The Effect of NFA Buffer Stocks on the Retail Price of Rice in the Philippines

Agham C. Cuevas[1]

Abstract

The study uses a Vector Error Correction model to show that a long run relationship/ causality exists between NFA stocks and world price and domestic retail price of rice in the Philippines. No short run relationship was found for NFA stocks and retail price while a short run relationship exists for world price and retail price. This implies that while NFA stocks can affect retail prices, a significant amount of time may occur before its effects are transmitted. An Autoregressive Distributed Lag-Error Correction model was also utilized. Results establish a strong short-run relationship between retail prices, total stocks, and world prices. Policywise, this result points to the importance of total supply management implying the need for proper timing in the purchase and release of NFA stocks for it to be effective in stabilizing prices

Keywords: *vector error correction model, autoregressive distributed lag model, rice*

Introduction

Episodes of rice price spikes in the Philippines and dwindling stocks of the National Food Authority (NFA) in the recent past have placed the government's performance in rice buffer stocking under increasing scrutiny as the country continues to pursue rice self-sufficiency while trying to maintain price stability. The NFA's two primary mandates are to ensure food security and to stabilize the supply and price of rice. The latter mandate means that the NFA tries to influence prices on two fronts, i.e., to stabilize the price of rice consistent with farm prices that are remunerative to the country's rice farmers and to manage reasonable retail prices for the country's consumers. The food security mandate of the agency, on the other hand, requires that the NFA maintain and manage buffer stocks through the importation of rice (Aquino *et al.* 2013). Direct attribution has often been made to dwindling NFA stocks as one of the main causes of rising prices (see Briones and Galang 2014). Monthly data from 2011 to 2018 seem to show that the declining stocks, particularly government/NFA stocks, coincided with rising prices during the year (Figure 1). For example, in 2017, stocks have been ebbing monthly beginning January and reaching their trough in September which corresponded to rising prices in roughly the same period. More recent incidences of rising rice prices have also been attributed to the alarming depletion of NFA stocks despite the fact that it comprises only 10% of total rice stocks (Figure 2).

[1]Department of Economics, College of Economics and Management, University of the Philippines Los Baños, College, Laguna 4031, Philippines,
email: accuevas1@up.edu.ph

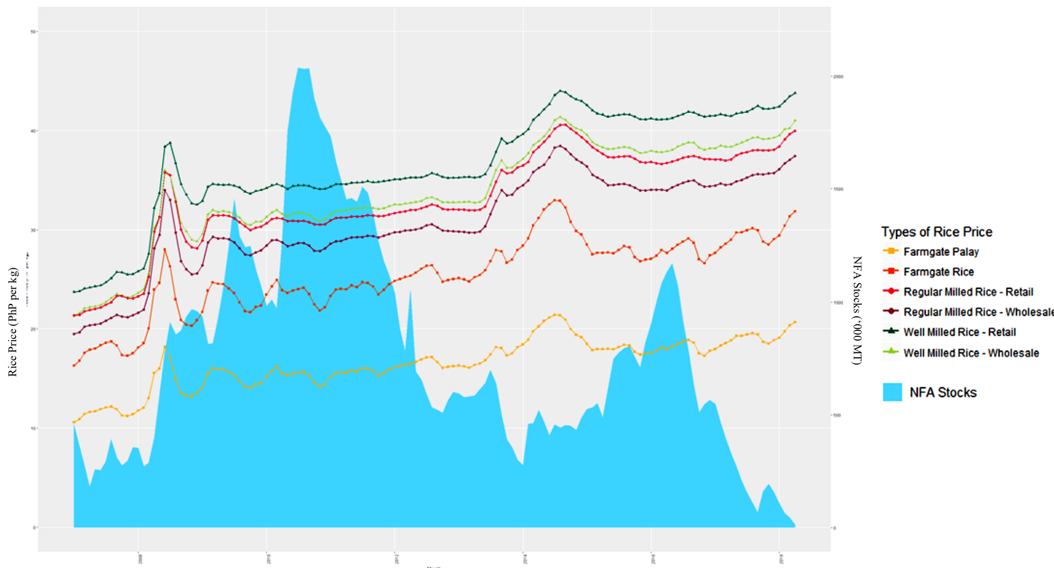

Figure 1. Monthly total rice stock inventory and prices, Philippines, 2012-2018
Source of basic data: National Food Authority nfa.gov.ph

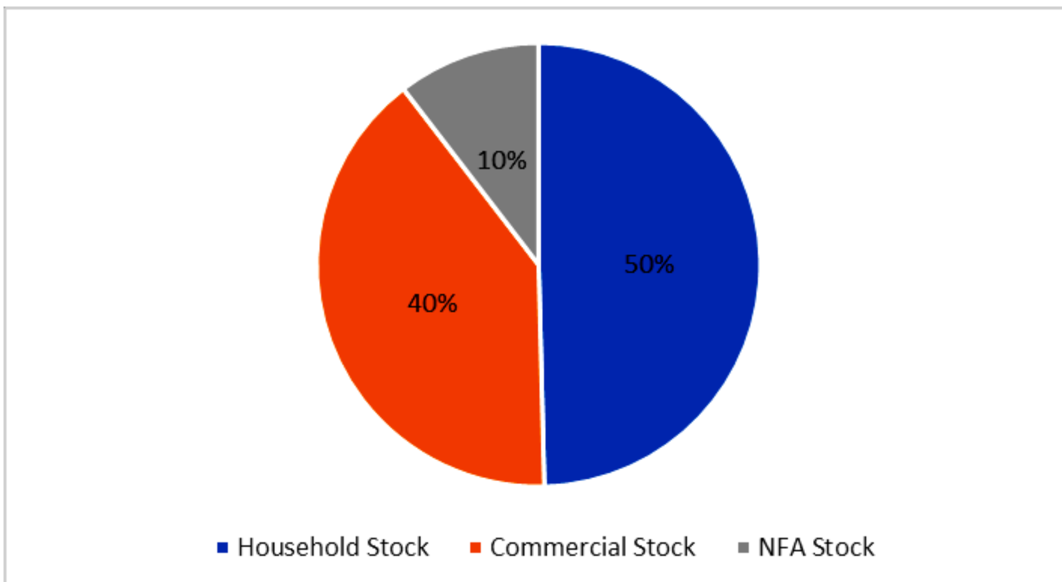

Figure 2. Composition of total rice stocks, Philippines, 2017
Source of basic data: National Food Authority nfa.gov.ph

However, correlation does not necessarily imply causality. While these two events – price spikes and dwindling NFA rice stocks - may seem to occur contemporaneously, a more in-depth look is needed to ascertain whether the relationship between these two events is purely static in nature or it has a dynamic component. A full understanding of the relationship between these two variables is warranted in order to arrive at a conclusion that could add to the policy debate on government rice procurement.

This paper aims to analyze the statistical relationship between Philippine domestic rice prices and NFA buffer stocks using monthly time series data. It seeks to empirically validate the abovementioned claims on how the NFA's buffer stock performance affects rice prices. Furthermore, this paper looks at how world price fluctuations are transmitted to local prices that may further help explain the rice price spikes. It also analyzes the effect of total stocks on retail prices to provide an alternative explanation to the price spikes. The paper is structured as follows: the next section briefly describes the rice industry in the Philippines followed by the methodology. The results are then presented. The last section concludes the paper by providing a brief summary and some policy implications.

The Rice Industry

Significance of the Industry

As the main staple food of Filipinos, rice is the most important agricultural crop in the Philippines. Per capita rice utilization has generally been increasing with the growing population, thus expanding demand (Figure 3).

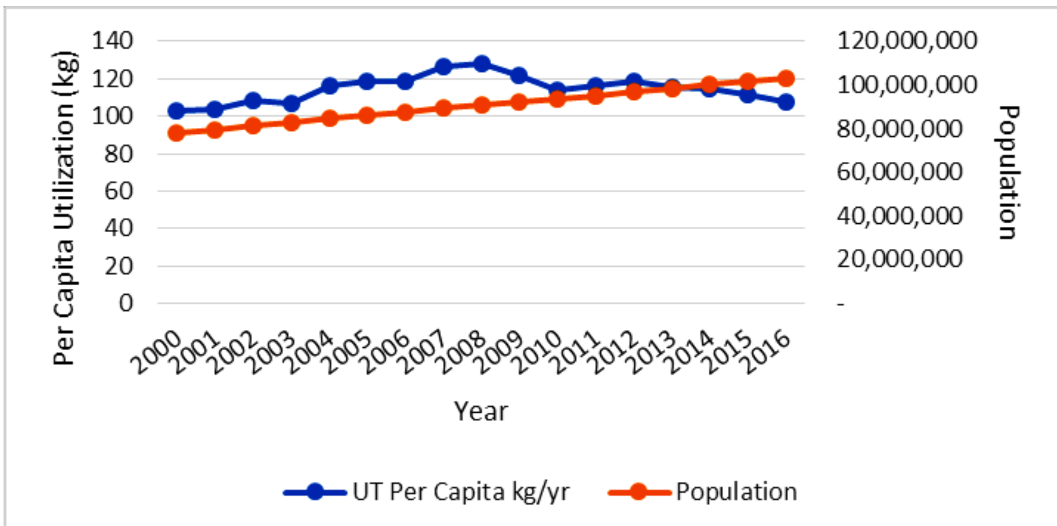

Figure 3. Annual per capita rice utilization and population, Philippines, 2000-2018
Source: BAS, 2016; worldometers.info

Of the total agricultural produce of the country, about 20% comes from rice. It is grown in 2.2 million farms, which is about 45% of the total number of farms in the country and covers a physical land area of 4.75 million hectares (ha) or about 49% of the total agricultural area (Bureau of Agricultural Statistics or BAS now Philippine Statistics Authority or PSA 2013). There are about 2.5 million rice farmers in the country, predominantly male with an average age of 50 years old. The average farm size in major producing areas remains below 1.5 ha. The country is also one of the top importers of rice in Asia. In 2017, the country imported a total of 1.4 million metric tons (MMT) of rice (Figure 4).

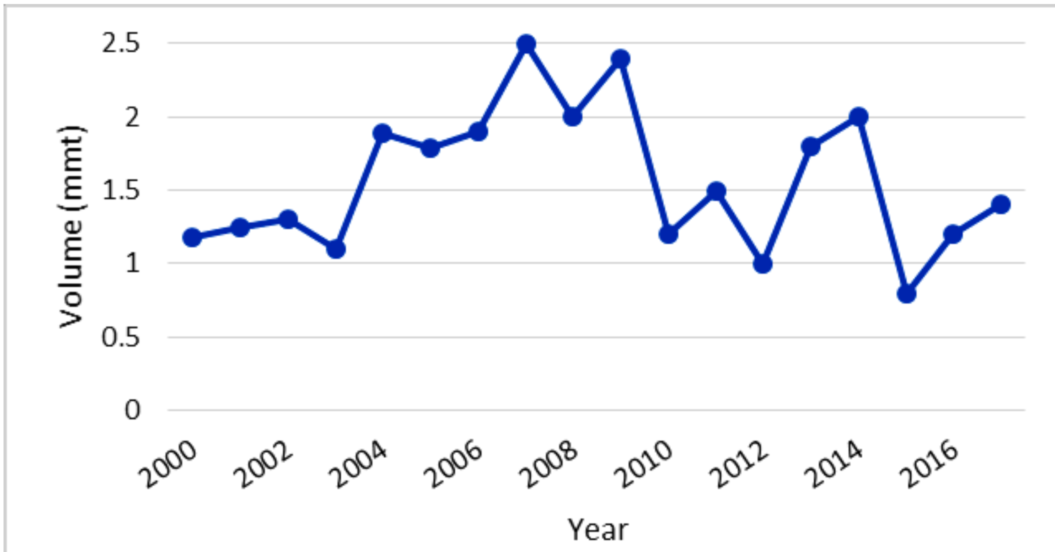

Figure 4. Annual volume of rice imports, Philippines, 2000-2017
Source: World Rice Statistics

Production Trends

Total *palay* (rough rice) production in 2017 reached 19.28 MMT valued at PhP 350 million. This surpassed the 2016 production of 17.63 MMT by 9.36%. Harvest area also expanded by 5.5% from 4.56 million ha in 2016 to 4.81 million ha in 2017. Consequently, average yield per hectare has increased by 0.3% from 2014 up to 2017. Figure 5 shows the average yield per hectare of irrigated, rainfed, and total *palay* from 2006 to 2017 (PSA 2017 countrystat.psa.gov.ph).

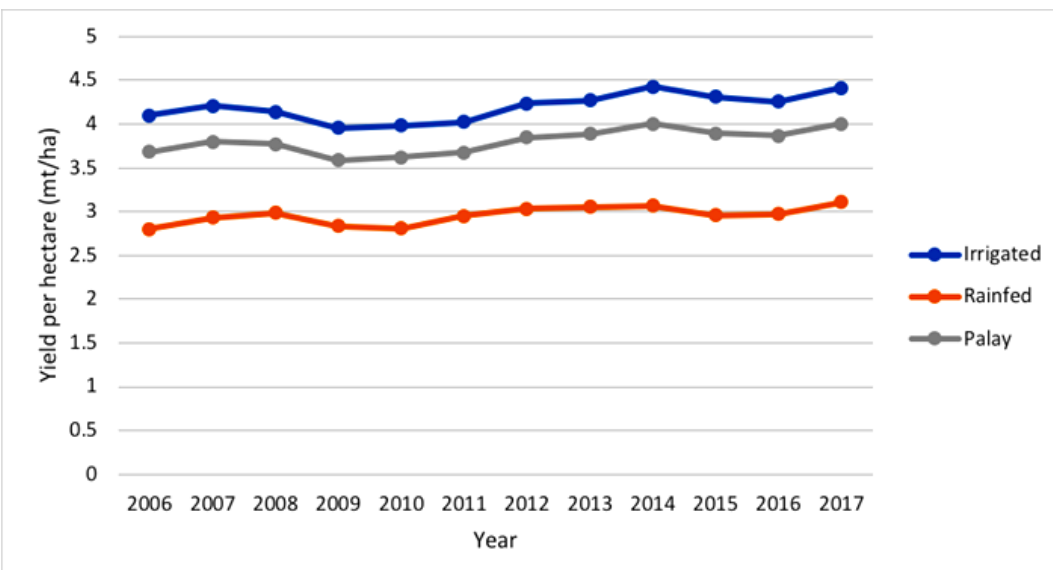

Figure 5. Average yield per hectare of rice (MT/ha), Philippines, 2006-2017
Source: PSA countrystat.psa.gov.ph 2017

Top Rice Producing Regions

The top producing provinces in 2017 are Nueva Ecija, Isabela, Pangasinan, Cagayan, Iloilo, Camarines Sur, Tarlac, North Cotabato, and Leyte. They contributed a total of 8.48 MMT or about 44% of the country's total harvest (Table 1). Nueva Ecija, known as the rice granary of the Philippines, is the consistent top rice-producing province with an average yield of 4.35 MT/ha with a total production of 1.13 MMT in 2017.

Table 1. Top rice producing provinces, Philippines, 2017

Province	Production (MT)	Area Harvested (HA)	Yield (MT/HA)
Nueva Ecija	1,125,065	258,367	4.35
Isabela	1,006,120	222,871	4.51
Pangasinan	1,285,685	279,291	4.60
Cagayan	1,884,091	324,042	5.81
Iloilo	579,013	135,075	4.29
Camarines Sur	683,385	182,831	3.74
Tarlac	937,269	286,550	3.27
North Cotabato	481,487	118,416	4.07
Leyte	500,238	125,868	3.97
Total	8,482,353	1,933,311	4.39

Source: PSA countrystat.psa.gov.ph 2017

Specific Issues and Bottlenecks

The rice industry, despite being one of the most heavily invested on by government within the agriculture sector, has been plagued by both production and marketing inefficiencies. The following enumerates some of the salient causes and manifestations of these inefficiencies.

High Transport Costs

Transport costs are high because of institutional problems related to sea freight and inadequate infrastructure compared to many other developing Southeast Asian countries. This is mainly due to poor road conditions and inadequate port facilities. Local government units have an important role to play in strengthening road and port infrastructure. However, there are institutional disincentives for them to spend for farm-to-market roads.

High Postharvest Losses

Postharvest facilities present a physical bottleneck. A 2010 postharvest loss assessment conducted by the Philippine Center for Postharvest Development and Mechanization (PhilMech) estimated losses due to inadequate facilities at 16.47%. Drying, for example, is often done through solar and pavement sun drying which results in a 5.86% loss and dried paddy with relatively high moisture content. This accounts for 36% of the total postharvest losses (Department of Agriculture 2013). A 2007 survey of postharvest facilities conducted by then Bureau of Postharvest Research and Extension (BPRE), now PHilMech, showed that the single pass mill is the predominant type of rice mill in the country with an 88% share of total capacity. Milling recovery of this type of mill is low at around 57-60% (Department of Agriculture) with low-grade classification of milled rice. Modern rice mills' share of total capacity (multi-pass facilities with 65-70% milling recovery) is only 12% at the time of the survey. More recent data show a national average milling recovery of 65% (http://www.pinoyrice.com/resources/rice-facts-and-figures), still below the ideal of 68-72% for white rice.

Dependence of Farmers on Traders for Price Information

This can be partly traced to the inadequate and lack of timely public sector information system for prices, production, and area harvested. Communication facilities to disseminate these data are also limited. Farmers' organizations are also weak in terms of management and marketing skills, which tends to increase their dependence on traders and millers.

Lack of Access to Credit/Capital

Farmers often find it hard to satisfy the requirements of lending banks forcing them to borrow from informal sources who either charge high interest rates or contract the borrower's produce at a low price.

Methodology

Time-Series Data, Stationarity, and Cointegration

Time series data comprise a sequence of observations of the defined variable at a uniform interval over a period of time in successive order. Most common series are in annual, quarterly, monthly, weekly, and daily frequencies. Economic time series data often possess unique features such as clear trend, high degree of persistence of shocks, higher volatility over time, and meandering and sharing co-movements with other series. In time series analysis, it is important to understand the behavior of variables, their interactions, and integrations over time. If major characteristics of time series data are understood and addressed properly, a simple regression analysis using such data can also reveal the pattern of relationships among variables of interest (Shrestha and Bhatta 2018).

The relationship of one set of time series data to another can either be 1) static/ contemporaneous, meaning, that the dependent variable (Y) reacts instantaneously to changes in the independent variable (X) at time *t*, or 2) dynamic/lagged, meaning that Y does not fully react to a change in X at time *t*. For the latter case, a dynamic model will thus estimate both a contemporaneous relationship at time *t* and a lagged relationship at time $t - 1$.

Time series data may have some kind of relationship with their previous values. If the current value of Y is determined by its past value and some adjustment factors, the model is characterized as an autoregressive (AR) model. Adjustment factors are estimated from the relation of current values with their past values. If the current value is based solely on the immediate preceding value, it is termed as first order autoregressive, AR (1); if it is based on two preceding values, second order autoregressive, AR (2), and so on.

Time series trends can either be stationary or non-stationary. The series is non-stationary if it does not tend to return to its long-run average value, hence, its mean, variance and co-variance also change over time. On the other hand, if the value of a time series has the tendency to revert to its long-run average value and the properties of the data series are not affected by the change in time only, then it is said to be stationary. Most economic time series grow (or decline) over time. If a time series behaves in this manner, then the series contains a time trend. A series that contains a time trend is non-stationary.

Standard regression techniques, such as ordinary least squares (OLS), require that the variables be stationary. Cointegration analysis provides a framework for estimation, inference, and interpretation when the variables are not stationary. Instead of being stationary, many economic time series appear to be "first-difference stationary". This means that the level of a time series is not stationary, but its first difference is (i.e., for a variable X, $X_t - X_{t-1}$ is the first difference). First difference stationary processes are also known as integrated processes of order 1, or I(1) processes. Stationary processes are I(0).

The regression of a non-stationary time series on another non-stationary time series can often produce non-sensical or spurious results. This phenomenon is known as spurious regression and one way of guarding against it is to find out if the time series is cointegrated. Cointegration means that despite being individually non-stationary, a linear combination of two or more time series can be stationary. Cointegration of two (or more) time series suggests that there is a long-run, or equilibrium, relationship between them. Simply put, two series are said to be cointegrated if they follow the same long-run path and any deviations will ultimately return back to the mean (i.e., equilibrium).

Engle and Granger (1987) showed that if the two series X and Y are individually I(1) (i.e., integrated of order one) and cointegrated, then there would be a causal relationship at least in one direction. Granger's Representation Theorem states that if X and Y are cointegrated, then the relationship between the two can be expressed as an error correction mechanism (ECM). The theorem also demonstrates how to model a cointegrated I(1) series in a vector autoregression (VAR) format. VAR can be constructed either in terms of the level of the data or in terms of their first differences, i.e., I(0) variables, with the addition of an error correction term to capture the short-run dynamics. The standard Vector Error Correction Model (VECM) is given by the equation:

$$\Delta Y_t = \alpha + \sum_{i=1}^{m} \beta_i \Delta Y_{t-i} + \sum_{j=1}^{r} \gamma_j \Delta X_{t-j} + \delta ECM_{t-1} + u_t \qquad (1)$$

$$\Delta X_t = a + \sum_{i=1}^{m} b_i \Delta X_{t-i} + \sum_{j=1}^{r} c_j \Delta Y_{t-j} + dECM_{t-1} + v_t \qquad (2)$$

where α and *a* are drift components, β_i and c_j are the coefficients of the lagged values of Y, γ_j and b_i are the coefficients of the lagged values of X, δ and *d* are the coefficients of the error correction term, while u_t and v_t are the error terms.

Pesaran *et al.* (2001), on the other hand, proposed a new method for testing cointegration called a conditional ARDL (autoregressive distributed lag) model and ECM, also known as 'ARDL bounds testing procedure'. The conditional ARDL-ECM equation can be written as:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 X_{t-1} \sum_{i=1}^{m} \beta_i \Delta Y_{t-i} + \sum_{j=1}^{r} \gamma_j \Delta X_{t-j} + \delta ECM_{t-1} + \varepsilon_t \qquad (3)$$

where ε_t is the error term. The reduced form solution of equation (3) showing the long run-relationship is represented as:

$$Y_t = \Phi_0 + \Phi_1 X_t + \epsilon_t \qquad (4)$$

where $\Phi_0 = -\alpha_0/\alpha_1$, $\Phi_1 = -\alpha_1/\alpha_2$ and ϵ_t is the error term.

The main advantage of this procedure is that it can be applied without prior knowledge whether the series are purely I(0), I(1), or mutually cointegrated. In addition, it can be applied to the series with a small sample size.

Data Description and Sources

The study utilized monthly data of domestic retail price of well-milled rice (WMR), beginning NFA stocks, beginning total stocks, and price (FOB) of Thai 5% broken expressed in pesos/per kilo (PhP/kg) (as proxy for world rice price), from January 2007 to September 2018 for a total of 141 observations. However, following a test for structural break, data were censored to 130 observations, starting from December 2007 and ending in September 2018, with the break coinciding with the onset of the 2007-2008 world food crisis. The main source of secondary time series data is the Philippine Statistics Authority (2018).

Analytical Tools

The study utilized a bivariate vector error correction (VEC) model to establish the relationship between retail prices and NFA stocks. While the VEC model was also the original method of choice to establish the relationship between retail prices and total stocks, the test for stationarity would later on reveal that the series is I(1) and I (0), respectively, necessitating the use of an autoregressive distributed lag (ARDL) model instead. A multivariate version which includes world price as a determinant was also implemented using VEC and ARDL. This was done to determine whether the results are robust to the inclusion of other determinants.

Using equations (1) and (2), the VEC model is expressed by the following regression equations:

$$\Delta retail_t = \alpha_0 + \beta_1 \Delta retail_{t-1} + \beta_2 \Delta retail_{t-2} +, \dots, + \beta_m \Delta retail_{t-m} + \gamma_1 \Delta stocks_{t-1} + \gamma_2 \Delta stocks_{t-2} +, \dots, + \gamma_r \Delta stocks_{t-r} + \delta ECM_{t-1} + u_t \quad (5)$$

$$\Delta stocks_t = \alpha_0 + b_1 \Delta stocks_{t-1} + b_2 \Delta stocks_{t-2} +, \dots, + b_r \Delta stocks_{t-r} + c_1 \Delta retail_{t-1} + c_2 \Delta retail_{t-2} +, \dots, + c_m \Delta retail_{t-m} + dECM_{t-1} + v_t \quad (6)$$

for the bivariate case, and

$$\Delta retail_t = \alpha + \beta_1 \Delta retail_{t-1} + \beta_2 \Delta retail_{t-2} +, \dots, + \beta_m \Delta retail_{t-m} + \gamma_1 \Delta stocks_{t-1} + \gamma_2 \Delta stocks_{t-2} +, \dots, + \gamma_r \Delta stocks_{t-r} + \theta_1 \Delta worldprice_{t-1} + \theta_2 \Delta worldprice_{t-2} +, \dots, + \theta_p \Delta worldprice_{t-p} + \delta ECM_{t-1} + u_t \quad (7)$$

$$\Delta stocks_t = \alpha_0 + b_1 \Delta stocks_{t-1} + b_2 \Delta stocks_{t-2} +, \dots, + b_r \Delta stocks_{t-r} + c_1 \Delta retail_{t-1} + c_2 \Delta retail_{t-2} +, \dots, + c_m \Delta retail_{t-m} + \tau_1 \Delta worldprice_{t-1} + \tau_2 \Delta wor\square dprice_{t-2} +, \dots, + \tau_p \Delta worldprice_{t-p} + dECM_{t-1} + v_t \quad (8)$$

$$\Delta worldprice_{t-1} = \lambda_0 + \pi_1 \Delta worldprice_{t-1} + \pi_2 \Delta worldprice_{t-2} +, \dots, + \pi_p \Delta worldprice_{t-p} + \rho_1 \Delta \square tocks_{t-1} + \rho_2 \Delta stocks_{t-2} +, \dots, + \rho_r \Delta stocks_{t-r} + \phi_1 \Delta retail_{t-1} + \phi_2 \Delta retail_{t-2} +, \dots, + \phi_m \Delta retail_{t-m} + + \varphi ECM_{t-1} + e_t \quad (9)$$

for the multivariate case, where $retail_t$ = retail price of well-milled rice, $stocks_t$ = beginning NFA stocks, and $worldprice_t$ = world price of rice.

Using equation (3), the ARDL-ECM model is represented by the equation:

$$\Delta retail_t = \alpha_0 + \alpha_1 retail_{t-1} + \alpha_2 totalstocks_{t-1} + \beta_1 \Delta retail_{t-1} + \beta_2 \Delta retail_{t-2} +, \dots, + \beta_m \Delta retail_{t-m} + \gamma_1 \Delta totalstocks_{t-1} + \gamma_2 \Delta totalstocks_{t-2} +, \dots, + \gamma_r \Delta totalstocks_{t-r} + \delta ECM_{t-1} + \varepsilon_t \quad (10)$$

for the bivariate case, and

$$\Delta retail_t = \alpha_0 + \alpha_1 retail_{t-1} + \alpha_2 totalstocks_{t-1} + \beta_1 \Delta retail_{t-1} + \beta_2 \Delta retail_{t-2} +, \dots, + \beta_m \Delta retail_{\square-m} + \gamma_1 \Delta totalstocks_{t-1} + \gamma_2 \Delta totalstocks_{t-2} +, \dots, + \gamma_r \Delta totalstocks_{t-r} + \theta_1 \Delta worldprice_{t-1} + \theta_2 \Delta worldprice_{t-2} +, \dots, + \theta_p \Delta worldprice_{t-p} + \delta ECM_{t-1} + \varepsilon_t \quad (11)$$

for the multivariate case, where totalstockst = total beginning stocks.

The Augmented Dickey-Fuller (ADF) test was used to determine the order of integration and test the existence of unit roots. The ADF test for a unit root is as follows:

$$\Delta y_t = \mu + \delta y_{t-i} + \sum_{i=1}^{m} \beta_i \Delta y_{t-i} + e_t \quad (12)$$

where $\delta = \alpha\text{-}1$, α = coefficient of $y_{(t\text{-}i)}$, Δy_t = first difference of y_t i.e. $y_t\text{-}y_{(t\text{-}i)}$. The null hypothesis of ADF is $\delta = 0$ (the series has a unit root) against the alternative hypothesis of $\delta < 0$ (the series does not have a unit root). If the null is not rejected, the series is non-stationary whereas rejection means the series is stationary.

Then the optimum lag length was determined based on Akaike's information criterion (AIC). This was done to determine up to what time period to consider in evaluating the contribution of past values of the regressors to the changes in the dependent variable.

For the VEC model, the Johansen test for cointegration was used to determine the number of cointegrating equations which would indicate the presence or absence of potential long run equilibrium relationships between the variables.

The ARDL bounds testing procedure, on the other hand, was used to determine the existence of a long run relationship in the ARDL-ECM model.

The forecast error variance decomposition (FEVD) was also computed for the VEC model. The FEVD measures the fraction of the forecast error variance of an endogenous variable that can be attributed to shocks to itself or to another endogenous variable.

Results and Discussion

Test of Stationarity

The results of the Augmented Dickey-Fuller (ADF) test (see Appendix 1) show that domestic retail price of well-milled rice, domestic retail price of regular milled rice, beginning NFA stocks, and price (FOB) of Thai 5% broken expressed in pesos/ per kilo all have unit roots. Therefore, they are non-stationary at level form but are stationary at first difference implying an order of integration of 1, i.e., I(1). The beginning total stocks series, on the other hand, was proven to be stationary at level form and therefore integrated at 0, i.e., I(0).

The VEC Model

The optimal lag length was determined to be two time periods in the bivariate model and four time periods for the multivariate model based on the Akaike's information criterion (AIC) (see Appendix 2). The trace statistics of the Johansen test for cointegration (Appendix 3), on the other hand, indicates that the null hypothesis that there is one or fewer cointegrating equation cannot be rejected. This means that there exists a linear, stable and long-run relationship among the variables, such that the disequilibrium errors would tend to fluctuate around a zero mean. This confirms the presence of a potential long run equilibrium relationship between retail prices and the NFA stocks for the bivariate model and between retail prices, world prices, and NFA stocks for the multivariate model.

The Vector Error Correction Model (Appendices 4 and 5) regression shows that the coefficient of the error correction term, which measures the speed of adjustment of retail price to its equilibrium level, is negative and statistically significant at the 1% level (both for the bivariate and multivariate cases). This implies that there is a long run relationship/causality running from world prices and NFA stocks to domestic retail price.

The long-run equation for the bivariate model was determined to be

$$retail + 0.0109527stocks - 45.61416,$$

while for the multivariate model, it is

$$retail + 0.00479stocks + 0.982841worldprice - 60.2379.$$

Clearly, the inclusion of another determinant has reduced the long run influence of NFA stocks on retail price.

A short-run causality test (Appendix 6) was implemented, and results show that there is no short run causality running from NFA stocks to retail price for both the bivariate and multivariate models, while a short-run causality exists from world price to retail price.

The forecast error variance decomposition (FEVD) of the bivariate and multivariate models were also computed (Appendices 7 and 8). As was earlier stated, the FEVD measures the fraction of the forecast error variance of an endogenous variable that can be attributed to shocks to itself or to another endogenous variable. For the bivariate model, for a 12-month period, only 8% of the total change in retail prices can be attributable to shocks in NFA stocks. This dramatically decreases to just 1% in the multivariate model wherein 5% is attributable to shocks in world prices. The rest is accounted for by own price shocks.

ARDL-ECM Model

Optimal lags computed using the AIC criterion are four (4) time periods for retail price and two (2) time periods for total stocks for the bivariate model. For the multivariate case, optimal lags are four (4) time periods for retail price and three (3) time periods for both total stocks and world price (see Appendix 9). The error correction term, while negative in both models are not statistically significant indicating the absence of any long run relationship among the variables. This is confirmed by the long run coefficients for both models not being statistically different from zero. The bounds test fails to reject the null hypothesis of no level relationship among the variables implying that there is no statistical evidence for the existence of a long-run/cointegrating relationship (see Appendix 10).

Short run coefficients, however, are statistically significant for both total stocks and world price. The contemporaneous effect of total stocks on retail prices are negative for both the bivariate and multivariate models implying that as total stocks increase, retail price decreases. World price, on the other hand, has a positive contemporaneous effect on retail price implying that in the short run, increase in the world price increases domestic retail prices.

Conclusion and Recommendations

This study, through the use of a Vector Error Correction model, showed that a long run relationship/causality exists between NFA stocks and world price and domestic retail price of rice. No short run relationship was found for NFA stocks and retail price while a short run relationship exists for world price and retail price. This implies that while NFA stocks can affect retail prices, a significant amount of time may occur before its effects are transmitted.

On the other hand, the Autoregressive Distributed Lag-Error Correction model establishes a strong short-run relationship between retail prices, total stocks, and world prices. Policywise, this result points to the importance of total supply management implying the need for proper timing in the purchase and release of NFA stocks for it to be effective in stabilizing prices. Based on the model, it is more likely that the reduction in total stocks may have caused the price spikes in retail prices in the short run. Hence, a stable supply will prevent sudden price spikes. Addressing the bottlenecks in the rice industry earlier identified can also help ensure the stability of total supply.

The very small share of NFA stocks in the forecast error variance of retail price also puts into question the overall effectivity of NFA buffer stocking as a policy instrument for price stabilization. Restricting supply through the regulation of imports puts pressure for prices to increase, and the length of time and magnitude of the effect that NFA stocks have on the retail price does little for it to effectively ease the pressure on prices in the short run.[2]

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[2]As of November 2018, the proposal for Rice Tariffication is being favorably considered in the Philippine Congress. The proposal eliminates the quantitative restrictions in the importation of rice from other countries in order to prevent spikes in retail rice prices that contribute to high inflation. In order to provide protection to local farmers from competition of cheaper rice, tariffs on imported rice will be imposed at 35%. The expected revenues will be used as Rice Fund to provide the needed support services to farmers. A Rice Roadmap has been formulated in order to provide a long-term strategic rice agenda to enable the rice industry to adjust to the new trade policy environment.

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Appendix 1
Test for Stationarity

Dickey-Fuller test for unit root for retail price (level form)
Number of obs = 130

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.355	-3.500	-2.888	-2.578

MacKinnon approximate p-value for Z(t) = 0.6034

Dickey-Fuller test for unit root (first difference form)
Number of obs = 130

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.788	-3.500	-2.888	-2.578

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root for stocks (level form)
Number of obs = 130

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.000	-3.500	-2.888	-2.578

MacKinnon approximate p-value for Z(t) = 0.7533

Dickey-Fuller test for unit root for stocks (first difference form)
Number of obs = 130

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-7.458	-3.500	-2.888	-2.578

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root for world price (level form)
Number of obs = 130

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.730	-3.500	-2.888	-2.578

MacKinnon approximate p-value for Z(t) = 0.0690

Dickey-Fuller test for unit root for world price (first difference form)
Number of obs = 130

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-7.793	-3.500	-2.888	-2.578

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root for total stocks (level form)
Number of obs = 130

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.378	-3.500	-2.888	-2.578

MacKinnon approximate p-value for Z(t) = 0.0003

Appendix 2
Optimal Lag Selection

Selection-order criteria
Sample: 2007m12 - 2018m9 Number of obs = 130

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1346.33				3.5e+06	20.7436	20.7615	20.7877
1	-927.468	837.73	4	0.000	5915.34	14.361	14.4148	14.4934
2	-896.297	62.342	4	0.000	3894.61*	13.943*	14.0327*	14.1636*
3	-894.856	2.8809	4	0.578	4051.56	13.9824	14.1079	14.2912
4	-889.623	10.466*	4	0.033	3976.38	13.9634	14.1248	14.3605

Endogenous: retail stocks
Exogenous: _cons

Selection-order criteria
Sample: 2007m12 - 2018m9 Number of obs = 130

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1701.33				4.9e+07	26.2204	26.2473	26.2866
1	-1161.15	1080.4	9	0.000	13833.7	18.0484	18.156	18.3131
2	-1120.44	81.416	9	0.000	8495.55	17.5606	17.7488	18.0238
3	-1097.17	46.547	9	0.000	6824.72	17.341	17.6099*	18.0028*
4	-1084.7	24.937*	9	0.003	6477.2*	17.2877*	17.6372	18.1479

Endogenous: retail stocks worldprice
Exogenous: _cons

Appendix 3
Test for Cointegration

Johansen tests for cointegration
Trend: constant Number of obs = 130
Sample: 2007m12 - 2018m9 Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	-904.68211	.	16.7708	15.41
1	9	-896.38388	0.11985	0.1744*	3.76
2	10	-896.29668	0.00134		

Johansen tests for cointegration
Trend: constant Number of obs = 130
Sample: 2007m12 - 2018m9 Lags = 4

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	30	-1103.922	.	38.4477	29.68
1	35	-1089.1859	0.20285	8.9755*	15.41
2	38	-1084.7523	0.06593	0.1083	3.76
3	39	-1084.6981	0.00083		

Appendix 4
Vector Error Correction Model (Bivariate)

```
Vector error-correction model

Sample:  2007m12 - 2018m9                       Number of obs     =        130
                                                AIC               =   13.94941
Log likelihood = -889.7115                      HQIC              =   14.10178
Det(Sigma_ml)  =   3017.29                      SBIC              =   14.32439

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_retail             8     .622744   0.4269   90.88337   0.0000
D_stocks             8     94.0421   0.2011   30.70589   0.0002
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_retail     |
        _ce1 |
         L1. |  -.0375146   .0112391    -3.34   0.001    -.0595428   -.0154864
             |
      retail |
         LD. |   .4800122   .0875323     5.48   0.000     .3084521    .6515724
        L2D. |    .172323   .0960035     1.79   0.073    -.0158405    .3604864
        L3D. |  -.2603598   .0861775    -3.02   0.003    -.4292645   -.091455
             |
      stocks |
         LD. |   .0008733    .000587     1.49   0.137    -.0002772    .0020238
        L2D. |  -.0006283   .0006325    -0.99   0.321    -.0018679    .0006114
        L3D. |  -5.61e-06   .0006031    -0.01   0.993    -.0011877    .0011765
             |
       _cons |   .1408192   .0574512     2.45   0.014     .0282168    .2534215
-------------+----------------------------------------------------------------
D_stocks     |
        _ce1 |
         L1. |  -3.664792    1.69724    -2.16   0.031    -6.991322   -.3382631
             |
      retail |
         LD. |   3.483006   13.21847     0.26   0.792    -22.42471    29.39072
        L2D. |  -6.913076   14.49772    -0.48   0.633    -35.32809    21.50194
        L3D. |   13.48672   13.01387     1.04   0.300       -12.02    38.99343
             |
      stocks |
         LD. |   .3738536   .0886444     4.22   0.000     .2001138    .5475934
        L2D. |   .0831512   .0955135     0.87   0.384    -.1040517    .2703542
        L3D. |   -.004979   .0910778    -0.05   0.956    -.1834883    .1735303
             |
       _cons |  -.0014415   8.675852    -0.00   1.000     -17.0058    17.00292
------------------------------------------------------------------------------

Cointegrating equations
Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                 1   16.17914   0.0001
-------------------------------------------

Identification:  beta is exactly identified
                 Johansen normalization restriction imposed
------------------------------------------------------------------------------
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
      retail |          1          .        .       .            .           .
      stocks |   .0109527    .002723     4.02   0.000     .0056158    .0162896
       _cons |  -45.61416          .        .       .            .           .
------------------------------------------------------------------------------
```

Appendix 5
Vector Error Correction Model (Multivariate)

Vector error-correction model

Sample: 2007m12 - 2018m9		Number of obs	= 130
		AIC	= 17.33611
Log likelihood = -1082.847		HQIC	= 17.73047
Det(Sigma_ml) = 3448.009		SBIC	= 18.30666

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_retail	14	.557422	0.5634	149.7006	0.0000
D_stocks	14	96.436	0.2012	29.21856	0.0098
D_worldprice	14	1.40731	0.4038	78.56625	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_retail						
_ce1						
L1.	-.0339846	.0115054	-2.95	0.003	-.0565348	-.0114344
retail						
LD.	.4420084	.1068783	4.14	0.000	.2325307	.651486
L2D.	.2178503	.1096993	1.99	0.047	.0028437	.4328569
L3D.	-.1433248	.0929085	-1.54	0.123	-.3254221	.0387725
L4D.	-.0626426	.0884482	-0.71	0.479	-.2359979	.1107127
stocks						
LD.	.0007371	.0005367	1.37	0.170	-.0003147	.0017889
L2D.	-.0005683	.0005674	-1.00	0.317	-.0016803	.0005437
L3D.	-.0002034	.0005682	-0.36	0.720	-.001317	.0009103
L4D.	.000143	.0005308	0.27	0.788	-.0008974	.0011833
worldprice						
LD.	-.0017318	.0372094	-0.05	0.963	-.0746609	.0711973
L2D.	.1732948	.0384349	4.51	0.000	.0979637	.2486259
L3D.	-.032358	.042349	-0.76	0.445	-.1153606	.0506445
L4D.	-.058253	.041156	-1.42	0.157	-.1389173	.0224113
_cons	.2038472	.0606941	3.36	0.001	.084889	.3228054
D_stocks						
_ce1						
L1.	-1.399169	1.990479	-0.70	0.482	-5.300436	2.502097
retail						
LD.	4.810537	18.49032	0.26	0.795	-31.42983	41.05091
L2D.	-8.487522	18.97836	-0.45	0.655	-45.68442	28.70938
L3D.	21.52689	16.0735	1.34	0.180	-9.976576	53.03037
L4D.	1.479555	15.30185	0.10	0.923	-28.51153	31.47064
stocks						
LD.	.3677527	.0928443	3.96	0.000	.1857811	.5497242
L2D.	.0783908	.0981587	0.80	0.425	-.1139967	.2707783
L3D.	.0178952	.0982983	0.18	0.856	-.174766	.2105563
L4D.	-.1521092	.0918287	-1.66	0.098	-.3320901	.0278716
worldprice						
LD.	4.346982	6.437358	0.68	0.500	-8.270008	16.96397
L2D.	.9627909	6.649379	0.14	0.885	-12.06975	13.99533
L3D.	-2.113962	7.326529	-0.29	0.773	-16.47369	12.24577
L4D.	-.2110989	7.120136	-0.03	0.976	-14.16631	13.74411
_cons	-.0531237	10.50029	-0.01	0.996	-20.63331	20.52706
D_worldprice						
_ce1						
L1.	-.1489514	.0290474	-5.13	0.000	-.2058832	-.0920196
retail						
LD.	.4114239	.2698322	1.52	0.127	-.1174375	.9402854
L2D.	-.7003016	.2769542	-2.53	0.011	-1.243122	-.1574814
L3D.	.611381	.234563	2.61	0.009	.1516459	1.071116
L4D.	-.2704872	.2233024	-1.21	0.226	-.7081518	.1671774
stocks						
LD.	.0001855	.0013549	0.14	0.891	-.00247	.0028411
L2D.	.0003704	.0014324	0.26	0.796	-.0024371	.0031779
L3D.	-.0003844	.0014345	-0.27	0.789	-.0031959	.0024271
L4D.	.0017035	.0013401	1.27	0.204	-.000923	.00433
worldprice						
LD.	.4168328	.0939414	4.44	0.000	.2327111	.6009545
L2D.	-.0970176	.0970354	-1.00	0.317	-.2872036	.0931683
L3D.	-.1120473	.1069172	-1.05	0.295	-.3216012	.0975065
L4D.	.1465459	.1039053	1.41	0.158	-.0571047	.3501965
_cons	.4525062	.1532324	2.95	0.003	.1521764	.7528361

```
Cointegrating equations
Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                   2   34.83924   0.0000
-------------------------------------------
Identification:  beta is exactly identified
                 Johansen normalization restriction imposed
------------------------------------------------------------------------------
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
      retail |          1          .        .       .            .           .
      stocks |     .00479   .0018622     2.57   0.010     .0011402    .0084399
  worldprice |    .982841   .2282407     4.31   0.000     .5354975    1.430185
       _cons |  -60.23879          .        .       .            .           .
------------------------------------------------------------------------------
```

Appendix 6
Test for Short Run Relationship

```
test ([D_retail]: LD.stocks L2D.stocks L3D.stocks)

 ( 1)  [D_retail]LD.stocks = 0
 ( 2)  [D_retail]L2D.stocks = 0
 ( 3)  [D_retail]L3D.stocks = 0

           chi2(  3) =    2.51
         Prob > chi2 =    0.4738

test ([D_retail]: LD.stocks L2D.stocks L3D.stocks L4D.stocks)

 ( 1)  [D_retail]LD.stocks = 0
 ( 2)  [D_retail]L2D.stocks = 0
 ( 3)  [D_retail]L3D.stocks = 0
 ( 4)  [D_retail]L4D.stocks = 0

           chi2(  4) =    2.46
         Prob > chi2 =    0.6525

test  ([D_retail]: LD.worldprice L2D.worldprice L3D.worldprice L4D.worldprice)

 ( 1)  [D_retail]LD.worldprice = 0
 ( 2)  [D_retail]L2D.worldprice = 0
 ( 3)  [D_retail]L3D.worldprice = 0
 ( 4)  [D_retail]L4D.worldprice = 0

           chi2(  4) =   35.37
         Prob > chi2 =    0.0000
```

Appendix 7
Forecast Error Variance Decomposition Table (Bivariate Model)

step	(1) fevd	(2) fevd
0	0	0
1	1	0
2	.998425	.001575
3	.999045	.000955
4	.996025	.003975
5	.984524	.015476
6	.963817	.036183
7	.934616	.065384
8	.900791	.099209
9	.865481	.134519
10	.83108	.16892
11	.798569	.201431
12	.768254	.231746
13	.740062	.259938
14	.71387	.28613
15	.689572	.310428
16	.667095	.332905
17	.646365	.353635
18	.627292	.372708
19	.609766	.390234
20	.593664	.406336
21	.578858	.421142
22	.565222	.434778
23	.552643	.447357
24	.541017	.458983
25	.530251	.469749
26	.520263	.479737
27	.510981	.489019
28	.502338	.497662
29	.494276	.505724
30	.486743	.513257
31	.479691	.520309

(1) irfname = final, impulse = retail, and response = retail
(2) irfname = final, impulse = stocks, and response = retail

Appendix 8
Forecast Error Variance Decomposition Table (Multivariate Model)

step	(1) fevd	(2) fevd	(3) fevd
0	0	0	0
1	1	0	0
2	.993549	.004163	.002287
3	.991035	.002036	.006929
4	.988273	.001895	.009833
5	.988983	.003294	.007723
6	.979826	.007716	.012458
7	.956977	.012238	.030786
8	.927787	.016511	.055702
9	.898256	.020692	.081052
10	.871536	.024525	.103939
11	.848814	.028251	.122935
12	.831132	.031635	.137233
13	.818583	.034587	.146831
14	.809846	.037131	.153023
15	.803342	.039295	.157363
16	.797842	.041147	.161011
17	.792712	.042734	.164554
18	.787744	.044111	.168145
19	.782894	.045336	.17177
20	.778188	.046454	.175358
21	.773685	.047495	.17882
22	.769457	.048473	.18207
23	.765553	.049395	.185052
24	.761979	.050263	.187758
25	.758701	.05108	.190219
26	.755674	.051845	.19248
27	.752854	.052562	.194584
28	.750209	.053232	.196559
29	.747716	.05386	.198424
30	.745358	.054449	.200193
31	.743125	.055005	.201871

(1) irfname = final2, impulse = retail, and response = retail
(2) irfname = final2, impulse = stocks, and response = retail
(3) irfname = final2, impulse = worldprice, and response = retail

Appendix 9
Autoregressive Distributed Lag-Error Correction Model

```
ARDL(4,2) regression

Sample: 2007m12 -  2018m9                          Number of obs     =        130
                                                   R-squared         =     0.3781
                                                   Adj R-squared     =     0.3425
Log likelihood = -120.62423                        Root MSE          =     0.6317

------------------------------------------------------------------------------
    D.retail |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ADJ          |
      retail |
         L1. |  -.0232728   .0128469    -1.81   0.073    -.0487045     .002159
-------------+----------------------------------------------------------------
LR           |
 totalstocks |
         L1. |  -.0151341   .0094491    -1.60   0.112    -.0338395    .0035713
-------------+----------------------------------------------------------------
SR           |
      retail |
         LD. |   .4978729   .0879155     5.66   0.000     .3238354    .6719104
        L2D. |   .1563266   .0975622     1.60   0.112    -.0368075    .3494607
        L3D. |  -.2935815   .0891363    -3.29   0.001    -.4700358   -.1171272
             |
 totalstocks |
         D1. |  -.0003087   .0001507    -2.05   0.043     -.000607   -.0000104
         LD. |   .0003307   .0001481     2.23   0.027     .0000375     .000624
             |
       _cons |   1.876565   .6185788     3.03   0.003     .6520263    3.101103
------------------------------------------------------------------------------
ARDL(4,3,3) regression

Sample: 2007m12 -  2018m9                          Number of obs     =        130
                                                   R-squared         =     0.6284
                                                   Adj R-squared     =     0.5903
Log likelihood = -87.148346                        Root MSE          =     0.4986
------------------------------------------------------------------------------
    D.retail |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ADJ          |
      retail |
         L1. |  -.0116126    .012116    -0.96   0.340    -.0356077    .0123825
-------------+----------------------------------------------------------------
LR           |
 totalstocks |
         L1. |  -.0295788   .0314607    -0.94   0.349    -.0918851    .0327275
             |
  worldprice |
         L1. |  -.7173689   1.052785    -0.68   0.497    -2.802355    1.367617
-------------+----------------------------------------------------------------
SR           |
      retail |
         LD. |   .3253657   .0756826     4.30   0.000     .1754804     .475251
        L2D. |   .1483895   .0817395     1.82   0.072    -.0134912    .3102702
        L3D. |   -.301557   .0763331    -3.95   0.000    -.4527308   -.1503833
             |
 totalstocks |
         D1. |  -.0004028   .0001238    -3.25   0.001    -.0006479   -.0001577
         LD. |   .0003767   .0001181     3.19   0.002     .0001429    .0006105
        L2D. |  -.0002081   .0001302    -1.60   0.113     -.000466    .0000497
             |
  worldprice |
         D1. |   .1515512   .0321444     4.71   0.000     .0878908    .2152115
         LD. |  -.0544003   .0327233    -1.66   0.099    -.1192071    .0104064
        L2D. |    .223413   .0299508     7.46   0.000     .1640969     .282729
             |
       _cons |   1.610356   .7475002     2.15   0.033     .1299706    3.090741
------------------------------------------------------------------------------
```

Appendix 10
ARDL-ECM Bounds Test for Cointegration

```
Pesaran, Shin, and Smith (2001) bounds test

H0: no level relationship                                  F =     4.835
Case 3                                                     t =    -1.812

Finite sample (1 variables, 130 observations, 5 short-run coefficients)

Kripfganz and Schneider (2018) critical values and approximate p-values

   | 10%               | 5%                | 1%                | p-value
   |     I(0)     I(1) |     I(0)     I(1) |     I(0)     I(1) |     I(0)     I(1)
---+-------------------+-------------------+-------------------+-----------------
 F |    4.040    4.815 |    4.949    5.802 |    6.999    7.998 |    0.055    0.099
 t |   -2.558   -2.907 |   -2.863   -3.225 |   -3.455   -3.838 |    0.362    0.494

do not reject H0 if
    both F and t are closer to zero than critical values for I(0) variables
      (if p-values > desired level for I(0) variables)
reject H0 if
    both F and t are more extreme than critical values for I(1) variables
      (if p-values < desired level for I(1) variables)

Pesaran, Shin, and Smith (2001) bounds test

H0: no level relationship                                  F =     3.309
Case 3                                                     t =    -0.958

Finite sample (2 variables, 130 observations, 9 short-run coefficients)

Kripfganz and Schneider (2018) critical values and approximate p-values

   | 10%               | 5%                | 1%                | p-value
   |     I(0)     I(1) |     I(0)     I(1) |     I(0)     I(1) |     I(0)     I(1)
---+-------------------+-------------------+-------------------+-----------------
 F |    3.155    4.159 |    3.806    4.907 |    5.262    6.547 |    0.085    0.209
 t |   -2.542   -3.187 |   -2.850   -3.519 |   -3.452   -4.153 |    0.737    0.853

do not reject H0 if
    both F and t are closer to zero than critical values for I(0) variables
      (if p-values > desired level for I(0) variables)
reject H0 if
    both F and t are more extreme than critical values for I(1) variables
      (if p-values < desired level for I(1) variables)
```