Do Rice Prices Follow a Random Walk? Evidence from Markov Switching Unit Root Tests for Asian Markets

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Do Rice Prices Follow a Random Walk? Evidence from Markov Switching Unit Root Tests for Asian Markets

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This study revisits the issue of mean reversion in the import rice prices of Asian countries over the period between 1995 and 2015. Augmented Dickey Fuller tests with a conventional linear regression model support the presence of a unit root in the levels of the price data. However, when regressions allow for Markov switching in coefficients and variances to capture periodic shifts in levels and volatilities, there is strong evidence against the unit-root null hypothesis in favor of stationarity over much of the observation period.

KEYWORDS *Unit root, Markov switching, structural change, rice price*

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HIGHLIGHTS

- This paper tests for mean reversion across six Asian countries' rice price levels.
- Structural breaks in the means and variances are identified.
- Augmented Dickey Fuller tests with a conventional linear regression model support the presence of a unit root in price levels.
- Allowing for Markov switching in coefficients and variances, the unit-root null is rejected in favor of stationarity.

INTRODUCTION

Rice is a staple food for nearly half of the world's population. Given the significance of the world's rice markets, the behavior of rice prices is a topic of a large volume of international trade literature, particularly in case studies of emerging markets (e.g., Lee and Valera, 2016). Much research in this body of literature focuses on major rice exporting countries, with little attention given to rice importers. Of particular interest is the behavior of import rice prices over time, which have potential impacts on domestic prices as well as implications for trade policies.

Whether rice prices are characterized as stationary or non-stationary processes over time bears policy relevance particularly for many Asian countries, which constitute the world's largest rice markets. Those countries are also the world's largest rice importers. As for most developing countries, food security has been a priority for their governments, which have regularly intervened their domestic rice markets in an effort to stabilize prices for both consumers and farmers. For instance, Indonesia has maintained such programs through its government agency Badan Urusan Logistik (BULOG). Singapore's Ministry of Trade and Industry has controlled its domestic wholesale rice market through an import license policy. China and the Philippines have instituted trade restrictions aiming to insulate their domestic grain prices from spillovers of price spikes overseas (Dawe and Slayton, 2010). In Malaysia, Padiberas Nasional Berhad (BERNAS) is the country's sole rice importer that manages its domestic rice stock. The National Food Authority (NFA) of the Philippines has also frequently intervened its domestic rice market by setting price ceilings and providing subsidies to both consumers and farmers (Mariano and Giesecke, 2014; Mariano *et al*., 2015; Yao *et al*., 2007).

The time-series properties of rice prices are also important for market participants who engage in global rice trade based on their expectations of future price changes. If rice prices are characterized as non-stationary or random-walk processes, then even infrequent shocks or government interventions that affect the markets will have permanent effects, and the resulting price volatilities might grow without bounds in the long run. It is also impossible to forecast future movements of those prices based on their past behavior. On the contrary, if rice prices follow stationary processes even along broken trends, then any surges above the prices' historical trends will be followed by market forces that push these prices back to their historical paths. In this case, trade policies aiming at controlling domestic market prices might have short-lived effects.

The stochastic behavior of rice prices is the subject of a burgeoning literature. The vast majority of this literature shows evidence in support of non-stationarity or unit-roots in global rice price data. For instance, using monthly export prices for the U.S. and Argentina, John (2014) provided evidence of nonstationarity based on the augmented Dickey Fuller (ADF) test. Chulaphan *et al.* (2013) showed collaborating evidence for the price levels of rice exports from Thailand, Vietnam, and the U.S. Ghoshray (2008), John (2013), Yovapolkul *et al.* (2006), and Warr (2008) also provided empirical findings in support of a unit root for both import and export prices of rice in a number of Asian countries, including Thailand, Vietnam, India, and Indonesia.

The common empirical methodology of the above studies draws on tests for unit roots originally developed by Dickey and Fuller (1979). Those standard unit-root tests are based on linear regression models that do not allow for occasional structural shifts as a form of nonlinearity. However, it is well known in the literature that economic and financial time series occasionally exhibit structural breaks associated with events such as financial crises or abrupt shifts in government policy. Perron (1989) argued that standard unit-root tests have low power against alternatives in the presence of structural breaks in the level or the growth trend. He dealt with this problem using dummy variables to account for possible structural breaks in the time series. Instead of an *a priori* known date for the structural break, Banerjee et al. (1992), and Zivot and Andrews (1992) applied unit-root tests against one *endogenously* determined structural break. Lee (1996), and Lumsdaine and Papell (1997) further extended the latter methodology to two or more structural breaks. However, Leybourne *et al.* (1998) showed that standard unit-root tests can also lead to *over-rejections* of the null if there is a structural break under the null hypothesis. Another drawback of such methodology is the pre-specified number of structural breaks.

Another class of literature deals with structural change or nonlinearities in time series by assuming different behavior in different subsamples or regimes. One type of regime-switching models allow the dynamics of a time series to be determined by an *observable* variable in the form of thresholds. An example is the threshold autoregressive model (van Dijk *et al*., 2002). A similar framework instead characterizes regimes by an *unobservable* or latent stochastic process with a Markov structure. One advantage of the Markov switching approach is that it is straightforward to extend the original model for the conditional mean, as developed by Hamilton (1989), by allowing the unconditional variance of the time series to switch as well. In other words, the Markov switching model offers a rather general and convenient framework for the purpose of unit-root testing in the presence of *a priori* unknown multiple structural breaks due to either abrupt or gradual changes in the behavior of time series. Camacho (2005, 2011) and Camacho and Perez (2007) have used this model to analyze the stochastic trends of U.S. output series. As shown below, structural changes in both the mean and variance also play a vital role in the dynamic properties of historical rice prices.

The objective of this paper is to reexamine the stochastic property of rice price series for major rice importers in Asia. We contribute to the related literature by extending the conventional Dickey-Fuller-type regression model to a Markov switching framework, which describes discontinuous or sudden changes in the data generating process of a time series with a hidden Markov chain. The Markov switching model allows the rice price series to exhibit periodic shifts in their observed behavior between two different states or regimes. The features of the two states as well as their average durations are determined endogenously by the data. As a result, the unit-root test results allow for a switching behavior in the price series' levels as well as its variance.

Given the empirical results of our nonlinear regression models, this paper sheds new light on the stochastic property of the prices of a popular commodity in international trade. The rest of the paper proceeds as follows. The next section outlines the empirical methodology and describes the data. The third section presents the regression results and unit-root test statistics. The fourth section provides concluding observations.

2. METHODOLOGY AND DATA

2.1. Regression Models

This section outlines the empirical model that we employ to characterize the Asian rice price data. Let x_t be a rice price series. The conventional (linear) augmented Dickey Fuller (ADF) tests for a unit root in x_t can be conducted with the following autoregressive model:

$$\Delta x_t = \mu + \beta T + \rho x_{t-1} + \sum_{k=1} \delta \Delta x_{t-k} + \varepsilon_t, \qquad (1)$$

where Δ is a difference operator, μ is a constant capturing the drifting behavior in the random walk, T represents a linear time trend, and ε_t is an iid residual term distributed as $N(0, \sigma^2)$. Because economic time series are typically plagued by serial correlation, the original Dickey-Fuller (1979) regression is augmented with the lagged dependent terms ($\sum_{k=1} \delta \Delta x_{t-k}$). The null hypothesis of a unit root H_0: $\rho = 0$ is tested against the alternative H_1: $\rho < 0$. Since the *t*-statistic (t_ρ) for testing H_0 does not have a standard distribution, MacKinnon's (1991) non-standard critical values will be used. If the unit-root hypothesis is rejected, then the results can be interpreted as evidence for the time series to follow a mean-reverting stationary process.

The above testing procedure is widely known for failing to account for the effects of structural breaks in the time series. Earlier attempts to overcome this drawback include augmenting the regression model (1) with the possibility of one or more *a priori* unknown structural breaks in the data-generating process (e.g., Perron, 1989; Banerjee, Lumsdaine and Stock, 1992; Zivot and Andrews, 1992; Lee, 1996; Lumsdaine and Papell, 1997). Those structural breaks are assumed to be the outcomes of mostly isolated, non-recurring events. Hall *et al.* (1999), however, show that the power of ADF tests can be improved by incorporating an unobserved Markov-switching (MS) variable that detects periodical changes in the time series' autoregressive process.

Following Hamilton (1989) and Hall *et al.* (1999), we consider nonlinear dynamics by incorporating a Markov-switching process in the ADF regression model. Let $s_t \in \{1,2\}$ be an unobservable state variable of two regimes. The state variable s_t is governed by a discrete state Markov chain. The path that s_t follows from period *t*-1 to period *t* is captured by a probability transition matrix with the following elements:

$$p_{ij} = \Pr(s_t = j | s_{t-1} = i) \qquad \forall\, i, j = 1, 2, \qquad (2)$$

which describes the probability of switching from state i to state j, such that $\sum_{j=1} p_{ij} = 1 \; \forall \; i.$ The Markov switching representation for the time series x_t would then be expressed as:

$$\Delta x_t = \mu(s_t) + \beta(s_t)T + \rho(s_t)x_{t-1} + \sum_{k=1} \delta_k(s_t)\Delta x_{t-k} + \varepsilon_t. \quad (3)$$

All coefficients in equation (3) are allowed to switch according to the state variable, s_t. This Markov-switching framework can also be extended to the variance term as well (Kanas and Genius, 2005; Cevik et al., 2013). In this case, the residual term is assumed to be $\varepsilon_t \sim N\big(0, \sigma^2(s_t)\big)$. This means that σ^2 is allowed to switch according to a two-state, first-order Markov process governed by the state of s_t.

As suggested by Hamilton (1989) and Hall *et al.* (1999), equation (3) can be estimated using Hamilton's (1994) two-step EM algorithm. This algorithm involves an iterative procedure to obtain maximum-likelihood (ML) estimates for the parameters and transition probabilities governing the Markov process.

As for the linear model captured by equation (1), the unit-root test with the MS-ADF model of equation (3) can be based on the t_ρ statistic. However, since the distribution of t_ρ under the null hypothesis is unknown, we adopt Hall *et al.* (1999) and Cevik et al.'s (2013) approach by generating critical values using bootstrapping with 10,000 replications.

To determine which model specification performs the best in characterizing the rice price series, we employ a likelihood-ratio (LR) test, whose statistic can be expressed as: $LR = 2[L_1 - L_2]$, where L_i is the log-likelihood value of a particular model i. The LR test has a χ^2 distribution with the number of degrees of freedom equal to the number of restrictions. However, since the transition probabilities in Markov-switching models are not identified in the linear model, the LR test does not have the standard χ^2 distribution. In this case, we follow Cevik *et al.* (2013) and employ the upper-bound p-values as suggested by Davies (1987).

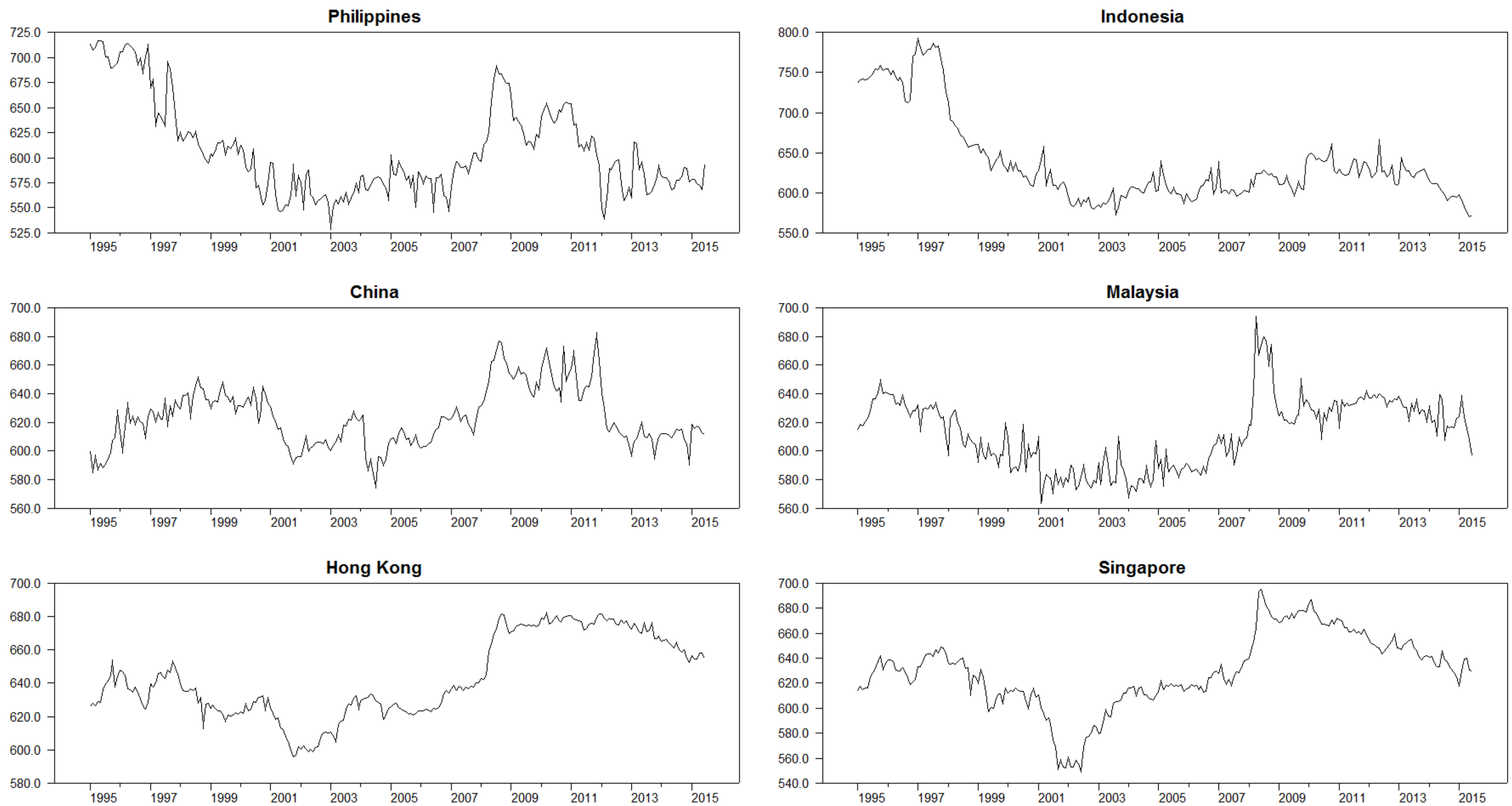
2.2 Data

Our empirical work involves monthly observations of prices of rice imports for six Asian economies—China, Hong Kong, Indonesia, Malaysia, Philippines, and Singapore—over the period between January 1995 and June 2015. The commodity belongs to the specific category of milled rice (i.e., semi-milled or wholly milled, whether or not polished or glazed). The import rice price data in U.S. dollars are obtained from the *Global Trade Atlas Navigator*. To adjust the commodity prices for inflation, we express the six price series in constant dollars by first dividing the individual rice series by their own countries' consumer price index (CPI). The CPI data are obtained from the *International Financial Statistics*. Since monthly data might exhibit seasonal behavior that is beyond the focus of our study, we applied U.S. Census Bureau's X-12-ARIMA seasonal adjustment program to the time series. For estimation, the seasonally-adjusted data representing the variable x_t are 100 times the log values of the six individual import rice price levels.[2]

Figure 1 shows the patterns of the six individual rice price series. At first glance, the behavior of the import rice price levels varies appreciably across markets as well as over time. In particular, Hong Kong and Singapore experienced relatively less volatility in rice prices than other Asian countries. Together with Malaysia, those two city-states experienced a sudden jump in rice prices during the Asian rice crisis of 2007-2008. The Philippines and China also witnessed corresponding price surges in 2008, but their prices also exhibited similar volatility patterns in other periods. Between October 2007 and April 2008, global rice prices tripled. Some observers argued that the rice export restrictions by India and Vietnam in 2007, followed by the Philippines' rice import tenders for Vietnamese rice imports in 2008 resulted in the surges in the world's rice prices along with high volatility during that rice "crisis" episode (Lee and Valera, 2016).

[2] The seasonality issue was pointed out by one journal reviewer. Despite changes in production between harvesting season and planting season, our rice price data do not exhibit discernible seasonal patterns. As such, using the original non-seasonally-adjusted data instead does not alter most estimation results reported in this paper.

Figure 1: Import Rice Price Levels.



The effects of the Asian financial crisis in 1997 are also apparent. While Indonesia's rice market appeared to be less subjected to the 2007-2008 price shocks, the prices of its rice imports in constant dollars surged in 1997 before falling below the pre-1995 levels the following year partly due to currency depreciation and high inflation. The currency exchange values for the Philippines, Indonesia and Malaysian depreciated dramatically during the Asian financial crisis, with the Indonesian rupiah affected the most. Indonesia responded to the soaring import rice prices in 1998 with several market operation policy measures and subsidization under its RASKIN program, along with an open import policy (Dawe and Slayton, 2010). Meanwhile, the agricultural policy of Malaysia had shifted toward the production of high-value crops along with industrialization. This policy shift helped contribute to a nearly 30% increase in Malaysia's rice imports between 1997 and 1998 (Daño and Samonte, 2005). Except for China, the rice prices around Asia trended down after the Asian financial crisis until 2001, and then rose gradually through the depths of the Great Recession in 2009.

One notable observation stands out from Figure 1: The Asian regional rice market underwent periods of relative tranquility interrupted only by shocks that inflicted high price volatility. The price levels of those regional rice markets responded in varying degrees to the Asian financial crisis of 1997-1998 and later the rice crisis in 2007-2008, and subsequently the global recession in the aftermath of the U.S. financial meltdown. Some market responses were obviously drastic while others seemed rather gradual or modest. In addition, the extent of volatility differed not only across markets but also between various time periods.

3. Empirical Results

This section describes our findings on the stochastic property of the Asian rice price series with the alternative models outlined in Section 2 above. Table 1 shows the estimation results for the linear, or non-switching, ADF regression model captured by equation (1). In preliminary regressions, the coefficient estimates (β's) for the linear time trend are not statistically significant in most cases. Since omitting the trend variable T also does not meaningfully alter the estimates for other explanatory variables, all reported regression results do not include this term. The autoregressive order k is determined by the Akaike Information Criterion (AIC). As shown in Table 1, one lag value is included for four of the six data series. For the price series of Hong Kong and Indonesia, three lag values are included.

Table 1: Linear ADF Regression Model Regression.

	Philippines		China		Hong Kong		Indonesia		Malaysia		Singapore	
μ	36.07	*	47.97	*	14.28	***	21.20	***	43.40	*	11.21	**
	(2.53)		(3.01)		(1.77)		(1.65)		(2.54)		(2.27)	
ρ	-0.08		-0.06		-0.10		-0.15	*	-0.31	**	0.04	
	(1.24)		(0.99)		(1.50)		(2.31)		(2.05)		(0.43)	
$\sum_{k=1}\delta_k$	-0.06		-0.08		0.21		-0.14		-0.07		-0.02	
Lag order k	1		1		3		3		1		1	
σ^2	192.74		64.05		13.64		125.94		112.48		38.62	
Likelihood value	-982.04		-848.19		-656.54		-925.48		-914.10		-775.33	
ADF-t_ρ	-1.24		-0.99		-1.50		-2.31		-2.05		-0.43	

Notes: Absolute values of *t*-statistics are in parentheses. * , **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The bottom row of Table 1 lists the conventional ADF-t_ρ statistics for testing the null hypothesis of a unit root. The unit-root null cannot be rejected for the data of all six time series over the period 1995-2015. The estimates for the constant term μ are statistically significant, meaning that rice price levels follow a random walk with drift. Evidence in support of the unit-root, or I(1), process corroborates with earlier findings for some Asian domestic rice price series (e.g. Imai et al., 2008; Rapsomanikis, 2011; Alam et al., 2012; Chulaphan et al., 2013).

If structural breaks exist in the observed data series, then the ADF test results with the linear regression model of equation (1) might be misleading. As evident in Figure 1, an upward level shift occurred in 2008 for the majority of the price series except perhaps for Indonesia, which instead experienced sudden downward shifts a decade earlier in 1998. Similarly, the variability of some price series, notably for China and the Philippines, also appears to evolve across the observation period. To explore the possibility of structural breaks in regressions, Table 2 shows the results of two Chow-type stability tests with *a priori* unknown break points, namely Andrews and Ploberger's (1994) *Sup-F* and *Mean-F*. The two statistics are computed for the price series by testing alternatively for constancy in all coefficients in equation (1) and for constancy in the variance of its residuals.

Table 2: Tests for Structural Breaks.

	Philippines		China		Hong Kong		Indonesia		Malaysia		Singapore	
All Coefficients:												
Sup-F	13.63	**	10.51	**	14.27	**	14.26	**	12.15	**	12.32	**
Date	2007:01		2010:06		2008:12		1998:08		2007:08		2002:06	
Mean-F	4.18	**	2.83	***	5.24	**	5.33	**	3.78	**	3.32	***
Variance:												
Sup-F	8.13	***	7.10	***	4.61		7.13	***	7.66	***	2.46	
Date	2002:05		2012:03		2001:12		2012:06		2008:12		2002:08	
Mean-F	1.19		1.39		1.88		2.04		1.31		0.78	

Notes: ** and *** denote statistical significance at the 5%, and 10% levels, respectively.

The top panel of Table 2 shows the *Sup-F* and *Mean-F* statistics for constancy in coefficient estimates. The null hypothesis of constancy is rejected for most series, meaning that their regressions are subject to structural instability, particularly abrupt shifts in model parameters. The dates associated with the *Sup-F* statistics further indicate that the majority of structural breaks are associated with the Asian rice crisis of 2007-2008 that apparently exhibited rather lasting effects on price levels as well as their volatility. The identified break for Indonesia reflects its macroeconomy facing high inflation and currency depreciation in 1998.

The bottom panel of Table 2 shows the corresponding test statistics for constancy in variances. The *Sup-F* statistics indicate that the variance of residuals is not constant over time for four markets, namely the Philippines, China, Indonesia, and Malaysia. In contrast to their corresponding results for coefficients, the *Sup-F* statistics for Hong Kong and Singapore are not statistically significant, neither are their *Mean-F* statistics. The latter findings are consistent with the casual observations of their historical data in Figure 1, which exhibit least volatility by comparison.

The overall results in Table 2 provide motivation for extending the conventional ADF test to a Markov switching framework, as characterized by equation (3). For illustration purposes, we report regression results for three specific model specifications. In the first case, only the constant term μ is allowed to exhibit Markov switching behavior with two states. This captures the possibility of level shifts in the regression model. The second case allows for Markov switching behavior in the residual's variance in addition to the constant term. In the third case, all coefficients and the residual's variance in the regression model (3) follow the two-state Markov switching process.

Table 3 shows the estimation results of the ADF regression model with a Markov switching constant term. For all of the six price series, the estimate for the constant term is noticeably higher in state two (s=2) than in state one (s=1). The sizes of the coefficient estimates (μ's) in both states also differ appreciably from their corresponding estimates in Table 1. The point estimates for ρ, however, remain quite similar between the two models.

Table 3: Regression with Markov-Switching Constant.

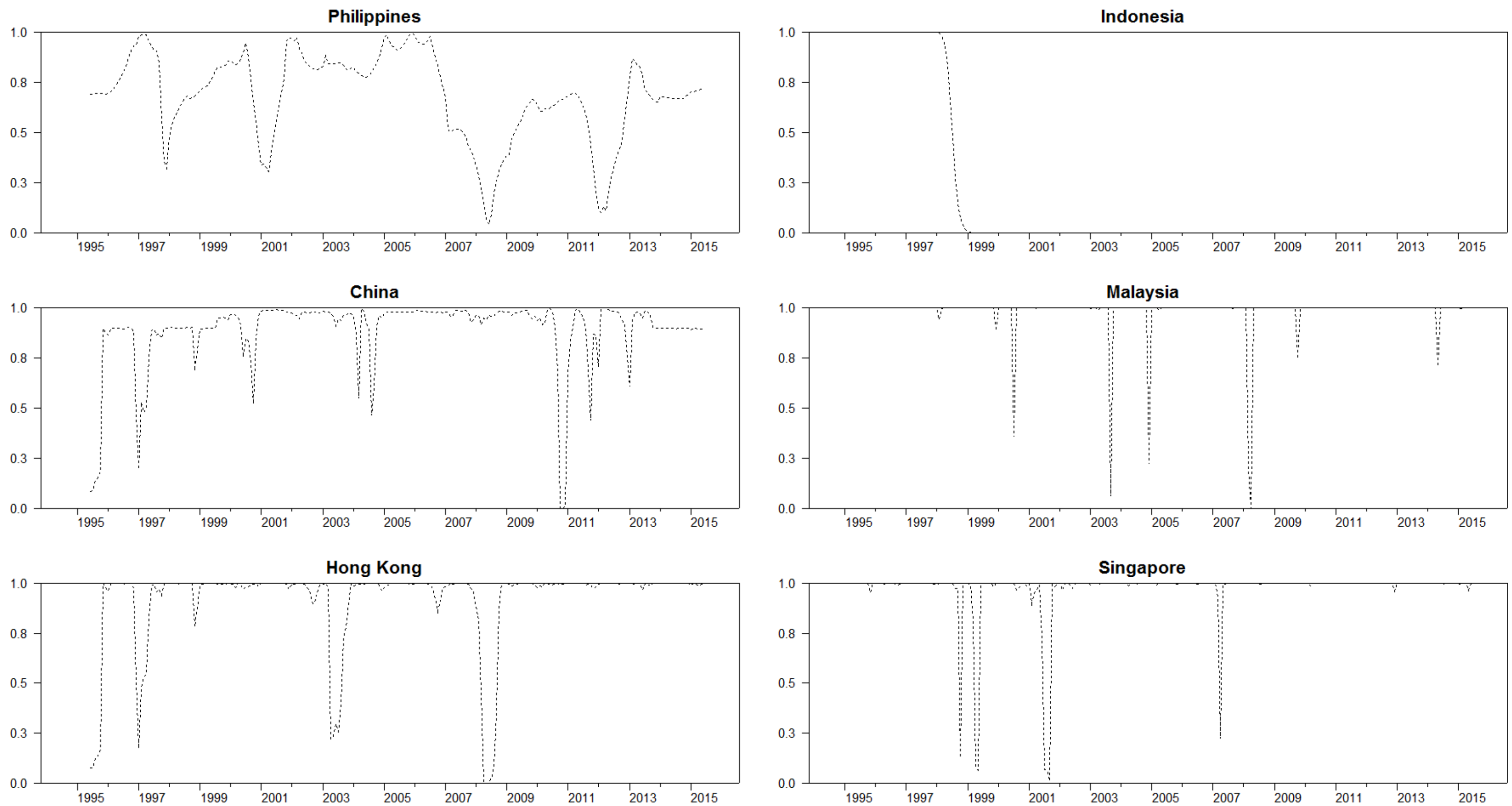
	Philippines		China		Hong Kong		Indonesia		Malaysia		Singapore	
$\mu\ (s=1)$	-0.02		-0.54		0.25	*	1.42	***	0.63	***	0.24	*
	(1.50)		(1.21)		(2.60)		(1.87)		(1.65)		(4.70)	
$\mu\ (s=2)$	41.18	*	53.03	*	28.58	*	27.27	*	63.83	*	20.04	*
	(46.09)		(25.76)		(3.23)		(21.15)		(34.68)		(31.81)	
ρ	-0.08	***	-0.06	***	0.14	*	-0.25	*	-0.31	***	0.04	*
	(1.86)		(1.68)		(2.99)		(2.59)		(1.65)		(3.44)	
$\sum_{k=1}\delta_k$	-0.58		-0.66		0.01		-0.48		-0.27		-0.03	
Lag order k	1		1		3		3		1		1	
σ^2	190.79		63.20		11.33		123.34		111.20		29.02	
p_{11}	0.72	**	0.91	*	0.97	*	0.03	*	0.94	**	0.98	*
	(2.05)		(2.85)		(5.10)		(3.10)		(2.22)		(9.32)	
p_{12}	0.11		0.35		0.27	***	0.56	**	0.65		0.02	**
	(0.05)		(0.30)		(1.73)		(2.10)		(1.23)		(2.26)	
Likelihood value	-967.37		-841.60		-644.67		-915.06		-887.43		-756.25	
ADF-t_ρ	-1.86		-1.68		-2.99	***	-2.59		-1.65		-3.44	**
LR test vs. linear model	29.34	*	13.20	**	23.73	*	20.83	*	53.34	*	38.17	*

Notes: Absolute values of *t*-statistics are in parentheses. *, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

When the regression allows for Markov switching in the constant term to capture the switching behavior in means, the ADF-t_ρ statistics show evidence of stationarity in the levels of the Singaporean and Hong Kong data. As for results with the standard unit-root regression model (Table 1), the unit-root null cannot be rejected for the other four data series. Nevertheless, the model with Markov switching in the constant term seems to provide a better characterization of all six price series than the linear regression model does. The bottom row of Table 3 shows the LR test statistics essentially for testing the restriction that the constant term is the same between two states. All statistics are in favor of the Markov switching model specification. Moreover, the estimate of variance σ^2 is also appreciably lower in most cases relative to the corresponding estimates from the linear model.

Table 3 also displays estimates for the probability of state one, p_{11}, and the transition probability, p_{12}. The results suggest that the probability of staying in one state is especially high for Singapore and Hong Kong. Those estimates are further confirmed by the plots of smoothed probability of state one (s=1) in Figure 2. Evidence of few regime shifts particularly for Singapore highlights the impact of its historical import license policy for the country's wholesale rice market (Tobias *et al*., 2012). In the case of Hong Kong, which is a major importer of Hom Mali rice from Thailand, the evidence of few regime shifts reflects its import license policy under the Rice Control Scheme that aims to maintain a buffer stock of rice for domestic consumption (Tobias *et al*., 2012).

Figure 2: Probability of State 1 for Markov-Switching Constant.



Indonesia has also maintained an intervention program aiming to insulate its domestic market from sudden price spikes overseas. The plot of its probability series is dominated by a single dramatic shift, which captures the impact of its economic turmoil in 1998. After steep declines during the late 1990s due in part to historically high inflation reaching 80% in 1998, Indonesia's import rice price in constant dollars stabilized with a gradual uptrend during much of the next decade.

Evidence of sudden regime shifts in Figure 2 reflects, among other things, the impact of developments within the broader region of Asia as well as macroeconomic conditions that exerted varying impacts on individual countries' inflation rates as well as their currency values. For the Philippines, Hong Kong, Singapore and Malaysia, the patterns of smoothed probability series clearly show an abrupt but temporary shift in association with the Asian rice crisis of 2007-2008.

The probability series appears to be least persistent for the Philippines, meaning that this largest rice importer in the world has been subject to most frequent regime shifts by comparison. Dawe and Slayton (2010) pointed out that, despite its various intervention programs, the Philippines did not prove to be effective in preventing its domestic rice market from spillovers of developments in the world market, especially during the rice crisis of 2007-2008.

The second model specification that we consider is Markov switching in the variance of the residual term in addition to the constant term. The estimation results are displayed in Table 4. Except for Hong Kong, the χ^2 statistics for equal variances show strong evidence in support of heterogeneity in variance (i.e., heteroskasticity) over time. Compared with the previous unit-root test results (Tables 1 and 3), the ADF-t_ρ statistics show stronger evidence of stationarity in the price level data. Except for China, the unit-root null hypothesis is rejected at the 10% significance level or higher.

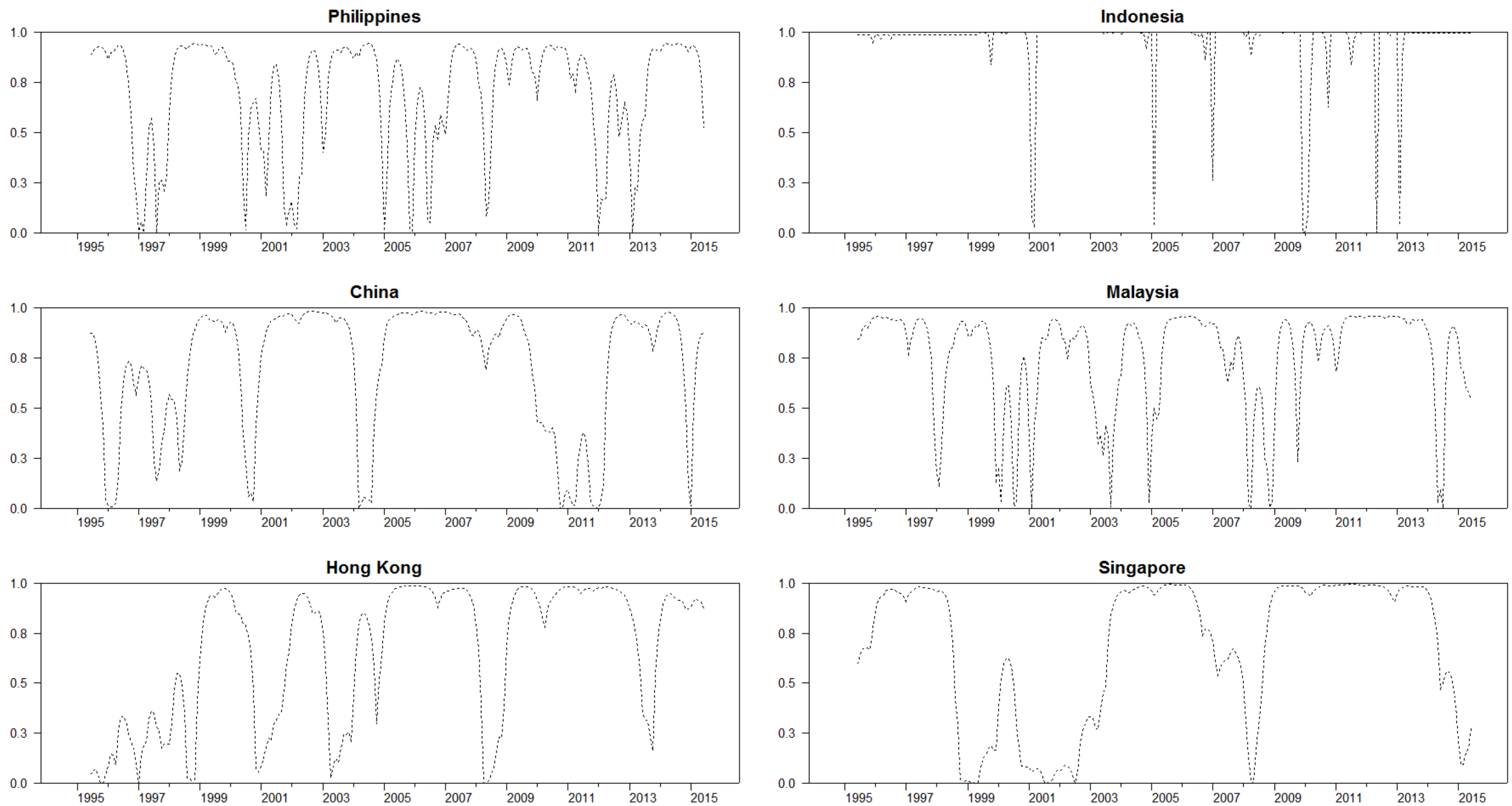
Table 4: Regression with Markov-Switching Constant and Variance.

	Philippines		**China**		**Hong Kong**		**Indonesia**		**Malaysia**		**Singapore**	
$\mu\ (s=1)$	0.01		0.17		0.04	*	0.51	**	-0.06		0.03	*
	(1.59)		(1.61)		(2.33)		(1.97)		(1.31)		(1.67)	
$\mu\ (s=2)$	48.12	**	52.67	*	10.74	**	32.21	*	54.63	**	35.17	***
	(40.42)		(34.96)		(2.10)		(61.26)		(1.98)		(1.81)	
ρ	-0.06	*	-0.05	*	-0.09	*	-0.48	*	-0.38	*	0.03	*
	(2.94)		(2.75)		(2.98)		(3.16)		(5.97)		(3.43)	
$\sum_{k=1}\delta_k$	0.01		0.28		-0.17		-0.76		-0.50		-0.20	
Lag order k	1		1		3		3		1		1	
$\sigma^2(s=1)$	96.37	***	32.03	*	6.82	*	62.97	*	56.24	*	19.31	*
	(1.97)		(4.32)		(6.77)		(4.41)		(4.81)		(7.65)	
$\sigma^2(s=2)$	209.61	*	61.54	*	11.94	*	143.68	*	101.22	*	26.38	*
	(19.70)		(10.03)		(7.32)		(10.59)		(10.40)		(9.21)	
p_{11}	0.50	*	0.53		0.87	*	0.93	*	0.91	*	0.87	*
	(11.98)		(0.24)		(37.35)		(3.05)		(19.19)		(39.18)	
p_{12}	0.27		0.14	***	0.11		0.11		0.28	***	0.07	
	(0.46)		(1.92)		(1.46)		(0.13)		(1.73)		(1.22)	
Likelihood value	-950.37	***	-826.10		-633.57		-900.44		-820.18		-720.43	
ADF-t_ρ	-2.94	***	-2.75		-2.98	***	-3.16	**	-5.97	*	-3.43	**
χ^2 test for equal variances	15.25	*	15.58	*	2.08		22.15	*	19.56	*	8.29	*
LR test vs. linear model	63.34	*	44.19	*	45.94	*	50.07	*	187.84	*	109.80	*
LR test vs. MS constant	34.00	*	31.00	*	22.21	*	29.25	*	134.50	*	71.63	*

Notes: Absolute values of t-statistics are in parentheses. *, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The estimates for the probability of state one, p_{11}, are close to one for Indonesia. This relatively high point estimate implies a longer average duration of that state, which corresponds to a relatively lower conditional mean and smaller variance for the Indonesian price series. Corroborating evidence can be observed in Figure 3, which plots the smoothed probabilities of state one over the observation period. The plots essentially reveal the extent of volatility changes in addition to level shifts. In Figure 3, the durations of being close to state one vary remarkably across the six markets. Indonesia shows the most persistence in high probability for being in state one, while the Philippines and Malaysia appear to show most variability in their probability series. Those patterns reflect the timing of level shifts in the prices series as well as changes in their volatility due in part to developments in the world or domestic economies. As the estimates for $\sigma^2(s)$ in Table 4 suggest, state one corresponds to a lower variance for all six markets, particularly during the first half of 2000s when those economies experienced relatively low overall inflation as they continued to recover from the turmoil during financial crisis of 1997-1998.

Figure 3: Probability of State 1 for Markov-Switching Constant and Variance.



The next model specification is the full version of the Markov switching model as represented by equation (3), which allows for Markov-switching behavior in all coefficients as well as the variance of the residual term. Table 5 displays the estimation results. Apparently, estimates from this model differ appreciably from those of the previous two model specifications. In particular, the differences between the constant term's two states are remarkably larger. Higher estimates can also be realized for the variance in the second state, i.e., $\sigma^2(s = 2)$, than in the first state. The χ^2 statistics for testing equal variances further confirm the extent of heterogeneity in the variance of most price series except for Hong Kong.

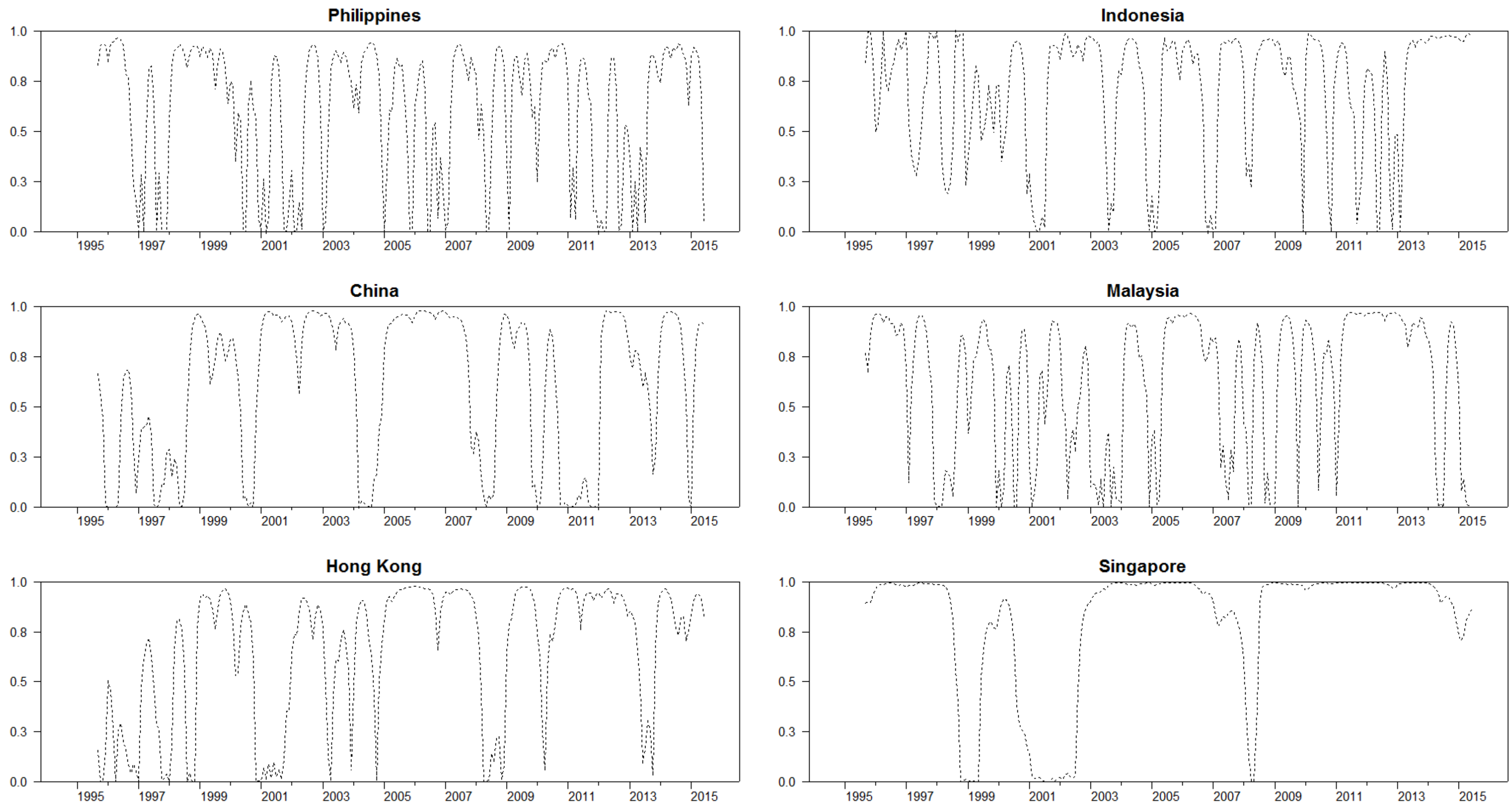
Table 5: Regression with Markov-Switching Coefficients and Variance**.**

	Philippines		China		Hong Kong		Indonesia		Malaysia		Singapore	
$\mu\ (s=1)$	0.08		0.24	**	-0.07		-0.48		2.54	*	4.15	
	(1.18)		(2.03)		(0.57)		(1.39)		(2.48)		(1.19)	
$\mu\ (s=2)$	76.14	**	59.96	*	11.75	*	32.37	**	23.63		49.80	**
	(2.17)		(35.08)		(2.58)		(2.63)		(0.18)		(2.23)	
$\rho\ (s=1)$	-0.88	**	-1.06	*	-0.26	*	0.03	*	-0.52	*	-0.81	*
	(3.19)		(3.08)		(3.49)		(3.96)		(4.63)		(3.83)	
$\rho\ (s=2)$	-0.06		0.06		-0.14		-0.04		-0.43		0.18	
	(0.48)		(0.74)		(1.03)		(0.31)		(0.78)		(1.36)	
$\delta_1(s=1)$	0.06		0.09		-0.05		0.03		-0.09		0.03	**
	(0.98)		(1.04)		(0.57)		(0.42)		(1.36)		(2.29)	
$\delta_1(s=2)$	-0.02	**	-0.26	***	0.22	**	-0.56	*	-0.14	***	-0.07	
	(2.18)		(1.93)		(2.32)		(2.55)		(1.78)		(0.49)	
$\delta_2(s=1)$					0.18	***	-0.16					
					(1.84)		(0.84)					
$\delta_2(s=2)$					0.06		-0.06	*				
					(0.28)		(1.06)					
$\delta_3(s=1)$					-0.01	*	-0.25	***				
					(2.46)		(1.92)					
$\delta_3(s=2)$					-0.02		-0.05	***				
					(0.61)		(1.68)					
$\sigma^2(s=1)$	43.77	*	19.01	*	4.26	*	31.52	*	19.14	*	12.46	*
	(5.37)		(5.31)		(5.95)		(4.40)		(4.41)		(3.41)	
$\sigma^2(s=2)$	406.78	*	121.21	*	28.48	*	213.59	*	245.34	*	56.03	**
	(5.55)		(5.32)		(5.14)		(4.06)		(4.86)		(4.94)	
p_{11}	0.67	*	0.74	*	0.75	*	0.68	***	0.83	**	0.84	*
	(3.22)		(3.66)		(3.17)		(1.78)		(1.99)		(4.44)	
p_{12}	0.54	***	0.26	*	0.34		0.47	**	0.34	*	0.24	
	(1.73)		(4.69)		(1.56)		(4.58)		(3.75)		(3.21)	
Likelihood value	-935.24		-806.07		-621.66		-699.14		-700.69		-595.90	
ADF-$t_\rho(s=1)$	-3.19	**	-3.08	**	-3.49	**	-3.96	**	-4.63	*	-3.83	**
ADF-$t_\rho(s=2)$	-0.48		-0.74		-1.03		-0.31		-0.78		-1.36	
χ^2 test for equal variances	19.24	*	14.72	*	2.77		18.84	*	18.60	*	8.27	*
LR test vs. linear model	93.59	*	84.25	*	69.77	*	452.68	*	426.82	*	358.86	*
LR test vs. MS constant	64.26	*	71.05	*	46.03	*	431.85	*	373.48	*	320.69	*
LR test vs. MS constant + variance	30.26	*	40.05	*	23.82	*	402.61	*	238.98	*	249.06	*

Notes: Absolute values of *t*-statistics are in parentheses. *, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively

Figure 4 plots the corresponding estimates for the smoothed probability of state one, p_{11}, over the observation period. Compared to the plots generated by the preceding MS model specifications, those series are less persistent across the observation period as a result of the consideration of possible regime switches in all coefficients in the model as well as its variance. For all price series, state one (s=1) corresponds to smaller estimates for both the constant and variance, i.e., lower growth in price levels along with less market volatility. Major deviations from that state coincide with the Asian financial crisis of 1997-1998 and the rice crisis a decade later.

Figure 4: Probability of State 1 for Markov-Switching Coefficients and Variance.



In comparison with other models, evidence of stationarity in the rice price series is stronger in this Markov switching model specification. Based on the ADF-t_ρ tests, the null hypothesis is rejected in favor of stationarity for all price series during state one (s=1). For state two (s=2), however, the null hypothesis cannot be rejected for any series. As the average duration of state one is longer than the average duration of state two for all six price series, the test results essentially suggest that the rice price data are dominated by a stationary as opposed to unit-root process over the observation period.

The bottom three rows of Table 4 display results of LR tests for this version of the MS model against the preceding three model specifications. All test statistics are statistically significant at the 1% level. Those test results suggest that this particular nonlinear model specification, which allows for state-dependent coefficients and variance, characterizes the dynamic behavior of Asian rice prices better than the linear model as well as all other variants of the MS model.

4. Conclusion

Accurate characterization of the time-series properties of rice prices is crucial for performing rice market forecasts and trade policy analyses. If their data-generating process contains a unit root, then stochastic innovations would have a permanent effect on the levels of the series; otherwise, the effects might be short-lived. To this end, we have applied the ADF tests to six Asian import rice price series with a linear, non-switching regression model as well as three alternative Markov-switching model specifications. In line with the consensus in the empirical literature concerning the stochastic property of commodity prices, there is scant evidence against the unit-root null from our linear model regressions. When the autoregressive process and the unconditional variance are allowed to follow a Markov-switching process with two states, however, the ADF statistics provide strong evidence in favor of stationarity among the six price series over the majority of the observation period between 1995 and 2015.

For the six price series in our sample, which includes the world's largest rice importers, the nonlinear model with Markov-switching in both the coefficients and variance provides the best characterization. According to our model estimation results, those time series are stationary for at least some subperiods, and occasional shocks might have temporarily altered their data-generating processes. When market prices are best characterized by nonlinear, Markov-switching processes, trading strategies and international trade policies should differ from the cases in which the market prices either follow a random walk or continue to evolve around an unbroken trend.

Essentially, we have found strong empirical evidence to support that the world's prices of rice imports have been largely affected by long-run economic fundamentals as opposed to temporal shocks or policy interventions. This bears implications for the way policymakers evaluate the efficacy of government policy responses (e.g., Martin and Anderson, 2012) to a given shock to the world rice market that may not likely manifest itself as a permanent shift in market prices.

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