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Revisiting the Palm Oil Boom in Southeast Asia

The Role of Fuel versus Food Demand Drivers

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ABSTRACT

In the last 30 years, palm oil production has known a ninefold increase, with almost all production growth concentrated in Malaysia and Indonesia. Several public reports have associated the palm oil boom with extensive deforestation, often pointing to the increase in biofuel demand in developed nations as a main driver of this phenomenon. Other demand drivers, especially as related to the food sector, have not been studied as much. In particular, regulations on genetically modified (GM) food in European nations and on trans fats in a number of developed countries have reportedly induced food companies to switch from soybean oil to palm oil and could therefore have contributed to additional demand for palm oil. This article provides a first analysis of the drivers of growth in palm oil production during the 1980–2010 boom, using a price dynamics analysis of the markets for palm oil, soybean oil, and crude oil. Soybean oil is selected as the leading vegetable oil in food markets, and crude oil is taken to represent the energy sector. We estimate two models of the oil price system: a vector auto regression model that treats all three prices as stationary and a vector error correction model that allows co-integration among the three prices.

The two models consistently find that palm oil prices do not appear to respond to short-run fluctuations in crude oil prices. Instead, short-run dynamics in palm oil prices are a function of lagged palm oil prices and current and lagged soybean oil prices. Thus, short-run fluctuations in crude oil prices do not appear to be a driver of the boom in palm oil production. Short-run fluctuations in soybean oil prices, however, do affect palm oil markets. We also find a long-run equilibrium relationship among prices of palm oil, soybean oil, and crude oil. In the long run, prices of palm oil and crude are negatively correlated. These results point to a potentially important relationship in the short and long run between palm oil markets and soybean oil markets, but this analysis does not point to the crude oil market as an important driver of the palm oil boom.

Keywords: palm oil, biofuel, price cointegration

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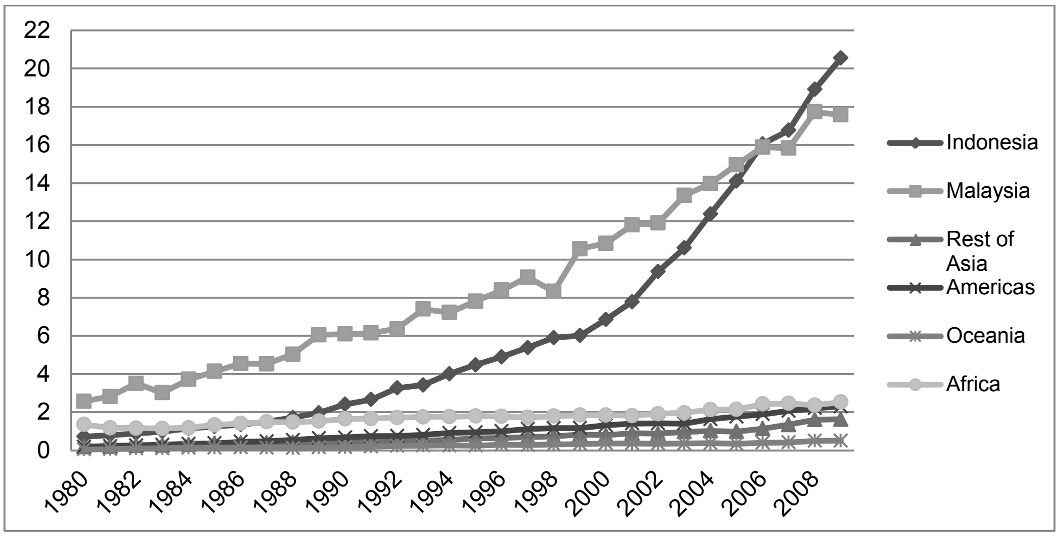
ABBREVIATIONS AND ACRONYMS

ADF	Augmented Dickey-Fuller
AIC	Akaike information criterion
API	American Petroleum Institute gravity
CIF	cost, insurance, and freight
FOB	free on board
GM	genetically modified
IRF	impulse response functions
SBIC	Schwarz Bayesian information criterion
VAR	Vector autoregression

1. INTRODUCTION

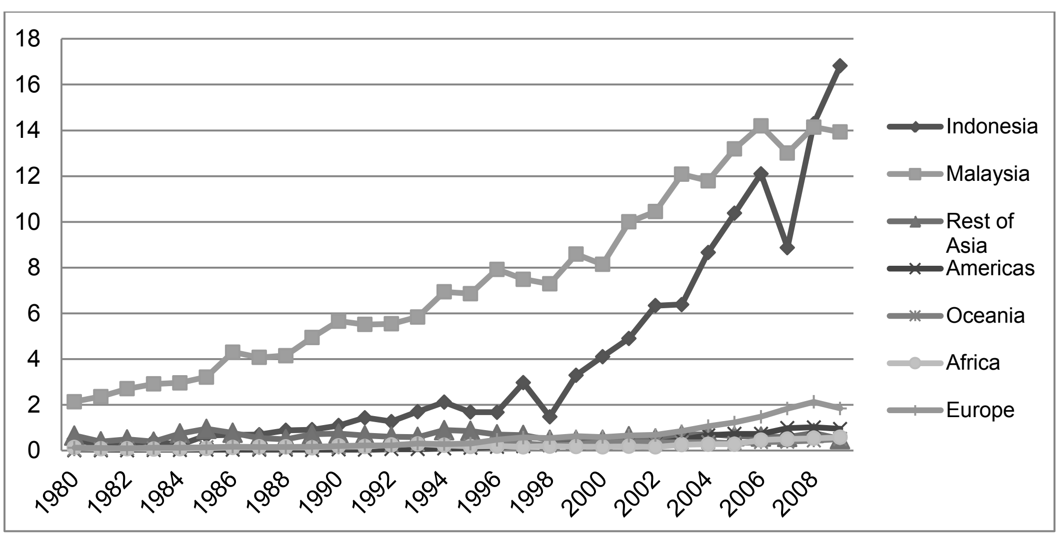
The production, trade, and market share of palm oil have grown dramatically in the last two decades. From 1980 to 2009, the global production of palm oil grew from 5 million tons to more than 45 million tons, equivalent to an annual average growth of 7.8 percent (FAO 2011). From traditional use in West Africa and originally colonial plantations in tropical countries in Southeast Asia, palm oil has become one of the leading vegetable oils in the world market, sharing this role with soybean oil. Most of the production has been concentrated in two Asian countries, Malaysia and Indonesia, as shown in Figure 1.1. These two countries combined account for approximately 90 percent of world palm oil exports in recent years, as shown in Figure 1.2 (FAO 2011).

Figure 1.1—Production (in million metric tons) of palm oil, 1980–2009



Source: FAO 2011.

Figure 1.2—Total exports (in million metric tons) of palm oil, 1980–2009

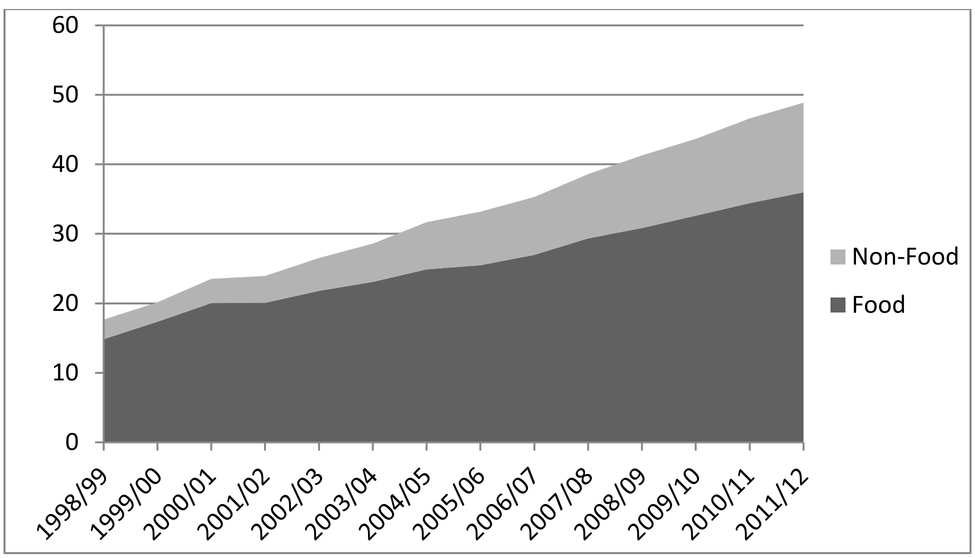


Source: FAO 2011.

While this palm oil boom has created positive outcomes for local agricultural incomes (see, for example, Zen, Barlow, and Gondowarsito 2005 for the case of Indonesia), it has also been criticized for its effects on deforestation (Proforest 2003). Increased production of palm oil has been associated with clearing of old growth forests, resulting in reported biodiversity losses and increased greenhouse gas emissions (see, for example, Kessler et al. 2007). In the past few years, the issue has been highlighted in international news headlines, leading major food and consumer product companies, like Nestlé and Unilever, to actively engage in certification for sustainable palm oil production (Bird 2010; Byrne 2010), if not completely ban the use of palm oil in their products. Furthermore, countries in the European Union adopted a regulation on the sustainable use of biofuel to reduce the potential for domestic and imported products to affect biodiversity and generated greenhouse gas emissions (for example, see European Council, 2009).

The recent surge in biofuels production is often one of the first culprits to be named as a cause of the palm oil boom, particularly in popular press articles that rhetorically link the fuel in the readers' car tanks to deforestation of rainforests on the other side of the world (Byrne 2010). Conceptually there is some reason to suspect that the biofuel surge could play a role, inasmuch as vegetable oils can be converted to biodiesel or can serve as a substitute in food and industrial uses for those oils that have been pulled into energy production (Carter et al. 2007). Palm oil can be used in both roles, either as a fuel stock for energy production or as a consumable substitute that fills the shortage left by the appropriation of vegetable oil for biodiesel.

Figure 1.3—Global consumption (in million metric tons) of palm oil: food versus non-food uses



Source: Derived from USDA-FAS (2012).

However, other possible drivers of the palm oil boom have received much less attention. As shown in Figure 1.3, despite the growth in non-food uses over the last decade (consumption share growing from 16 to 26 percent), palm oil has remained primarily used for food consumption. Reduced support policies in the soybean sector in line with the policies of the World Trade Organization and increased demand for edible oil in large developing countries (China and India) were reportedly generating palm oil growth even before the introduction of biofuel policies and have continued to push Malaysia and Indonesia to increase their palm oil production. More recently, new food regulatory developments may have contributed to fueling palm oil demand in the last decade. More specifically, genetically modified (GM) food, trans fat labeling regulations, and associated GM-free and trans fat–free private standards in developed countries have been reported as candidate drivers of palm oil demand (for example, by PRWeb 2008), without being linked explicitly to the palm oil boom and its consequences.

The European Union's regulations of GM food require food companies to display whether oils are derived from GM crops. This labeling requirement, combined with continued anti-GM perceptions among consumers, has pushed companies to avoid using any GM ingredient in their food products (Carter and Gruere 2003). Some companies have adopted explicit GM-free private standards, while others have simply avoided GM ingredients since labeling was mandated (Gruere 2006; Gruere and Sengupta 2009). Originally these practices resulted in a shift from GM soybean sources to non-GM soybean sources, however, growing adoption of GM soybeans limited non-GM soybean availability.[1] With this growth in GM soybean adoption, companies have shifted their purchase to other oils, including palm oil, the cheapest alternative. While the extent of this phenomenon is not well known, it has been recognized by observers as a significant reason for the replacement of soybean oil by palm oil in food products in Europe (Partos 2004; Proforest 2003) and was an expected effect of a proposed mandatory GM food labeling regulation in India in 2006 (Patton 2006).

Similarly, changes in health-related regulations and standards for food have reportedly resulted in the increased appeal of palm oil, despite its own well-known health disadvantages. Palm oil includes a relatively significant amount of saturated fats, whose consumption is associated with an increased ratio of high-density lipoprotein (HDL, or *bad*) cholesterol, which can result in low content in polyunsaturated fatty acids, which become trans-fatty acids (so-called trans fats) in the processing of food (chemical hydrogenation). Trans fats have recently been reported as a source of bad cholesterol, which can lead to coronary heart diseases (see, for example, Tribe and Kalla 2005). With increased attention on trans fats, potentially worse for heath than saturated fats, trans fat labeling regulations have been introduced in the United States in 2006, and food companies have voluntarily shunned away from trans fat–inducing vegetable oils, like soybean oil, in favor of canola and palm oil (Partos 2005).

The role of these potential demand factors that would have driven food companies to switch ingredients primarily from soybean oil to palm oil, if confirmed, could have important policy implications. First, imposing the labeling of highly processed food products that do not contain GM traces but that contain ingredients derived from GM crops could have had negative environmental consequences. Second, the food industry movement against trans fat, while justified for health reasons, may not have been truly beneficial if it resulted in an increase in palm oil consumption and a renewed interest in the use of palm oil in food, despite its inherent risks.

A full understanding of the causes and consequences of the rapid growth in palm oil production requires analyzing the economic forces that link the production of palm oil to specific sources and determinant consumption of palm oil, and more broadly to the markets for vegetable oil and for feedstocks for biofuels. This study aims to provide a first step toward understanding these economic relationships, through an exploratory study of the price relationships across the vegetable oil markets and related fuel markets.

The objective of the study is to explore the long- and short-term price dynamics between palm oil, soybean oil, and crude oil markets to try to assess the role of fuel versus food demand drivers in the palm oil boom. In the absence of available disaggregated long term data on consumption of palm oil by type of use, prices of the two other oils are taken as proxies for different consumption sources. Crude oil is selected to represent the energy market as a whole. On the other hand, soybean oil demand was the primary target of the above-mentioned food regulations, and apart from palm oil, it represents the most important edible oil on the market, and leading competitor with palm oil on the global market. Soybean oil is also a source of input for biodiesel production, but the share of use for biodiesel remains limited, even if it has grown overtime, as shown for recent years in Table 1.1.

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1 The rapid adoption of GM soybeans has been partially enabled by the liberalization of import policies in China as part of its acceptance into the WTO in 2002, as well as its conditional acceptance of GM soybean imports (Tuan, Fang, and Cao, 2004). U.S. soybean exports to China have grown rapidly in this period, accounting for more than 25 percent of total 2009 production; concurrently, GM soybean adoption in the U.S. reached 91 percent, an acceptance level only possible given permissive Chinese imports (FAOSTAT, 2011; USDA-ERS, 2012).

Table 1.1—Soybean oil use (in thousand pounds) between 2005/06-2008/09

Years	Biodiesel use	Other (food and feed)	Share of biodiesel
2005/06	1,555,026	17,958,608	8%
2006/07	2,761,567	18,574,448	13%
2007/08	3,245,322	18,334,765	15%
2008/09	1,907,058	16,384,862	10%

Source: USDA (2010).

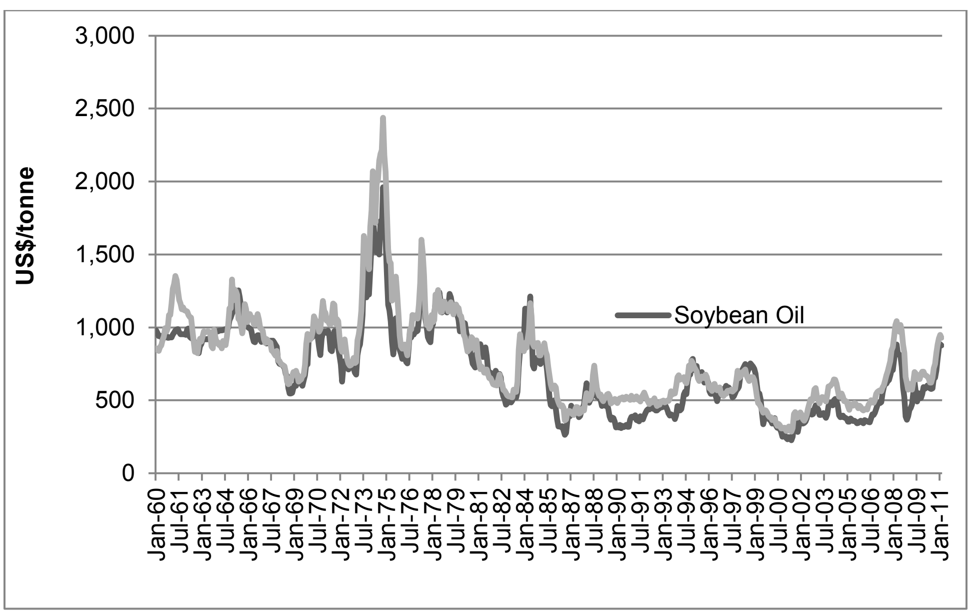
As a caveat, this study does not provide a structural analysis of palm oil demand; it does not allow isolating the effect of specific national regulations (on GM or trans fats) on palm oil demand. Instead, the study here provides a unique overview of the dynamic price relationships among edible oils and energy markets and tests the hypothesis of whether palm oil market growth has been driven by one or the other type of driver. More specifically, it enables us to test whether there may be a relationship between increased palm oil demand and soybean oil demand, which stands as a necessary condition for food regulations to be considered as partial drivers of the boom. Finding that palm oil was related only to the energy-related demand would disqualify the role of food regulations. Therefore, our analysis serves as a necessary first step toward a better understanding of the possible role of new food regulatory requirements in palm oil production and, indirectly, in possible deforestation in Southeast Asia.

2. DATA USED IN THE ANALYSIS

The dataset comprises prices from the World Bank Commodity Price Dataset, also referred to as the *Pink Sheet*. This dataset is a compilation of monthly prices for a collection of commodities, sorted into broad categories of energy, beverages, fats and oils, grains, other food, timber, other raw materials, fertilizers, and metals and minerals (World Bank, 2011).

We focus on prices of three of these commodities: crude oil, palm oil, and soybean oil. The crude oil price is a weighted average of the spot prices for Brent crude 38° API (American Petroleum Institute gravity), Dubai Fateh crude 32° API, and West Texas Intermediate crude 40° API. These prices are all free on board (FOB) values taken at United Kingdom ports; Dubai; and Midland, Texas, respectively. The soybean oil price series is the price of crude-grade oil of any origin (FOB) ex-mill the Netherlands. The palm oil series is based on Malaysia oil at 5 percent bulk cost, insurance, and freight (CIF) prices to northwestern Europe. Crude oil is reported in nominal US dollars[2] per barrel, while palm and soybean oil prices are reported in nominal US dollars per ton. We deflate all prices using the Producer Price Commodity Index published by the US Bureau of Labor Statistics; this series best fits the nature of the data and shows no resulting difference from other possible deflating indexes. We conduct our analysis on monthly prices dating from January 1960 through February 2011, as well as a subset of the data from January 1982 through February 2011. Figure 2.1 plots the data for soybean oil and palm oil prices. Figure 2.2 plots the data for crude oil prices.

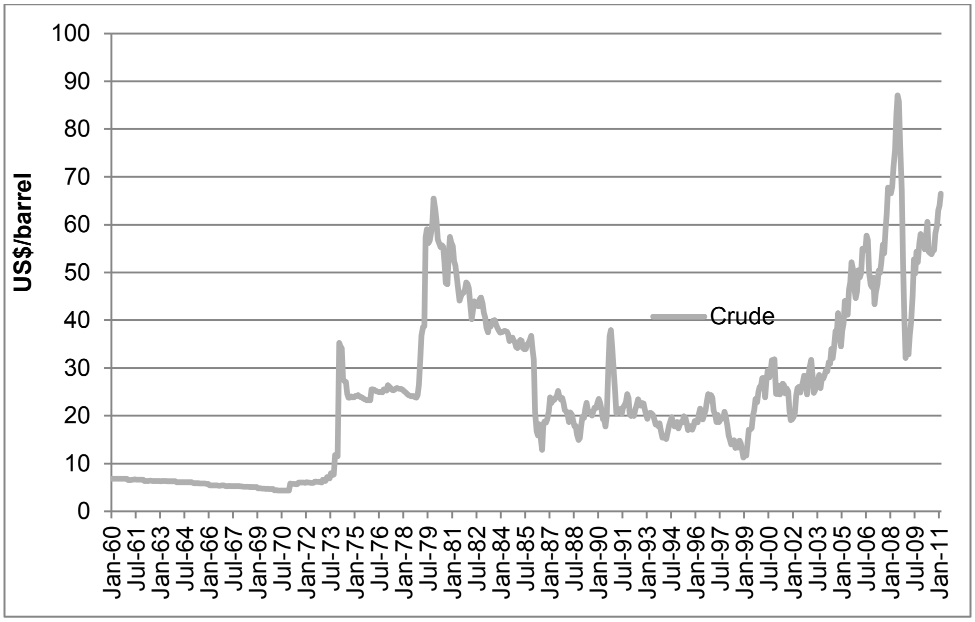
Figure 2.1—Prices of soybean oil and palm oil, January 1960–February 2011, real (1986) US $/ton



Source: World Bank Commodity Price Data.

[2] All dollar amounts are in US dollars.

Figure 2.2—Prices of crude oil, January 1960–February 2011, real (1986) $/barrel



Source: World Bank Commodity Price Data.

Notes: These figures suggest, at first view, a close correlation between soybean oil and palm oil prices, and a less visible relationship between crude oil prices and those of the two other oils. But assessing any possible cross-relationship, including any possible time correlation, requires delving into statistical analysis.

3. EXPLORING THE RELATIONSHIPS AMONG PRICES OF PALM OIL, SOYBEAN OIL, AND CRUDE OIL

Vector Autoregression Analysis

We first examine price dynamics in the context of a vector autoregression (VAR) model. Since the modeling framework requires all included variables to be stationary, we include the crude oil prices in first differences. Stationarity of the first-differenced crude oil prices was confirmed using an augmented Dickey-Fuller (ADF) test.

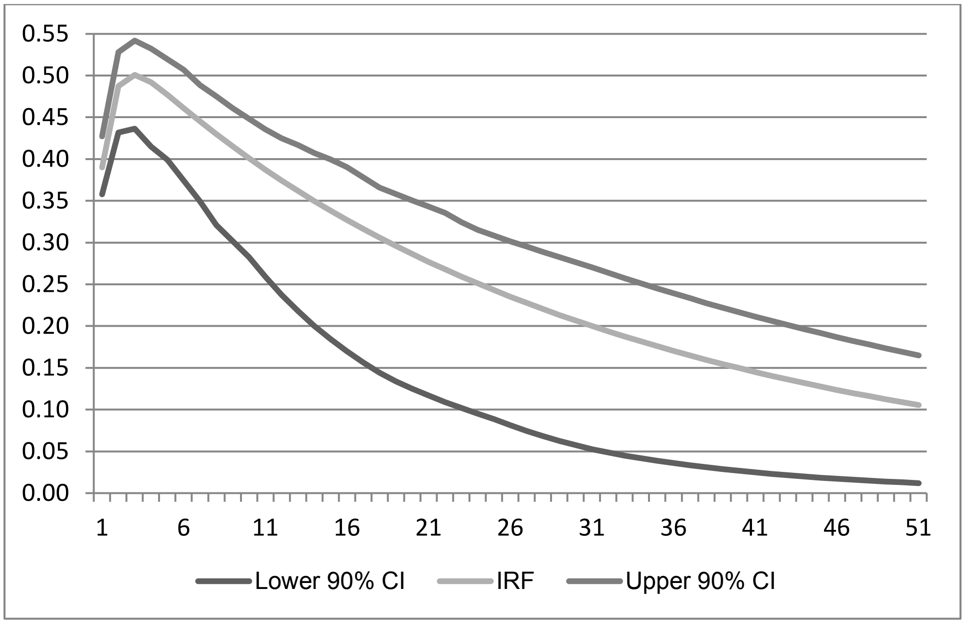
Given the small size of the vegetable oil market relative to that of the crude oil market, we assume that crude oil prices are exogenous to the system but potentially influence prices of the edible oils. It is also worth noting that the structure of the VAR model conditions that one price can have a contemporaneous effect on both prices, while the other price can have a contemporaneous effect only on itself. This is a restriction necessary for identifying the system. In this case, soybean oil is structured to have contemporaneous and lagged effects on palm oil prices, while palm oil is able to have only lagged effects on soybean oil. This ordering is derived from the economic intuition of the observed markets. The VAR model framework can be expressed as

$$\boldsymbol{y}_t = \boldsymbol{\beta} + \sum_{i=1}^{q} \boldsymbol{\pi}' z_{t-i} + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t, \qquad (1)$$

where y_t is a 2 x 1 vector of the soybean and palm oils in levels at time t, z_t is a common regressor of crude oil prices in first differences at time t, β is a 3 x 1 vector of estimated constants, π is a q x 1 vector of estimated coefficients, and Π_i is a 2 x 2 matrix of estimated coefficients for the i^{th} lag of the series. The optimal lag length p was determined to be two lags by iterating through all reasonable lag lengths and comparing the Akaike information criterion (AIC) and Schwarz Bayesian information criterion (SBIC) statistics for each model.

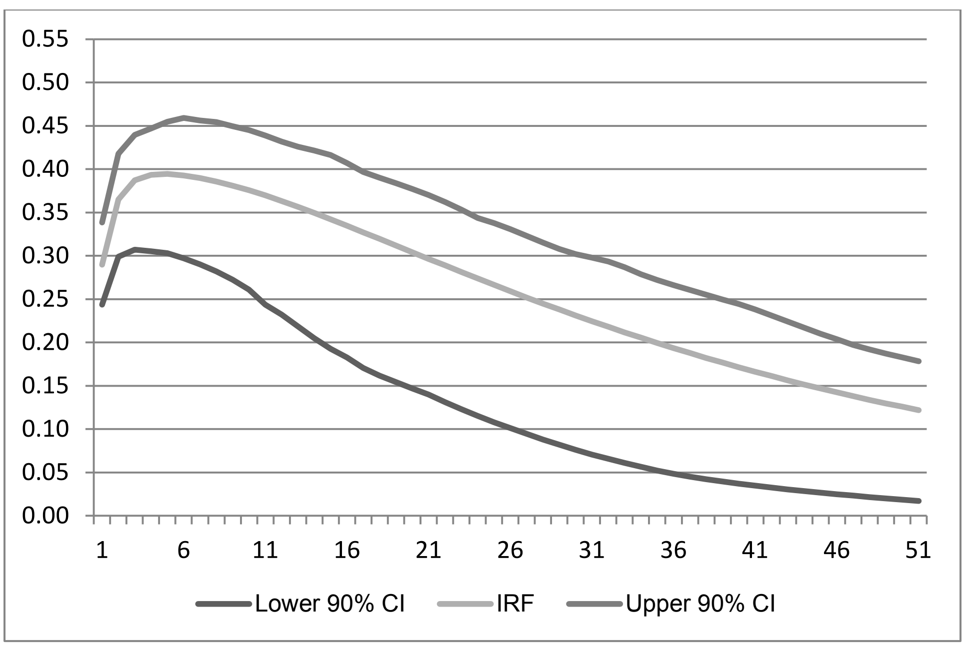
The key outputs from the VAR model are the plots of the orthogonalized impulse response functions (IRFs). These functions map out the response of palm and soybean oil prices to positive shocks in their own price and the other price. We present the IRF plots, including the 90 percent confidence intervals, in Figures 3.1–3.4, with plots for palm oil, our primary interest, in Figures 3.1 and 3.2. One of the first points to stand out is duration of the impact on palm oil price from a shock to either palm oil or soybean oil price. In both cases the lower bound of the 90 percent confidence interval is greater than zero even four years after the initial shock. It is also worth noting that the IRF for palm oil price in response to shocks to the soybean oil price (Figure 3.2) is only slightly less than the own-price IRF for palm oil. That is to say, palm oil prices respond to innovations in the soybean oil price series nearly as much as they respond to direct innovations in the palm oil market.

Figure 3.1—Plot of IRF for palm oil price in response to a positive shock in its own price



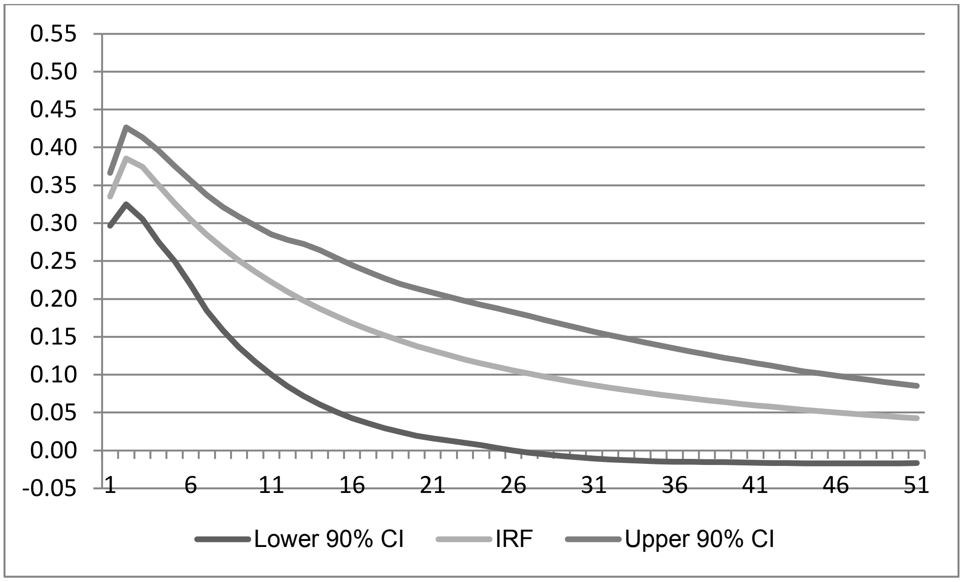
Source: Authors.

Figure 3.2—Plot of IRF for palm oil price in response to a positive shock in the price of soybean oil



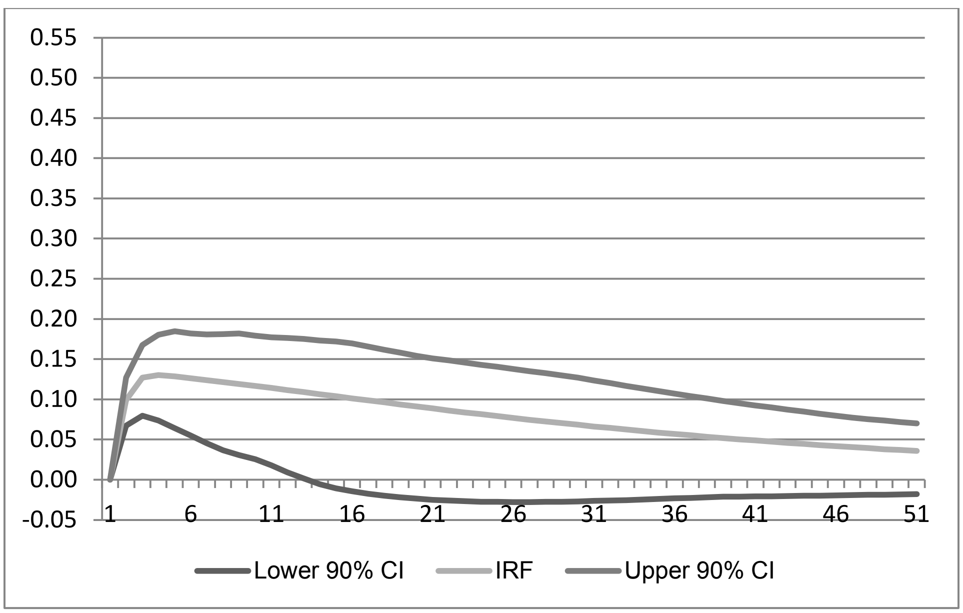
Source: Authors.

Figure 3.3—Plot of IRF for soybean oil price in response to a positive shock in its own price



Source: Authors.

Figure 3.4—Plot of IRF for soybean oil price in response to a positive shock in the price of palm oil



Source: Authors.

The IRF plots for soybean oil prices are presented in Figures 3.3 and 3.4. One important finding is that the impact of palm oil price innovations on soybean oil prices is considerably smaller than the converse. The palm oil shocks show the same slow incorporation as soybean oil did, but they do not outweigh the own-price effects in the soybean oil market at any point. Moreover, the lower confidence bound for the palm oil price shock dips below zero after only 12 months. Statistically speaking, it appears that the palm oil effect on soybean oil prices dies out completely fairly quickly. Overall, the indication is that soybean oil prices have greater impact on palm oil prices than the converse, and that changes in the soybean oil market are likely to have lingering effects on palm oil prices.

Modeling Oils Prices with Potential Unit Roots: Testing for Cointegration

The preceding VAR analysis presumes that model variables are stationary in levels or, more specifically, I(0). The assumption of stationarity for prices of edible oils and crude is quite strong. Indeed, previous work on these prices has found nonstationarity over various time periods (for some examples, see Ardeni 1989; Zapata and Fortenbery 1996; Sabuhoro and Larue 1997; Chaudhuri 2001; Yang, Bessler, and Leatham 2001). Here we describe standard stationarity tests for the price series.

The original, full dataset included observations dating back to January 1960. Standard stationarity tests over this full dataset indicated prices for palm oil and soybean oil were stationary. This unexpected result could be due to mis-specification—for example, failing to account for structural breaks (Perron 1989; Amsler and Lee 1995; Lee, Huang, and Shin 1997).

Given the implausibility that edible oils prices were stationary over the full length of the data and the apparent volatility in the more recent years of the data, we investigated whether these series were stationary over a subset of the data. The lag length for each price series was determined by estimating the ADF function for up to twelve lag lengths and testing for the significance of the last lag. ADF tests were then conducted iteratively on subsets of the data, by iteratively eliminating the earliest year of the dataset until all three series (crude, soybean, and palm oil) were found to be nonstationary.

Results from the ADF tests for each of the three oil prices in levels and first differences are reported in Table 3.1. For each series we conducted the test with alternative deterministic components, and the table reports F-statistics for the significance of the deterministic components. The key parameter to make inference on stationarity is τ; $\tau = 0$ under the null hypothesis that the series is nonstationary. We fail to reject the null for all three level series for the period January 1982–February 2011, concluding that the level series are nonstationary over this period.

Table 3.1—ADF stationarity tests for prices of soybean oil, palm oil, and crude, 1982–2011

Type	Lags	ρ	ρ p-value	τ	τ p-value	F-statistic	F-statistic p-value
				Soybean oil in levels			
No constant	10	-0.3432	0.6045	-0.22	0.6072		
Constant	10	-28.0471	0.0016	-2.87	0.0504	4.22	0.0739
Trend	10	-27.4997	0.0128	-2.84	0.1854	4.18	0.3377
				Palm oil in levels			
No constant	10	-0.8036	0.5079	-0.44	0.5238		
Constant	10	-25.9643	0.0026	-2.83	0.0560	4.06	0.0838
Trend	10	-25.6364	0.0195	-2.75	0.2179	3.99	0.3757
				Crude oil in levels			
No constant	6	-0.0803	0.6642	-0.05	0.6646		
Constant	6	-3.8368	0.5562	-1.04	0.7285	0.63	0.9130
Trend	6	-8.8938	0.5113	-2.12	0.5305	3.66	0.4433
				Soybean oil in first differences			
No constant	10	-288.204	0.0001	-5.24	< 0.0001		
Constant	10	-209.116	0.0001	-5.24	< 0.0001	13.78	0.0010
Trend	10	-299.907	0.0001	-5.26	< 0.0001	13.87	0.0010

Table 3.1—Continued

Type	Lags	ρ	ρ p-value	τ	τ p-value	F-statistic	F-statistic p-value
			Palm oil in first differences				
No constant	10	-588.544	0.0001	-5.60	< 0.0001		
Constant	10	-588.374	0.0001	-5.59	< 0.0001	15.68	0.0010
Trend	10	-649.914	0.0001	-5.62	< 0.0001	15.83	0.0010
			Crude oil in first differences				
No constant	6	-12173.57	0.9999	-8.16	< 0.0001		
Constant	6	-10444.85	0.9999	-8.16	< 0.0001	33.34	0.0010
Trend	6	-2714.04	0.9999	-8.33	< 0.0001	34.73	0.0010

Source: Authors.

Given this result, the VAR model of the previous section is inappropriate, since it may suffer from spurious regression. However, it has been demonstrated that nonstationary variables may have long-run relationships that the data series consistently revert back to over time. These cointegrating relationships, as they are known, provide a stationary residual series that can be used to introduce the long-run information from the nonstationary variables into a stable model. The resulting formulation is referred to as a cointegration model. A conventional model for cointegrated series is the Engle-Granger (1987) methodology for error correction:

$$\boldsymbol{\Delta y}_t = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} e_t + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \boldsymbol{\Delta y}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{2}$$

where $\boldsymbol{\Delta y}_t$ is an m x 1 vector of the first differences of the m-variables at time t, $\boldsymbol{\beta}_0$ is an m x 1 vector of estimated constants, $\boldsymbol{\beta}_1$ is the estimated parameter on the error correction term, $\boldsymbol{\Pi}_i$ is an m x m matrix of estimated parameters for the i^{th} lag, and $e_t$is the residual from the model

$$y_{1t} = \alpha_0 + \sum_{j=2}^{m} \alpha_j y_{jt} + e_t. \tag{3}$$

The error correction model accounts for both the long- and short-run interactions between variables in a system. A popular update to this methodology is that of Johansen (1991), which examines the rank of the matrices estimated in a standard VAR model constructed of only the lagged variables, excluding the error correction terms.

However, the drawback to both the Engle-Granger and Johansen methods is that they require all the variables to be of the same order of integration, generally being all I(1). Given the uncertainty in the order of integration for the variables in use, we adopted the autoregressive distributed lag (ARDL) model developed by Pesaran, Shin, and Smith (2001) for testing cointegration when the orders of integration of the individual series are uncertain, but either I(0) or I(1). The model framework was

$$\Delta y_t = \alpha_0 + \alpha_1 t^* + \boldsymbol{\pi}' \boldsymbol{v}_{t-1} + \sum_{i=0}^{p_y} \varphi_{xi} \Delta x_{t-i} + \sum_{j=1}^{p_x} \varphi_{yj} \Delta y_{t-j} + \sum_{k=0}^{p_z} \varphi_{zk} \Delta z_{t-k} + \varepsilon_t, \tag{4}$$

where Δ is the first-difference operator; y_t, x_t, and z_t are prices for palm oil, crude oil, and soybean oil, respectively; t^* is a time trend; and $\boldsymbol{v}_t = [y_t, x_t, z_t]'$. The optimal lags p_y, p_x, and p_z were determined by grid search over all possible lag-length combinations (12^3 = 1,728 combinations in total). For each combination, the AIC and SBIC values for the model were calculated and stored. The models were then sorted by both AIC and SBIC parameters and compared. As might be expected, the SBIC ordering provided a much more parsimonious lag combination of $p_y = 1$, $p_x = 1$, and $p_z = 2$. However, simple serial correlation testing of the residuals of this model on their own lags indicated that some autocorrelation remained in the residuals. The AIC ordering established a lag combination of $p_y = 6$, $p_x = 1$, and $p_z = 6$; this combination eliminated autocorrelation from the residuals. As a result, the distributed lags for this model were chosen to be 6–1–6.

Testing for cointegration was done through a bounds-testing procedure over the joint significance of the $\boldsymbol{\pi}'$ parameters. This bounds-testing procedure is a core contribution of Pesaran, Shin, and Smith (2001), who developed an F-type test (PSS F-statistic) for cointegration that does not assume all variables to be integrated of the same order. In this test, the null hypothesis is that the terms in the $\boldsymbol{\pi}$ vector are jointly equal to zero, indicating no cointegrating relationship exists. Alternatively, if the F-test rejects the null and finds that the error correction terms do statistically contribute to the model, then a cointegrating relationship is believed to be present. The critical bounds were developed through Monte Carlo analysis over the two extremes of all I(0) variables and all I(1) variables. The drawback to this procedure is that it allows for an undetermined space in which the existence of cointegration can be statistically neither confirmed nor rejected. The estimates from this model are provided in Table 3.2. From Table CI(v) in Pesaran, Shin, and Smith (2001), the critical values for a model with unrestricted intercepts and an unrestricted trend at a significance level of 5 percent, given three regressors, are 4.01 and 5.07, respectively. The estimated PSS F-statistic was 6.108; we therefore rejected the null of no cointegration and concluded that a cointegrating relationship exists among the prices for palm oil, soybean oil, and crude oil.

Table 3.2—ARDL linear co-integration model estimates

Variable	Estimate	Std. error	p-value
$palm_{t-1}$	-0.09270	0.02342	9.30E-05
$crude_{t-1}$	-0.21690	0.13017	0.09663
soy_{t-1}	0.08664	0.02670	0.00130
t*	0.00445	0.04496	0.92124
$\Delta palm_{t-1}$	0.27450	0.05434	7.29E-07
$\Delta palm_{t-2}$	-0.02008	0.05551	0.71778
$\Delta palm_{t-3}$	0.09279	0.05630	0.10030
$\Delta palm_{t-4}$	0.09636	0.05678	0.09061
$\Delta palm_{t-5}$	-0.12595	0.05554	0.02400
$\Delta palm_{t-6}$	-0.11585	0.05450	0.03430
$\Delta crude_{t}$	-0.03389	0.61017	0.95574
$\Delta crude_{t-1}$	0.00819	0.61107	0.98930
Δsoy_{t}	0.79773	0.04290	< 2e-16
Δsoy_{t-1}	-0.16095	0.06187	0.00971
Δsoy_{t-2}	-0.08090	0.06171	0.19078
Δsoy_{t-3}	-0.05004	0.06236	0.42296
Δsoy_{t-4}	0.04068	0.06186	0.51123
Δsoy_{t-5}	0.11839	0.06222	0.05797
Δsoy_{t-6}	0.14093	0.06056	0.02058
Constant	0.02585	0.05111	0.61340
Adjusted R-square: 0.6355			
PSS F-statistic: 6.1082			

Source: Authors.
Note: Dependent variable = first difference of palm oil.

Cointegration and Error Correction Estimations

Having found the three price series to be cointegrated, we estimated the cointegrating relationship by ordinary least squares. The estimated cointegrating relationship was

$$P_{palm} = -0.3178 + 1.0502P_{soy} - 1.7779P_{crude}(0.1149)(0.0282) \qquad (0.2936), \qquad (5)$$

where values in parentheses are standard errors and R-square = 0.8142.

Moreover, we estimated the conditional error correction model, replacing the lagged levels in the PSS cointegration test regression with the lagged residual from the cointegrating relationship. The results are reported in Table 3.3. The estimated coefficient on the lagged cointegrating residual is of the expected sign and is statistically significant at conventional thresholds. Thus, palm oil prices appear to respond to departures from long-run equilibrium in the oils complex.

Table 3.3—Vector error correction model

Variable	Estimate	Std. error	p-value
$\widehat{v_{t-1}}$	-0.09658	0.02435	0.00009
t*	-0.00392	0.03759	0.91694
$\Delta palm_{t-1}$	0.28700	0.05431	0.00000
$\Delta palm_{t-2}$	-0.01908	0.05558	0.73163
$\Delta palm_{t-3}$	0.09454	0.05618	0.09337
$\Delta palm_{t-4}$	0.08534	0.05663	0.13278
$\Delta palm_{t-5}$	-0.11105	0.05558	0.04654
$\Delta palm_{t-6}$	-0.09497	0.05501	0.08526
$\Delta crude_{t}$	0.12869	0.60141	0.83070
$\Delta crude_{t-1}$	-0.06789	0.60593	0.91086
Δsoy_{t}	0.81082	0.04221	0.00000
Δsoy_{t-1}	-0.18819	0.06152	0.00240
Δsoy_{t-2}	-0.08884	0.06134	0.14849
Δsoy_{t-3}	-0.05263	0.06202	0.39674
Δsoy_{t-4}	0.03724	0.06134	0.54422
Δsoy_{t-5}	0.10218	0.06175	0.09895
Δsoy_{t-6}	0.11304	0.06016	0.06116
Constant	0.00095	0.02160	0.96490
Adjusted R-square: 0.6409			

Source: Authors.
Note: Dependent variable = first difference of palm oil. $\widehat{v_{t-1}}$ is the residual from the estimated cointegrating relationship.

Estimated short-run dynamics reported in Table 3.3 are consistent with the VAR results reported above. In particular, the palm-oil price does not appear to respond to current or lagged fluctuations in crude oil prices but does respond in the short run to fluctuations in soybean oil prices. Moreover, changes in palm oil prices do not exhibit a trend.

We used these results to simplify the conditional error correction model, dropping the current and lagged changes of crude oil prices, as well as the time trend. The results are reported in Table 3.4. The estimates of the remaining variables remain virtually unchanged from the less parsimonious model. The short-run fluctuations are consistent with those found in the VAR analysis: Palm oil prices also respond to lagged changes in palm oil, as well as current and lagged changes in soybean oil prices, but not to changes in crude oil prices. The conditional error correction model offers the added insight that palm oil prices also respond to departures from the long-run equilibrium in the oils complex.

Table 3.4—Vector error correction model (short-run dynamics)

Variable	Estimate	Std. error	p-value
$\widehat{v_{t-1}}$	-0.09647	0.02395	0.00007
$\Delta palm_{t-1}$	0.28732	0.05394	0.00000
$\Delta palm_{t-2}$	-0.01904	0.05528	0.73071
$\Delta palm_{t-3}$	0.09467	0.05589	0.09123
$\Delta palm_{t-4}$	0.08566	0.05632	0.12925
$\Delta palm_{t-5}$	-0.11126	0.05530	0.04504
$\Delta palm_{t-6}$	-0.09478	0.05471	0.08413
Δsoy_{t}	0.81181	0.04154	0.00000
Δsoy_{t-1}	-0.18881	0.06077	0.00205
Δsoy_{t-2}	-0.08845	0.06100	0.14800
Δsoy_{t-3}	-0.05311	0.06159	0.38918
Δsoy_{t-4}	0.03702	0.06105	0.54464
Δsoy_{t-5}	0.10263	0.06145	0.09584
Δsoy_{t-6}	0.11272	0.05984	0.06049
Constant	-0.00098	0.01066	0.92655
Adjusted R-square: 0.6444			

Source: Authors.
Note: Dependent variable = first difference of palm oil. $\widehat{v_{t-1}}$ is the residual from the estimated cointegrating relationship.

Nonlinear Cointegration

A final concern with the analysis was the possibility of nonlinear movements in the long-run relationships among the oils studied. The relatively quick upward movement in prices, particularly over the last decade, could indicate a connection that the linear cointegration models were not able to pick up on. More to the point, the degree to which the prices changed and the rate at which the price movements converged suggest that the movements might be not only nonlinear but also changing in time. The issue, then, was whether or not the cointegrating variables could be better modeled within a nonlinear, smooth-transitioning framework. Such a framework was developed by Kapetanios, Shin, and Snell (2006) by adding a transition function to the cointegrating level variables. This smooth-transition model was applied to the data in this project, specifically testing for nonlinearity in the cointegrating relationships. Testing under two different nonlinear functional forms failed to reject the null hypothesis of a linear cointegrating relationship for both specifications. Accordingly, the long-term relationship in the data is better fitted with a linear model than a nonlinear specification. The statistical preference for a linear model strengthens the emphasis on soybean oil over crude oil as a driver in the palm oil market, inasmuch as a strengthening crude oil relationship would be expected to appear more clearly in a nonlinear relationship among the variables.

4. DISCUSSION AND CONCLUSION

The dramatic and well-publicized surge in palm oil production has inspired discussion regarding a number of possible reasons for the increase. Candidates for demand drivers include rising energy demands, increased biofuels production, a drop in food product demand for GM soybeans, and changing taste preferences related to health concerns. In particular, the possibility that energy market demands have inspired the increase in production has received considerable attention. Pictures of razed rainforests, coupled with the possibility of potential price inflation for these basic goods, have become a lightning rod for discussion. Consumption of biofuels by relatively affluent countries, and the associated increase in prices of agricultural commodities has also been controversial. However, to direct attention to biofuels without considering other possible drivers risks missing causes that are potentially more important to address.

This analysis examined the relationships among prices for palm oil, soybean oil, and crude oil. Soybean oil is one of the most prominently used vegetable oils and has a number of food and industrial uses. As such, it represents the full range of price drivers. Furthermore, it was the target of recent regulations on GM foods and trans fats. In contrast, crude oil represents a purely energy-based perspective. The analysis presented here employs different time series–based econometric models to identify interactions among the three price series in order to shed light on the cause of the growth of palm oil demand. We estimate two models of the oil price system: a simple VAR that treats all three prices as stationary as well as a vector error correction model that allows cointegration among the three prices. Statistical testing favors the error correction model, but our main results are robust to the choice of model.

A main finding is that palm oil prices do not appear to respond to short-run fluctuations in crude oil prices. Instead, short-run dynamics in palm oil prices are a function of lagged palm oil prices and current and lagged soybean oil prices. Thus, short-run fluctuations in crude oil prices do not appear to be a driver of the boom in palm oil production. Short-run fluctuations in soybean oil prices, however, do affect palm oil markets.

The error correction analysis indicates a long-run equilibrium relationship between prices of palm oil, soybean oil, and crude oil. Palm oil prices respond to departures from long-run equilibrium in this oils complex. Prices of palm oil and crude are negatively correlated in the long run. This finding is inconsistent with long-run growth in crude oil prices as a plausible explanation for growth in palm oil production. However, the positive correlation between prices of palm oil and soybean oil in the long run is consistent with the emergence of palm oil as a substitute for soybean oil.

Taken as a whole, these results point to a potentially important relationship in the short and long run between palm oil markets and soybean markets. At the same time, the crude oil market does not appear to be an important driver of the palm oil boom. These results are consistent with the importance of food and feed drivers, and not only biodiesel, in driving up demand for palm oil. While the results do not provide any definitive attribution to the palm oil boom, or any answer concerning whether regulatory issues affected the growth in palm oil supply, they do validate the plausibility of food-related factors playing a significant if not primary role in the observed boom, particularly in the last 15 years in Southeast Asia.

Further analysis should be conducted on the structural relationships between palm oil and soybean oil markets, especially accounting for bilateral demands and the role of specific policies.

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