for OECD countries, there is no evidence of any significant impact of oil price shocks on any change in industrial production. The implication is that for the proposed nonlinear function of oil prices, oil price shocks have a significant negative impact on industrial production for Indonesia, Malaysia, and the Philippines. Following the specification proposed by Hamilton (2003 and 2010), the null hypothesis that oil price shocks Granger cause industrial production cannot be rejected for all countries except Malaysia. The implication is that if price shocks were defined as the maximum oil price in 3 years, then there is a significant impact on industrial production in the case of Malaysia. Finally, using the specification suggested by Lee et al. (1995), the oil price shock has a significant impact on the same countries under the Kilian and Vigfusson (2009) specification. This time the null hypothesis of no causality from oil price shocks to industrial production is rejected at least at the 5% significance level for Indonesia, Malaysia, and the Philippines. The implication is that for these countries, oil price shocks predict output in the short run. The results suggest that these countries are vulnerable to external shocks, particularly oil price increases. One can conclude that for Philippines, Malaysia and Indonesia, the variability of oil prices would spill over into economic activity. For the other Asian countries considered in this study, there is no evidence of WTI oil price variability affecting industrial production.

For Brent oil prices, a very similar result is obtained. Under two of the three specifications considered (that is, Kilian and Vigfusson 2009, Lee et al. 1995) oil price variability is found to affect industrial production for Indonesia, Malaysia, and the Philippines. The null hypothesis of no causality is rejected at least at the 10% significance level. Using the Hamilton specification, oil price shocks affect industrial production only for Malaysia at the 5% significance level. For the remaining Asian countries, there is no evidence of causality from oil price shocks to industrial production. Finally when considering the Dubai oil price, both the Kilian–Vigfusson and Lee et al. specifications suggest causality from oil price shocks to industrial production for Indonesia, Malaysia, and the Philippines. The results in this case are relatively more robust in the sense that the null hypothesis of no causality is rejected at least at the 1% significance level. Using the Hamilton specification, oil price shocks affect industrial production for Malaysia and Indonesia at the 10% and 1% significance levels, respectively. An observation is that the oil prices play an important role in explaining the fluctuations of output in Indonesia and Malaysia, which are both net oil-exporting countries.

**Table 5: Oil Price Volatility and Industrial Production**

	OECD	India	PRC	Thailand	Indonesia	Malaysia	Philippines
WTI							
$\Delta P_t^{KV} \rightarrow \Delta y$	0.29	1.74	1.24	0.95	2.39*	6.03***	3.27**
$\Delta P_t^H \rightarrow \Delta y$	0.62	1.01	0.97	0.39	1.40	3.16***	0.88
$\Delta P_t^L \rightarrow \Delta y$	0.13	1.17	1.18	1.25	2.59**	5.66***	3.94***
Brent							
$\Delta P_t^{KV} \rightarrow \Delta y$	0.04	1.80	1.24	1.31	2.35*	5.76***	3.20**
$\Delta P_t^H \rightarrow \Delta y$	0.80	1.04	1.31	0.47	1.14	2.80**	0.83
$\Delta P_t^L \rightarrow \Delta y$	0.12	1.51	1.33	1.39	2.42**	5.42***	3.15**
Dubai							
$\Delta P_t^{KV} \rightarrow \Delta y$	0.06	1.59	1.64	0.68	3.72***	7.31***	3.87***
$\Delta P_t^H \rightarrow \Delta y$	1.18	1.57	1.61	0.43	2.08*	3.88***	1.42
$\Delta P_t^L \rightarrow \Delta y$	0.13	1.15	1.60	0.63	3.99***	6.96***	3.58***

\*\*\*, \*\* and \* denote significance at the 1%, 5% and 10% level respectively.

Note:  $\Delta P_t \rightarrow \Delta y$  to be read as oil price shocks do not Granger cause industrial production.

Sources: Superscript KV denotes the Mork (1989)/Kilian and Vigfusson (2009) approach, H denotes the Hamilton (2003 and 2010) approach, and L denotes the Lee et al. (1995) approach.

The results of the causation between oil price variability and inflation in Asian countries are reported in Table 6. With WTI oil prices, the impacts of oil price shocks on inflation are different according to the various specifications of an oil price shock. According to the Kilian–Vigfusson approach, oil price shocks are found to have a significant impact on inflation for Malaysia and Thailand. However, employing the specification proposed by Hamilton, a significant impact of oil prices on inflation is found to occur in the Philippines and Thailand. Using the Lee et al. approach, a significant impact of oil price shocks on inflation is found to exist only in Thailand. In the case of Thailand there is a significant impact of oil price shocks on inflation according to all three specifications. The effect of Brent oil price shocks on inflation is relatively lower. A significant impact for Thailand is found using the Kilian–Vigfusson and Hamilton specifications only. The Hamilton approach proves that a significant impact of oil price variability on inflation exists in the Philippines as well. A similar result is obtained when one observes the Dubai oil price shocks on inflation. Thailand is found to experience a significant impact on inflation as a result of an oil price shock defined by the specification of Hamilton and Lee et al. (1995). The Philippines is the only other country that is found to feel the impact of an oil price shock characterized by oil prices reaching a 3-year high. These results are very similar to



those of Cunado and Gracia (2005), who estimate a longer sample period (1975–2002), but for a lower frequency (quarterly) data.

**Table 6: Oil Price Volatility and Inflation**

	India	PRC	Thailand	Indonesia	Malaysia	Philippines
WTI						
$\Delta P_t^{KV} \rightarrow \Delta y$	1.68	1.20	2.05*	0.74	2.03*	0.59
$\Delta P_t^H \rightarrow \Delta y$	0.46	2.03*	4.26***	0.52	1.00	3.76***
$\Delta P_t^L \rightarrow \Delta y$	1.66	0.55	2.74**	1.06	1.16	0.93
Brent						
$\Delta P_t^{KV} \rightarrow \Delta y$	1.84	0.73	2.12*	0.80	1.82	0.39
$\Delta P_t^H \rightarrow \Delta y$	0.47	1.32	3.38***	0.78	0.80	4.04***
$\Delta P_t^L \rightarrow \Delta y$	1.25	0.64	1.90	1.14	1.67	0.58
Dubai						
$\Delta P_t^{KV} \rightarrow \Delta y$	2.23*	0.91	1.74	0.92	1.43	0.43
$\Delta P_t^H \rightarrow \Delta y$	0.61	1.69	3.90***	0.45	0.52/	4.58***
$\Delta P_t^L \rightarrow \Delta y$	1.76	0.95	2.19*	1.11	1.20	0.71

\*\*\*, \*\* and \* denote significance at the 1%, 5%, and 10% level, respectively.

Note:  $\Delta P_t \rightarrow \Delta y$  to be read as oil price shocks do not Granger cause inflation.

Sources: Superscript KV denotes the Mork (1989)/Kilian and Vigfusson (2009) approach, H denotes the Hamilton (2003 and 2010) approach, and L denotes the Lee et al. (1995) approach.

## C. Relationship between Oil and Commodity Prices

Empirical studies that have investigated the relation between fuel and agricultural commodity prices have employed the cointegration approach (Campiche et al. 2007, Yu et al. 2006, Hameed and Arshad 2008, and Kancs 2010). All these studies have employed a linear cointegration approach using the Johansen maximum Likelihood method.

However, theoretical studies by de Gorter and Just (2008 and 2009) suggest a nonlinear relation that is driven by their view that the price transmission is likely to occur when the price of fuel is sufficiently higher and/or corn price is considerably lower. This type of adjustment between fuel and agricultural prices calls for nonlinear threshold cointegration rather than a linear cointegration model. Given the nature of nonlinear adjustment described by de Gorter and Just (2008 and 2009), the threshold cointegration method that involves estimating a two-regime threshold VECM would be appropriate.

For this part of the study, daily data is used obtained from Datastream. The prices include those for crude oil (WTI, Brent, and Dubai), biodiesel, corn, sugar, soybean, rice, wheat, palm oil and copra. As discussed earlier in Section II, it was only since 2006 that the ethanol market established a link between crude oil and corn prices, which did not exist before (Tyner 2009). Given that the link found by previous studies is to be a recent phenomenon econometric estimations of data that would be of high frequency would provide reliable estimates. This would be possible using daily data. Unit root tests were carried out on the daily data as a prelude to testing long-run relationships between oil and other agricultural commodity prices. The results of the ADF and more powerful ERS test show that all the variables included in the VECM are nonstationary integrated variables, that is,  $I(1)$ .<sup>4</sup>

Before employing the nonlinear threshold cointegration model, the linear test for cointegration is made. The results of the Maximum Eigenvalue and Trace test statistics are given in Table 7. The results show that for all the price pairs, except (Biodiesel, Palm Oil) and (Biodiesel, Copra) the null hypothesis of no cointegration cannot be rejected. This implies that a long-run relationship exists between the two pairs of prices. Interestingly, both commodities, palm oil and copra, are mainly produced and exported by Asian countries.

**Table 7: Linear and Nonlinear Cointegration Tests**

Price pairs	Trace	Max. Eigenvalue	Sup-LM
Oil(Brent)/Corn	8.32	5.81	0.066*
Oil(Brent)/Sugar	3.53	2.13	0.180
Oil(Brent)/Soybean	8.25	5.01	0.997
Diesel/Soybean	14.65	10.09	0.331
Oil(Brent)/Rice	9.14	5.53	0.645
Oil(brent)/Wheat	6.04	3.58	0.713
Diesel/Palm Oil	46.81***	41.42***	0.480
Diesel/Copra	43.65***	41.02***	0.296
Oil(WTI)/Corn	8.89	6.27	0.227
Oil(WTI)/Sugar	3.76	2.66	0.221
Oil(WTI)/Rice	8.36	5.62	0.002***
Oil(WTI)/Wheat	6.27	4.38	0.740
Oil(Dubai)/Corn	8.90	6.47	0.106
Oil(Dubai)/Sugar	3.38	2.40	0.084*
Oil(Dubai)/Rice	8.04	5.41	0.87
Oil(Dubai)/Wheat	6.08	4.15	0.290

\*\*\* and \* denote significance at the 1% and 10% level, respectively.

Note: While the bootstrapped *sup-LM* test finds significance for a threshold at the 1% level for (WTI, Rice) pair and at the 10% level for (Dubai, Sugar) pair, no valid threshold VECM was found to exist for these pairs.

Source: Author's calculations.

<sup>4</sup> Results have not been included for brevity.

The tests of threshold cointegration proposed by Hansen and Seo (2002) are applied to all the pairs, that is, the *sup-LM* test. The p-values are calculated using a parametric bootstrap method with 1,000 simulation replications. The lag length of the threshold VECM, or TVECM, is selected according to the SBC. The results of the *sup-LM* test are reported in the last column of Table 7. According to the *sup-LM* test the null hypothesis of linear cointegration is not rejected for any of the pairs except (Brent, corn); (WTI, rice); and (Dubai, Sugar).

The robust cointegrating relationship between the (Biodiesel, Palm Oil) and (Biodiesel, Copra) pairs yields the following long-run relationships between biodiesel and vegetable oils:

$$e_t = P_t^{BD} - 0.71P_t^{PO} + 3.91$$

$$z_t = P_t^{BD} - 0.75P_t^{CO} + 3.57$$

where  $e_t$  denotes the long-run cointegrating relation between biodiesel and palm oil, and  $z_t$  denotes the long-run cointegrating relation between biodiesel and copra.

$P_t^{BD}$ ,  $P_t^{CO}$  and  $P_t^{PO}$  denote the price of biodiesel, copra, and palm oil, respectively.<sup>5</sup> The above cointegrating relationship between biodiesel and palm oil suggests that if the price of palm oil were to change, then 71% of the change would be transmitted to the price of biodiesel. Alternatively, a unit change in the price of biodiesel would lead to a more than proportional 1.41 change in the price of palm oil. On the other hand, when considering the cointegrating relationship between biodiesel and copra, if the price of copra were to change, then 75% of the change would be transmitted to biodiesel prices. Alternatively, a unit change in the price of biodiesel would lead to a more than proportional 1.33 unit change in the price of copra. Clearly, a very robust relationship is found to exist between the price of palm oil popularly produced and exported from two Asian countries, and biodiesel. Copra is not directly used to produce biodiesel, however, coconut oil, which is extracted from copra, can be used to manufacture biodiesel. Given this indirect relationship in the production process, a long-run relationship is observed between the two prices.

The results of the error correction model that describe the dynamics between the two cointegrating pairs are shown in Table 8 below. Considering the (Biodiesel, Palm Oil) price pair, one can observe that both prices adjust to correct any deviation that arises between the long-run equilibrium relationship between the two prices. Biodiesel prices are found to adjust to any deviation at the rate of 3.9% every day compared to palm oil prices, which adjusts to any deviation at the rate of 1.9% per day. The Granger causality tests on the short run coefficients reveal no short-run causal relation between the prices. Moving on to the (Biodiesel, Copra) price pair, the speed of adjustment coefficient for

<sup>5</sup> Restrictions on the cointegrating vector were made to identify the long run cointegrating relationship. The cointegrating vector was restricted to (1,-1) to test whether a 1:1 relationship between biodiesel with copra and palm oil. However, these restrictions were rejected.

biodiesel prices is significant implying that any deviation from the long-run equilibrium relationship between the two prices would be corrected at the rate of 6.4% per day. However, the speed of adjustment parameter for copra is found to be insignificant, which seems to imply that copra prices are evolving independently over time. The short-run causality results show that current changes in biodiesel prices have an impact on future copra prices, while any changes in copra prices have no impact on diesel prices in the short run. These results need to be treated with some degree of caution as copra would be expected to have an indirect impact on biodiesel prices. This is because copra itself is not used for producing biodiesel, but coconut oil, which can be extracted from copra, would be expected to have a direct link.

**Table 8: Results of the ECM**

	$\Delta P_t$ (Diesel)	$\Delta P_t$ (Palm Oil)	$\Delta P_t$ (Diesel)	$\Delta P_t$ (Copra)
$e_{t-1}$	-0.039 (0.006)	-0.013 (0.006)		
$Z_{t-1}$			-0.064 (0.019)	-0.004 (0.009)
$\Delta P_{t-1}$ (Diesel)	0.003 (0.032)	0.012 (0.033)	0.015 (0.032)	-0.056 (0.029)
$\Delta P_{t-1}$ (Palm Oil)	0.036 (0.032)	0.019 (0.033)		
$\Delta P_{t-1}$ (Copra)			0.017 (0.036)	-0.051 (0.033)

Note: Numbers in parentheses denote standard errors.

Source: Author's calculations.

In the (Corn, Crude Oil) price pair for which a threshold is found to exist, a valid threshold VECM is obtained. However, no valid threshold VECM is found to exist for the (WTI, Rice) and (Dubai, Sugar) pairs.<sup>6</sup> Consequently only the following two-regime TVECM is estimated using Hansen and Seo (2002) to obtain the following results:

$$\Delta P_t^{OIL} = \begin{cases} -0.001 - 0.01w_{t-1} - 0.02\Delta P_{t-1}^{OIL} + 0.09\Delta P_{t-1}^{CORN}; & w_{t-1} \leq 0.06 \\ (0.001) & (0.01) & (0.05) & (0.05) \\ 0.01 - 0.16w_{t-1} + 0.11\Delta P_{t-1}^{OIL} + 0.07\Delta P_{t-1}^{CORN}; & w_{t-1} > 0.06 \\ (0.004) & (0.04) & (0.06) & (0.06) \end{cases}$$

$$\Delta P_t^{CORN} = \begin{cases} -0.001 - 0.002w_{t-1} - 0.07\Delta P_{t-1}^{OIL} + 0.01\Delta P_{t-1}^{CORN}; & w_{t-1} \leq 0.06 \\ (0.001) & (0.004) & (0.04) & (0.04) \\ 0.02 - 0.13w_{t-1} + 0.04\Delta P_{t-1}^{OIL} - 0.02\Delta P_{t-1}^{CORN}; & w_{t-1} > 0.06 \\ (0.01) & (0.09) & (0.14) & (0.16) \end{cases}$$

The numbers in parentheses denote the standard errors of the parameter estimates. Considering the (Corn, Oil) pair, the TVECM estimates show that the estimated threshold to be 0.06. The cointegrating vector is estimated to be  $w_t = P_t^{OIL} - 0.748P_t^{CORN}$ . The long-run relationship suggests that for any change in the price of crude oil, there would be a

<sup>6</sup> The results have not been reported for brevity, but are available from the author on request.

more than proportional effect on the price of corn. The price transmission elasticity would be approximately 1.33, implying that for a unit increase in crude oil prices, corn prices will increase by 1.33. The first regime, that is  $w_{t-1} \leq 0.06$ , contains 85% of the observations, which can be referred to as the usual regime. In this regime, corn prices are more than 6% above the equilibrium oil price. However, it is in the second regime where  $w_{t-1} > 0.06$  contains 15% of the observations. In this regime, referred to as the unusual regime, corn prices are more than 6% points below the equilibrium oil prices. In the first regime, the error correction coefficients are small and insignificant. This shows that when oil prices are not sufficiently high enough with respect to the estimated threshold, there is no adjustment to the long-run equilibrium between oil and corn prices. In other words, there is no price transmission. However, when considering the “unusual regime” when oil prices are sufficiently high and/or corn prices are sufficiently low, the error correction coefficients are found to be relatively higher and significant. The estimated speed of adjustment coefficient for oil prices is 0.16, suggesting that 16% of any deviation between the long-run relationship of corn and oil prices is corrected the next day. For corn prices the adjustment is relatively slower, estimated at 0.13; however, the coefficient is statistically insignificant at conventional levels. These results lend support to the theoretical foundations made by de Gorter and Just (2008 and 2009).

## VI. Policy Conclusions

This section describes the policy implications of the empirical results with reference to the underlying trends in commodity prices, the effects of oil price shocks on the macroeconomy, and the relationship between energy and agricultural commodity prices.

### A. Trends and Persistence in Energy Prices

The persistence in oil prices may reflect oil's position as the world's most actively traded commodity. Thus pressure to develop markets to allow international arbitrage has resulted in more efficient markets than those of coal and gas. The key finding to note is that all commodities display a significant level of persistence thus, for the policy maker, price shocks are likely to be long lasting rather than short-term, transitory ones. Given the prevalence of multiple breaks, Pindyck's (1999) proposition of prices with fluctuating trends or large discrete changes combined with nonstationary or near unit root processes might make these energy commodities less amenable to stabilization policies than those for whom shocks will be transitory. Considering the approximate investment horizon of 30 years in oil and gas fields, such persistence would imply that ignoring the mean reverting component is of little consequence.

In summary, do any of the theories outlined in the introduction appear to be well represented by these findings? The answer would seem to be that no one theory can fully explain the price paths. This might be unsurprising given the shifting institutional background that accompanies each regime. For example, coal's negative yet insignificant trend parameter in Regime 2 could be the result of innovation in the mining industry and a dramatic increase in the number of mines, as captured by Berck and Roberts' (1996) model of declining prices and Slade's (1988) nested model where the efficient market dominates the deterministic component. Given for the most part no single theory can capture the overall movements of these commodities, it is a fairly trivial task to represent localized trends, given that there exists at least one theory that captures each observed outcome. The more pressing question is what is driving the changes in the localized underlying processes, and can they be identified? Such a question indeed warrants further investigation. This paper has examined and discussed the temporal properties of oil, natural gas, and coal prices. The results have significant consequences for energy-related econometric analysis, forecasting, investment decisions, and macroeconomic policy making. All series exhibit multiple breaks in trend and level that may have resulted in spurious conclusion of a unit root in previous studies. The limitation is recognized that critical values in many of the unit root tests are not invariant to sample size and break point, thus one may wish to use bootstrapping techniques to generate appropriate unit root critical values.

Significant persistence has implications for macro economic policy makers, such that if the wider macroeconomy inherits this property, this may challenge natural rate hypotheses as shocks will be permanent rather than transitory, limiting the efficacy and sustainability of debt-financed stabilization policies. The instability of trends over the sample period suggests that no single theory fully represents the evolution of energy prices over the last 30 years. Given these findings, this work could be built upon by modeling the long-run price paths of the series examined using the correct deterministic or stochastic process.

## **B. Oil Price and Macroeconomy**

To the extent that policy intervention may be appropriate, there are policies that can be implemented to reduce the vulnerability of countries' economic activity to oil price shocks. Brown and Yucel (2002) suggest that countries should reduce exposure to volatile world oil prices by building up a strategic oil reserve that could lead to reduced oil imports when oil prices are volatile. The oil reserve would allow countries to purchase oil when prices are low and reduce oil imports when prices are high. Brown and Yucel (2002) suggest a further measure that involves raising taxes on oil products or taxes that vary inversely with world oil prices. This would reduce the volatility of oil prices that is transmitted to countries. With this policy, households would perceive mitigated price movements, which in turn would make oil demand more inelastic. Countries that have energy resources but an undiversified economic base without stabilizing mechanisms would need to have

their economies protected from oil price shocks (Mehrara and Sarem 2009). Oil price shocks can lead to sharp fluctuations in output that can in turn lead to costly instability. These countries would have a case for holding larger than normal reserves, minimizing outstanding public debt, and allowing for fiscal flexibility. In the future, to achieve sustainable growth, countries such as Malaysia, Indonesia, and the Philippines would require policies that enlarge and diversify their economic base, enhance their capacity to withstand adverse external shocks, and reduce their exposure to oil price volatility.

For oil exporters such as Indonesia and Malaysia, while an oil price increase will cause household incomes to fall, the income of oil companies would receive a boost. This would lead to an increase in government revenue that could allow for tax cuts or income subsidies for households. Given that an oil price increase would improve the country's terms of trade, exchange rate appreciation may occur that would help dampen inflationary pressure. The monetary policy implications would be to respond to higher inflation as a consequence of an increase in fuel prices. For oil exporters, there are potential increased incomes of oil companies that can offset the loss of household income. As a consequence, inflation may be high at the start, but the exchange rate appreciation that will occur as a result of higher oil prices can reduce inflation. Therefore monetary policy can be eased fairly quickly. From the fiscal policy side, countries that are net oil exporters would experience an increase in revenue that may lead to a budget surplus, particularly if oil production is controlled by the state. This process can be allowed to continue in the short term, while in the medium term, fiscal policy can be eased to allow some of the income to increase in the household sector. For a country such as Indonesia where oil production is increasingly becoming limited, some of the revenue could be saved or invested for the future. These policies would be effective for countries such as Malaysia, the Philippines, and Thailand that have moved toward floating exchange rates and have independent central banks that operate inflation targets.

Different policy implications exist for oil-importing countries, particularly major importers such as the PRC and India, when faced with oil price increases. In this case, monetary policy will need to be tightened to deal with higher inflation. If the countries are major importers of oil, it is likely that the terms of trade would deteriorate, leading to a depreciation of the exchange rate, which can further accentuate the impact on inflation. From the fiscal policy side there would be a need to address the deficit in the balance of payments as a result of the more expensive imports. However, this can be dealt with in the medium term as long as monetary policy measures have been implemented to deal with inflation in the short term. The PRC, until 2005, operated a fixed exchange rate that would have proven difficult in the face of oil price shocks. The current account under these conditions would move into deficit, leading to a sale of foreign reserves and accumulation of debt.

One of the problems of policy implementation by Asian countries in the face of oil price shocks is the interaction of monetary and fiscal policy. For example, a response to higher

oil prices has been to increase subsidies to cushion the effect of the price shock. This has at times made the subsidies very expensive (such as the case for Malaysia). In some instances governments may be forced to reduce subsidies. This leads to implementing policies at a later time, and in most cases a larger monetary policy response is required to deal with a higher increase in prices.

For example, in Indonesia, retail petrol and diesel prices rose steadily until 2005 when a sharp increase in prices occurred. At the time, the cost of subsidies was estimated to be 4.7% of GDP (World Bank 2006). In the same year a large reduction in subsidies was made accompanied by a 125% increase in the price of petrol and diesel. Though an increase in income support measures was introduced to tackle the distributional impacts of the price increase, subsidies continued to be a significant cost to the budget (ADB 2006b). In the case of Malaysia, in 2005, tax exemptions and subsidies cost the government 2.9% of GDP (ADB 2006a). When oil prices experienced decreases the government used it to reduce subsidies (World Bank 2006).

### **C. Oil Prices and Agricultural Commodity Prices**

Summarizing the results of the relationship between oil prices and agricultural commodity prices, there is weak evidence of any relationship. Employing a linear method of cointegration, a linear cointegration relationship exists between biodiesel and copra prices, and biodiesel and palm oil prices. A nonlinear threshold cointegration result exists between oil and corn prices. The presence of a cointegrating relationship between two prices suggests that the two prices move together over time forming a long-run equilibrium relationship.

Biofuel production has expanded significantly in recent years, which has affected the linkages between fuel and agricultural commodities. The lack of cointegration between most of the other agricultural commodities and fuel may be as a result of the fact that international agricultural prices are affected by the production of commodities in developing countries. Developing countries tend to use less fuel-based inputs such as machinery and fertilizers, and more labor-intensive technologies. The expansion of biofuels induces higher production of biofuel agricultural commodities (that is, corn and soybeans), which in turn increase agricultural factor prices. Higher factor prices in turn increase the price of nonbiofuel agricultural commodities. The lack of price transmission may be a result of various institutional and market rigidities present on rural factor markets (e.g., land rental contracts, constrained access to capital). The empirical results find some support for interdependencies between prices of agricultural commodities and energy prices.

Do these results have any bearing on the biofuels policy of Asian countries? In the case of the PRC, corn-based bioethanol was promoted and continued until May 2007 when it issued a new policy that energy crops should not compete with grain. The government



blocked new projects using food-based ethanol and encouraged a switch to new sources such as sorghum, batata, and cassava (Sun 2007). India has been promoting bioethanol and biodiesel through fixed prices and tax incentives. The government is considering production of ethanol from sweet sorghum, sugar beet, cassava, and tapioca, and production of biodiesel from nonedible seed bearing trees or shrubs like jatropha to address the fuel versus food issue (Subramanian 2007). Discussions are taking place regarding the production of biofuel crops on wastelands throughout the country. Malaysia is one of the major producers of palm oil that can be used for the production of biodiesel. However, due to the high price of palm oil, the production of biodiesel has been limited (Nagarajan 2008). Indonesia, being one of the major producers of palm oil (along with Malaysia) is actively aiming to produce biodiesel. This has been a policy measure in the face of falling oil production and increased domestic consumption. Oil exports have also suffered as they have been found to be falling at a faster rate than production. However, biofuel production in Indonesia has faced hurdles. For example, in April 2007, due to rising palm oil prices, state-owned Indonesian oil companies had to cut the blend in their sale of biodiesel (*Daily Times* 2007). Very recently, Indonesia had to impose export taxes on palm oil to discourage exports and promote palm oil for domestic use. Thailand, meanwhile, embarked on plans to increase the use of biofuels through tax breaks for a 10% ethanol blend (Waranusantikule 2008). A temporary increase in consumption took place in 2004 and in 2005, after which consumption increases stalled. While the government took steps to increase the price difference between gasoline and the ethanol blend (Kojima et al. 2007), the government has not been able to fully implement the blending mandate for ethanol due to opposition from the automobile industry (Worldwatch Institute 2007). The Philippines is the world's largest exporters of coconut oil. A 2007 biofuel law mandated a 1% coconut oil blend for diesel, and the current target has been revised to 5% for 2010. The viability of jatropha methyl ester is being closely examined (Marasigan 2007).

There is no general consensus regarding the best policies for biofuels. Nevertheless, it is still important to develop policies to address the issues posed by biofuels, which many Asian countries have already decided to strongly promote. The strong link between palm oil and biodiesel can serve as a signal to encourage certain Asian countries such as Indonesia or Malaysia to promote biofuels, though production may not be enough to meet existing utilization targets. Besides, setting targets or promotion measures without building in policy safeguards for a sustainable increase in biofuel production could lead to deforestation or other environmental damage.

Mitchell (2008) argues that the large increase in rice prices was largely a result of an increase in wheat prices rather than from changes in rice production or stocks. Thus the sharp rise in rice prices could be indirectly related to the increase in biofuels. The results of the econometric analysis do not show any evidence of a link between rice and biofuels. One needs to note that it is difficult to compare these estimates with estimates from other studies because of different methodologies, widely different time periods considered, and different commodities examined.

From a policy perspective, these interrelationships of agricultural and oil prices warrant careful consideration in the context of the recent energy crisis, which may very well continue in the future. While some studies have indicated that the search for alternative sources of energy such as biofuels is likely to cause a surge in food prices, the empirical evidence gives a mixed view regarding this possibility. For commodities such as sugar, soybeans, and wheat, there is no direct evidence of biofuel production causing a spike in commodity prices with a tightening of supply constraints.

## Appendix

### Estimation of Trends/Breaks: Lee and Strazicich (2003 and 2004), Kellard and Wohar (2006)

To briefly describe the Lee and Strazicich (2003) method, consider the following data generating process (DGP):

$$P_t = \psi' X_t + u_t \text{ and } u_t = \phi u_{t-1} + \varepsilon_t; \text{ where } \varepsilon_t \text{ iid } N(0, \sigma^2) \quad (\text{A.1})$$

where  $P_t$  is the price series and the two changes in level and trend are given by

$$X_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]', \text{ where}$$

$$DT_{jt} = \begin{cases} t - TB_j & \text{for } t \geq TB_j + 1 \\ 0 & \text{otherwise} \end{cases} \quad \text{for } j = 1, 2.$$

$TB_j$  denotes the points at which the breaks occur. Note that the DGP contains breaks in the null hypothesis when  $H_0 : (\phi = 1)$  and the alternative hypothesis when  $H_A : (\phi < 1)$ . The break fractions are denoted as  $\lambda_j = TB_j/T$  where  $T$  denotes the total number of observations.

When employing the Lee and Strazicich (2004) method that considers a single structural break, the single change in level and trend in equation (A.1) is now given by

$$X_t = [1, t, D_t, DT_t]', \text{ where}$$

$$DT_t = \begin{cases} t - TB & \text{for } t \geq TB + 1 \\ 0 & \text{otherwise} \end{cases}$$

$TB$  denotes the points at which the breaks occur. The break fraction is denoted as  $\lambda = TB/T$ .

The LM unit root test statistic can be estimated by the following regression:

$$\Delta P_t = \phi' \Delta X_t + \gamma \bar{Y}_{t-1} + \sum_{i=1}^p \psi_i \Delta \bar{Y}_{t-i} + u_t \quad (\text{A.2})$$

where  $\bar{Y}_t = P_t - \mu - X_t \bar{\phi}$ ,  $t = 2, 3, \dots, T$ ;  $\bar{\phi}$  are coefficients on the regression of  $\Delta P_t$  on  $\Delta X_t$ ;  $\mu$  is given by  $P_1 - X_1 \bar{\phi}$ .<sup>7</sup> The lagged terms  $\Delta \bar{Y}_{t-i}$  are added to correct for serial correlation. The augmentation is determined using the general to specific method. The LM test statistics are given by the  $\tau$  statistic testing the null hypothesis  $H_0 : (\gamma = 0)$ . The LM unit root test determines the break points endogenously by utilizing a grid search. To eliminate endpoints, trimming of the *infimum* (inf) is made at 10%. The breakpoints are determined where the test statistic is minimized.

The LM test is given as  $LM_\tau = \inf \hat{\tau}(\lambda)$ .

If up to two structural breaks in any price series can be identified, the next step would be to determine whether the sign of the trend is negative or positive and whether it is significant or not. Besides, it would be of interest to observe whether the trend changes signs in the different regimes that are outlined by the structural breaks. In order to determine how the trend has shifted over time, the data generating process is modeled in the manner conducted by Kellard and Wohar (2006). For the trend stationary process, the logarithm of the commodity price series is regressed against a constant and a time trend and one or two intercept and slope dummy variables corresponding to the results of the structural break tests. The error structure is modeled as an ARMA(p,q) process. Thus the estimation process is carried out using the following equations:

$$P_t = \gamma + \delta_1 t + \delta_2 D_{L1,t} + \delta_3 D_{T1,t} + \delta_4 D_{L2,t} + \delta_5 D_{T2,t} + u_t \quad (\text{A.3})$$

$$u_t - \phi_1 u_{t-1} - \dots - \phi_p u_{t-p} = \varepsilon_t - \psi_1 \varepsilon_{t-1} - \dots - \psi_q \varepsilon_{t-q} \quad (\text{A.4})$$

where  $\varepsilon_t$  is a white noise process.  $D_{Li}$  and  $D_{Ti}$  ( $i = 1, 2, 3$ ) denote the level and slope dummy, respectively;  $i$  refers to the regime defined by the prior identification of the break dates. The regimes are defined as:

regime 1 = start date to  $TB_1$

regime 2 =  $(TB_1 + 1)$  to  $TB_2$

regime 3 =  $(TB_2 + 1)$  to end date

Following Kellard and Wohar (2006), equation (A.3) is reparameterized to facilitate the estimation of the trend coefficient in the three different regimes. Equation (A.3) was reparameterized in the following way:

$$P_t^* = \gamma R_{L1,t} + \delta_1 R_{T1,t} + (\gamma + \delta_2) R_{L2,t} + (\delta_1 + \delta_3) R_{T2,t} + (\gamma + \delta_2 + \delta_4) R_{L3,t} \\ + (\delta_1 + \delta_2 + \delta_3) R_{T3,t} + u_t \quad (\text{A.5})$$

where  $R_{Li,t}$  denotes the intercept dummy for a level shift in regime  $i$ , ( $i = 1, 2, 3$ ) and  $R_{Ti,t}$  denotes the slope dummy for a trend shift in regime  $i$ , ( $i = 1, 2, 3$ ). For the three regime model,  $P_t^*$  is defined as:

<sup>7</sup>  $P_j$  and  $X_j$  denote the first observations of the  $P_t$  and  $X_t$  sequences, respectively.

$$P_t^* = \begin{cases} P_t & \text{if } 1 \leq t \leq TB1 \\ P_t - \delta_1(TB1 - 1899) & \text{if } TB1 + 1 \leq t \leq TB2 \\ P_t - \delta_1(TB1 - 1899) - \delta_3(TB2 - TB1) & \text{if } t > TB2 \end{cases}$$

To facilitate comparison with KW, the estimation was conducted by exact maximum likelihood and the ARMA order (p,q) was selected through the SBC allowing all possible models with  $p + q \leq 6$ .

### Median Unbiased Estimator and the Parametric Bootstrap; Hansen (1999)

The median unbiased estimator rule involves calculating the median-unbiased estimator of the autoregressive coefficient, (say  $\hat{\phi}$ ). Let  $\hat{\phi}$  be an estimator of the true  $\phi$  whose median function  $m[\phi]$  is uniquely defined  $\forall \phi \in (-1,1]$ . Then  $\hat{\phi}_u$  is the median unbiased estimator and is defined as follows:

$$\hat{\phi}_u = \begin{cases} 1 & \text{if } \hat{\phi} > m[1] \\ m^{-1}[\hat{\phi}] & \text{if } m[-1] < \hat{\phi} \leq m[1] \\ -1 & \text{if } \hat{\phi} \leq m[-1] \end{cases}$$

where  $m[-1] = \lim_{\alpha \rightarrow -1} m[\alpha]$ , and  $m^{-1} : (m[-1], m[1]) \rightarrow (-1,1)$  is that the inverse function of  $m[\cdot]$  that satisfies  $m^{-1}(m(\phi)) = \phi$  for  $\phi \in (-1,1]$ . In other words, if there is a function such that for each true value of  $\phi$  it yields the median value of  $\hat{\phi}$ , then one can use the inverse function to obtain the median unbiased estimate of  $\phi$ .

In applying the Hansen procedure, the bootstrap quantile function is first defined as:

$q_n^*(\phi | \alpha) = q_n(\phi | \alpha, \hat{\pi}(\alpha))$  where  $\alpha$  is the parameter of interest and  $\pi$  is the nuisance parameter and  $n$  denotes the sample size. The  $\beta$  level bootstrap confidence region is defined by the formula

$$C = \{\alpha : q_n^*(\phi_1 | \hat{\alpha}) \leq S_n(\alpha) \leq q_n^*(\phi_2 | \hat{\alpha})\}$$

where  $\phi_1 = 1 - (1 - \beta)/2$  and  $\phi_2 = (1 - \beta)/2$ , so that  $\beta = \phi_2 - \phi_1$

For a given  $\alpha$  let  $G_n^*(x | \alpha) = G_n(x | \alpha, \hat{\pi}(\alpha))$  be the bootstrap distribution of the sample.

Random samples,  $X_n^*$  are drawn from this distribution. The bootstrap quantile function,

$q_n^*(\phi | \alpha) = q_n(\phi | \alpha, \hat{\pi}(\alpha))$  is calculated where  $\alpha$  is chosen from a grid  $A_G = [\alpha_1, \alpha_2, \dots, \alpha_G]$ .

The estimated function is smoothed by using a kernel regression. For a given  $\alpha$ , the kernel estimate is:

$$\hat{q}_n^*(\phi | \alpha) = \frac{\sum_{j=1}^G K\left(\frac{\alpha - \alpha_j}{h}\right) \hat{q}_n^*(\phi | \alpha_j)}{\sum_{j=1}^G K\left(\frac{\alpha - \alpha_j}{h}\right)}$$

where  $K$  is the kernel function and  $h$  is the bandwidth.

### VAR/VECM Method of Cointegration: Johansen (1988), Hansen and Seo (2002)

The Johansen and Juselius (1990) method involves estimating the following vector error correction model (VECM):

$$\Delta P_t = \mu + \Pi P_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_{t-i} + \varepsilon_t$$

where  $\Delta P_t$  is a  $2 \times 1$  vector of first differenced price series. This way of specifying the system contains information on both the short- and long-run adjustment to changes in  $P_t$  via the estimates of  $\Gamma_i$  and  $\Pi$ , respectively. If  $P_t$  is  $I(1)$  and a single cointegrating vector then the rank of  $\Pi$  is equal to 1. In this case  $\Pi$  can be factorized into  $\alpha\beta'$ , where  $\alpha$  and  $\beta$  are two  $2 \times 1$  matrices. The matrix  $\alpha$  represents the speed of adjustment to equilibrium, while  $\beta$  is a matrix of long-run coefficients such that the term  $\beta'P_{t-1}$  represents a cointegrating relationship that is  $I(0)$ , which ensures that  $P_t$  converge to their long-run steady state solutions.

Hansen and Seo (2002) formulate a two-regime VECM as follows:

$$\Delta P_t = \begin{cases} \Pi_1 Z_{t-1}(\beta) + \varepsilon_t & \text{if } \omega_{t-1}(\beta) \leq \gamma \\ \Pi_2 Z_{t-1}(\beta) + \varepsilon_t & \text{if } \omega_{t-1}(\beta) > \gamma \end{cases},$$

where  $Z_{t-1}(\beta) = [1 \quad \omega_{t-1}(\beta) \quad \Delta Z_{t-i}]'$  where  $i = 1, 2, \dots, k$  depending upon the lag length chosen;  $\omega_{t-1}$  is the  $I(0)$  error correction term (equivalent to the  $\beta'P_{t-1}$  term in the Johansen model described above);  $\Pi_1$  and  $\Pi_2$  are the coefficient matrices that describe the dynamics in the two regimes; and  $\gamma$  denotes the threshold parameter. To determine whether a threshold effect exists, Hansen and Seo (2002) propose a heteroskedastic consistent LM test statistic for the null hypothesis of linear cointegration against the alternative of threshold cointegration denoted by:

$$\sup LM^0 = \sup_{\gamma L \leq \hat{\lambda} \leq \gamma U} LM(\hat{\beta} \quad \gamma)$$

In this test, the search region for the threshold parameter is  $[\gamma L \quad \gamma U]$  where  $\gamma L$  is the  $\pi_0$  percentile of  $\omega_{t-1}$  and  $\gamma U$  is set according to the  $(1 - \pi_0)$  percentile. The value of  $\pi_0$  is set to 0.15 as suggested by Andrews (1993). Bootstrap methods are employed, following Hansen and Seo (2002) to obtain the p-values.

## Data Description and Sources

Monthly price data for Brent, WTI, and Dubai are measured in US dollars per barrel (US\$/bbl). The source is the International Financial Statistics Database published by the International Monetary Fund. Data span: January 1975 to December 2009.

Monthly price data for gas is taken from the Energy Information Administration (EIA 2008). Gas is the US wellhead price in US dollars per thousand cubic feet, and coal is in US dollars per metric ton. Data span: January 1976 to December 2009.

Monthly price data for Australian thermal coal is measured in US dollars per ton. Source is the International Financial Statistics Database published by the International Monetary Fund. Data span: February 1979 to December 2009. All monthly energy prices are deflated to June 1985 prices using the US Producer Price Index prepared by the US Bureau of Labor Statistics.

Data on industrial production index was obtained from the following sources:

The People's Republic of China: monthly data from the National Bureau of Statistics; data span: January 1995 to December 2009. India: monthly data from the Department of Statistics; data span: April 1981 to December 2009. Thailand: monthly data from the Bank of Thailand, data span: January 1987 to December 2009. Indonesia: monthly data from the National Bureau of Statistics; data span: January 1993 to December 2009. Malaysia: monthly data from the Department of Statistics; data span: January 1994 to December 2009. Philippines: monthly data from the National Statistical Office; data span: January 1993 to December 2009.

Data on consumer price index for all the Asian countries obtained from the International Financial Statistics.

Description of daily data for the analysis on biofuels: Source: DataStream; data span: 2 November 2006 to 3 May 2010.

Rice: Thai Long Grain 100% B Grade FOB US \$/ton

Soybeans: No. 1 Yellow, cents (Cts) per bushel

Wheat No. 2 Hard (Kansas) Cts/Bushel

Sugar ISO Daily Price Cts per pound;

Palm Oil: Malaysia Rdam US dollars per ton

Biodiesel: B100 FOB Midwest US dollars per gallon

Crude Oil: Brent FOB (US\$/bbl)

WTI NYMEX Spot (US\$/bbl)

Dubai Arab Gulf FOB (US\$/bbl)

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### **About the Paper**

Atanu Ghoshray conducts a study on the underlying price dynamics of energy prices and its impact on the macroeconomy of Asian countries. The paper studies underlying trends to help identify the time series path of nonrenewable energy resources and determine the persistence of oil price shocks. The study also examines the causal relation between oil prices and the macroeconomy allowing for nonlinear models that have been recently advocated in the literature. The study describes the relation between oil prices and agricultural commodities. From a policy perspective, these interrelationships of agricultural and oil prices warrant careful consideration in the context of the recent energy crisis, which may very well continue in the future.


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ADB's vision is an Asia and Pacific region free of poverty. Its mission is to help its developing member countries reduce poverty and improve the quality of life of their people. Despite the region's many successes, it remains home to two-thirds of the world's poor: 1.8 billion people who live on less than \$2 a day, with 903 million struggling on less than \$1.25 a day. ADB is committed to reducing poverty through inclusive economic growth, environmentally sustainable growth, and regional integration.

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