El Niño, La Niña, and world coffee price dynamics

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Abstract

Coffee is produced in equatorial and subequatorial regions of the world, which are also most affected by El Niño Southern Oscillation (ENSO). ENSO events have a tendency to amplify weather conditions such as droughts or excess precipitation in the affected regions, resulting in production shortage or excess supply, subsequently impacting agricultural commodity prices. In this research we assess effects of ENSO events on world coffee price dynamics using the monthly data between March 1989 and December 2010. We employ smooth transition autoregression framework to examine nonlinear dynamics of ENSO and coffee prices, and illustrate the results of this research using generalized impulse-response functions. We find that ENSO events indeed have short-term impacts on coffee prices. The research findings are of interest to coffee producers and intermediaries in the coffee markets as well as researchers in the fields of environmental and development economics.

JEL classifications: C32, Q11, Q54

Keywords: El Niño Southern Oscillation; Coffee prices; Smooth transition autoregression; Generalized impulse-response functions

1. Introduction

Coffee is mostly produced and exported by developing countries in equatorial and subequatorial regions of the globe. There are two distinct varieties of coffee, of which higher quality Arabica beans are mostly produced in South American and West African countries, while lower quality Robusta beans are predominantly produced in Southeast Asia and Oceania (see Fig. 1). Arabica coffee is further divided into Brazilian Naturals, Other Milds, and Columbian Milds, of which the latter is considered as the highest quality coffee (Ghoshray, 2009). Coincidentally, these coffee producing regions are also most affected by the El Niño Southern Oscillation (ENSO)—a climatic phenomenon that causes extreme droughts or excess precipitation in these parts of the world. Consequently, ENSO-related weather shocks are likely to substantially impact world coffee production and, therefore, prices.

The systematic fluctuations of El Niño and La Niña events are linked to oscillations of the ocean–atmosphere system in the tropical Pacific region. In normal conditions, trade winds blow west across the tropical Pacific. During an El Niño phase trade winds weaken in the central and western Pacific, which results in unusually warm sea surface temperatures (SST) in the central and eastern Pacific. Apparent consequences of an El Niño phase are increased rainfall across the west coast of Central and South America, and drought in the Western Pacific region. The counterpart of El Niño is La Niña, which is associated with very intense trade winds, and colder-than-normal SST in the region. La Niña results in increased precipitation in the Oceania and droughts across the eastern Pacific region. El Niño and La Niña events reoccur every two to seven years and together define the phenomenon known as the El Niño Southern Oscillation, or ENSO.

In recent years there has been a growing interest in studying the role of large-scale medium-frequency weather anomalies in the performance of various economic variables. In this respect, particular attention has been paid to the relationship between the ENSO phenomenon and commodity price movements (e.g., Brunner, 2002; Holt and Inoue, 2006; Keppenne, 1995; Letson and McCullough, 2001). For example, Brunner (2002) has examined linkages between ENSO events, commodity prices, and measures of inflation and GDP growth for G7 countries, within the context of a vector autoregression (VAR). Likewise,
using yearly data spanning back to the late 1800s, Berry and Okulicz-Kozaryn (2008) have assessed the co-cyclicality of ENSO anomalies and macroeconomic performance including inflation and output.

Naturally, weather anomalies affect production and prices of agricultural commodities the most. In a series of papers, Handler and Handler (1983), Handler (1984), and Handler (1990) have provided evidence that deviations in Midwest corn yields from long-term trends are often linked to SST anomalies in the equatorial Pacific Ocean. Keppenne (1995) has examined the relationship between monthly soybean futures price movements and ENSO behavior, revealing their close linkages with the La Niña phase of the ENSO cycle. In a similar study, Letson and McCullough (2001) have analyzed relationships between monthly soybean cash prices and ENSO events, but found no meaningful connection between these two series. Chimeli et al. (2008) have investigated effects of SST anomalies on Brazilian corn yields and prices, reporting negative correlation between ENSO and corn production, and positive correlation between ENSO and corn prices. Finally, Ubilava and Holt (2009) have assessed effects of ENSO on world vegetable oil prices within the context of a smooth transition vector error correction (STVEC), finding evidence of asymmetric price responses to ENSO shocks.

Considering the mounting evidence of an economically meaningful relationship between ENSO and world commodity prices, it is striking that very little work has been done to investigate ENSO effects on coffee prices. This is in spite of the fact that the majority of coffee producing countries are directly affected by ENSO, resulting in production shortages or excess supply, thus, potentially impacting world coffee prices. A number of studies have examined ENSO dynamics, including the recent development in related climatology literature suggesting nonlinearities in ENSO cycles (e.g., An, 2009; Hall et al., 2001). The dynamics of coffee prices have long been studied as well. For example, Vogelvang (1992) has examined linear cointegration using quarterly coffee prices, while in a series of papers, Otero and Milas (2001), Milas and Otero (2002), and Milas et al. (2004) have applied nonlinear modeling techniques to assess cointegration between quarterly time series of coffee prices. Finally, Ghoshray (2009) has employed monthly series to examine coffee price dynamics, finding evidence of asymmetries in pairwise cointegrated coffee spot prices.

While ENSO cycles and coffee price movements have been examined in the literature, the issues have not been considered jointly. This article addresses this gap in the literature. The purpose of the current research is to assess dynamics of coffee prices in response to weather shocks related to ENSO events. Consistent with the previous literature, the analysis allows for the possibility of nonlinear dynamics in ENSO cycles as well as in coffee prices.

2. Econometric framework

Consider a linear univariate autoregressive model of order \( p \), AR(\( p \)), expressed in the first differenced form as

\[
\Delta y_t = \theta' x_t + \varepsilon_t,
\]

where \( \Delta \) is a first-difference operator; \( y_t \) is a dependent variable; \( x_t = (1, y_{t-1}, \Delta y_{t-1}, \ldots, \Delta y_{t-p+1}, z_{1,t}, \ldots, z_{m,t})' \) is a vector of right-hand-side variables, where \( z_{i,t}, i = 1, \ldots, m \), are exogenous variables; \( \theta = (\alpha, \beta_0, \psi_1, \ldots, \psi_{p-1}, \psi_1, \ldots, \psi_m) \) is a vector of parameters, where \( \beta_0 \) is the unit root parameter, such that the restriction \( \beta_0 = 0 \) imposes unit root process. Finally, \( \varepsilon_t \) is an additive error process such that \( \varepsilon_t \sim iid(0, \sigma^2) \).

A multivariate version of the autoregression—a VAR of order \( p \), VAR(\( p \)), expressed in a vector error correction (VEC) form, can be presented as follows:

\[
\Delta X_t = \mu \hat{e}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Psi z_t + v_t,
\]

where \( X_t \) is a vector of dependent variables and \( z_t = (z_{1,t}, \ldots, z_{m,t})' \) is a vector of exogenous variables; \( \hat{e}_t = \beta'(X_t, 1)' \) is a
vector of estimated error-correction terms, where cointegrating vectors, \( \beta \), are obtained using Johansen’s (1988) procedure. Further, \( \hat{e} \) represents a stationary process, even though dependent variables in \( X \) are nonstationary; \( \mu \) denotes a vector of speed-of-adjustment parameters, and \( \Gamma_i, i = 1, \ldots, p - 1 \), and \( \Psi \) are matrices of parameters to be estimated. Finally, \( v_t \) is a vector of error terms, such that \( v_t \sim \text{iid}(0, \Sigma_v) \), where \( \Sigma_v \) is a nondiagonal residual covariance matrix.

Equations (1) and (2) may be augmented in a number of ways, including threshold autoregressions (Tong, 1990; Tsay, 1989), Markov switching models (Hamilton, 1989), and artificial neural networks (Kuan and White, 1994). An alternative approach for modeling nonlinear features of time series data—and, moreover, an approach that combines elements of the aforementioned methods—is the smooth transition autoregressive (STAR) framework of Luukkonen et al. (1988) and Terasvirta and Anderson (1992). \(^1\) STAR-type models are widely applied in studies attempting to model the asymmetric cyclical variations and turbulent periods (e.g., Hall et al., 2001; Terasvirta, 1995). Class of smooth transition regressions can be specified as

\[
\Delta y_t = \theta_0 x_t + \theta'_1 x_t G(s_t; \gamma, c) + \epsilon_t, 
\]

where \( G(s_t; \gamma, c) \) is a so-called transition function, by construction bounded between 0 and 1, and where \( s_t \) is a transition variable, and \( \gamma \) and \( c \) are, respectively, smoothness and location parameters.

Likewise, in the case of a system of equations, a STVEC model is specified as

\[
\Delta X_t = \mu_0 \hat{e}_{t-1} + \sum_{i=1}^{p-1} \Gamma_{0,i} \Delta X_{t-1} + \Psi_0 \tilde{z}_t + \left( \mu_1 \hat{e}_{t-1} + \sum_{i=1}^{p-1} \Gamma_{1,i} \Delta X_{t-1} + \Psi_1 \tilde{z}_t \right) \tilde{G}(s_t; \gamma, c) + v_t, \tag{4}
\]

where \( \tilde{G}(s_t; \gamma, c) \) is a vector of transition functions associated with each of the equations in the system, and which, moreover, can be restricted to be the same across the equations. The rest of the parameters and variables are as defined previously.

In empirical applications, logistic and exponential transition functions are used most frequently, respectively, forming logistic STAR (LSTAR) and exponential STAR (ESTAR) models. These transition functions are defined as follows:

\[
G^L = \left[ 1 + \exp[-\gamma(s_t - c)] \right]^{-1} \tag{5}
\]

\[
G^E = \left[ 1 - \exp[-\gamma(s_t - c)^2] \right]. \tag{6}
\]

\(^1\) For the sake of brevity we will only briefly outline the STAR modeling procedure. Refer to Terasvirta and Anderson (1992), Terasvirta (1994), and Eitrheim and Terasvirta (1996) for the detailed description.

In a transition function the smoothness parameter, \( \gamma \), is a nonnegative parameter. The LSTAR model approaches a linear AR model when \( \gamma \to 0 \), and a threshold autoregressive model (TAR) when \( \gamma \to \infty \). On the other hand, ESTAR approaches a linear AR model when either \( \gamma \to 0 \) or \( \gamma \to \infty \).

The null hypothesis of linearity, i.e., \( H_0: \gamma = 0 \), cannot be directly tested in a STAR model, due to unidentified nuisance parameters—a phenomenon that is also known as the Davies’ (1987) problem. Specifically, in the context of Eq. (3), the nonlinear STAR model will reduce to the linear AR model either by imposing the restriction \( \gamma = 0 \) or by setting a vector of parameters \( \theta_1 = 0 \). As a consequence, the standard test statistics are no longer applicable to directly test \( H_0: \gamma = 0 \) against \( H_1: \gamma \neq 0 \), because of the lack of knowledge of the asymptotic distributions of the associated test statistics. The problem may be circumvented by approximating the transition function, \( G(s_t; \gamma, c) \), using the Taylor expansion, and then applying the testing sequence to the resulted auxiliary regression (Luukkonen et al., 1988). A third-order Taylor series expansion yields a sufficiently suitable auxiliary regression:

\[
\Delta y_t = \theta'_0 x_t + \sum_{i=1}^{3} \theta'_i x_t s^i_t + \xi_t, \tag{7}
\]

where the error term, \( \xi_t \), combines the original error term, \( \epsilon_t \), and the approximation error from the Taylor expansion. Of course, now it is possible to apply conventional testing methods to Eq. (7). Specifically, the general test of linearity against the STAR-type nonlinearity is equivalent to testing the null hypothesis of \( H_0: \theta_1 = \theta_2 = \theta_3 = 0 \), where \( \theta_i, i = 1, 2, 3 \), are vectors of parameters from the auxiliary regression. An additional benefit of testing nonlinearities using a third-order auxiliary regression is that tests against the LSTAR and ESTAR models are also embedded in the testing framework. Specifically, given that the null is rejected, a test against a LSTAR model is equivalent to testing the null hypotheses of \( H^0_{00}: \theta_3 = 0 \) and \( H^0_{01}: \theta_1 = 0, \theta_2 = \theta_3 = 0 \). Alternatively, a test against an ESTAR model is equivalent to \( H^0_{02}: \theta_2 = 0 \mid \theta_1 = 0 \). From these null hypotheses the one yielding the smallest probability value is used to decide on the functional form of the nonlinear model. Finally, the \( F \) version of the LM test statistic has been advocated for small and moderate samples (e.g., Van Dijk et al., 2002). After the STAR model is estimated, a similar framework is used to perform a set of diagnostic tests against remaining nonlinearity, parameter nonconstancy, and residual autocorrelation.\(^2\)

In the case of a system of equations with an identical transition function across equations, an approach that has most commonly been applied in the literature (e.g., Milas and Otero, 2002; Serra et al., 2011), we use a testing sequence proposed by Camacho (2004), where a system of auxiliary equations is expressed as

\(^2\) For more details regarding the testing procedure, including the model evaluation and diagnostic tests, refer to Luukkonen et al. (1988), Terasvirta and Anderson (1992), and Eitrheim and Terasvirta (1996).
\[ \Delta X_t = \mu_0 \delta_{t-1} + \sum_{i=1}^{p-1} \Gamma_{0,i} \Delta X_{t-i} + \Psi_0 z_t \\
+ \sum_{j=1}^{2} \left( \mu_j \delta_{t-1} + \sum_{i=1}^{p-1} \Gamma_{j,i} \Delta X_{t-i} + \Psi_j z_t \right) \tilde{S}_j + \xi_t, \]

where \( \tilde{S}_t \) is a transition variable stacked in a vector form, while other variables are as defined above. Similar to the univariate testing framework, a linearity test against STVEC specification is equivalent to the null hypotheses of \( H_0^e : \mu_1 = \mu_2 = \Gamma_{1,i} = \Gamma_{2,i} = \Psi_1 = \Psi_2 = 0, i = 1, \ldots, p-1 \). If the linearity hypothesis is rejected, a sequence of embedded tests are applied to assess the null hypotheses against an exponential STVEC, \( H_e : \mu_2 = \Gamma_{2,i} = \Psi_2 = 0 \), and a logistic STVEC, \( H_l : \mu_1 = \Gamma_{1,i} = \Psi_1 = 0 | \mu_2 = \Gamma_{2,i} = \Psi_2 = 0 \).

In practice, the transition variable is often \textit{a priori} unknown. Therefore, a number of candidate transition variables are usually used in the aforementioned testing procedures. The suitable transition variable is chosen to be the one yielding the lowest probability value associated with \( H_0^e \) and \( H_e \), respectively, for the STAR and STVEC models. After the suitable transition variable and associated transition function are selected, STAR models are estimated using a nonlinear optimization procedure.

### 3. Data

This research uses data covering the period between March 1989 and December 2010. We use monthly time series of the ENSO anomaly, \textit{Niño 3.4}, derived from the index tabulated by the Climate Prediction Center at the National Oceanic and Atmospheric Administration (NOAA). This index measures the difference in sea surface temperature in the area of the Pacific Ocean between 5°N–5°S and 170°W–120°W, and is a strong indicator of ENSO occurrence. The monthly measure of \textit{Niño 3.4} is an average of daily values interpolated from the weekly measures obtained both from satellites and actual locations around the Pacific. The anomaly is the deviation of the \textit{Niño 3.4} monthly measure from the average historical measure of the period of 1971–2000, for that particular month (the related and additional information may be accessed on the NOAA (2011) website at http://www.noaa.gov).

Coffee prices were obtained from the International Coffee Organization (ICO) website. In this research we use the data of four coffee prices: Columbian mild Arabicas (Columbian Milds), other mild Arabicas (Other Milds), Brazilian and other natural Arabicas (Brazilian Naturals), and Robustas. The prices are indicator prices compiled by the ICO and are based on daily ex-dock prompt shipment prices in New York, Bremen/Hamburg, and Le Havre/Marseilles markets (refer to the ICO (2011) website at http://www.ico.org for further details). Note that the estimation period starts shortly after the collapse of the International Coffee Agreement (ICA), when the export quotas were eliminated, and prices have since been determined under the free market conditions (see also Ghoshray, 2009). For estimation purposes, we deflated the nominal coffee prices using the Producer Price Index (PPI) for all commodities obtained from the U.S. Bureau of Labor Statistics. Further, in order to mitigate potential heteroscedasticity, typically associated with the price data (e.g., Carter and Smith, 2007; Holt and Inoue, 2006), and also to analyze effects in percentage terms, real prices were transformed to the natural logarithms. From here forward, whenever coffee price is mentioned it is to be considered as real price in natural logarithmic form, unless otherwise stated.

Plotting the coffee prices together allows us to see that prices in general co-move, and occasional divergences are eventually followed by convergences (see Fig. 2). It is also apparent that higher quality Columbian coffee sets the upper bound of coffee prices, while the lower quality Robusta coffee defines their lower bound. As for the relationship between the ENSO events and the coffee price movements, it is notable that the prices tend to diverge during and after strong La Niña episodes (e.g., in 1996–1997 and 2007–2008), and converge following strong El Niño episodes (e.g., in 1998). Of course, the movement and comovement of coffee prices are likely to be affected by other factors too. For example, the 1994 surge of coffee prices due to ENSO-related frosts in Brazil coincided with the formation of the Association of Coffee Producing Countries (e.g., Muradian and Pelupessy, 2005). Finally, it should be noted that due to the data limitation issues we capture only several complete ENSO cycles. However, the observed sample period does include the 1998 Niño episode—arguably one of the strongest ENSO occurrences of the past several decades, as well, the data include the early 2000s and the most recent prevalent episodes of La Niña. Thus, we believe that by capturing the most extreme ENSO occurrences we will be able to derive economically relevant inferences of the ENSO–cocoa price relationship, especially in the context of the regime-dependent modeling.

### 4. Estimation

This section outlines the empirical framework used in this research to investigate the relationship between ENSO and coffee prices. Following Brunner (2002) we treat ENSO as a strictly exogenous variable in the model. That is, we assume that coffee prices are contemporaneously correlated with ENSO, but not the other way around. This assumption implies orthogonality of ENSO shocks with coffee price innovations. As such, we first model the ENSO equation independently, in a univariate mode. We then estimate the system of coffee price equations where ENSO enters as an exogenous variable in the model. That is, we assume that coffee prices, while the lower quality Robusta coffee defines their lower bound. As for the relationship between the ENSO events and the coffee price movements, it is notable that the prices tend to diverge during and after strong La Niña episodes (e.g., in 1996–1997 and 2007–2008), and converge following strong El Niño episodes (e.g., in 1998). Of course, the movement and comovement of coffee prices are likely to be affected by other factors too. For example, the 1994 surge of coffee prices due to ENSO-related frosts in Brazil coincided with the formation of the Association of Coffee Producing Countries (e.g., Muradian and Pelupessy, 2005). Finally, it should be noted that due to the data limitation issues we capture only several complete ENSO cycles. However, the observed sample period does include the 1998 Niño episode—arguably one of the strongest ENSO occurrences of the past several decades, as well, the data include the early 2000s and the most recent prevalent episodes of La Niña. Thus, we believe that by capturing the most extreme ENSO occurrences we will be able to derive economically relevant inferences of the ENSO–cocoa price relationship, especially in the context of the regime-dependent modeling.

#### 4.1. The ENSO equation

We start off with the linear AR model for the ENSO equation with the lag length set to 6, based on the Akaike information criterion (AIC). In order to account for seasonal effects we include monthly dummy variables in the equation. Using this
Note: coffee prices represent natural logarithms of real coffee prices denoted in 2010 U.S. dollars.

The next step is to test for nonlinearities in the regression and select the suitable transition variable and corresponding transition function. A common practice is to use lagged levels of the dependent variable as a transition variable. So, one set of the candidate transition variables is defined as

$$s_d = y_{t-d},$$

where $d = 1, \ldots, D$, and where $D$ is the maximum lag length considered, which in this research is set to 12. In the context of the current equation, $y$ denotes the ENSO variable used in the estimation. Alternatively, a moving average functional form of the dependent variable (see Kilian and Taylor, 2003) may also be used as a transition variable, which is specified as

$$s_d^\ast = \frac{1}{d} \sum_{i=1}^{d} y_{t-i},$$

where $d = 1, \ldots, 12$ is the maximum lag length for each moving average representation. The nonlinearity tests are performed for a total of 24 candidate transition variables. The test results are presented in Table 1. As outlined in the previous section, along with the overall test of nonlinearity against STAR specification we also assess the hypotheses against LSTAR and ESTAR functional forms. The test results suggest strong evidence of nonlinearity in the dynamics of ENSO. Also, the results favor the logistic functional form over the exponential specification of the STAR model. We estimate LSTAR models using these transition variables by first considering the variable yielding the lowest $P$-value, and select the suitable transition variable while taking into account the improvement in fit, defined by the AIC, as well as the remaining nonlinearity test results. Once the model is estimated, we perform diagnostic assessment by addressing tests of remaining parameter nonconstancy and residual autocorrelation.

### 4.2. The system of coffee price equations

Let $X_t = (P_{CM}^t, P_{OM}^t, P_{BN}^t, P_{RB}^t)'$ be a vector of time series, where dependent variables are prices of Columbian Milds, Other Milds, Brazilian Naturals, and Robustas, respectively. The ADF tests failed to reject the unit root hypotheses in levels, but all four coffee prices appeared to be stationary in first differenced form. However, given the close substitutability and apparent comovement of these time series, a linear combination of coffee prices is likely to be a stationary process such that the system of equations can be modeled in a VEC form. Johansen’s test statistics were in the vicinity of the critical value associated with $\alpha = 0.10$ significance level. Thus, we maintained one cointegrating vector in the system and proceeded with the vector error correction specification, anticipating that in the regime-dependent framework prices may adjust to their long-run equilibrium in one regime, but may not in another. The lag length of the endogenous variables in the system was set to be equal to 2, based on the system-wide AIC. Additionally, we included the current and the lagged ENSO variables in the system. Each equation also contains monthly dummy variables to control for seasonal effects.

The next step is to test for possible nonlinearities in the system of vegetable oil prices by applying the system-wide testing framework as described in the previous section. We assess potential nonlinearities with respect to the lagged levels of the error correction term, as well as its moving average functions, using specifications defined by Eqs. (9) and (10). The results of
Table 1
Nonlinearity and parameter nonconstancy test results

<table>
<thead>
<tr>
<th>ENSO</th>
<th>Transition variable</th>
<th>$H_0^*$</th>
<th>$H_{10}$</th>
<th>$H_{02}$</th>
<th>$H_{01}$</th>
<th>Transition function</th>
<th>Coffee prices</th>
<th>Transition variable</th>
<th>$H_0^*$</th>
<th>$H_{1}$</th>
<th>$H_{1}$</th>
<th>Transition function</th>
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<td>4.0E-02</td>
<td>3.6E-04</td>
<td>1.6E-06</td>
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<td>$s_{t-7}$</td>
<td>2.4E-06</td>
<td>9.9E-03</td>
<td>1.9E-05</td>
<td>ESTAR</td>
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<td>3.8E-02</td>
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<td></td>
<td>$s_{t-6}$</td>
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<tr>
<td>Remaining nonlinearity test results</td>
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<td>3.6E-02</td>
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<tr>
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<td>$t^*$</td>
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</table>

Note: values in the table are probability values, unless otherwise stated, associated with the hypotheses heading the respective column; variables denoted by $s_{t-d}$, $d = 1, \ldots, 12$, represent $\text{ENSO}_{t-d}$ and $\hat{\epsilon}_{t-d}$, for the ENSO and the system of coffee price equations, respectively; likewise, variables denoted by $s_{t-\bar{q}^d}$, $d = 1, \ldots, 12$, represent $\sum_{j=1}^{\bar{q}^d} \text{ENSO}_{t-j}$ and $\frac{1}{\bar{q}^d} \sum_{j=1}^{\bar{q}^d} \hat{\epsilon}_{t-j}$, for the ENSO and the system of coffee price equations, respectively. Remaining nonlinearity test results are with respect to the transition variables used in the estimated two-regime STAR and STVEC models. Further, $t^* = t/T$, where $T$ is the total number of observations. Finally, AIC$^{lin}$ and AIC$^{nlin}$ are Akaike information criteria of the linear and nonlinear models, respectively.

The procedure is presented in Table 1. Note that in this case the test results assess possible nonlinearities only in the autoregressive component of the equations. The seasonal components revealed little evidence of nonlinearities and, moreover, the fitted STVEC models did not show improvement in fit based on the AIC. We therefore proceeded with the estimation so that the parameters associated with the monthly dummy variables enter the equations in a linear form only. The test results suggest the exponential form of the STVEC model. These results are indicative of a potential presence of some sort of transactions cost band (see, for example, Balke and Fomby, 1997), wherein prices follow a unit-root process inside, but a mean-reverting process sufficiently outside of the band. Much like in the case of the ENSO equation, we estimate a number of exponential STVEC models using the candidate transition variables. We select the suitable transition variable while taking into account the improvement in fit, defined by the system-wide AIC, as well as the remaining nonlinearity test results. Finally, the estimated coffee price equations are further assessed by performing tests of remaining parameter nonconstancy and residual autocorrelation.

So, the final version of the empirical model has the following form:

$$
\Delta \text{ENSO}_t = \alpha_0 + \beta_0 \text{ENSO}_{t-1} + \sum_{j=1}^{5} \phi_{0,j} \Delta \text{ENSO}_{t-j} + \Psi_0 D_t
$$

$$
+ \left( \alpha_1 + \beta_1 \text{ENSO}_{t-1} + \sum_{j=1}^{5} \phi_{1,j} \Delta \text{ENSO}_{t-j} + \Psi_1 D_t \right) G_1(s_{1,t}; \gamma_1, \epsilon_1) + \epsilon_t
$$

(11)

$$
\Delta X_t = \mu_0 \hat{\epsilon}_{t-1} + \Gamma_0 \Delta X_{t-1} + \sum_{q=0}^{\bar{q}} \Phi_{0,q} \text{ENSO}_{t-q} + \Psi_0 D_t
$$

$$
+ \left( \mu_1 \hat{\epsilon}_{t-1} + \Gamma_1 \Delta X_{t-1} + \sum_{q=0}^{\bar{q}} \Phi_{1,q} \text{ENSO}_{t-q} \right) G_2(s_{2,t}; \gamma_2, c_2) + v_t
$$

(12)

where

$$
\begin{bmatrix}
\epsilon_t \\
v_t
\end{bmatrix} \sim \text{iid} \left( \begin{bmatrix} 0 \\
0 \\
\sigma^2 \\
0 \\
\sum v
\end{bmatrix} \right),
$$

and $\text{ENSO}_t$ is an SSTA anomaly, and $X_t$ is a vector of coffee prices, as described above; $\alpha_0, \beta_0, \phi_{k,j}$ are parameters, $\mu_k$ and $\Phi_{k,q}$ are vectors of parameters, and $\Gamma_k$ and $\Psi_0$ are matrices of parameters to be estimated, where $k = 0, 1, 2, j = 1, \ldots, 5$, and $q = 0, 1$. $G_1(s_{1,t}; \gamma_1, \epsilon_1)$ is a logistic STAR function and $G_2(s_{2,t}; \gamma_2, c_2)$ is an exponential STAR function, where transition variables are $s_{1,t} = s_{t-5}^*$ and $s_{2,t} = s_{t-11}^*$, respectively.

5. Results and discussion

The estimated STAR and STVEC models represent improvements based on the AIC, compared to the respective linear AR and VEC models (see Table 1). The estimated transition functions of the ENSO STAR and the coffee price STVEC models are as follows:
\[ \hat{G}_1(s_1; \gamma_1, c_1) = \left\{ 1 + \exp \left[ -\frac{4.722_{[1.615]} (s_{1}^* - 0.590_{[0.078]})}{\sigma_1} \right] \right\}^{-1} \]

\[ \hat{G}_2(s_2; \gamma_2, c_2) = \left\{ 1 + \exp \left[ -\frac{2.419_{[0.783]} (s_{2} - 0.048_{[0.005]})}{\sigma_1} \right] \right\}, \]

where \(\sigma_1\) and \(\sigma_2\) are standard deviations of the associated transition variables; values in the square brackets are asymptotic standard errors of the estimated smoothness and location parameters. The low values of the \(\gamma\) parameters in each of the models suggest a smooth and continuous curvature of the associated transition functions. These transition functions, along with the transition variables, are also illustrated in Figs. 3 and 4. Note that in the case of the ENSO equation, switch between the regimes is centered around 0.6 °C of the SST anomaly, that is, when ENSO enters the strong El Niño phase. Alternatively, in the case of the system of coffee price equations, the location parameter of the exponential transition function is approximately 0.05, suggesting that the transactions cost band is centered slightly above the historically observed long-run
equilibrium of coffee prices. Considering the smoothness of the estimated transition functions, however, at any given period of time a set of parameters underlying the dynamics of each respective regime, \( \theta_{n,t} \), will be a weighted average of the \( \theta_{0,t} \) and \( \theta_{1,t} \) parameters of each extreme regime, where weights are \( \{1 - G(s_t; \gamma, c)\} \) and \( \{G(s_t; \gamma, c)\} \), respectively, based on a realization of the transition function in that period.

The estimated unit root parameters of the ENSO equation and the speed-of-adjustment parameters of the system of coffee price equations\(^4\) are presented in Table 2. The parameters in the rows denoted by \( \varphi_0 \) and \( \varphi_1 \) are estimated parameters associated with the two regimes of the STAR and STVEC models. Following the notation as in Eqs. (11) and (12), \( \beta_{0,t} = \varphi_0 \) and \( \mu_{0,j} = \varphi_{0,j} = 1, \ldots, 4 \), when \( G(s_t; \gamma, c) = 0 \), and \( \beta_{1,t} + \beta_{1,j} = \varphi_1 \) and \( \mu_{1,j} = \varphi_{1,j} = 1 \), when \( G(s_t; \gamma, c) = 1 \). For the observations associated with \( 0 < G(s_t; \gamma, c) < 1 \) the parameters are calculated as described in the previous paragraph. In the case of ENSO dynamics we observe an apparent mean-reverting process during El Niño phases, while La Niña phases appear to be affiliated with a unit root process. This well reflects the observed patterns of the ENSO cycle: historically, El Niño phases have lasted for shorter periods, often leading to La Niña events, while La Niña phases have usually lasted for more extended periods, gradually returning to normal conditions (refer also to Fig. 2). In the coffee price equations, the speed-of-adjustment parameters are not statistically significant in either of the two regimes. In spite of this, it is instructive that there is stronger evidence of mean-reverting behavior in the outside of the band regime as compared to the alternative, the inside of the band regime.

Table 2 reports probability values of residual normality and autoregressive conditional heteroskedasticity tests. The test results imply that some of the coffee price equations fail the assumptions of normality and homoskedasticity—phenomena that are usually associated with the price data. The remaining residual autocorrelation results, however, are comforting in the sense that no evidence of autocorrelation is detected. Thus, we can proceed with the bootstrap simulation exercise as described below.

In order to better illustrate the effects of ENSO shocks on coffee price dynamics, we employ generalized impulse-response functions (GIRFs)\(^5\) of Koop et al. (1996). We calculate GIRFs associated with positive and negative shocks of ENSO. To do so, we randomly draw (without replacement) a set of 60 histories covering the period between January 1991 and December 2010. Further, we randomly draw (with replacement) 500 vectors of idiosyncratic shocks (innovations) of lengths equal to 60 (five-year horizon) from the pool of residuals of the estimated ENSO STAR model as well as the estimated STVEC model of the coffee price equations. As such, we generate a total of 30,000 vectors of GIRFs with 60-month horizon. The ENSO shock size is set to 1. The expected GIRFs for each coffee price are obtained by averaging a set of impulse responses across histories and vectors of random innovations, thus, projecting the response functions to a 1 °C SST anomaly (see Fig. 5).

Several interesting features are revealed in these plots. First, the impulse responses of all three Arabica coffee varieties have a very similar pattern, which is different from the impulse responses of the Robusta coffee prices. This is hardly surprising, because not only the Arabica coffee varieties are produced in geographical proximity, but are also closer substitutes to each other, which is less of a case for Robustas.

More interestingly, ENSO shocks appear to have opposite effects on Robustas and Arabica varieties in the intermediate and the long run. Specifically, El Niño shocks, or positive deviations of the SST, tend to negatively affect prices of all three varieties of Arabica Milds, resulting in up to 10% price decrease. The same effect, although of a much smaller magnitude, is observed in the case of Robusta prices. However, a few months after the shock the Robusta coffee prices tend to revert, resulting in increased prices. This outcome is hardly counterintuitive, considering the geography of coffee production. For example, El Niño events create unfavorable weather conditions for producers in Southeast Asia—a region producing predominantly Robusta coffee, and somewhat favorable weather conditions in Central American countries—major suppliers of Columbian and Other Milds (see Fig. 1). As a result, Robusta prices increase and prices of Arabica Milds decrease following El Niño events. The opposite effect is observed during La Niña events. Thus, considering that the Robusta coffee prices are consistently below the prices of the Arabica varieties, La Niña shocks have a diverging effect on higher and lower quality coffee prices, while El Niño shocks result in converging prices. Put differently, these results suggest that the price difference between higher quality

\(^4\) The rest of the estimated parameters are omitted for the sake of brevity, but are available upon request.

\(^5\) This approach has been extensively used in the applied literature (e.g., Chen and Lee, 2008; Holt and Inoue, 2006), and for the sake of brevity we will only present the research-specific details in this article.
Arabica Milds and lower quality Robustas will decrease after El Niño events, and will increase after La Niña events.

Finally, asymmetries can be observed in coffee price responses to El Niño and La Niña shocks. La Niña shocks appear to have a more persistent effect on the coffee prices, as compared to El Niño shocks. This outcome is greatly driven by the nonlinear dynamics of the ENSO cycle, which tends to remain in a La Niña regime for an extended period of time, but rapidly returns to normal conditions after an El Niño event.

6. Conclusions

ENSO has long been considered one of the driving factors of agricultural production, especially in the regions adjacent to the tropical Pacific. This evidence is hardly anecdotal, because ENSO events may cause droughts or increased precipitation in this part of the world. The corollary is that ENSO will likely impact prices of those commodities which are predominantly produced in countries across the west coast of Central and South America, and the Western Pacific region. One such commodity is coffee.

This article modeled a system of four coffee variety prices and the ENSO equation. Strict exogeneity of the ENSO variable was assumed so that the ENSO events affect coffee prices, but not vice versa. The analysis examined possibilities of nonlinear dynamics in the ENSO equation, as well as coffee price equations. Consistent with the previous literature, evidence supports the hypothesis of smooth transition type nonlinearities in the ENSO equation and the system of coffee price equations.

ENSO-related asymmetries are observed in coffee prices. The results of this study revealed a few features of interest, which can be summarized as follows: ENSO does impact coffee prices, and the effect is statistically significant for a period of up
to one year. Because the production geography of the different coffee varieties is somewhat clustered, ENSO events tend to affect the prices differently: a positive ENSO shock—El Niño—has a positive effect on prices of Robustas, but a negative effect on prices of Arabicas. The opposite is true for a La Niña shock. However, impacts of El Niño and La Niña are not symmetric, due to regime-specific asymmetries associated with ENSO and coffee prices. The results of this study ought to be of interest to coffee producers in developing countries, as well as processors and intermediaries in the coffee markets.

References


