ABSTRACT

PORNSAWANG, CHOTIMA. Three Essays on Rice: Consumption, Production and Prices. (Under the direction of Dr. Roderick M. Rejesus).

This dissertation is composed of three essays about rice. The first essay analyzes the income elasticity of demand for rice using a macro panel approach. On the basis of heterogeneous parameter models, our average "global" income elasticity estimate is generally positive and statistically significant. This is in contrast with the negative and significant income elasticity estimate from the homogeneous parameter models. Moreover, the evidence indicates that rice is still an inferior good in Asian countries, including high income Asian countries (e.g., Korea and Thailand), while it is a normal good in other regions of the world. Research finding reveals that low and lower-middle income Asian countries (e.g., Bangladesh, Malaysia and Philippines) have positive rice income elasticities. Meanwhile, countries that have experienced recent growth in population and income (e.g., China and India) still have significantly positive income elasticities.

The second essay provides the evidence of productivity and production risks across land tenure statuses in the Central Luzon region. Based on an unbalanced parcel-level data, we estimate a stochastic production function to examine the land tenure effects on the mean, variance, skewness and kurtosis of the rice yield distribution. New insight has been obtained and shows that ownership and fixed rent contracts face lower production risk (i.e., relative risk premium) compared to share arrangements. Taking land redistribution program in to account, the 1988 CARP may result in productivity improvement and risk reduction over time given the inverse productivity puzzle of smaller farm sizes for new owners from the land redistribution scheme.

The analyses of market integration and price leadership in the low quality rice sector are conducted in the third essay. Using a VEC model, our bivariate cointegration analysis suggests that there exists interdependence of the 25% broken rice prices between Thailand, Vietnam and Pakistan. However, in the multivariate analysis, we find that Indian low quality rice price is cointegrated with low quality rice prices of the other three countries. Assumed parameter restrictions on the VECM, the market price leadership is investigated by using long-run exclusion and weak exogeneity tests. Based on these tests, we find strong evidence (at the 5% level of significance) that Pakistan and India tend to be price leaders in the low quality rice market, while Vietnam tends to be a price follower in both subsamples. In contrast to some of the previous studies on the low quality rice market, we find that Thailand is likely a price follower in this market for the 1996 to 2007 period.

We further investigate the short-run dynamic price relationships among the countries in the low quality rice market using contemporaneous correlation analysis of VEC residuals, Directed Acyclic Graphs (DAG), impulse response functions, and forecast error variance decompositions. Although India serves as a price leader in this market segment, except with Pakistan prices, its price co-movement among other two countries are weak in the case of Indian non-basmati export ban 2007. Moreover, evidence from the additional analysis of dynamic price relationships indicates that there is stronger interdependence of prices among Thailand, Vietnam, and Pakistan, where Thailand and Pakistan tend to be the price leaders and Vietnam is a price follower.

Three Essays on Rice: Consumption, Production and Prices

by
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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Economics

Raleigh, North Carolina

2015

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DEDICATION

To my parents, my teachers and my friends.

BIOGRAPHY

Chotima Pornsawang was born in Songkhla, Thailand. She obtained her bachelor's degree at Kasetsart University in 2001. She received her master's degree in Economics from Thammasat University in 2004. After working as a lecturer at Prince of Songkla University, Thailand, she received scholarship from the Thai Government and Prince of Songkla University to pursue her doctoral degree in Economics at North Carolina State University in 2009.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisor, Dr. Roderick M. Rejesus. My dissertation cannot be completed without his guidance and constant encouragement. I would like to acknowledge Dr. Barry K. Goodwin, Dr. Mitchell Renkow, and Dr. Walter N. Thurman for their constructive comments and suggestions on econometric issues and economic implications in the real world. I am also indebted to the Thai Government and Prince of Songkla University, Thailand for financial support throughout my doctoral study at NC State University. I would like to thanks my cohorts Alimamy Kamara and Moon Hee Cho, for cheering me up during my difficult times.

In addition, I am so grateful for my friends in Raleigh -- Sitthichai Tanthasith (my personal editor, trainer and trip advisor), Waraporn Piyawit, Bunthita Chattae, and Suchawan Pornsukarom. Thank you to the UNT Gang -- Jetjaroen Klangwang, Maysaya Thitisaksakul, Anyanee Kamkaew, my friends in the Department of Economics, Kasetsart University -- Itthipong Mahathanaseth, Santi Sanglestsawai, Witsanu Attavanich for sharing their idea and experiences, and all my colleagues in the Department of Economics, Prince of Songkla University for their moral support. Most importantly, I would like to express my special thanks to my family and Santi Srisomboon for their endless love and support during my Ph.D. study.

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CHAPTER 1

Introduction

Owing to the fact that half of the world's population consumes rice as a major food staple, it is not questionable that rice plays a significant role in coping with issues pertaining to basic food needs. Asia is a prime domination of global rice issues thanks to the fact that approximately 90 percent of world's rice production and consumption is witnessed in this region. When focusing on the rice market, several factors, such as the consequences of emerging new economies (e.g., China and India), climate changes, domestically agricultural and trade policies lead to the rice price instability. As such, rice price fluctuations directly affect the rice-consuming countries' well-being. This dissertation aims to tackle food security, one of the primary concerns especially rice commodity in three aspects – consumption, production and international trade.

With concerns about food insecurity, there have been many previous studies about determinants of rice demand and about the income elasticity of rice consumption across countries or regions. Understanding of rice demand elasticities at the global level have important implications for addressing problems related to poverty, food security, and economic development (specifically in Asia). The first essay (Chapter 2) reexamines the income elasticity of demand for rice using a macro panel approach for 58 countries over the period 1985-2011. This essay incorporates the heterogeneous slope of income elasticity across countries, unobserved time-invariant factors and cross-sectional dependence issues.

Analysis of rice is not limited to the demand aspect, unproductivity and risks of production may result in the food vulnerability. Due to the limitation of arable land, the effective land rental market and land redistribution program induce to equity and efficiency in resource allocation. Employing developing country as a case study, the second essay (Chapter 3) determines how land tenure arrangement (i.e., landownership, share tenancy, fixed rent agreements) influences productivity and production risk in the Philippines rice sector. Specifically, we utilize a moment-based estimation approach to examine the effect of land tenure arrangement on the mean, variance, skewness, and kurtosis of rice yields. Evaluation of relative risk premium across tenure statuses provides the explanation why farmers choose a particular land tenure arrangement.

As we learned from the 2008 food crisis, the food price surge widely impacted both domestic and international markets, regardless of size and wealth of nations. Therefore, given the price linkages among countries, analysis of price transmission and market integration attribute to the better predictability of price volatility for rice importing countries and policy makers. The third essay (Chapter 4) contributes to the literature on the analysis of dynamic rice export price relationships in the low quality rice market (i.e., 25% broken rice). In particular, there have been a few of studies that focused explicitly on the low quality segment and none have explored the role of India, one of the largest producer and consumer of rice in the world in this market. Additionally, we examine “shocks” related to changes in domestic and/or trade policies in major exporting countries, such as the implementation of an export ban for Indian non-basmati rice in 2007.

CHAPTER 2

Estimating Income Elasticities of Demand for Rice: A Macro Panel Approach

2.1 Introduction

Rice is a major staple commodity, especially in Asia where 90 percent of world's rice is produced and consumed. According to the World Food Situation (FAO, 2015), global rice production[1] increased from 406.5 million tons in 2004 to 495.9 million tons in 2014. Worldwide rice consumption reached over 475 million tons in 2014, from only about 151 million tons in the 1960s. Accordingly, global per capita rice consumption surged from 48 kilograms in 1960 to 58 kilograms in 2014 (FAO, 2014). Note that more than 80 percent of total rice utilization is as food, and roughly 20 percent of other usages are to feed, seeds, and industrial uses.

As seen in Figure 2.1, most major regions of the world have noticeably higher average rice consumption per capita during the more recent 2000-2009 period compared to the prior 1990-1999 period, with the sole exception of Asia. Most of the existing literature suggests that the decrease in per capita rice consumption in Asia is driven by income growth in such countries as Japan, Singapore, South Korea, Taiwan, China, India, and Thailand. Higher incomes in these countries brought about increased demand for a more diversified

[1] Rice production is expressed in milled terms (FAO, 2015).

diet and rice became an inferior good (Ito et al. 1989; Timmer et al 2010). Countries with growing incomes are moving away from rice to other high-value food products like meats, fish, and vegetables. This is the typical explanation put forward for the negative income elasticities observed in these major Asian countries.[2]

With the expected further growth in income for large Asian countries like China and India, a number of studies have predicted that per capita consumption of rice will fall in the medium- to long- term (Rosegrant et al., 2001; Abdullah et al., 2005; Timmer et al., 2010).[3] The influential paper by Timmer et al. (2010), for example, argues that global rice consumption will modestly increase and peak through the 2020s (~475 million tons), but will dramatically decline to only about 383 million tons by 2050. The predicted 2050 rice consumption levels here are akin to consumption figures observed in the mid-1990s. In all these studies, the main drivers for this rapid reduction in global rice consumption are negative income elasticities (in China and India, particularly), slower population growth, and lower rural-to-urban migration.[4]

[2] Although it is generally accepted that high income Asian countries tend to have negative income elasticities (especially when estimated using time series data), there are still a few studies that demonstrate that income elasticities may be positive in these wealthy Asian nations (or at least higher than the studies cited above). See Huang et al., 1991; Taniguchi and Chern, 2000; Chern et al., 2002.

[3] Note that there are exceptions to these studies. Seck et al. (2012) project that global rice consumption will rise to 496 million tons in 2020 and further increase to 555 million tons by 2035. They explain that aggregate global consumption is still expected to rise through 2035 due to increased demand in Africa, Latin America, and other parts of Asia; despite continued declines in per capita consumption in China and India (as well as in other wealthy Asian countries). Rejesus et al. (2012) also indicate that global rice consumption could still rise to 650 million tons by 2050, although forecast intervals this far into the future tends to be very wide.

[4] From our perspective, projections from these studies imply that reduction in per capita consumption due to income growth will be large enough (on aggregate) to more than outweigh the expected increase in rice demand due to population growth worldwide (from approximately 6 billion today to about 9 billion by 2050). This tends to run counter to many claims that increased food production is needed by 2050 to be able to feed the projected population of 9 billion people.

However, most of these projections rely on income elasticity estimates derived from econometric models that are based on aggregate global or regional (i.e. by continent) time-series data. As such, the income elasticities used in the aforementioned rice projection studies mask the heterogeneity in rice consumption patterns across regions, across countries, and across demographic groups within countries (Seck et al., 2012). Moreover, many econometric estimation issues (i.e. potential bias from omitted unobservables and nonstationarity/unit roots) have not been properly addressed in most studies that estimate income elasticities for rice. Without a careful econometric identification strategy to address omitted unobservable variables, it is possible that unobserved structural changes are misattributed as income effects such that the estimated income elasticities are lower than they actually are (Huang et al., 1991; Huang and Bouis, 1996). Not properly addressing nonstationarity when it exists in the data also results in misspecification errors that render the inferred income elasticity estimates questionable.

Ideally, one would like to have household level panel data for all rice consuming countries to capture the heterogeneity in consumption across countries (as well as within country), and to also properly address the problematic econometric issues listed above (Timmer et al., 2010; Rejesus et al., 2012). However, this type of disaggregate data set is typically not consistently available over time for the majority of rice consuming countries (especially the low income ones). Therefore, the next best strategy is to use a "macro" panel data of rice consuming countries over a period of time (i.e. a large number of *N* countries with moderately large *T* time periods). A macro panel will allow one to account for heterogeneity in consumption across countries and address problematic econometric estimation issues (i.e. unobserved time-invariant variables and nonstationarity).

The objective of this study is to reexamine the income elasticity of demand for rice using a macro panel data set of 58 countries over the period 1985-2011. Associated state-of-the-art macro panel data econometric techniques are utilized to achieve this objective. To the best of our knowledge, no study has yet used these macro panel econometric techniques to estimate income elasticities for rice. We use macro panel estimators specifically designed for data where both the cross-section (N) and the time-series (T) dimension of the data are moderately large, and at the same time allow for: (1) unobserved cross-sectional dependence, (2) parameter heterogeneity across cross-sectional units, (3) omitted time-invariant unobservables, and (4) non-stationarity (Pesaran and Smith, 1995; Pesaran, 2006; Eberhardt and Teal, 2010; Eberhardt, 2012)

Because rice is a staple food for a large proportion of the world’s population and demand for this good is highly inelastic (especially among the world’s poor), production shortfalls can cause price spikes (such as in 2007-2008) that would then result in large consumer welfare losses. Therefore, better understanding of rice elasticities at the global level have important implications for addressing problems related to poverty, food security, and economic development (specifically in Asia). In addition, more precise income elasticity estimates from macro panel models are expected to provide better projections of future global rice consumption. Consequently, projections of future patterns of rice consumption would provide valuable information that is useful in establishing future rice production targets to assure global food security.

2.2 Empirical Approach

2.2.1 Model specification

In this section, we develop an empirical specification based on a standard demand framework. This specification is consistent with previous studies that have used aggregate time-series data to estimate income elasticities of rice (See Ito et al., 1989; Timmer et al., 2010). Specifically, global rice consumption per capita is assumed to be a function of income per capita, rural population share, real export rice price and real wheat price. Using a log-log functional form, we can specify a global rice demand equation as follows:

(1) $$C_{it} = \alpha_i + \beta_{1i} GDP_{it} + \beta_{2i} AGSHARE_{it} + \beta_{3i} RRP_{it} + \beta_{4i} RWP_{it} + \upsilon_i + e_{it}$$

where C_{it} is per capita rice consumption in country i ($i = 1,..,N$) at time t $(t = 1,2,..,T)$. *GDP* is real income per capita. *AGSHARE* is the ratio of rural population to total population. *RRP* denotes the real Thai 5% broken rice export price. *RWP* refers to the export price of a substitute commodity (in this case, wheat). The last two terms are country specific effects (υ_i) and a random error term (e_{it}). It is worth nothing that these log-transformed coefficients can be interpreted as elasticities.

Based on economic theory, demand for rice and its price have an inverse relationship. We expect that rice consumption will be lower when rice prices are higher. Moreover, we believe that there is a positive relationship between the price of wheat and rice demand. Whether rice is a normal good or an inferior good depends on whether rice income is positively or negatively related to changes in rice demand. Agricultural population share is chosen as a proxy for urbanization and the expected sign of this variable is positive. In other words, a country in which the rural population is greater relative to the urban population we anticipate that country to have higher demand for rice.

2.2.2 Econometric Methodology

Following Eberhardt and Teal (2010), we set up our econometric approach by utilizing a random coefficient model (RCM). Suppose that the relationship of global rice consumption and its determinants is a linear heterogeneous panel model as follows:

(1) $C_{it} = \alpha_i + \beta_i' X_{it} + e_{it}$, $\quad i = 1,\dots, N \; ; \; t = 1,\dots, T$

(2) $X_{it} = \phi_i + \lambda_i f_t + \psi_i g_t + u_{it}$, $\quad u_{it} \sim iid\ (0, \sigma^2_{Xi})$,

(3) $e_{it} = \lambda_i f_t + \varepsilon_{it}$, $\quad \varepsilon_{it} \sim iid\ (0, \sigma^2_{ei})$,

(4) $\alpha_i = \alpha + \nu_{\alpha i}$, $\quad \nu_{\alpha i} \sim iid\ (0, \sigma^2_{\alpha})$,

(5) $\beta_i = \beta + \nu_{\beta i}$, $\quad \nu_{\beta i} \sim iid\ (0, \sigma^2_{\beta})$.

where the true disturbance (e_{it}) and parameters (α_i , β_i) are distributed randomly over cross sectional units (e.g. equation (3) – (5)).

For instance, X_{it} refers to real GDP per capita which is a key variable of interest. The β_i in equation (1) implies that income elasticities can be different across countries, but they are constant over time. In equation (2), the determinant of rice consumption is a linear function of the unobserved common factors (f_t) and country-specific factors (g_t) (see

Eberhardt and Teal, 2010). Additionally, we assume that $\nu_{\alpha i}$ and $\nu_{\beta i}$ are independent to the regressors (X_{it}) and e_{it}.

2.2.2.1 Homogeneous slope estimation

Pooled OLS (POLS)

If equation (1) is estimated using Pooled Ordinary Least Squares (POLS) regression, then one is implicitly assuming that the intercepts and all parameters are the same across countries (i.e. homogeneity in the parameters across countries). With parameter homogeneity, it implies that the unobserved common factors (f_t) and country-specific factors (g_t) have the same impact across countries. Substituting α_i and β_i into equation (1), we will get

(6) $$C_{it} = \alpha + \beta' X_{it} + \varsigma_{it}^{POLS}, \qquad \varsigma_{it}^{POLS} = e_{it} + \nu_{\alpha i} + \nu_{\beta i} X_{it}.$$

The estimator $\hat{\beta}_{POLS}$ will be unbiased and consistent only when the regressors (X_{it}) and POLS residuals (ς_{it}^{POLS}) are uncorrelated.

Individual fixed effects (FE)

To avoid biased estimates from unobserved variables, one can include time-invariant fixed effects that represent the cross sectional units in the data (i.e. country dummies or country fixed effects in our case). Following from equation (6), the intercepts can be assumed to vary across countries using country fixed effects:

(7) $$C_{it} = \alpha_i + \beta' X_{it} + e_{it}, \quad e_{it} \sim \text{iid } (0, \sigma^2)$$

where $\alpha_i = \alpha + \eta_i$ and η_{it} is individual country fixed effects.

One can then subtract equation (7) with time-demeaned variables to get a FE estimator as follows:

$$C_{it} - \overline{C}_i = \beta'(X_{it} - \overline{X}_i) + (\eta_i - \overline{\eta}_i) + (e_{it} - \overline{e}_i)$$

where $\overline{C}_i = T^{-1}\sum_{t=1}^{T} C_{it}$ and $\overline{X}_i = T^{-1}\sum_{t=1}^{T} X_{it}$ are the cross-section means. And this can be simplified as:

(8) $$\tilde{C}_{it} = \beta'\tilde{X}_{it} + \tilde{\xi}_{it}^{FE}$$

The FE estimator ($\hat{\beta}_{FE}$) above will be consistent and unbiased unless the regressors and disturbances ($\tilde{\xi}_{it}^{FE}$) in (8) are still correlated (i.e. through time-varying unobservables).

Two-way fixed effects (2FE)

A two-way fixed effects model is an extension of the fixed effects estimation in (8) by simply adding time effects. In other words, we allow the intercepts to vary across cross-sections and across time, but still assume constant slope coefficients:

(9) $$C_{it} = \alpha_i + \alpha_t + \beta' X_{it} + e_{it}, \qquad e_{it} \sim \text{iid } (0, \sigma^2),$$

where $\alpha_i = \alpha + \eta_i$ and $\alpha_t = \alpha + \rho_t$. Individual effects and time effects are denoted as η_i and ρ_t. We subtract equation (9) with time means and cross-section unit means. The 2FE specification can be specified as:

$$C_{it} - \overline{C}_i - \overline{C}_t + \overline{C} = \beta'(X_{it} - \overline{X}_i - \overline{X}_t + \overline{X}) + (\eta_i - \overline{\eta}_i) + (\rho_t - \overline{\rho}_t) + (e_{it} - \overline{e}_i - \overline{e}_t + \overline{e})$$

(10) $$\dot{C}_{it} = \beta'\dot{X}_{it} + \dot{\xi}_{it}^{2FE}$$

where $\overline{C}_t = N^{-1}\sum_{i=1}^{N} C_{it}$ and $\overline{X}_t = N^{-1}\sum_{i=1}^{N} X_{it}$ are the time means. $\overline{C} = (NT)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N} C_{it}$ and $\overline{X} = (NT)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}$ are the overall means of rice consumption and of its determinants.

The same as in the FE model, regressors and the disturbance term must be uncorrelated in order to obtain consistent 2FE estimates ($\hat{\beta}_{2FE}$).

2.2.2.2 Heterogeneous slope estimation

Heterogeneity in rice consumption behavior may arise due to observed factors (e.g. income, urbanization, and prices) and/or unobserved common factors. According to Sadorsky (2013), common factors are time-specific effects that can impact different countries (i.e. across cross-sectional units), such as technological spillover and global shocks (e.g. a food price crisis). Three different heterogeneous estimators that take unobserved common factors into account are utilized in this study and are explained below.

Mean Group Estimator (MG)

The MG approach developed by Pesaran and Smith (1995) applies OLS to each panel/country to obtain panel-specific slope coefficients and then averages the panel specific coefficients. For large *T* and *N*, the MG estimator is consistent.

(11) $C_{it} = \alpha_i + \beta_i' X_{it} + e_{it}, \qquad e_{it} \sim iid\ (0, \sigma_i^2)$

$$\hat{\beta}_{MG} = N^{-1}\sum_{i}\hat{\beta}_i$$

where β_i is the country-specific coefficient vector.

The MG estimator assumes that unobserved common factors are identical and cross-sectional units are independent. If these assumptions are invalid, the estimates are biased and inconsistent. The estimates $\hat{\beta}_i$ will be spurious if the residuals (e_{it}) are non-stationary as well (Coakley et al., 2006; Pesaran, 2006).

*Common correlated effects mean group (*CMG*)*

Pesaran (2006) proposed the CMG estimator which accounts for different unobserved common factors and cross-sectional dependence. The individual country's rice demand equation is the combination of cross-section averages of the dependent and independent variables as specified below (equation 12):

$$(12) \qquad C_{it} = \alpha_i + \beta_i' X_{it} + z_{0i}\overline{C}_t + \sum_{m=1}^{k} z_{mi}\overline{X}_t + e_{it} \;; \qquad e_{it} \sim \text{iid } (0, \sigma_i^2),$$

where the *m* determinants of rice demand consist of GDP, AGSHARE, RRP and RWP (i.e. m = 1, 2, 3, 4) as well as $\overline{C}_t = \overline{\alpha} + \overline{\beta}'\overline{X}_t + \overline{e}_{it}$. From equation (3), $\overline{\varepsilon}_t = 0$, then we get

$$(12a) \qquad \overline{C}_t = \overline{\alpha} + \overline{\beta}'\overline{X}_t + \overline{\lambda}' f_t$$

$$(12b) \qquad f_t = \frac{(\overline{C}_t - \overline{\alpha} + \overline{\beta}'\overline{X}_t)}{\overline{\lambda}}$$

Regressing equation (12) by OLS, the CMG estimate ($\hat{\beta}_{CMG} = N^{-1}\sum_i \hat{\beta}_i$) is the mean of the slope coefficients across countries. These cross-sectional averages account for the unobserved common factors (f_t) as shown in equation (12b). Although the common factors contain unit roots, the consistency of CMG estimator is still valid as long as the regression residuals are stationary (Kapetanios et al., 2011).

Augmented Mean Group estimator (AMG)

Following Eberhardt and Teal (2010), the AMG estimator can be viewed as a two stage regression:

$$(13) \qquad \Delta C_{it} = \beta_i' \Delta X_{it} + \sum_{t=2}^{T} d_t \Delta D_t + e_{it} \qquad \hat{d}_t \equiv \hat{\mu}_t^*$$

$$(14) \qquad C_{it} = \alpha_i + \beta_i' X_{it} + \pi_i \hat{\mu}_t^* + e_{it}$$

$$\hat{\beta}_{AMG} = N^{-1} \sum_i \hat{\beta}_i$$

In the first stage (equation 13), the augmented country regression model is estimated by first difference OLS with T-1 year dummies. The coefficients ($\hat{d}_t$) on the differenced year dummies (ΔD_t) capture the averaged evolution of unobservable common factors over time or called “common dynamic processes” across countries. In the second stage (equation 14), the AMG estimates can be derived by regressing rice consumption for each of the *N* countries on its determinants as well as the unobserved common factors ($\hat{\mu}_t^*$).

Similar to the MG estimation, both the AMG and CMG techniques require the stationarity of residuals. These estimators not only allow heterogeneity in the parameters but also cross-sectional dependence. The AMG approach incorporates the impacts of latent common factors in “common dynamic process,” whereas the CMG estimator includes the unobservable common factors in the error term. Eberhardt and Bond (2009) showed through Monte Carlo simulations that AMG and CMG performed similarly well in terms of bias or root mean square error (RMSE) even in the presence of nonstationary variables and cross-sectional dependence.

2.3 Data

We compiled annual data for 58 countries in 6 regions (Asia, Africa, the Americas and the Caribbean, Europe, the Middle East and Oceania) from 1985 to 2011. Rice consumption per capita was provided by the International Rice Research Institute (IRRI) through the information they gathered from USDA and FAO (i.e. the IRRI World Rice Statistics Online Facility; See http://ricestat.irri.org:8080/wrs2/entrypoint.htm). GDP per capita (in constant 2005 US dollar values) and rural population share (percentage of the population residing in rural areas) is from the World Databank at the World Bank website where data are available for the 1960-2013 periods (See more details in Appendix 2.A.). An additional main determinant of demand is price of commodity. We utilize the export prices of Thai 5% broken rice and (US) no.2 soft red winter wheat as proxies for world rice price and world wheat price[5]. We compute real prices of rice and wheat by dividing the nominal prices with the consumer price index (CPI) of each country.[6]

Ideally, we aim to include as many countries in the data and, for each country, the longest time-series available. However, some countries and years have "unreasonable" values, which we had to drop from the data. Especially for real prices of rice and wheat, 42 out of 1,566 total observations are detected as outliers (e.g. 36 for the Asian counties' price

[5] Due to the sometimes limited availability of domestic rice price and wheat price data for each country, we assume the validity of law of one price. Specifically, the nominal prices of export and import for rice (wheat) between country *i* and country *j* are the same.

[6] In the World databank, the consumer price index of 2010 is considered the base (i.e. equal to 100). We adjust this base year from 2010 to 2005 so as to correspond with the GDP per capita normalization at 2005 constant prices.

series and 6 for the African countries' price series).[7] Subsequently, we interpolate and fill missing data if they are not at the start and at the end of the time period of analysis. For four countries where there are missing data at the beginning of a series (i.e. at most two years), we fill these data with the sample mean for the country. These procedures allow us to have a balanced panel, which facilitates estimation and allows for implementation of panel unit root tests (i.e. the Levin-Lin-Chu test discussed below).

Table 2.1 displays the descriptive statistics for all variables at the global level.[8]Annual global rice consumption per capita is around 29.39 kilograms and real GDP per capita (at constant 2005 values) is approximately $12,167 per person. Half of the world's population lives in rural areas. According to the World Rice Statistics and Wheat Yearbook (2015), nominal export price of Thai 5% broken rice and wheat no.2 soft red winter, on average, are around $318/ton (IRRI, 1985-2011) and $154/ton (USDA, 1985-2011), respectively. Our real export prices are higher than the nominal export prices for the same period. On average, real export rice price and export wheat price at constant 2005 values are $378.26/ton and $181.41/ton.

[7] We use Grubbs test (Grubbs, 1969 and Stefansky, 1972) to identify outliers in the data set. Outliers mean observations that are outside 95% (99.7%) confidence interval (i.e. 2 (3) standard deviations of the mean data). The process is that a new variable (equal to 1 if the observation is an outlier and 0 otherwise) was generated for each variable in the data. Then each new variable is tested whether outliers lie beyond the confidence interval setting. If so, the sample outliers are dropped out of the data set. This iteration continues until no more outliers.

[8] The descriptive statistics at the regional level (i.e. by continent) are shown in Appendix 2.B.

2.4 Empirical results

2.4.1 Panel unit root tests

To test for the presence of panel unit roots in our data, we first use the test proposed by Levin-Lin-Chu (LLC). As shown in Table 2.2 (top panel), the LLC test results indicate that all variables are stationary both in levels and when the variables are first differenced. However, it is important to note that one of the main assumptions in LLC panel unit root test is cross sectional independence across panels (i.e. across countries in our case).

Baltagi et al. (2007) indicate that failure to control cross-sectional dependence in the LLC panel unit root test results in an over-rejection of the null hypothesis of non-stationarity. Therefore, we also apply Pesaran's (2004) cross-sectional independence test (hereafter called the CD test) to determine whether cross-sectional dependence is present in our data (and in the residuals of our regression model). The CD test of cross sectional dependence suggests that all the variables in our data (in levels) are correlated across countries (See Table 2.2). With the exception of the rice consumption per capita variable, we also reject the null hypothesis of cross-sectional independence when the data are first differenced.

Given that the CD test indicates the presence of cross-sectional dependence, results from the traditional LLC panel unit root test may not be reliable. Hence, we also implemented Pesaran's (2007) unit root test, which allows for cross-sectional correlation in the panels (hereafter called the CIPS test).[9] Results of the CIPS test are shown in the bottom

[9] The CIPS test is also robust to the presence of serial correlation, in addition to cross-sectional dependence. The CIPS test provides the same conclusions even we change the number of lags up to three orders.

panel of Table 2.2. The CIPS test results indicates that only the rice consumption per capita variable is stationary in levels. However, except for the AGSHARE variable, the remaining variables are stationary when first differenced. This indicates that estimating the rice consumption equation in (1) would likely require estimation procedures that are robust to non-stationarity.

According to Baltagi (2008) and Phillips and Sul (2007), ignoring possible cross-sectional dependence in macro-panel data sets may also result in less efficiency in standard OLS estimation procedures and may lead to biased and inconsistent parameter estimates. The impact of this cross-sectional dependence will depend upon the extent of correlation across the panels. Therefore, an estimation procedure that is robust to cross sectional dependence would also be preferable in our case.

2.4.2 Homogeneous parameter estimation

We first estimate the rice consumption in equation (1) with various estimators that assume identical slope parameters across cross sectional units, such as: pooled OLS (POLS), fixed-effects (FE) and two-way fixed effects (2FE). [10, 11] Results from these initial estimation procedures are shown in Table 2.4.1.

[10] After running the simple POLS, we ran both the fixed effects and random effects panel estimators and conduct a Robust Hausman test to decide which estimator is more suitable in our context. Based on test result, the fixed-effects estimation (FE) panel estimator is more appropriate than the random-effects method in our data. The p-value of the test rejects the null at 1% significance level. Therefore, we use the fixed-effects and two-way fixed effects estimations here.

[11] Note that we also ran a model where we first difference (FD) the log values (i.e. the so-called "growth" specification that should control for non-stationarity). However, all the parameter estimates from these FD regression models were insignificant and are not reported here. The results are available from the authors upon request.

Without trend, the POLS regression shows that the estimated coefficient of real GDP per capita is negative and significant at the 1% level of significance. This negative relationship between real GDP per capita and rice consumption is also evident in the 2FE regression models (although the estimate from the standard FE model is statistically insignificant). Note that the 2FE model may be a more preferable specification than FE in this case because F-tests on the time dummies rejected the null hypothesis that all the year dummies are equal to zero. When a time trend is included in the specification, the estimated income elasticity using POLS and FE still reveal a negative and statistically significant relationship between GDP and rice consumption (Table 2.4.1). In addition, the magnitude of the estimated statistically significant income elasticity is very similar (approximately -0.30) in models both with and without trend.

One potential issue with the specification in (1) is the possible endogeneity of rice and wheat prices due to time-varying unobservables (i.e. time-varying unobservables affecting both the outcome rice consumption variable and the price variables). Therefore, we also implement homogenous parameter estimation procedures that incorporate instrumental variable (IV) approaches to potentially control for these time-varying unobservables. This requires finding appropriate IVs that are correlated with current year rice and wheat export prices, but are uncorrelated with current year time-varying unobservables (e.g. rice supply shocks or cost shifters.[12]

[12] The proxies of supply or cost shifter would include such variables as producer price index (PPI), wage, and prices of fertilizer and pesticide. We did not explicitly control for all these factors, although we argue that the IV approach and the panel data methods used in the paper adequately controls for these unobservables.

In this study, we examine lagged rice and wheat export prices (i.e. lagged two periods) as possible instruments. [13] The idea is that these prices may be correlated enough with current year prices, but are uncorrelated with current year rice demand shocks. This is akin to the logic used in the Arellano-Bond dynamic panel estimators that used lagged dependent variables as instruments. Results of exogeneity and over-identification test suggest that these two-period lagged price variables are appropriate IVs.[14]

Overall, results of our IV-type homogenous slope estimations still indicate that the parameter associated with real GDP per capita is negative and statistically significant at the 1% level (See Table 2.4.2). Moreover, the two-stage least squares (2SLS) model (which is the IV analogue of POLS) with trend and the two-way fixed effects models (with and without trend), resulted in statistically significant income elasticities that have similar magnitudes to the previous non-IV homogenous models (i.e. around -0.3).

In sum, using econometric estimation approaches that assume parameter homogeneity and utilizing country level macro-panel data, we generally find that income elasticities of rice tend to be negative (i.e. it is an inferior good). This is fairly consistent with previous global studies that utilize global time series data (Timmer et al., 2010). However, note again that

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[13] Note that we also investigated Real Effective Exchange Rate (REER) as a potential instrument. But this potential IV did not pass the over-identification test. Referring to the World Bank's definition, real effective exchange rate (REER) is the nominal effective exchange rate (a measure of the value of a currency against a weighted average of several foreign currencies) divided by a price deflator or index of costs (http://data.worldbank.org/indicator/PX.REX.REER). We also considered using weather variables (like rainfall levels) as potential instruments since this variable is likely correlated with wheat and rice price, but it is "exogenous" (determined by nature) such that it is unaffected by unobservables the influence consumption. However, there are a number of countries in our data where this data is incomplete. Hence, we were not able to use it as an IV in this paper. We leave analysis of rice consumption using rainfall as an IV for future work.

[14] Note, that serial correlation was detected when we estimated global rice demand using the homogeneous slope estimation with instruments. The presence of serial correlation in the homogenous slope estimation would likely render the use of lagged instruments problematic and inference from this estimation procedure may be less reliable (i.e., homogeneous income elasticity estimates may be biased downwards).

these homogeneous parameter models assume cross-sectional independence and homogeneity in the slope parameters, which may not be appropriate in the case of rice consumption across different countries.

2.4.3 Heterogeneous parameter estimation

The homogeneous parameter estimates from the previous estimation approaches may produce misleading conclusions when there is heterogeneity in the slope parameters across countries and when cross-sectional dependence exists (Sadorsky, 2013). To account for these issues, we estimate our rice consumption function in equation (1) using three panel econometric approaches that allow for heterogeneity in the parameter estimates and that is appropriate for country-level panel data with moderately sized N and T – the Mean Group (MG) estimator, the Common Correlated effects Mean Group (CMG) estimator, and the Augmented Mean Group (AMG) estimator. These approaches provide a way to estimate heterogeneous cross-sectional income elasticities that are consistent and unbiased, even if there are nonstationary variables in the model (Coakley et al., 2006).

In Table 2.5, we present the mean estimates of our heterogenous parameter models: MG. CMG, and AMG.[15] The estimated coefficients are simple average of the estimates across countries. Similar to the homogenous estimation results, the model with trend seems

[15] Regressions with first-differenced variables (i.e. the "growth" specification) are not presented here, because the heterogeneous estimation approaches is already robust to non-stationarity (Kapetanios et al., 2011). Additionally, the estimation results from these specifications do not perform very well in the sense that most of the main variables of interest were not statistically significant. This is consistent with our FD model results from the homogeneous parameter regressions.

to have a better fit than the one without trend specification. For this reason, we only present model with trend specification where the variables are estimated in levels.[16]

First, we examine a specification where we excluded the rice export and wheat export prices (e.g. Model 1). Excluding these price variables are meant to alleviate endogeneity problems arising from time-varying unobservables that affect both the outcome (rice consumption) and the price variables. Second, we estimate a model (Model 2) that includes all the independent variables specified in our original rice consumption function in equation (1), which includes rice and wheat prices. Admittedly, this model may have issues that arise from the endogeneity problem alluded to above. Third, we investigate a model (Model 3) where all determinants of rice consumption as specified in equation (1) are included, but use an IV-type estimation procedure (i.e. akin to a 2SLS procedure using predicted prices in the second stage estimation). We use the lagged rice and wheat export prices in this model, which is consistent with the approach in the homogeneous parameter estimation where we find these variables as appropriate IVs based on over-identification tests. Note that the stationarity of residuals is a requirement for consistent heterogeneous estimates in the MG, CMG and AMG techniques. The CIPS tests reveal that all regressions have stationary residuals indicating that this is not a problem in the estimation (Sadorsky, 2013).

In all three models examined (and using any of the heterogeneous panel estimators), the sign of the mean income elasticity estimate across countries is positive. This is in contrast

[16] Regression results from the heterogeneous model without trend are available from the author. As suggested by a reviewer, we also calculated a simple consumption share weighted average of the estimated country-level income elasticities (i.e., for the whole world and major geographic regions).These results are reported in Appendix 2.F. Note however, that the standard errors of these share-weighted average income elasticities are not reported since it cannot be easily incorporated in the standard error calculation procedures of Pesaran and Smith (1995) for these heterogeneous panel models.

to the negative global income elasticity estimates from the homogeneous parameter models in the previous section. But note that the positive income elasticity tend to be statistically significant (at least at the 10% level) only for the MG and AMG models. To examine this further, we conducted a Hausman (1978) specification test to examine whether the MG or the AMG approach is the more appropriate estimation procedure. The results indicate that we fail to reject the null hypothesis that the AMG estimator provides consistent estimates (for Model 1 and 3).[17]

Note that the estimated income elasticities in Model 2 and Model 3 are smaller than the estimated income elasticity in the model without export prices (Model 1). For instance, the income elasticity in Model 1 is approximately 0.58, while income elasticities in the model with export prices vary around 0.35 for the AMG estimator. The statistically significant income elasticity estimates range between 0.34 and 0.67 across models. This means that a one percent rise in per capita real GDP is associated with an increase in rice consumption by about half of a percent (all other things being equal).

To visualize the heterogeneity in the income elasticities across countries we present bar charts in Figures 2.2 to 2.4 that show the estimates from the MG and AMG estimation procedures (across all three model specifications). Overall, the signs and ordering of countries have similar patterns across all model specifications and estimation procedures. In Appendix 2.C, we provide the income elasticity estimates for all countries and also the estimated mean elasticities within each region/continent. For individual countries across the

[17] Based on the Hausman test, the test statistics are 1.64 (p-value = 0.65) in model 1 and 5.13 (p-value = 0.4) in model 3, respectively. This indicates that the AMG outperforms the MG estimator for our model of rice demand.

globe, our results show that the number of countries with positive income elasticity estimates account for 60 percent of the total countries in the sample as plotted histograms shown in Appendix 2.D).

Approximately 30 percent of those countries have statistically significant income elasticities for rice. In other words, these results tend to suggest that rice consumption per capita will likely increase (on average) when income increases (if one accounts for heterogeneity in the income elasticities across all countries in the world). This is opposite to the assumptions and predictions of most previous studies that used income elasticities of demand in forecasting future global rice consumptions (Timmer et al, 2010).

With our heterogeneous panel estimators, we can also investigate heterogeneity in income elasticity estimates across different regions/continents. The estimated income elasticity of demand for rice in Asia is ranges from -0.04 (Model 1) to -0.02 (Model 3) using the AMG estimation procedure. The interpretation is that average Asian rice consumption will decline by about 0.03 percent with a 1 percent growth in income per capita. This result is in line with previous studies which have shown that rice is an inferior good in Asia (especially for the high income Asian countries).

In particular, the income elasticities for high income Asian countries, such as Korea, and Thailand, are negative (See Appendix 2.E). Surprisingly, Japan's income elasticity is positive, but insignificant in Model 1; however it is positive and significant at 10% level in Model 3. The positive income elasticitiy for rice in Japan is consistent with findings from Taniguchi and Chern (2000) using household level data. Low and lower-middle income Asian countries still have higher demand for rice when they experience the economic expansion (e.g. higher real GDP growth rate). For instance, our results indicate that countries like Bangladesh, Malaysia, and the Philippines have positive income elasticities based on our heterogeneous panel estimations. Countries that experienced recent income growth (e.g. China and India) also still have statistically significant positive income elasticities, which are robust for all models and estimation procedures.

Outside of Asia, rice tends to be a normal good based on our results from the heterogeneous panel estimation procedures. Income elasticities in Africa, Europe, and Oceania are all positive and ranges from 0.70 to 1.10. This suggests that an income increase in these regions is likely to result in higher rice consumption. The higher absolute magnitudes of the income elasticities in regions outside of Asia, also suggest that demand for rice in these regions are more income elastic (i.e. more sensitive to income changes).

2.5 Discussion and Conclusion

Rice is a major staple food in a number of regions and countries in the world. In addition, rice is an important source of dietary energy across the globe. More than 40 percent of global dietary energy supply is derived from three main cereal crops consisting of rice (20%), wheat (19%) and maize (5%), respectively (FAO, 2004). Over the last decade, most regions of the world have experienced higher than average rice consumption per capita compared with their experience in the 1990s. With concerns about food insecurity across the globe, there have been many previous studies about determinants of rice demand and about the income elasticity of rice consumption across countries or regions.

In this study, we reexamine the income elasticity of demand for rice with the use of a macro panel data for 58 countries from 1985 to 2011. Most previous studies that project future rice consumption patterns typically assume that income elasticity of rice at the global level is negative (i.e. demand for rice decreases as income increases). However, a number of these studies only estimate single global income elasticity for rice using more aggregate consumption data, which ignores the possible heterogeneity of rice income elasticities across countries (See Timmer et al., 2010).

However, studies that estimate individual country rice income elasticities (i.e. based on country level time-series models or cross-sectional household models) typically found mixed results in terms of whether income elasticities are positive or negative.[18] Therefore, it is important to investigate the income elasticity of demand for rice where heterogeneity and potential cross-sectional dependence across countries are properly addressed (i.e. would the average "global" income elasticity for rice be positive or negative when cross-sectional heterogeneity is accounted for?).

As a first step, however, we first estimate the relationship between rice consumption and income (i.e. GDP per capita) across countries under the homogeneous slope assumption (i.e. assuming that the slopes or income elasticities are the same across countries). In particular, we apply pooled OLS, fixed-effects, and two-way fixed effects regression models to estimate income elasticities in the first phase of the empirical analysis. These regression

[18] See Huang, David, and Duff (1991), Taniguchi and Chern (2000), and Chern et al. (2002) for examples of studies that found positive income elasticities. See Ito, Peterson, and Grant (1989, 1991) and Timmer et al. (2010) for examples of studies that found negative income elasticities.

models were also run where instrumental variables were used to account for potential endogeneity of prices in the specification.

Results from the homogeneous parameter estimation approaches serve as the basis for comparing the results from the estimation procedures that accounts for heterogeneity in income elasticities across countries (See below). Based on the results from these homogeneous parameter models, we generally find a negative and significant relationship between rice consumption and income using the balanced macro-panel data available (i.e. negative rice income elasticity). Therefore, the results from the homogeneous parameter estimation techniques suggest that rice is generally an inferior good at the "global" level, which largely supports findings and assumptions used in previous literature.

Next we utilized macro-panel estimation procedures that account for possible heterogeneous slopes (or income elasticities) across countries. In these heterogeneous models, the estimated "global" coefficient of income (real GDP per capita) is the average of the income elasticities across countries. The estimated parameters from these heterogeneous panel estimation procedures are unbiased and consistent even if cross-sectional dependence and non-stationarity are present in the data (Coakley et al., 2006).[19] We utilized three heterogeneous estimators in this study – the Mean Group (MG) estimator, the Common Correlated effects Mean group (CMG) estimator, and the Augmented Mean Group (AMG) estimator. One major advantage of these heterogeneous estimators is that we are able to consider income elasticities separately by countries (or continents).

[19] Our specification tests indicate that cross-sectional dependence (across countries) exists in our data. Hence, the three heterogeneous parameter estimation procedures would be preferred in this case because it is robust to this problem.

Results from these heterogeneous parameter models indicate that our overall average "global" income elasticity estimate is generally positive and statistically significant. This is in contrast with the negative and significant income elasticity estimate from the homogeneous parameter models. However, when we calculate the mean income elasticities across regions, we find that the estimated income elasticity for rice in Asia ranges from -0.04 (for the specification in model 1) to -0.02 (for the specification in model 3) when we consider the preferred AMG estimation. But we find a positive association between rice consumption and per capita real GDP in the other regions outside of Asia. These results indicate that rice is still likely an inferior good in Asia (in general), while it is a normal good in other regions of the world.

In addition, the findings also show that income elasticities of rice in high income Asian countries (e.g. Korea and Thailand) are negative. Low and lower-middle income Asian countries (e.g. Bangladesh, Malaysia and Philippines) generally have positive rice income elasticities. Meanwhile, countries that have experienced recent growth in population and income (e.g. China and India) still have significantly positive income elasticities. One thing to note is that we show only unweighted coefficient averages of income elasticity (i.e. income elasticities are equally weighed across countries).

The empirical results from the heterogeneous parameter models have important implication for modeling future rice consumption patterns and the associated policy inferences coming from these types of rice projection models. Our results indicate that there is significant heterogeneity in income elasticities across countries. Therefore, studies that forecast future rice consumption patterns should be cognizant of this observation and should incorporate it in their models. Studies that assume homogeneous negative income elasticity for rice may be seriously overestimating the negative effect of income growth on future global rice consumption.

Moreover, results from these projection (or forecast) models that assume homogeneous, negative rice income elasticity may then lead to inappropriate policy recommendations. For example, if the negative income elasticity assumption is used for all countries in a projection model, then it is likely that future rice consumption will be predicted to fall substantially (see Timmer et al., 2010), and policies may be enacted to reduce support (and funding) for research that can increase rice production and supply worldwide. Donors may also use results from these forecast models to reduce support to rice-related agricultural research. Food security problems may then be exacerbated because of the wrong inference derived from forecast models that uses homogeneous negative elasticity estimates.

Table 2.1. Descriptive Statistics in Global data.

Variable	Obs	Mean	Std. Dev.	Min	Max
Rice consumption per capita (kilogram)	1785	29.39	37.23	0.20	178.30
Real GDP per capita at 2005 constant price	1785	12,167.16	15,170.27	111.79	67,804.55
Rural population share (% of total population)	1785	45.50	25.00	1.75	94.01
Real rice price ($/ ton)	1785	378.26	142.22	170.21	1,007.45
Real wheat price ($/ton)	1785	181.41	56.71	90.17	423.84

Note: the region-by-region descriptive statistics are in Appendix 2.B.

Table 2.2. Panel Unit Root test.

	Variables									
	constant					constant and trend				
	lnrcon	lngdp	lnagshare	lnrrp	lnrwp	lnrcon	lngdp	lnagshare	lnrrp	lnrwp
Cross-sectional Independence: LLC test										
In levels	-4.343***	-3.016***	3.962***	-3.250***	-3.176***	-3.941***	-4.817***	-7.192***	-3.643***	-3.136***
1st differences	-19.938***	-11.016***	-4.699***	-12.627***	-11.810***	-15.111***	-9.048***	-1.744***	-9.986***	-9.194***
Cross-sectional Dependence: CIPS test										
In levels	-2.726***	-1.792	-1.385	-1.269	-1.205	-2.762**	-1.662	-1.780	-2.052	-2.056
1st differences	-5.060***	-3.394***	-1.256	-3.213***	-3.406***	-5.109***	-3.956***	-1.723	-3.297***	-3.503***

Notes: (1)*, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. (2) The Levin-Lin-Chu's (2003) LLC test result shows adjusted t^* statistics and p-value. (3) The Pesaran's (2007) CIPS test with two periods lag order of serial correlation.

Table 2.3. Test for cross-sectional dependence.

Variable	CD test	p-value	Averaged absolute correlation
In levels			
lnrcon	23.29	0.000	0.466
lngdp	121.76	0.000	0.767
lnagshare	165.02	0.000	0.894
lnrrp	187.24	0.000	0.886
lnrwp	180.51	0.000	0.854
1st difference			
dlnrcon	1.33	0.184	0.166
dlngdp	27.97	0.000	0.245
dlnagshare	5.99	0.000	0.600
dlnrrp	199.38	0.000	0.962
dlnrwp	198.26	0.000	0.956

Note: under the null hypothesis of cross-section independence, the CD test follows a standard normal distribution (i.e. CD~N(0,1)).

Table 2.4.1. Homogeneous parameter estimation.

	Without trend			With trend	
	POLS	FE	2FE	POLS	FE
lngdp	-0.301***	-0.013	-0.304*	-0.298***	-0.312**
	(15.32)	(0.34)	(1.94)	(15.26)	(2.2)
lnagshare	0.226***	-0.730***	-0.128	0.248***	-0.156
	(5.71)	(10.68)	(0.53)	(6.59)	(0.72)
lnrrp	0.003	-0.011	0.236	0.0002	-0.011
	(0.02)	(0.33)	(0.31)	(0.00)	(0.43)
lnrwp	-0.09	-0.057	-0.166	0.108	0.014
	(0.55)	(1.46)	(0.26)	(0.65)	(0.39)
t				0.024***	0.019***
				(6.39)	(3.88)
intercept	4.847***	5.721***	4.950*	3.387***	5.584***
	(8.32)	(10.68)	(1.91)	(5.48)	(3.92)
R-sq	0.238			0.257	
RMSE	1.132			1.118	
R-sq overall		0.150	0.233		0.227

Notes: (1) Dependent variable is per capita rice consumption. (2) Values in brackets are absolute t-statistics based on robust test. (3) *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. (4) RMSE is the root mean square error.

Table 2.4.2. Homogeneous parameter estimation (Instrumental regression).

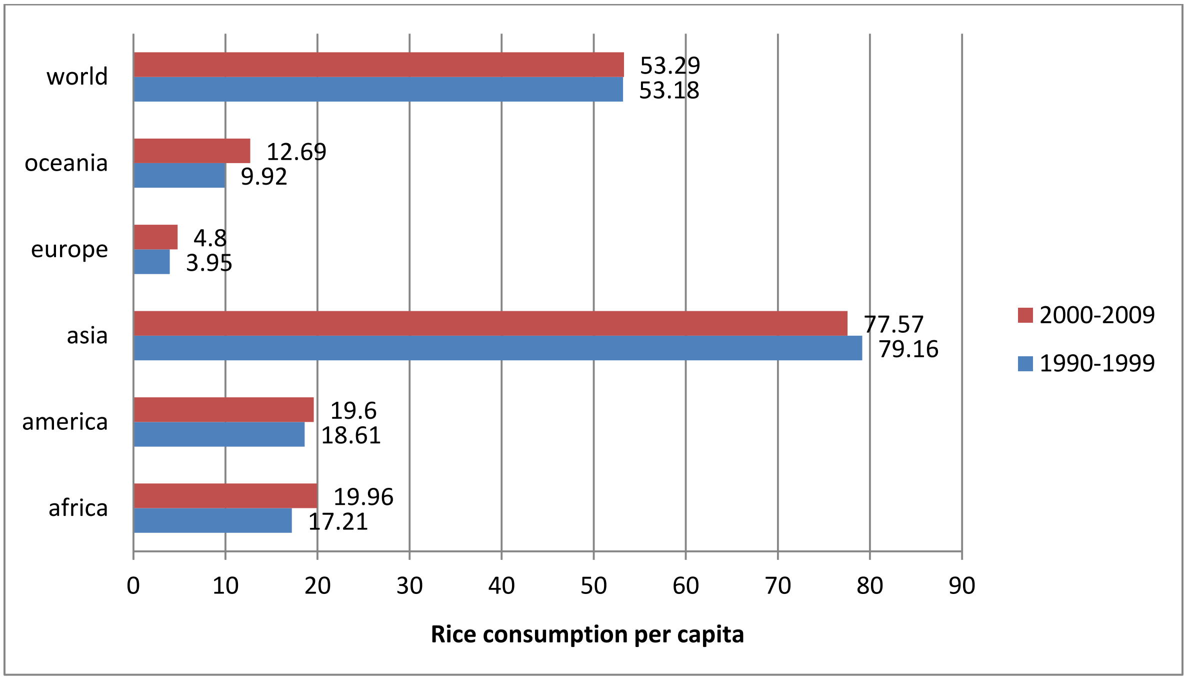
	Without trend			With trend	
	2SLS	FE-IV	2FE-IV	2SLS	FE-IV
lngdp	-0.059 (1.48)	0.007 (0.17)	-0.314*** (6.44)	-0.337*** (7.97)	-0.322*** (6.79)
lnagshare	-0.657*** (8.88)	-0.697*** (9.32)	-0.096 (1.11)	-0.097 (1.21)	-0.135 (1.59)
lnrrp	-0.129** (2.51)	-0.106** (2.09)	-1.179 (0.8)	-0.014 (0.29)	-0.006 (0.18)
lnrwp	0.059 (0.86)	0.049 (0.73)	1.266 (0.87)	0.016 (0.26)	0.008 (0.20)
t				0.02*** (13.99)	0.02*** (12.42)
intercept	5.956*** (9.83)			5.571*** 9.78	
RMSE		0.250			0.237
R-sq overall	0.111	0.093	0.236	0.236	0.187
Overidentify test		0.251	0.514		0.289

Notes: (1) Dependent variable is per capita rice consumption. (2) Values in brackets are absolute z-statistics. (3) *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. (4) RMSE is the root mean square error (5) p-value of Sargan statistic is reported the overidentification test.

Table 2.5. Heterogeneous parameter estimation: Coefficient averages computed in levels.

	Model 1 (Prices excluded)			Model 2 (Prices included)			Model 3 (Prices included - IV)		
variable	MG	CMG	AMG	MG	CMG	AMG	MG	CMG	AMG
lngdp	0.666^{***}	0.146	0.576^{***}	0.489^{**}	0.430	0.366^{*}	0.492^{***}	0.185	0.337^{*}
	(3.17)	(0.56)	(2.97)	(2.09)	(1.31)	(2.97)	(2.61)	(0.70)	(1.88)
lnagshare	3.153	3.382	2.701	4.085	1.476	3.514	3.868	6.216	4.112
	(0.92)	(0.85)	(0.81)	(1.26)	(0.30)	(1.08)	(1.03)	(0.95)	(0.96)
lnrrp				0.007	0.086	-0.960^{***}	-0.011	0.582	0.403^{***}
				(0.3)	(0.03)	(4.34)	(0.32)	(0.90)	(3.53)
lnrwp				-0.008	0.014	0.875^{***}	0.018	-0.927	-0.553^{***}
				(0.24)	(0.00)	(4.67)	(0.41)	(1.08)	(3.41)
country trend	0.017	0.03	0.006	0.023	-0.008	0.009	0.026	0.025	0.03
	0.83	(0.36)	(0.31)	(1.07)	(0.12)	(0.46)	(1.09)	(0.36)	(1.24)
common trend			0.937^{***}			1.016^{***}			0.967^{***}
			(3.92)			(4.53)			(3.91)
intercept	-17.033	- 21.476	-14.239	-19.915	- 7.355	-15.682	-18.756	-24.595	-18.187
	(1.16)	(0.66)	(1.00)	(1.46)	(0.26)	(1.13)	(1.17)	(0.80)	(0.98)
RMSE	0.141	0.117	0.137	0.127	0.10	0.122	0.126	0.095	0.122
CD test	0.01	-2.55^{**}	-2.06^{**}	0.1	-1.48	-2.27^{**}	0.30	-2.15^{**}	-2.56^{**}
CIPS test	-3.270^{***}	-4.466^{***}	-3.526^{***}	-3.782^{***}	-4.869^{***}	-4.217^{***}	-3.826^{***}	-4.808^{***}	-4.015^{***}

Notes: (1) Dependent variable is per capita rice consumption. (2) Values in brackets are absolute t-statistics. (3) *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. (4) The 1%, 5% and 10% critical values for Pesaran's (2007) CIPS with constant and trend deterministic are -2.78, -2.65 and -2.58, respectively. (5) Estimated coefficients are un-weighted average across countries.



Source: data from FAO (www.irri.org).

Figure 2.1: Changes in global average rice consumption.

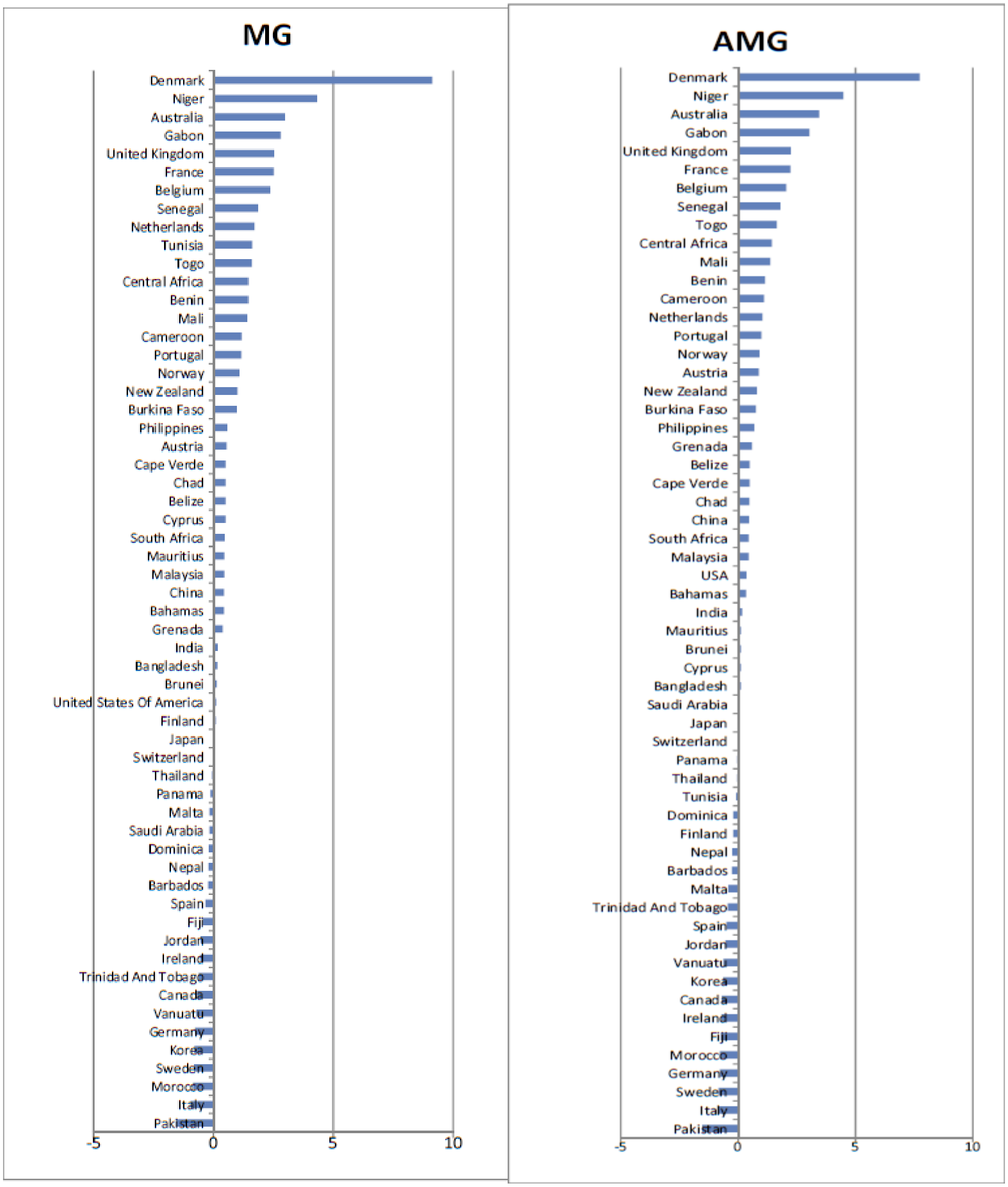


Figure 2.2

Figure 2.2. Comparison between MG and AMG estimated income elasticities (Model 1).

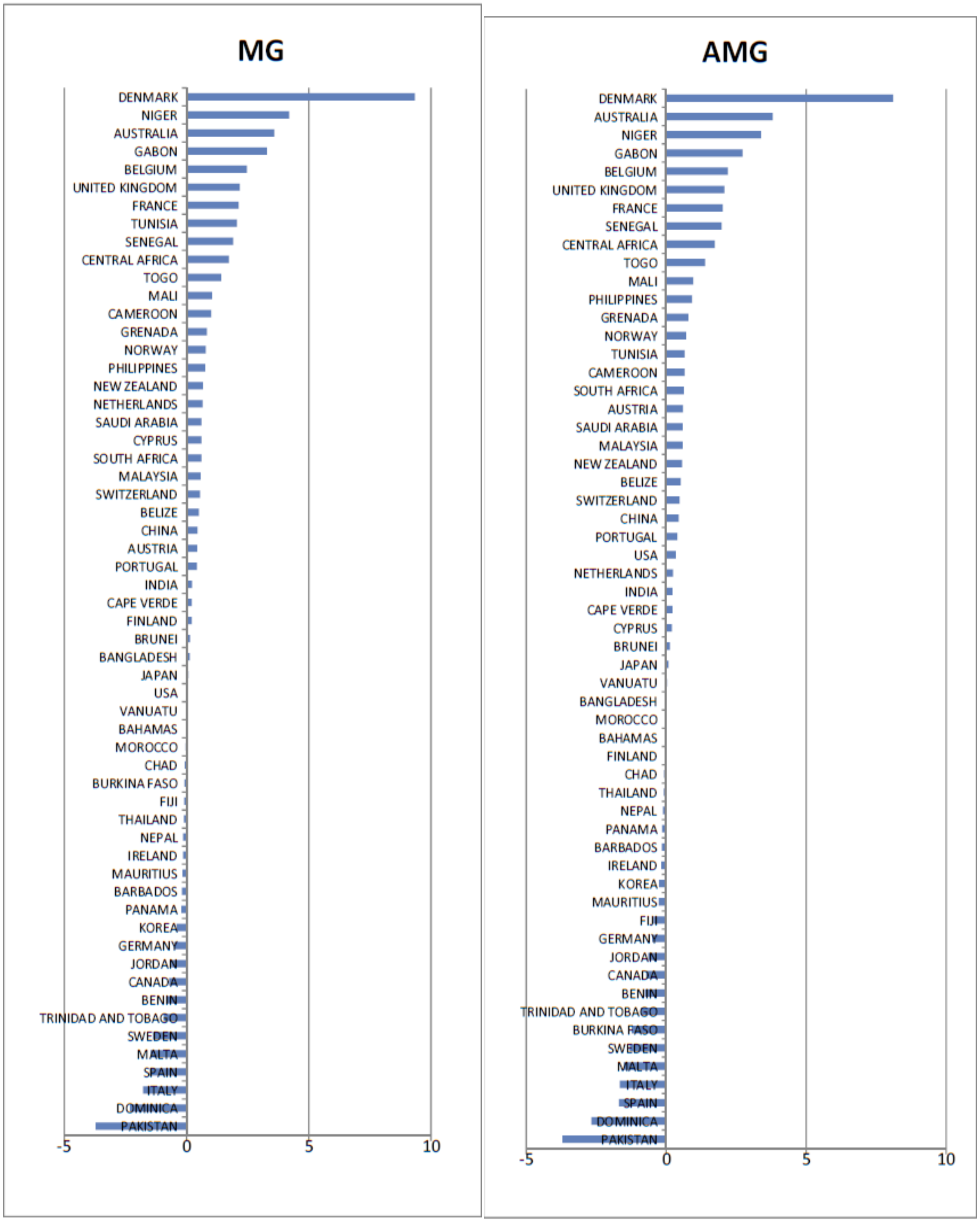


Figure 2.3

Figure 2.3. Comparison between MG and AMG estimated income elasticities (Model 2).

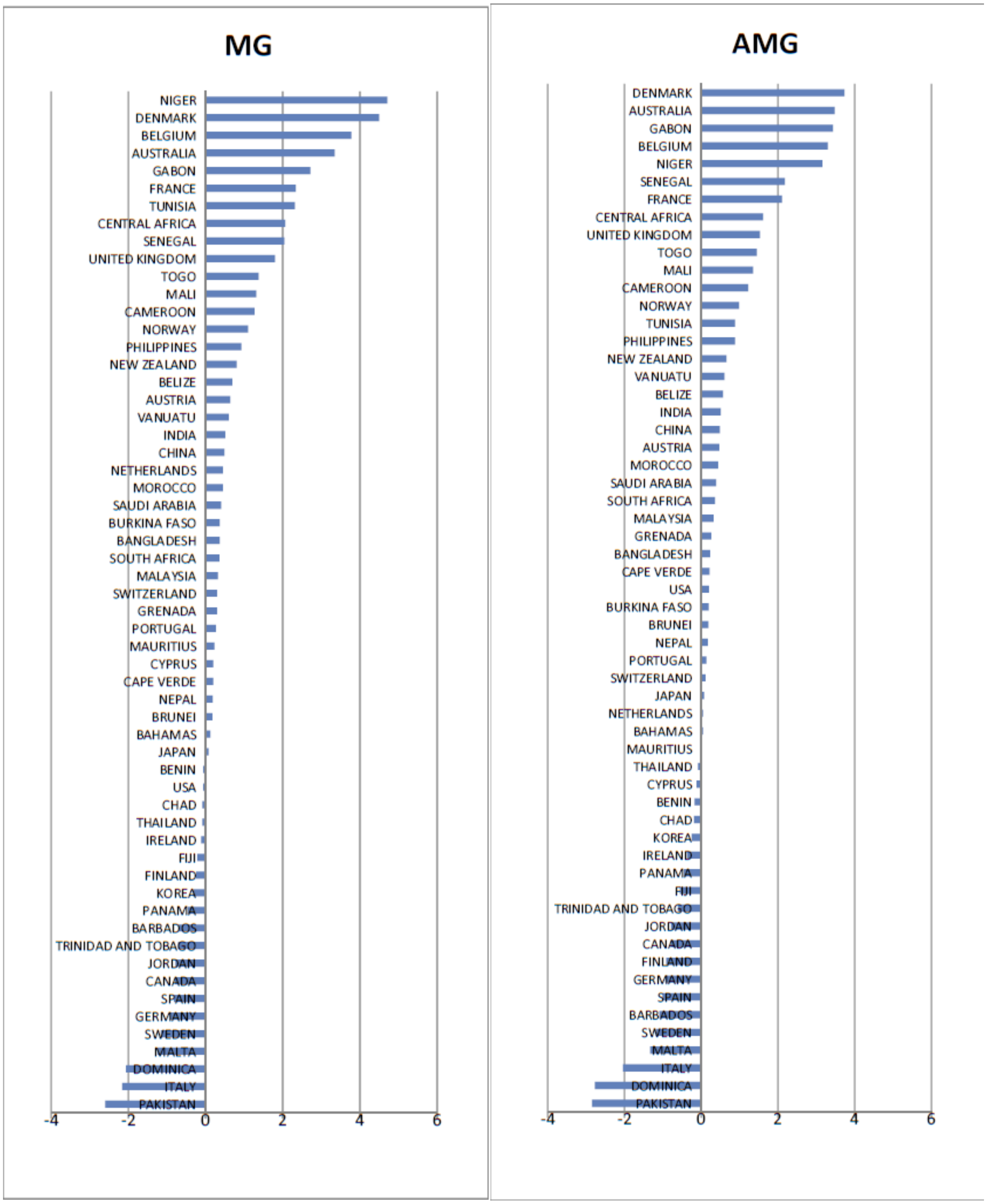


Figure 2.4

Figure 2.4. Comparison between MG and AMG estimated income elasticities (Model 3).

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CHAPTER 3

Land Tenure, Productivity, and Production Risks in the Philippine Rice sector

3.1 Introduction

Food security has been a crucial issue in the Philippines especially after the food "crisis" of 2008. Therefore, the Philippines has aimed to increase own-food production, decrease dependence on food imports, and attain food self-sufficiency. In particular, rice is a dominant staple food for Filipinos, with annual rice consumption per capita (milled equivalent) of 97.5 kilograms based on data from 1961 to 2011 (IRRI, 2015). One of the country's goals is to achieve self-sufficiency in rice to meet domestic demand. As such, rice production, harvested area, and yields have trended upwards over the past several years (Figure 3.1). The increases in paddy production over the years primarily came from adoption of high-yielding rice varieties, expansion of area planted, and improvement in rice irrigation systems. Consequently, average growth rate of rice yield is around 2.4 percent per year.

In spite of upward trending rice productivity levels, the proportion of total domestic rice production to total domestic rice consumption (also called the rice self-sufficiency ratio) has been less than one over the last 20 years (Figure 3.2). This means that rice produced domestically is not enough to cover local demand, and the Philippines have relied heavily on rice imports.[20] One reason for the shortfalls in meeting domestic demand from local production (and the rise in imports) is production losses due to natural disasters. For example, the Philippines was hit by 18 typhoons per year from 2001 to 2012 and it has been affected by severe droughts in 2007 and 2011 (Rola et al., 2015 pp. 65). Nevertheless, the Philippines is still striving to reduce reliance on rice imports and this is evident in 2011 when rice imports dramatically decreased by 70 percent relative to the previous year (Figure 3.3).

One approach taken by the Philippine government to potentially increase rice productivity in the country is through a land redistribution scheme called the Comprehensive Agrarian Reform Program (CARP), which was launched in 1988. In this program, the government will buy land from landowners with more than seven hectares and sell them to landless farmers (who are typically the ones actually tilling the land through share leases or fixed rent contracts with landlords).[21]

Land tenure improvement is one of programs in CARP,[22] which involves land transfer and non-land transfer categories. Relating to land transfer, land acquisition and distribution are on compulsory acquisition and voluntary offer land to sell and transfer. For this redistribution scheme, the idea is not only to provide land equity (i.e. more equitable land distribution in the agricultural sector), but also to enhance overall agricultural productivity -- given the long-run economic incentives to take care of the land that ownership supposedly provides. The accumulative land distribution accomplishment during 1972 to 2014 covers

[20] Between 1996 and 2011, the Philippines imported rice from three major exporters: Vietnam (69.62 percent), Thailand (16.11 percent) and China (7.9 percent).
[21] CARP beneficiaries also receive other benefits from government, such as marketing assistance, financial support, and technical backstopping, which aims to promote self-reliance among the beneficiaries.
[22] Three program components in CARP consist of land tenure improvement, beneficiaries' development program and agrarian justice support (Gordoncillo, 2012).

98.6% of the gross area, in which a total of 4.69 million hectares were distributed to 2.75 million agrarian reform beneficiaries according to the 2014 report of Department of Agrarian Reform (DAR).

With respect to the productivity effects of redistributive land reform, the reduction in productivity could happen in the cases of misallocating land or resources from large farms with high productivity to small farms with low productivity, and changing technology adoptions according to tenure securities. However, “inverse productivity” puzzle has been observed in a number of studies worldwide where farms with smaller sizes still tend to have higher yields per unit area (i.e. smaller farms tend to be more productive). Previous studies indicate that land market inefficiency, labor market failures and potential differences in land fertility contribute to the empirically observed “inverse” relationship between farm size and productivity (see Sen, 1975; Benjamin, 1995; Banerjee, Gertler and Ghatak, 2002; Lamb, 2003).

Alternatively, land redistribution programs could result in positive productivity effects (especially among poorer farmers in developing countries). The argument is that secure land tenure (i.e. ownership) increases incentives for productivity-enhancing agricultural investments (IFAD, 2008; Abdulai, Owusu and Goetz, 2011). However, results from previous studies that examined the relationship between land tenure arrangements and agricultural productivity has been mixed. Some of the previous empirical studies find a positive impact of tenure security on agricultural productivity (see Banerjee et al., 2002; Goldstein and Udry, 2008; Kyomugisha, 2008; Abdulai et al., 2011). While in other studies, no strong evidence was found with regards to the relationship between land ownership and productivity (Place and Hazell, 1993; Place and Otsuka, 2002).

In the Philippine context, there are a couple of recent studies that have investigated the effect of land ownership and tenure arrangements on technical efficiency (or productivity) of rice farms. Koirala, Mishra and Mohanty (2014) apply the simulated maximum likelihood approach to examine the effect of landownership on technical efficiency of Philippine rice farmers in Central Luzon from 2007 to 2012. Their result indicates a positive effect of landownership on rice production. In other words, the owner-cultivator tends to be more productive relative to those farms with alternative tenure types. Michler and Shively (2015) also investigate the relationship of ownership type and technical efficiency of rice parcels in Palawan province in the Philippines. Their finding shows that land tenure arrangement influences rice farm's technical efficiency. But the mean technical efficiency scores are not statistically different between parcels that are always owned and those parcels that have always been rented.

Although there has been a number of studies that examined the effect of land tenure status on productivity (or technical efficiency), to the best of our knowledge, there has been no study that has investigated the relationship between land tenure status and rice production risk. Therefore, the objective of this study is to determine how land tenure arrangement (i.e., landownership, share tenancy, fixed rent agreements) influences productivity (e.g., mean yields) and production risk. Specifically, we utilize a moment-based estimation approach (See Antle and Crissman, 1990; Shi, Chavas and Lauer, 2013) to examine the effect of land tenure arrangement on the mean, variance, skewness, and kurtosis of rice yields in the

Philippines. The risk effect of land tenure arrangement is embodied through the estimated effects on variance, skewness, and kurtosis. The analysis relies on a newly constructed parcel-level panel data set from the Central Luzon region of the Philippines (called the Central Luzon Loop Survey data), which includes data for various years in the period 1966 to 2012 (for both wet and dry seasons).

It is important to investigate the impact of land tenure arrangement on production risk to further understand the relative benefits (and/or costs) of land ownership vis-à-vis sharecropping tenure arrangements. As discussed above, security of land tenure through ownership makes farm-owners full residual claimants of the returns to farming, which then provides incentive to apply productivity-enhancing investments that can improve mean yields (Shaban, 1987). However, it should be noted that the incentive to apply productivity-enhancing investments may also lead to reduction in temporal yield risk over time and this potential benefit of land ownership has not been fully captured in the empirical literature.

Identifying the risk effects of land tenure arrangements may also have important implications in explaining why farmers choose a particular land tenure arrangement. Sharecropping contracts have been conceptualized as a risk-sharing device where smaller farmers (i.e., with less wealth) tend to choose this arrangement because of their inability to handle large fluctuations in yield (or prices) over time. Under full ownership or fixed rent contracts, the small farmer is the full residual claimant and bears all the risk in case of a loss. But with sharecropping, part of the downside risk will be shouldered by the landlord. Therefore, small farmers below a certain wealth threshold is typically expected to choose a share tenancy arrangement for the purpose of risk sharing. However, this argument implicitly assumes that the yield distribution (i.e., the riskiness in production) remains the same for all land tenure arrangements (i.e., it is exogenous).

But it could be the case that the land tenure status alters the yield distribution such that the productivity effect of ownership and/or fixed rent contracts can reduce downside risk enough (i.e., or narrow the yield distribution enough) such that the risk reduction from the ownership/fixed-rent status is the same as (or more than) the risk reduction in a sharecropping arrangement. In this case, the risk reducing effect of ownership or fixed rent contracts may make it preferable to low wealth producers as well.

On the contrary, Ghatak and Pandey (2000) have theoretically argued that the variance of output should be higher in farms that are cultivated under fixed rent contracts as opposed to sharecropping contracts (controlling for factors such as the characteristics of the landlord/tenant and land quality). The idea is that farmers on fixed-rent contacts have more incentives to pursue more risky production techniques since they can capture the full marginal returns from high outputs. In the next step, we further test if farmers with fixed rent contracts have higher production risk as compared to farmers in sharecropping arrangements.

3.2 Data Description and Empirical Setting

In this study, we utilize a parcel-level panel data set from the Central Luzon region of the Philippines for various years within the period 1966-2012. The Central Luzon region is a major rice-producing region in the main island of Luzon (where the Philippine capital Manila is located). The panel data came from the so-called “Loop Survey” where the rice farming households in the survey are located near a "loop" of highways that go through the main provinces in Central Luzon (north of Manila).

The "loop survey" is conducted every four years by the International Rice Research Institute (IRRI). The survey area covers six provinces in Central Luzon: Bulacan, Nueva Ecija, Pampanga, Pangasinan, La Union and Tarlac (see Figure 3.4). The objective of this survey is to monitor changes in household characteristics and rice production (e.g. yields, input uses, tenure, irrigation etc.) for both the wet and dry seasons. In the Central Luzon region, double cropping is normal and rice is established by transplanting.

After dropping missing data and obvious outliers, the remaining unbalanced panel data set had 2,170 total observations (i.e., 311 parcels for various years in the period 1966-2012).[23] Descriptive statistics on rice yields and input use of farmers in the data set are presented in Table 3.1. On average, rice farm size in the Central Luzon region is around 1.36 hectares, ranging from 0.1 to 9 hectares. Overall average yields are approximately 3,953.28 kg/ha. The average input use for labor is 68 person-days per hectare. Fertilizer application and chemical usage are 279.28 kg/ha and 2.47 kg/ha, respectively. When we consider yield and input use across tenure status, mean yields for owners tend to be slightly higher than fixed-rent farmers. Consistent with Michler and Shively (2015), fertilizer and chemical use are relatively higher for landowners relative to shareholders. The lowest mean yield are for sharecroppers at 3,082.64 kg/ha[24].

[23] Grubbs test is used to identify outliers in the data set. These are typically those observations that are more than three standard deviations away from the mean.
[24] In this study, we define "other" tenure status as a land pawning contract. The pawn-in arrangement is a kind of cultivation rights transfer which is mostly found in Philippine rice growing villages. Under the pawning arrangement, the moneylender (pawner) advances cash to the farmer (pawnee) and take over the rights in

At this point it is also important to examine the tenure status distribution of the farmers in the data set, before and after CARP implementation in 1988 (see Table 3.2). In general, 90 percent of the landholders possess farms of less than 3 hectares before and after CARP implementation. More than 60 percent of Central Luzon rice farmers operate farms less than 1.5 hectares before and after CARP implementation, with an average farm size of 1.36 hectares. After the 1988 implementation of CARP, the proportion of respondents who own their land in our sample increased from 23 percent to 53 percent of total farmers (regardless of farm size). In addition, we notice that there are about 10 percent more "small" farms (less than 1.5 hectares) after CARP implementation.

3.3 Empirical Approach and Estimation

3.3.1 Empirical Approach

To investigate the impact of land ownership (or land tenure status) on mean rice yields and risks, we build on the moment-based approach proposed by Antle and Crissman (1990). Following Just and Pope's (1978; 1979) framework, a stochastic production function can be specified as follows:

(1) $$Y = f(Z, \beta) + \nu,$$

(2) $$\nu = h(Z, \theta)\varepsilon.$$

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cultivated land as a sharecropper. The moneylender receives the difference between his share of output and the fixed rent mandated by law (Estudillo and Otsuka, 2010).

where Y is yield, Z is a vector of variable inputs and ν is an error term. The term $f(\cdot)$ is the mean production function, while $h(\cdot)\varepsilon$ is the term that captures production risk such that $h(\cdot) \geq 0$ represents the output variability (or output risk) function. The term ν is an additive error term with zero mean and variance $(h(\cdot))^2$, and ε is a homoskedastic error term with $E[\varepsilon] = 0$ and $(E[\varepsilon])^2 = 1$. The terms β and θ are parameters to be estimated.

Let $U(\cdot)$ be the von Neumann-Morgenstern utility function. Further, let c(Z), P and P^Z be the cost of input use, rice price and input price, respectively. Following Czekaj and Henningsen (2013), the farmer's input use decision problem is to maximize expected utility of net income:

$[\pi = Pf(Z,\beta) - c(Z) + Ph(Z,\theta)\varepsilon]$.

(3) $$\underset{Z}{\mathrm{Max}}\, E[U[Pf(Z,\beta) - c(Z) + Ph(Z,\theta)\varepsilon]].$$

Taking the first-order condition (FOC) of the objective function in equation (3) with respect to the *j*-th variable input, we get the following:

(4) $$E[U'(\pi)(f_j(Z,\beta) - P^Z + h_j(Z,\theta)\varepsilon)] = 0,$$

(4a) $$f_j(Z,\beta) = P^Z - \frac{h_j(Z,\theta)E[U'(\pi)\varepsilon]}{E[U'(\pi)]} = P^Z - h_j(Z,\theta)R,$$

(4b) $$R \equiv \frac{E[U'(\pi)\varepsilon]}{E[U'(\pi)]}.$$

where $U'(\pi) = \frac{\partial U}{\partial \pi}$ is the marginal utility of net income, and f_j and h_j denote the first derivatives of the mean production function and the output variability function with respect to the *j*-th variable input. At point $E(\pi)$, the risk preference function (R) is

(4c) $$R = -\frac{U''(E(\pi)h(Z,\theta)}{U'(E(\pi))} = r_2 h(Z,\theta),$$

where $r_2 = -\frac{U''(E(\pi))}{U'(E(\pi))} = -\frac{\partial^2[U(E(\pi)]}{\partial[E(\pi)]^2} \Big/ \frac{\partial[U(E(\pi)]}{\partial[E(\pi)]}$ is the Arrow-Pratt relative risk aversion coefficient.

According to Chambers (1983), $R > 0$ indicates risk averse farmers, $R = 0$ indicates risk neutral farmers, and $R < 0$ indicates risk loving producers (Czekaj and Henningsen, 2013). We can interpret the risk premium[25] (RP) as the cost of private risk bearing and it can be calculated from equation (3) by substituting the random net income (π) with its expected value $E(\pi)$ (Pratt, 1964):

(5) $$EU(\pi) = U[E(\pi) - RP].$$

Taking the first to the fourth order Taylor series approximation of $U[E(\pi) - RP]$, we obtain:

(6) $$E(U(\pi)) + \frac{1}{2}\frac{\partial^2 U}{\partial(E(\pi))^2}[\pi - E(\pi)]^2 + \frac{1}{6}\frac{\partial^3 U}{\partial(E(\pi))^3}[\pi - E(\pi)]^3 + \frac{1}{24}\frac{\partial^4 U}{\partial(E(\pi))^4}[\pi - E(\pi)]^4\} \approx E(U(\pi)) - \left(\frac{\partial U}{\partial E(\pi)}\right)RP \cdot$$

(7) $$RP \approx \frac{1}{\partial U / \partial E(\pi)}[-\frac{1}{2}\frac{\partial^2 U}{\partial(E(\pi))^2}[\pi - E(\pi)]^2 - \frac{1}{6}\frac{\partial^3 U}{\partial(E(\pi))^3}[\pi - E(\pi)]^3 - \frac{1}{24}\frac{\partial^4 U}{\partial(E(\pi))^4}[\pi - E(\pi)]^4],$$

(7a) $$RP_4 = \frac{1}{\partial U / \partial(E(\pi))}[\frac{1}{2}r_2 M_2 + \frac{1}{6}r_3 M_3 + \frac{1}{24}r_4 M_4],$$

[25] The risk premium is the amount of money that decision maker is willing to pay to eliminate the risk exposure from ν.

where $M_k = E[\pi - E(\pi)]^k$ is the *k*-th central moment of the net income distribution, and

$r_2 = -\frac{\partial^2 U}{\partial (E(\pi))^2}, r_3 = -\frac{\partial^3 U}{\partial (E(\pi))^3}, r_4 = -\frac{\partial^4 U}{\partial (E(\pi))^4}$, which are evaluated at $E(\pi)$.

From equation (7a), we can approximate the cost of risk decomposed to the effect of variance, skewness, and kurtosis on the risk premium. Note that when $k = 2$, the variance effect can be evaluated by using the standard Arrow-Pratt approximation. As $k > 2$, we need to know/assume the risk preference of the producer. For instance, if we assume that the rice farmer's risk preference is consistent with constant relative risk aversion (CRRA), then the farmer's utility function can be represented as:

$$(8) \qquad U(Y) = \frac{Y^{1-r}}{(1-r)}.$$

where Y could be output or revenue and r is a coefficient of relative risk aversion ranging from 1 to 5. From the assumed CRRA form of the utility function in (8), we can derive the absolute risk premium as follows:

$$(8a) \quad \frac{\partial U}{\partial Y} = Y^{-r}, \ \frac{\partial^2 U}{\partial Y^2} = -rY^{-r-1}, \ \frac{\partial^3 U}{\partial Y^3} = r(1+r)Y^{-r-2} \ \text{and} \ \frac{\partial^4 U}{\partial Y^4} = -r(1+r)(2+r)Y^{-r-3},$$

$$(8b) \quad RP = \frac{r}{2}\frac{M_2}{Y} - \frac{r(1+r)}{6}\frac{M_3}{Y^2} + \frac{r(1+r)(2+r)}{24}\frac{M_4}{Y^3},$$

$$(8c) \quad RP = \frac{r}{2}\frac{M_2}{M_1} - \frac{r(1+r)}{6}\frac{M_3}{(M_1)^2} + \frac{r(1+r)(2+r)}{24}\frac{M_4}{(M_1)^3},$$

where Y is evaluated at the mean value (M_1)[26]. Therefore, we can represent the relative risk premium (RRP) as a ratio of absolute risk premium to mean yield in equation (8d).

$$\text{(8d)} \quad \mathrm{RRP} = \frac{\mathrm{RP}}{\mathrm{M}_1}.$$

The relative risk premium represents the percentage of mean yield that a risk averse farmer is willing to pay in order to avoid an uncertain yield due to possible crop failure. This expression is convenient to interpret as the cost of risk because it does not rely on units of measure. Generally, farmers prefer higher productivity and lower production risks (e.g. lower variance, higher skewness, and smaller kurtosis). For example, if the land ownership effect is positive in the skewness equation, this indicates that farmers who own their land will likely have smaller downside risk from shocks (such as unfavorable weather). A negative kurtosis effect of land ownership, on the other hand, suggests that this tenure status contributes to decreasing the thickness of the tails of the yield distribution (i.e. decline in probability of rare events). More positive skewness and lower kurtosis values are indicative of lower risk.

3.3.2 Estimation strategies

To implement the empirical approach described above, we specify a rice yield equation as a Cobb-Douglas production function in logarithmic form:

$$\text{(9)} \quad \ln \mathrm{Y}_{p,i,t} = \alpha_0 + \sum_{j=1}^{3} \beta_j \ln \mathrm{X}_{jt} + \beta_4 \mathrm{LAND}_{p,i,t} + \beta_5 \mathrm{MV}_{p,i,t} + \beta_6 \mathrm{SEA}_{p,i,t} + \beta_7 \mathrm{IRR}_{p,i,t} + \nu_{p,i,t}.$$

[26] In the context of an output distribution, the general form of higher moment-based approach can be represented as $\mathrm{M}_k(\mathrm{Z}) = \mathrm{E}[\mathrm{Y}(\mathrm{Z}) - \mathrm{M}_1(\mathrm{Z})]^k$, k = 2, 3, 4 where the *k*-th moment of farmer *i* under uncertainty represent the variance, skewness, and kurtosis of yields (Shi et. al., 2013).

where Y represents yield as a function of inputs (Z) that is composed of the vector X_j, a set of dummy variables, and an error term (ν).The subscripts *j*, *i*, *p* and *t* refer to the *j*-th variable input (j = 1,2,3), *i*-th farmer (i=1,2,…,208), *p*-th parcel cultivated by farmer *i*, and *t*-th year (1966-2012), respectively; and β_n are unknown parameter vectors (n = 1,...,7).The term X_j is a vector of variable inputs (e.g., including: fertilizer (X_1), labor (X_2), and chemical inputs (X_3)). The dummy variables are land ownership status (LAND), phase of modern rice variety adoption (MV) as a proxy for technological change, season (SEA), irrigation type (IRR) (see list of all variables in Table 3.3). According to the moment-based framework of Antle and Crissman (1990), we estimate higher moments up to four in order to measure mean, variance, skewness and kurtosis effects.

3.4 Empirical Results

3.4.1 Nonparametric Kernel Density

Before estimating the parameters of the production function in equation (9), we first conducted some simple exploratory analysis of the yield data by estimating nonparametric kernel densities of yield by land tenure arrangement. Results of the estimated kernel densities are presented in Figure 3.5. From these densities, it is clear that the mean yields of sharecroppers are lower than those farmers with other tenure arrangements. For the case of farmer-owners and fixed rent farmers, this may reflect the positive productivity effects from being the full residual claimants of the returns to farming.

Figure 3.5 also seems to indicate that the yield density of the share contract tenure arrangement is more positively skewed (i.e., longer tail on the right) and has more probability mass on the left tail than the densities for the other tenure arrangement. Such an asymmetric yield distribution suggests that the exposure to downside risk of a sharecropper may possibly be lower than other tenure types. In terms of kurtosis[27], a higher peak than the normal distribution generally means that the empirical distribution has thinner tails. That is, there is a lesser chance of extreme yields as compared to the normal distribution. At the lower tail of the yield distribution, given that the shareholder has more peak and has a thicker tail than the owner's distribution implies that crop failures from rare events more frequently occur in the case of sharecropping (see Figure 3.6). In other words, the production risk of a shareholder that is driven by extreme downside events may be larger than for farmers who own their land. However, this is an exploratory analysis that does not control for other factors (i.e., inputs and other farmer/farm characteristics). The next step is to estimate the parameters of the production function specified in equation (9).

3.4.2 Production Function Estimation Results

To consistently estimate the empirical specification in equation (9), one needs to first account for the unobserved heterogeneity across farmers and over time. Thus, farm and year fixed effects are included in the specification to account for unobserved farmer heterogeneity

[27] Kurtosis measures degree of peak in yield distribution, and its thickness of tails mean the probability of extreme events, compared to normal distribution.

over time.[28] We then explored alternative functional forms for the mean yield function in (9) (e.g., translog, quadratic, Cobb-Douglas functional forms). Following Di Falco and Chavas (2009), we apply the Akaike's information criterion (AIC) and the Baysesian information criterion (BIC) to compare the performance of the different functional forms. The smaller AIC and/or BIC are, the better model fits the data (StataCorp., 2013).

Based on the AIC criterion, the performance of the translog and Cobb-Douglas production functions are similar when we included farm and year fixed effects (AIC = 614, 654 and 15,289 for translog, Cobb-Douglas, and quadratic functional forms, respectively). However, the BIC criterion suggests that the Cobb-Douglas is more suitable as compared to the translog functional form (i.e., BIC = 1560, 1446, and 16,368 for translog, Cobb-Douglas and quadratic forms, respectively). We also considered linear-log and log-linear specifications. Based on the AIC and BIC criterion, the log-log specification is more appropriate than other specifications in our study. Therefore, we choose the log-log specification of the Cobb-Douglas production function.

It is worth noting that the estimated coefficients of the independent variables in Table 3.4 represent the elasticities for the moments of rice yield distribution. For the first-moment (i.e., the mean yield function), elasticities presented in the second column are the percentage change in mean yield with respect to a percentage change in the respective independent variables. First, we find that fertilizer, labor and having irrigation are yield-enhancing inputs. The coefficient of 0.2 and 0.411 indicate that a percentage increase in fertilizer and labor per

[28] Note that the estimation is still at the parcel level but we are controlling for unobserved farmer heterogeneity through farmer level fixed effects. We tried the option where we included parcel level fixed effects, but this approach may have taken away all the variation in the data such that no independent variable was statistically significant in the estimation.

hectare would increase mean rice yield by 0.2 percent and 0.411 percent, respectively. These relationships of inputs with mean yields are consistent with many empirical studies (e.g., Antle and Crissman, 1990; Donkoh and Owusu, 2013; Koirala, Mishra and Mohanty, 2014 and Michler and Shively, 2015).

For our land tenure variable of interest, the results in Table 3.4 indicate that the estimated parameters for the fixed-renter and landowner in the mean yield function are positive and statistically significant. The shareholder dummy variable is the omitted category in the specification. This means that the fixed-renter and farmer-owner have statistically higher mean yields than the shareholder. The evidence corresponds to our kernel yield densities in Figure 3.4 where the farmer-owner tends to be more productive than the shareholder.

The fourth column in Table 3.4 shows the regression result for the yield variance equation. Results from this variance regression equation give insight on the potential risk effects of land tenure status in the Philippines. The parameter estimates associated with land tenure status are negative and significant. This suggests that the yield variance of farmer-owners, fixed-renters and the “other” tenure type are statistically lower than the yield variance of sharecroppers (controlling for input use and other farm characteristics).

To further capture the risk effects of land tenure status, one also needs to examine the effect on the skewness and kurtosis of the yield distributions. Note again that more positive skewness and lower kurtosis values are indicative of lower downside risk and a lower chance of crop failure. Results from the skewness and kurtosis regressions are presented in the sixth and eighth column of Table 3.4. Parameter estimates for all tenure types are negative and statistically significant for the skewness and kurtosis equations. This result suggests that the asymmetry in the rice yield distribution is significantly different across tenure status. The thickness of the tails of the yield distribution is statistically lower for all tenure types relative to the sharecropper. But the negative skewness effect may reflect higher risk for the fixed-rent, owner, and "other" categories, vis-à-vis the shareholder. Hence, an additional analysis that calculates the risk premium value (which incorporates the variance, skewness, and kurtosis effects) by land tenure status is conducted in the next section (Section 4.4.3).

Taken altogether, the results in Table 3.4 indicates that rice farmers in the Philippines who own their land or in fixed rent contracts tend to be more productive and face lower production risks relative to farmers in sharecropping arrangements. This suggests that the productivity enhancing incentives of ownership (or fixed rent contracts) may also lead to reduction in the production risks of farmers that choose these tenure arrangements. It is also possible that the parcels that land owners make available for share contracts tend to generally be of lower quality such that farmers in share leasing contracts tend to be less productive and higher risk. These results also suggest that Ghatak and Pandey's (2000) argument that fixed renters should be the ones with higher variance in output may not apply in our context. Although it may be true that fixed rent contracts encourage risk taking behavior, the "risky" investments may be beneficial in the long-run such that it smooths production over time and reduces risk.

Given that there was an influx of new landowners in the sample after 1988, it is also interesting to investigate whether the expected negative productivity effects due to entrance of new owners with smaller scale would dominate the productivity effects of CARP.

Therefore, we create an *after1988* dummy variable to represent the period after 1988 that coincides with the CARP. We add the *after1988* dummy to the specification in equation (9) and also interact it with the land tenure variables in the specification. This analysis would give some indication whether the land tenure effects may be different for the period after the 1988 CARP implementation.

To check the suitability of including the interaction terms in the specification, we conduct joint significance test, which resulted in rejection of the null hypothesis that the interaction coefficients are all zero (at the 5 percent level). This test result implies that including these interaction terms in the specification are appropriate. The parameter estimates associated with the *after1988* dummy indicates that the mean, variance, and skewness of yields after CARP implementation were not significantly different from the period before implementation. But the kurtosis seems to be significantly different after CARP implementation compared to before 1988.

In terms of the parameter estimates associated with the interaction terms, the estimated effects of land ownership and fixed-renter on mean, variance, skewness, and kurtosis were not significantly different between the period before and after implementation of CARP. Therefore, the expected negative productivity effects of new farm owners having smaller scale operations did not seem to have a substantial enough effect to cause a difference in the productivity and risk effects of farm ownership. The productivity enhancing effects of land ownership still seem to dominate even in this specification of the model.

3.4.3 Evaluation of production risks

In this section, we calculate the risk premium associated with each land tenure status to better understand how the variance, skewness, and kurtosis effects of tenure status together affect overall production risk (i.e., given that each of these higher moments of the distribution influence the resulting production risks). We first simulate two scenarios of rice cultivation for the years 1982 and 2011, to cover the years before and after CARP implementation. In these two scenarios we further assume the following: rainy season, irrigated production environment, and adoption of 4^{th} generation of rice varieties. Given constant mean input effects, the risk premium can be evaluated for each tenure type for the purpose of production risk evaluation. Then, we calculate the percentage of the risk premium relative to mean yield for each tenure status as shown in equation 8(d). Table 3.5 represents estimated relative risk premium (% of mean yield) across tenure types.

According to decomposition of the risk premium results in Table 3.5, the cost of variance is the largest component of relative risk premium (RRP). The evidence shows that the variance and skewness components of the cost of risk are the main drivers of changes in risk premium because the effects of kurtosis cost are very small (just around 0.01 percent of mean yield). The minimal role of the kurtosis effect is consistent with graphed densities of the yield distribution by tenure status (as seen in Figure 3.6). To the extent that thickness of tails for each tenure status is very close to normal distribution, this suggests that the kurtosis component in the risk premium calculation plays a smaller role.

In general, the evaluated relative risk premium in Table 3.5 corresponds to our previous regression results. First, our 2011 results reveal that the total relative risk premium for fixed renters and owners are smaller than shareholders. This indicates that fixed rent and owner-farmers are willing to pay less to eliminate their risk exposure. Alternatively, the fixed rent status and owner status tend to have lower risk than shareholders in 2011. For the 1982 results, however, the relative risk premium results are slightly different. In this case, the total risk premium for fixed renters are still smaller compared to shareholders. But the total risk premium for owners in 1982 is greater than that of shareholders. Nevertheless, results from Table 3.5 still indicate that fixed rent farmers and farmer owners tend to have lower risk relative to shareholders. This general trend suggests that the variance and kurtosis reducing effects of the fixed rent and ownership status tend to be greater than the skewness reducing effect, such that the overall risk premium of these two tenure statuses are smaller than the shareholder status.

Second, Table 3.5 reveals that the relative cost of risk with respect to land tenure tends to decrease over time. In comparison with one from 1982, average relative risk premium declined from 20.7 to 13.9 percent of mean yield in 2011. Specifically, the relative risk premium for each tenure type was lower by about 1 to 2 percent of total costs of risk in 2011. Finally, our estimated relative risk premium ranges from 14 to 25 percent of the mean yield across tenure types. This is moderately larger than what has been reported in previous literature. For instance, Kumbhakar and Tsionas (2008) evaluated costs of private risk of rice farmers in Tarlac province, Philippines. Using nonparametric approach, their relative risk premium is about 1 to 15 percent of estimated profit. However, note that our relative risk premium is evaluated in the context of a yield distribution rather than a profit distribution.

3.5 Discussion and Conclusion

The objective of this study is to investigate the productivity and risk effects of different land tenure arrangements utilized by rice farmers in the Central Luzon region of the Philippines. An unbalanced parcel-level panel data from the Central Luzon Loop Survey conducted by IRRI for various years in the period 1966 to 2012 was used to achieve the study objectives. Using a stochastic production function estimation approach that allows one to see the land tenure effects on the first four moments of the yield distribution, we find that farmers that own their land and those that are in fixed rent contracts tend to have higher productivity and lower production risks relative to those farmers in share rent arrangements. The inference that farm owners and fixed renters face lower risk was mainly based on the estimated parameters from the variance and kurtosis equation that showed variance reducing and kurtosis lowering effects.

The empirical finding that ownership and fixed rent contracts tend to lower production risk (relative to share arrangements) is an important insight that has not been demonstrated in previous literature. This suggests that the incentives provided by ownership and fixed rent contracts to invest in productivity enhancing practices also results in lower production risks over the longer run. Examining the period after CARP implementation in 1988, our analysis also indicates that the Philippines' land redistribution program may have resulted in improved productivity and risk reduction over time even with the smaller farm sizes for new owners from the land redistribution scheme.

Our results may also have implications in terms of the decision to choose fixed rent versus share rent contracts. We posit that the risk reduction effect of fixed rent relative to the share rent contracts may play a role in the decision of farmers when choosing their tenure arrangements. First, the lower productivity and higher risk observed for sharecroppers may also be explained by the negative incentive effects of sharecropping. The tenant who shares outputs with landowner will sacrifice a proportion of his marginal product as share rent. For this reason, he could undersupply efforts or other inputs in production. Another feasible explanation is that landlords only make lower quality of land available for share cropping arrangements such that farmers in share leasing contracts tend to be less productive and higher risk.

Second, small farmers with lower wealth may still consider fixed rent contracts preferable (even though share contracts more directly facilitate risk sharing) because of the possible longer-run risk reduction. There may be a combined “wealth” and “risk reduction” threshold that can determine when the fixed rent contract would be preferable over the share rent contract. This argument is supported by the theoretical study developed by Agrawal (1999). The author explains why fixed rent contract may be chosen if there are: (i) greater experience and skills of tenants, (ii) higher monitoring and supervision costs of landowner, and (iii) lower tenant’s risk premium due to less risky crop production such as improvement in crop varieties and cultivation techniques. In addition, the discussion above supports the observation in the data in which the proportion of farmers in share contracts is substantially smaller than the proportion of fixed renters.

The empirical results of our study also do not support Ghatak and Pandey's (2000) argument that fixed renters should be the ones with higher variance in output (because this type of contract encourages risk taking behavior). Although it may be true that fixed rent contracts encourage risk taking behavior, the "risky" investments may be beneficial in the long-run such that it smooths production over time and reduces risk. However, the Ghatak and Pandey's (2000) study theoretically analyzes optimal contract choice in the presence of limited liability for the tenant, which may not apply in our empirical context.

In addition, the incentives to "take care" embedded in fixed rent contracts (or ownership status for that matter) allows producers in this type of arrangement to better respond or adapt to onset of "slow moving" disaster events like droughts or pest infestation. For example, if there is some indication of drought at the start of a season, the fixed rent farmer (or owners) would have more incentive to deal with this potential disaster event early as compared to share croppers, since in the event of a drought loss the share cropper will share the loss with the landlord anyway. This type of embedded incentive to better respond to potential disaster events also may have likely contributed to the risk smoothing effects of the fixed rent and ownership arrangements. Given the empirical observations in this study, the next step may be to re-specify some of the theoretical models of land tenure choice (such as those models akin to Ghatak and Pandey (2000)) to better reflect empirical observations from this study.

Table 3.1. Summary Statistics.

Variable	tenure	obs	Mean	Std. Dev.	Min	Max
farm size (ha)	all	2170	1.36	0.91	0.06	9.00
	fixed-renter	948	1.36	0.82	0.14	7.00
	other	74	1.14	0.65	0.40	3.00
	owner	869	1.35	0.93	0.06	7.00
	shareholder	309	1.44	1.11	0.10	9.00
yield (Kilograms/ha)	all	2170	3953.28	1654.49	41.67	11172.00
	fixed-renter	948	3918.43	1655.15	41.67	11172.00
	other	74	4398.82	1596.61	172.00	10269.20
	owner	869	4241.14	1588.46	216.00	10063.80
	shareholder	309	3082.64	1487.75	439.02	9605.00
fertilizer uses per area (fert)	all	2170	279.28	166.94	0.00	1033.33
	fixed-renter	948	251.92	152.22	0.00	847.22
	other	74	328.54	153.81	69.93	820.00
	owner	869	331.79	164.20	0.00	1033.33
	shareholder	309	198.59	167.06	0.00	938.75
labor per area (labor)	all	2170	67.95	26.82	0.00	189.39
	fixed-renter	948	70.42	26.99	0.00	189.39
	other	74	67.14	22.07	27.66	124.50
	owner	869	65.91	25.39	0.00	176.50
	shareholder	309	67.28	30.68	0.00	176.33
chemical uses per area (chem)	all	896	2.47	2.72	0.00	14.00
	fixed-renter	411	2.55	2.58	0.00	13.75
	other	29	2.09	2.27	0.00	7.69
	owner	331	2.67	2.92	0.00	13.30
	shareholder	134	1.75	2.55	0.00	14.00

Note: “other” is defined as a tenure status which farmer is the pawned-in.

Table 3.2. Distribution of parcels by tenure status 1966-2012.

Farm size (ha)	Before the 1988CARP					After the 1988CARP				
	Fixed-renter	other	owner	sharecropper	Total respondents	Fixed-renter	other	owner	sharecropper	Total respondents
0-1.5	326 (33.64)	6 (0.62)	150 (15.48)	138 (14.24)	620 (63.98)	348 (28.98)	43 (3.58)	430 (35.80)	67 (5.58)	888 (73.94)
>1.5-3	169 (17.44)	2 (0.21)	58 (5.99)	67 (6.91)	296 (30.55)	75 (6.24)	13 (1.08)	196 (16.32)	10 (0.83)	294 (24.48)
>3.0-4.5	11 (1.14)	0 (0.00)	12 (1.24)	10 (1.03)	33 (3.41)	9 (0.75)	0 (0.00)	6 (0.50)	1 (0.08)	16 (1.33)
>4.5-6	4 (0.41)	0 (0.00)	7 (0.72)	5 (0.52)	16 (1.65)	1 (0.08)	0 (0.00)	1 (0.08)	0 (0.00)	2 (0.17)
6 up	1 (0.10)	0 (0.00)	1 (0.10)	2 (0.21)	4 (0.41)	0 (0.00)	0 (0.00)	1 (0.08)	0 (0.00)	1 (0.08)
total respondents	511 (52.73)	8 (0.83)	228 (23.53)	222 (22.91)	969 (100)	433 (36.05)	56 (4.66)	634 (52.79)	78 (6.49)	1201 (100)

Notes: (1) values in brackets are percentage of total respondents. (2) “other” means a tenure status that farmer is the pawned-in.

Table 3.3. List of variables.

Variables	Definition of variables	Unit
Y	rice yield	kg/ha
X1 (fert)	total quantity of fertilizer	kg/ha
X2 (labor)	total labor input	person-day
	(sum of family, exchanged and hired labors in the growing, harvesting and threshing of rice)	
X3 (chem)	total quantity of chemical use	kg/ha
	(sum of chemical use including insecticide, herbicide and molluscicide)	
tenure variables		
Owner	1 if farmer operates the own land or hires overseer, 0 otherwise	
Sharecropper	1 if farmer pays a certain proportion of his harvest to owner, 0 otherwise	
Fixed-renter	1 if farmer pays fixed cash-rent, 0 otherwise	
Other	0 if farmer is the pawned-in and borrower, 0 otherwise	
technological change		
MV1	1 if modern rice variety is in phase 1 (1966-1975), 0 otherwise	
MV2	1 if modern rice variety is in phase 2 (1976-1985), 0 otherwise	
MV3	1 if modern rice variety is in phase 3 (1986-1995), 0 otherwise	
MV4	1 if modern rice variety is in phase 4 (1996 to present), 0 otherwise	
irrigation type		
IRR1	1 for pump, 0 otherwise	
IRR2	1 for rainfed, 0 otherwise	
IRR3	1 for irrigated, 0 otherwise	
season		
SEA1	1 for dry season, 0 for wet season	

Table 3.4. Estimated coefficients of mean, variance, skewness and kurtosis equations in farm and tenure*after1988 dummies included case.

	Mean	Robust Std. Err.	Variance	Robust Std. Err.	Skewness	Robust Std. Err.	Kurtosis	Robust Std. Err.
lnfert	0.200***	0.041	-0.545***	0.208	-1.082**	0.458	-1.089***	0.412
lnchem	0.006	0.014	0.260***	0.093	0.330*	0.188	0.519***	0.184
lnlabor	0.411***	0.066	-0.520*	0.314	-2.128***	0.673	-1.040*	0.620
Pumped	-0.110	0.067	0.635*	0.369	-0.905	0.732	1.271*	0.728
Irrigated	0.019	0.058	0.860**	0.346	0.053	0.805	1.720**	0.685
Wet season	0.021	0.177	0.122	1.094	-5.016**	2.026	3.991***	1.450
mv_1	0.000	-	0.000	-	0.000	-	-3.748	2.483
mv_2	-0.007	0.103	-2.151**	0.851	4.663**	1.979	-4.302**	1.682
mv_4	0.044	0.135	0.161	0.562	-5.735***	2.083	0.323	1.110
Fixrent	0.223**	0.089	-0.764*	0.437	-1.995**	0.952	-1.528*	0.864
Other	-0.159	0.130	-2.986***	0.946	-6.858***	1.247	-5.973***	1.871
Owner	0.186**	0.086	-1.048**	0.506	-2.175**	1.071	-2.097**	1.000
after88	0.066	0.212	-2.192	1.313	-0.117	2.080	-4.385**	2.211
Fixrent*after88	0.162	0.144	-0.105	0.773	1.786	1.762	-0.209	1.528
Other *after88	0.427**	0.190	2.192*	1.271	3.917	2.507	4.384*	2.512
Owner *after88	0.075	0.145	0.869	0.736	2.452	1.777	1.737	1.454
constant	5.593***	0.361	-62.297***	1.860	8.072**	3.674	2.211	3.115
Number of obs	761		756		398		739	
R-squared	0.567		0.959		0.783		0.306	
Root MSE	0.337		2.195		2.957		4.390	

Notes: (1) all specifications include farm and year dummy variables. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively. (2) dummy variables for rainfed environment, dry season, modern rice variety in phase 3 (MV3) and shareholder status are omitted. (3) The number of observations is not equal in this study because the second, third and four moments of error terms are in log-log form.

Table 3.5. Estimated relative risk premium by tenure types.

Tenure	Relative risk premium				
	cost of variance	cost of skewness	cost of kurtosis	total cost of risk	Difference with shareholder
1982 (n = 197)					
fixed-renter	0.1382	0.0239	0.0010	0.1631	-0.0450
owner	0.2253	0.0241	0.0011	0.2505	0.0424
shareholder	0.1834	0.0237	0.0010	0.2081	0.0000
2011 (n = 112)					
fixed-renter	0.1495	0.0016	0.0009	0.1488	-0.0636
owner	0.1491	0.0019	0.0012	0.1485	-0.0639
shareholder	0.2163	0.0057	0.0017	0.2123	0.0000

Notes: (1) values in table are calculated from simulated mean, variance, skewness and kurtosis of rice production in 2011. (2) By construction, the higher-moment calculation is based on the first moment effect (see footnote in page 12). The evaluated relative risk premium will be inaccurate if the 1^{st} moment is not significant. Due to the insignificance of "other" in the mean function, its relative risk premium of 2011 is not presented here.

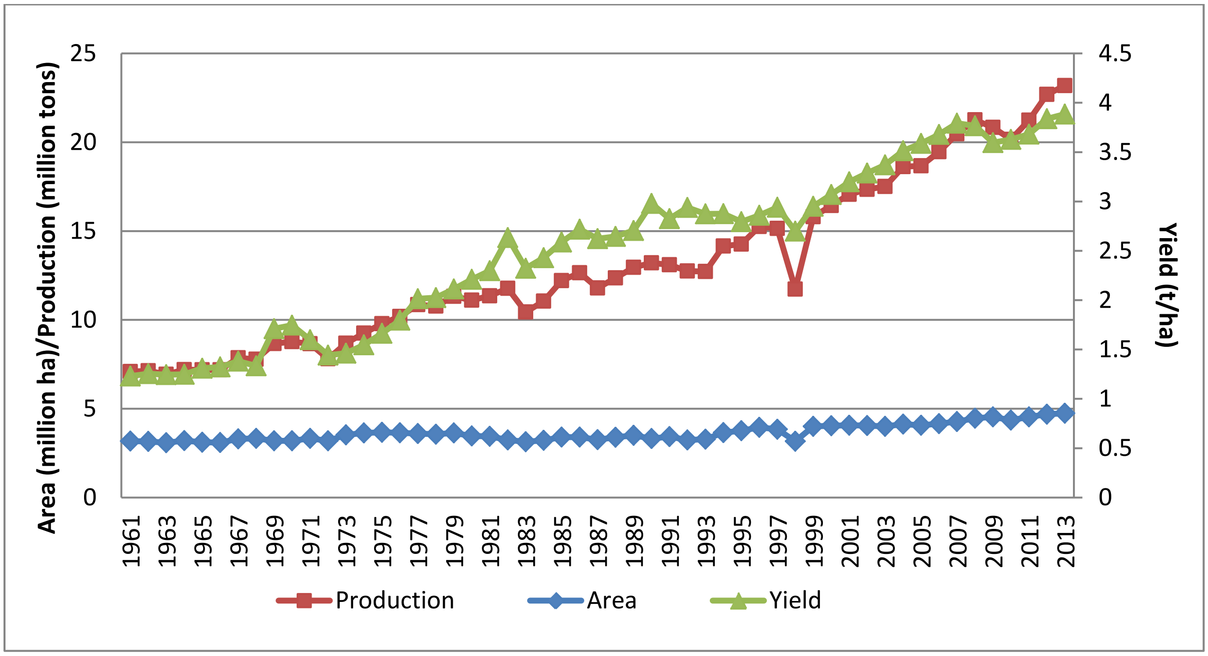


Figure 3.1

Figure 3.1. Area, paddy rice production and yield of ice (1961-2013)

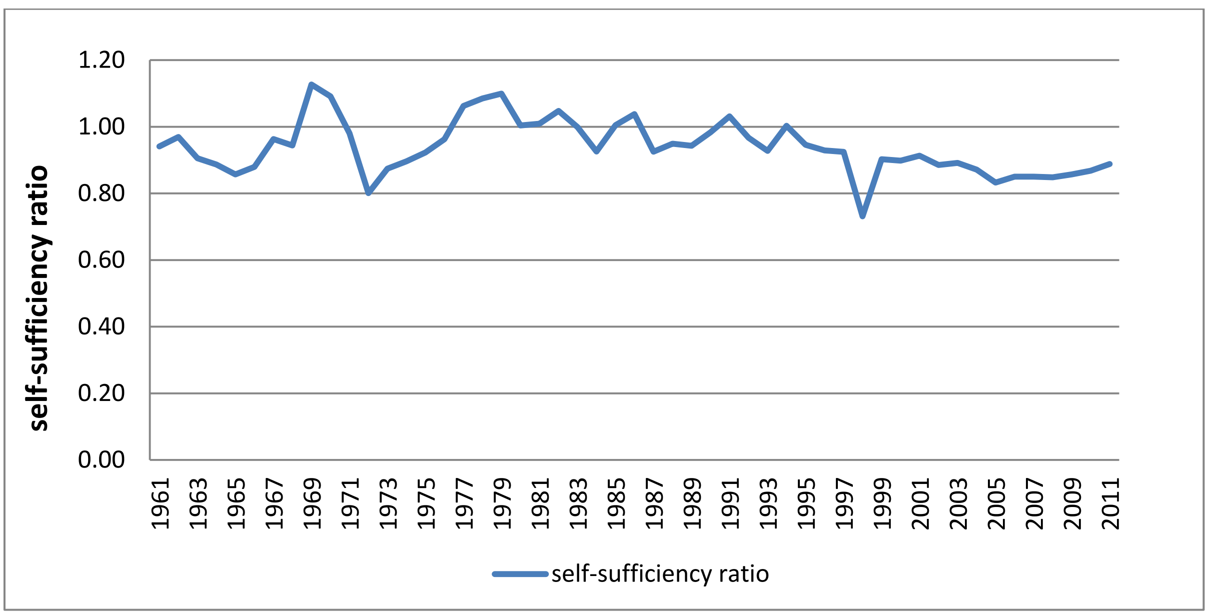


Figure 3.2

Figure 3.2. Self-sufficiency ratio of rice commodity (1961-2011).

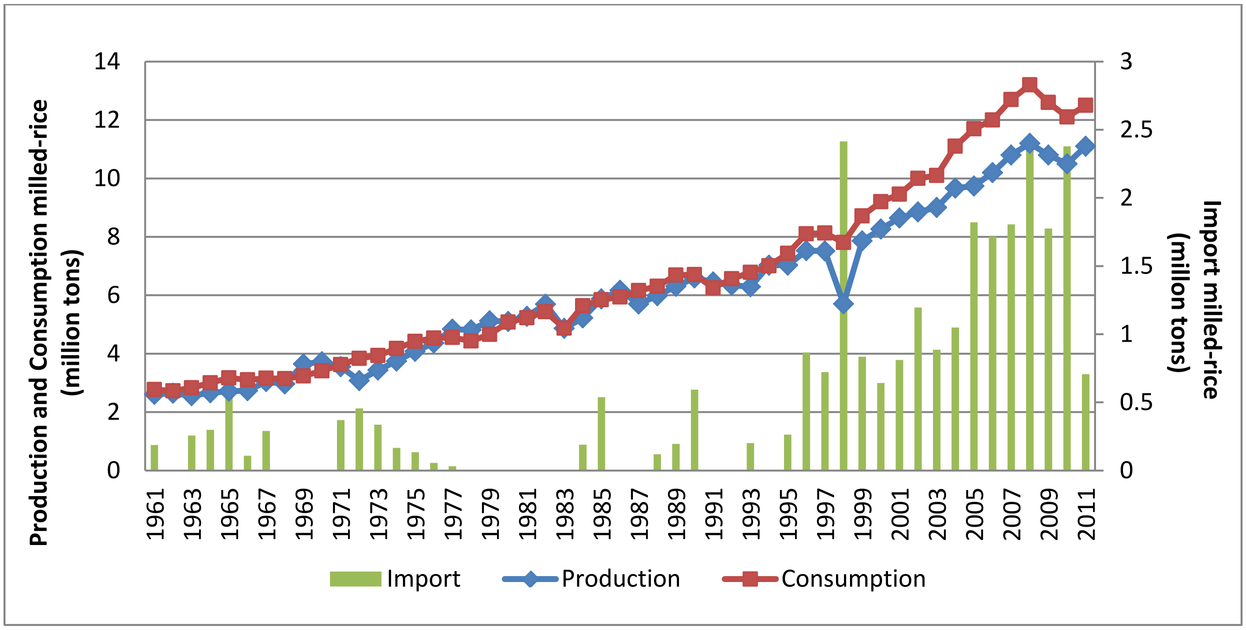
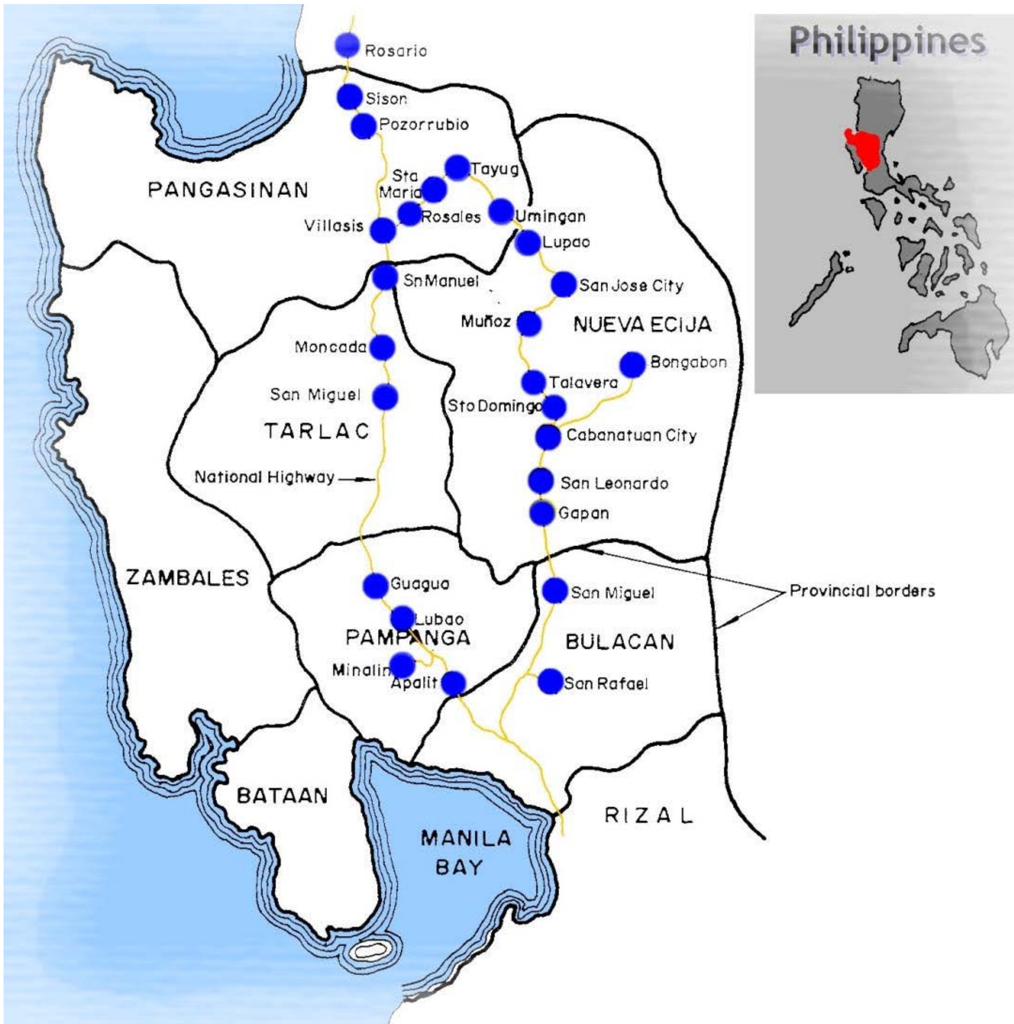


Figure 3.3

Figure 3.3. Production, consumption and import of milled rice (1961-2011).



Note: La Union province locates in the north of Pangasinan, which is not shown in the map.
Source: http://www.agribenchmark.org/fileadmin/Dateiablage/B-Cash-Crop/Projects/Rice-Initiative/Presentations-WS-130319/perspectives_rice_IRRI_130319.pdf

Figure 3.4

Figure 3.4. Surveyed area in Central Luzon Loop Survey, the Philippines.

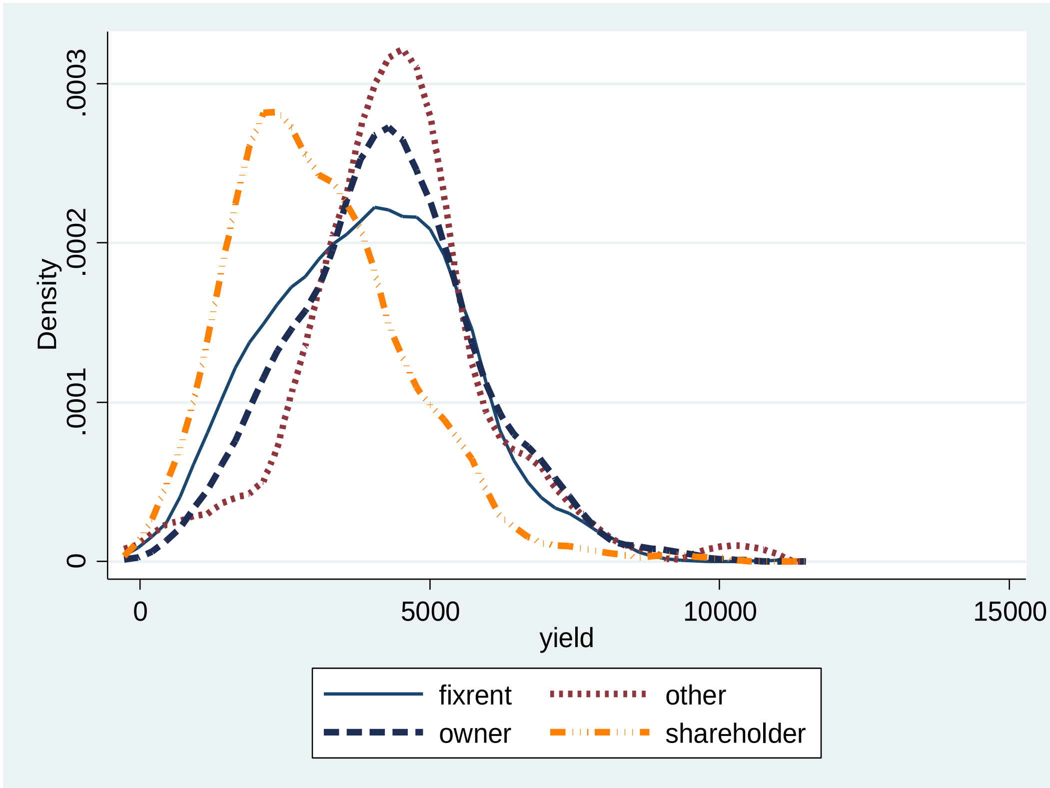


Figure 3.5

Figure 3.5. Kernel yield density parcel across tenure types (1966-2012).

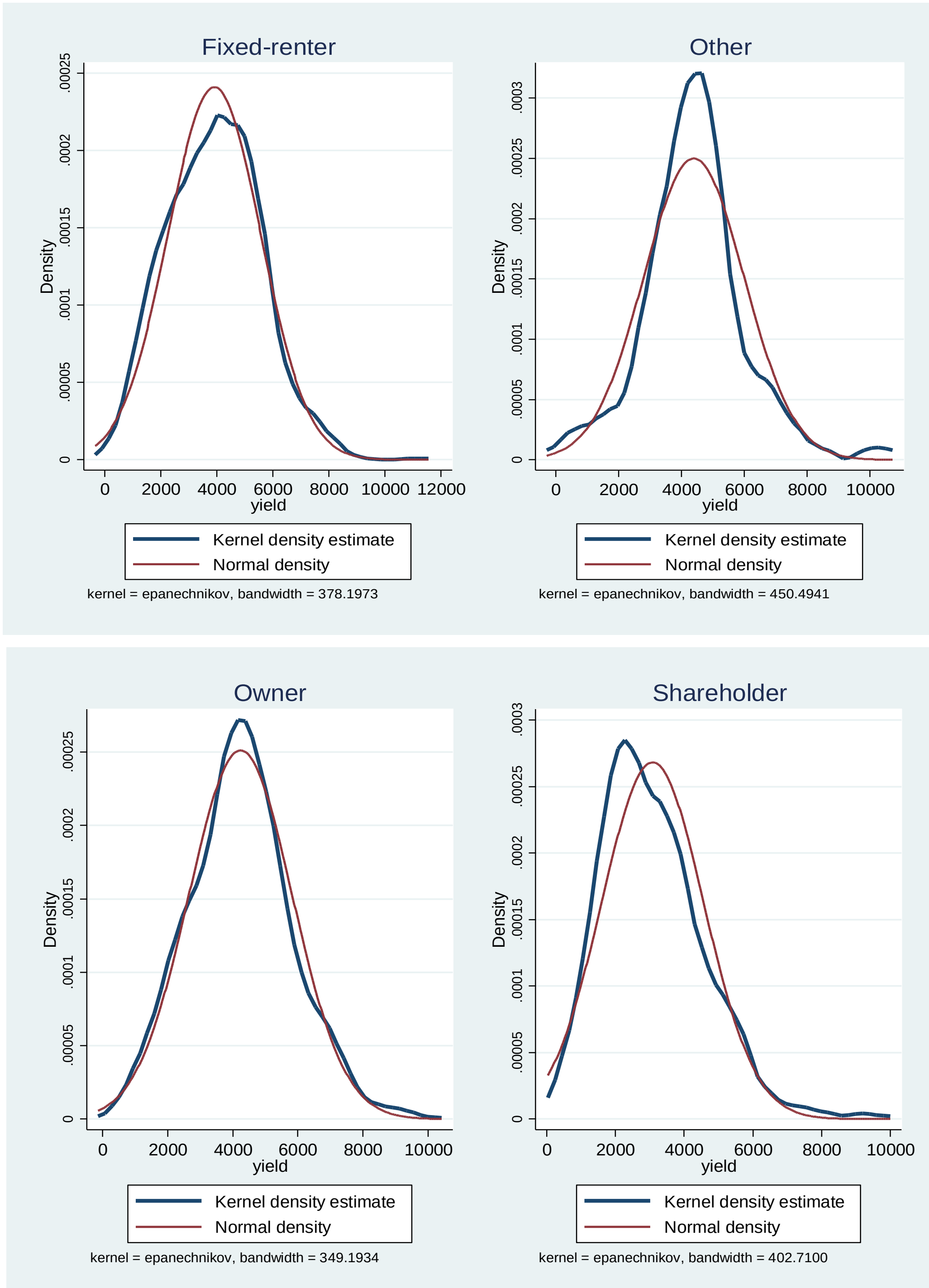


Figure 3.6

Figure 3.6. Kernel yield density compared to normal distribution across tenure types.

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CHAPTER 4

Market Integration and Price Leadership in the Low Quality Rice Export Market

4.1 Introduction

Over half of the world's population consumes rice as a major food staple (FAO, 2004). Therefore, rice plays a significant role in the food security status of rice-consuming countries, especially those that are developing nations. Recent research has paid attention to imperfect competition in the international rice market because of the domination by a few major rice producing/exporting countries, and the wide-ranging global price effects of the government policies in these countries. In particular, global rice exports are highly concentrated in the following countries – Thailand (27%), Vietnam (17%), India (15%), USA (11%) and Pakistan (9%).[29] These top rice exporting countries account for nearly 80 percent of market share in international rice trade (*Rice yearbook*, 2013). Hence, domestic agricultural and trade policies in these countries typically have profound effects on world rice prices.

The importance of agricultural and trade policies on world rice prices was clearly demonstrated during the food price crisis period from 2007 to 2008. Many rice exporting countries attempted to stabilize domestic rice prices during this period. For instance, the Vietnamese government applied rice export quotas, and the Indian government implemented

[29] Figures in parentheses are average total export market shares over 20 years as calculated by the author.

an export ban on non-basmati rice during this period. Arguably, these domestic policies have influenced the magnitude and duration of the rice price surge during the crisis. From January 2004 to May 2008, for example, the International Food Policy Research Institute (IFPRI) reported that rice prices increased by 224 percent, wheat prices were up 108 percent, and corn went up by 89 percent.

The food price surge widely impacted both domestic and international markets, regardless of size and wealth of nations. Therefore, given the price linkages among nations, analysis of price transmission and market integration have been critically important topics that economists and policymakers have examined. A better understanding of price movements, especially as it relates to how rice export prices react to "shocks" in other countries (i.e. due to a drastic change in these countries' rice policies), would enable rice traders and importers to more efficiently manage local inventories and marketing plans. For example, state importing agencies utilize these kinds of information to determine when and where to purchase additional stocks for their reserves; as well as when to optimally release stocks in the local markets.[30] Knowing which countries' export price significantly influence export prices in a specific rice market segment is also important for importing countries when assessing which countries' prices to monitor and to assess in terms of influencing domestic prices. In addition, for exporting countries that set minimum export prices, knowing export

[30] State importing agencies are government agencies that are tasked to assure adequate domestic rice supply in rice importing countries and to time the release of imported rice in the domestic market for domestic price stabilization purposes. If an importing country notices an increase in rice export prices for an exporting country that has been shown to strongly influence other exporting countries' prices, then this may be a signal for the importing country that overall prices in the market might increase and it is time to buy from other exporting countries where prices have not yet started to rise (or from a country where rice export prices are not strongly integrated/interdependent).

price movements and relationships are keys in establishing a minimum export price that would be competitive in the market.

Given the importance of recognizing rice export price movements and its relationships to one another, there have been a number of studies that analyze the different price relationships in different rice quality segments (i.e. high quality or low quality market segments). Early work by Nielsen and Yu (2002) apply Computable General Equilibrium (CGE) model to analyze rice importing countries' elasticities of substitution with respect to different country sources. At the initial step, the authors determines whether markets are integrated (i.e. rice can be characterized as a homogeneous good) by testing cointegration of export prices in several rice markets segmented by type and quality.

In addition, Jamora and Cramon-Taubadel (2012) treat rice as a heterogeneous good and employ multivariate cointegration analysis by rice quality cluster. The study provides evidence that long run equilibrium relations exist in the low and high quality rice clusters and the world rice market is highly segmented. Based on the results of their study, Jamora and Cramon-Taubadel (2012) suggest that many international rice prices are possible candidates to be used as a world benchmark price.

Both of the studies mentioned above determine price leadership status of rice exporting countries by following Le Goulven's (1999) approach. In general, Nielsen and Yu (2002) show that Thailand dominates and gains as a long run price leader in the international rice market. Additional findings from Jamora et al. (2013) point to Thai 25% brokens and Pakistan 25% brokens as long run price leaders, while Vietnam 25% brokens tend to be a price follower in the low quality rice export sector.

The objective of this chapter is to carefully examine the dynamics of rice export prices in the low quality rice sector (i.e. 25% broken rice). We particularly focus on four key exporting countries in the low quality market segment: Thailand, India, Vietnam, and Pakistan. As discussed above, there have been a few of studies that examined rice price relationships in different quality segments, but none have focused explicitly on the low quality market and none have explored the role of India in this market. Including India in the analysis of dynamic price relationships is important because it has become one of the largest producer and consumer of rice in the world. Moreover, India is one of the major suppliers of low quality long grain rice (as well as basmati rice) globally.

Our study also contributes to the literature by being one of the first to utilize a weekly rice price series (from 1996 to 2013) in the analysis of dynamic rice price relationships, instead of a monthly series. This significantly increases the number of observations in our data set and enables us to have a more detailed understanding of the price relationships in the low quality rice market. Moreover, the rich weekly series allows us to analyze how shocks in one country may affect price co-movement. In particular, we examine "shocks" related to changes in domestic and/or trade policies in major exporting countries, such as the implementation of an export ban for Indian non-basmati rice in 2007.

4.2 Background of the rice export market[31]

4.2.1 Global Rice Situation

More than 60 percent of global rice producing country is in Asia (see Figure 4.1). In 2013, China was the world's largest rice producers at 143 million tons with 30.3 percent of world production. India, serving as the world's second largest rice producer, produced at 105.24 million tons and Indonesia produced at 36.55 million tons. Rice production from India and Pakistan accounted for 22.3% and 7.7% of global production, respectively. According to FAO (1996-2013), Vietnam had the highest yields among major rice producers with an average of around 5 tons/hectare, while mean yields in the other major rice exporting countries are 3 tons/hectare.

On the export side, rice exports from India, Pakistan, Thailand, the US, and Vietnam accounts for approximately 80 percent of world trade. Thailand has been considered the largest rice exporting country until 2011 despite its low average yields from 1996 to 2013 (i.e. approximately 2.8 tons/hectare). But Thai rice exports decreased by 35 percent in 2012 from its 2011 export volume high of 10.6 million tons. As such, Figure 4.2 shows that Thailand also lost the "world's top rice exporter" status to India in 2012. India exported 10.3 million tons, while Thailand exported about 6.5 million tons that year. Vietnam also exported more than Thailand in 2012 selling 7.7 million tons. In 2013, India and Vietnam remained the first two leading rice exporting countries for the second consecutive year.

[31] In this paper, rice generally refers to milled rice (HS code: 100630), except in the discussion on yield, which refers to paddy rice production divided by harvested area.

Mohanty (2013) discussed three reasons why India recently took the crown as the world's top rice exporter. The three factors are: (i) depreciation in the exchange rate (Indian rupee), (ii) India dismissed the export ban on non-basmati rice in late 2011, and (iii) the positive impacts from Thailand's implementation of its mortgage scheme[32]. As a consequence of these factors, Indian broken and parboiled rice exports overtook Thailand as the world's top rice exporter.

On the import side, majority of rice importers are in Africa (i.e., Nigeria, Cote d'Ivoire and Senegal) and the Middle-East (i.e., Iran, Iraq and Saudi Arabia). In 2013, China became the top importer in the world, overtaking Nigeria who was the top importer from 2010 to 2012 (See Figure 4.3). Chinese imports mainly came from Vietnam and Pakistan, comprising 24 and 13 percent of total import value. In the near future, FAO projects that rice imports of African countries and China will continue to rise because of the expected increase in consumption in these countries and the likely higher domestic rice prices in China.

4.2.2 The Low Quality Rice Market

A recent study that examined the extent of integration in the international rice market has found that this market has high levels of segmentation (Jamora and Cramon-Taubadel, 2013). FAO segments the international rice market and trade based on one of three criteria (Calpe, 2004). The four types of rice classified by variety[33] consist of indica (long-grain

[32] The rice mortgage scheme is a price support program that the Thai government uses to assist farmers by pledging paddy rice into participating mills' warehouses at higher market price.
[33] World rice trade consists of more than 75 percent indica, about 11 percent japonica, nearly 9 percent aromatic rice and the rest glutinous rice (Childs & Hoffman, 1999).

rice), japonica (medium-grain), aromatic[34], and glutinous rice. In addition, percentage of broken kernels is used as a quality criterion for market segmentation. For instance, long-grain 5% broken rice is considered high quality rice, consisting of 95% whole grain and 5% broken rice. Rice with 10%-15% broken kernels is considered medium quality, and rice with more than 25% broken kernels is considered low quality. Moreover, rice export markets can be distinguished by the degree of processing it has undergone and are classified as paddy, husked, milled, and parboiled rice.

Although high quality rice accounts for 75 percent of total trade, the low quality rice segment is still an important part of the international market. Firstly, most demand for this type of rice comes from low-income countries in Africa and some Asian countries (e.g., Bangladesh, Indonesia) because price of this rice type is cheaper than high quality or premium rice. Secondly, rice production in some countries is insufficient to meet domestic consumption, like in Indonesia and the Philippines, due to increases in population and natural disasters (i.e. floods). Lastly, consumers in certain countries still prefer this rice type. For example, consumers in West and Central African countries -- such as Benin, Burkina Faso, Cameroon, Cote d'Ivoire, Guinea, Mali, Niger and Sierra Leone -- prefer 25% broken white rice (Rutsaert, Demont and Verbeke, 2013). Additionally, their governments offer price support through lower taxes on broken rice. For instance, the government of Senegal provides a 13% maximum fixed tax (Jamora and Cramon-Taubadel, 2013).

[34] The well-known aromatic rice is basmati rice exported by India and Pakistan as well as jasmine rice produced by Thailand.

In this study, low quality rice is defined as 25% broken long-grain white rice. Since most of the rice exported by the United States is high quality, we only consider the four other key exporters in the low quality rice market –Thailand, Vietnam, Pakistan and India. According to Childs and Hoffman (1999), Thailand exports high, medium, and low quality rice. Generally, Vietnam sells medium and low quality in rice market.[35] Except for basmati and some high quality Indian parboiled, India and Pakistan also export low grade rice to most other countries.

In these major exporting countries, the low quality rice segment comprises a major proportion of their rice trade. Vietnam exported less in high quality rice, but more in low quality rice. In comparison with 2012 figures,[36] the share of export volume for Vietnamese low quality rice increased by 6 percent in 2013, whereas the share of export volume for high quality rice decreased by 10 percent in 2013. This implies that low quality 25% broken rice exports are on an upward trend in Vietnam. Note that Vietnam's low quality rice is generally exported to the following regions: Asia (60%), Africa (39%), the U.S. (1.04%) and the EU (0.3%).

In general, there are two types of Thai white rice classified by quality. That is white rice with different percentages of broken kernels and white rice broken with different grades (e.g., white rice broken grade A). Thailand's rice export encountered a downward trend after

[35] In 2013, Vietnam's rice export accounted for 36 percent high quality (i.e., 5% broken), followed by 20 percent medium quality (i.e., 10% and 15% broken) and almost 18 percent low quality (i.e., 25% broken).
[36] These figures are calculated by using Vietnamese white rice export volume, which consists of white rice 5%, 10%, 15%, 25%, and 100%. The data is compiled by Trade, General Department of Vietnam Customs and Vietnam Food Association.

2011. Total rice export volume[37] decreased from 4.5 million tons in 2011 to 2.6 million tons in 2012. This is about 43 percent less in volume relative to exports of 2011. Specifically, in 2012, the proportion of 25% broken rice to the total rice export decreased by 93%, while the share of export volume for lower quality rice (i.e. 35% broken) increased by 18% as compared to 2011.

India and Pakistan are the world's leading producers and exporters of basmati and non-basmati rice. The market destinations of both exporters are actually identical: Iran, Iraq, and Saudi Arabia. Pakistan's non-basmati markets include Afghanistan, China, Indonesia, Kenya and Malaysia. Top Indian non-basmati export markets consist of Senegal, Cote d'Ivoire and Benin. According to USDA (2013), rice trade in India and Pakistan is carried out by the private sector, such as the Food Corporation of India. Therefore, their low quality rice export quantities and values are not officially reported; as a result, we cannot compare the market shares of this kind of rice in the international market.

4.3 Empirical Approach

4.3.1 Unit roots Tests

When we deal with time series data (as is the case in this study where we look at time series of prices), an essential first step is to test whether these data are stationary or not. In other words, one wants to check whether the series is invariant with respect to time, implying that its mean, variance and covariance are constant. This is important because inclusion of

[37] Total Thai export volumes of white rice consists of white rice 5%, 10%, 15%, 25%, 35%, 100% , white rice broken rice grade A. The data is provided by Thai Rice Exporters Associations.

non-stationary variables in a regression leads to an estimation problem called "spurious regression". With this problem, regression results typically have high R^2 and significant test statistics, even though it has no economic meaning (and therefore may give misleading inferences).

One of the procedures to verify existence of a non-stationary process is the Augmented Dickey-Fuller (ADF) test. This test has the advantage of allowing for a higher order of autoregressive process in order to deal with serial correlation. For instance, consider an AR(*k*) process in single equation with drift and time trend, where *k* is the appropriate lag order[38]:

(1) $$p_t = \mu + \delta t + \phi_1 p_{t-1} + \phi_2 p_{t-2} + \ldots + \phi_k p_{t-k} + \varepsilon_t\,, \qquad \text{or}$$

(2) $$\Delta p_t = \mu + \delta t + \left(\sum_{j=1}^{k} \phi_j - 1\right) p_{t-1} + \sum_{i=1}^{k-1} \phi_i \Delta p_{t-i} + \varepsilon_t\,.$$

Given $\gamma = (\sum_{j=1}^{k} \phi_j - 1) = 0$, the null hypothesis of having a unit root is when $\gamma = 0$ or $\sum_{j=1}^{k} \phi_j = 1$ (i.e., non-stationary). If the t-statistic of estimated γ exceeds the critical values, we are able to reject H_0, meaning that the series is integrated of order one. According to Perron's study (1989), the unit root test ignoring for structural break may induce a biased conclusion that the series has a unit root. As a consequence, the ADF outcome may be problematic. Andrews and Zivot (1992) propose a modified ADF test with a single

[38] We select the appropriate lag length by using an information criterion to verify that an error term follows a white noise process.

breakpoint by incorporating a dummy variable under the null hypothesis of a unit root with break.

Moreover, the Perron-Vogelsang and Clemente-Moñés-Reyes unit root tests offer two additional models: (1) an additive outliers (AO) model, which captures a sudden change in the mean of a series; and (2) an innovational outliers (IO) model, which allows for a gradual shift in the mean of the series (Baum, 2005). The Clemente-Moñés-Reyes test may perform better than Zivot-Andrews and Perron-Vogelsang unit root tests, because this procedure allows for double structural breaks on the data series. If these additional tests show no evidence of a structural break, the ADF tests can be considered valid.

4.3.2 The Vector Autoregressive Model and the Error Correction Model

We start our analysis with a Vector Autoregressive (VAR) model, which is a system of equations introduced by Sims (1980). This technique is applied to identify the joint dynamic relationship of a set of variables. The VAR system consists of a group of *n* variables, each of which is a linear combination of *k* lags of itself and of all of the other *n*-1 variables, as well as a white noise error term:

(3) $$p_t = \eta + A_1 p_{t-1} + A_2 p_{t-2} + ... + A_k p_{t-k} + \varepsilon_t .$$

where p_t is a *n x 1* vector of price variables, η is a *n x 1* vector of constants, and A_1 to A_k are *n x n* matrices of parameters. ε_t is a *n x 1* vector of disturbances which has zero mean, with i.i.d normally distributed covariance matrix of $\sum$ over time.

This study analyzes the joint behavior of four rice export price series in the low quality rice market segment. In equation (3), for example, Thai export price series (p_{1t}) is a function of (i) its own past price values up to *k* lags, (ii) the past values of the export price of the other three countries up to *k* lags, a constant term (η_1), and (iii) an error term (ε_{1t}) which is not related to the other three error terms associated with the other price series.

When we subtract p_{t-1} from both sides of equation and rearrange terms, we can rewrite (3) into the Vector Error Correction (VEC) form:

(4) $$\Delta p_t = \eta + (A_1 + A_2 + .. + A_k - I)p_{t-1} - A_2\Delta p_{t-1} - A_3\Delta p_{t-2} - ... - A_k\Delta p_{t-k-1} + \varepsilon_t$$

(5) $$\Delta p_t = \eta + \prod p_{t-1} + \sum_{i=1}^{k-1}\Gamma_i \Delta p_{t-i} + \varepsilon_t$$

where $\prod = \sum_{j=1}^{k} A_j - I$ which are long run impact matrices, $\Gamma_i = -\sum_{j=i+1}^{k} A_j$ which are the short run coefficient matrices for *i* = 2,…,*k*-1 and I is a *n x n* identity matrix.

Let rank ($\prod$) = r as the number of linearly independent cointegrating vectors. There are 3 cases for estimating the parameters. Firstly, if r = n, the price variables are stationary in levels, and a VAR in levels (equation 3) is appropriate. Secondly, if r = 0, there are no cointegrating relationships among the elements of p_t (i.e., $\prod$ does not contain long run information), and a VAR in the first difference (i.e., the VEC model in equation 4) is suitable. Lastly, when 0 < r < n, there exists *r* stationary linear combinations of p_t. In this case, a VAR in the first difference is mis-specified if there are long run relationships because $\prod p_{t-1}$ term does not appear (Engle and Granger, 1987). To account for the long-run relationships, $\prod$ can be expressed as $\prod = \alpha\beta'$ composed of the adjustment coefficients (α) and the cointegrating vector (β).

The VEC model outperforms the standard VAR model, which only relates the current values of a set of prices to their lagged values. In this model, the long run price relationship (β) is separated from the short run dynamics (α). This is to ensure that any deviations from the long run equilibrium are corrected and are only temporary. Moreover, we can answer our research questions regarding price leadership in the low quality rice market by imposing restrictions on these two parameters.

The cointegrating vector (β) describes how one rice export price reacts to changes in the others in the long run. When one transform the price series to logarithms, then β can be interpreted as the long run elasticity of price transmission. The value of β indicates the long-run percentage point change in country 1's export price in response to one percent change in the export price of country 2. The adjustment parameters (α) indicate the speed of the short run response toward deviation from long run equilibrium (i.e. a low coefficient means that there is slow adjustment to correct disequilibrium).

In a simple bivariate case, α_1 and α_2 must have opposite signs in order to ensure that an explosive equilibrium error does not occur if the two prices are cointegrated. Intuitively, if the growth in average prices for country 1 is too large relative to that of country 2, the growth in average prices for country 1 should fall back to country 2's level at the same time that price growth from country 2 increases (i.e., negative in α_1 and positive in α_2). In the multivariate case, the adjustment coefficient (α) for each price series is relevant to all parameters when disequilibrium is corrected in response to any external shocks (Johansen, 1995).

4.3.3 Hypothesis test for price leadership

We assess a particular country's role as a price leader within a market by testing restrictions on the cointegration matrix (β) and the speed of adjustment matrix (α). First, a test for long-run exclusion is conducted, where one examines whether the column i in the matrix of long-run coefficients are zeros (i.e. $H_0 : \beta_{ij} = 0$). The long-run exclusion test indicates whether a cointegrating relationship is present. Second, we examine whether a country's price is weakly exogenous with regards to the parameters of a particular cointegrating vector, by testing whether the row parameters in the speed of adjustment matrix are all zeros for a particular row i (i.e. $H_0 : \alpha_{ij} = 0$).

Four possible cases are used to examine long-run price leadership in a specific rice market segment. Le Goulven (1999) defined price leadership status in accordance to hypothesis tests on the following combinations of parameters:

(i) $\beta \neq 0, \alpha = 0$: price leader

(ii) $\beta \neq 0, \alpha \neq 0$: price follower

(iii) $\beta = 0, \alpha = 0$: segmented market

(iv) $\beta = 0, \alpha \neq 0$: regulator market

We modify Harris (1995) to illustrate to further explain the testing process above. Suppose that there are 3 cointegrating vectors (j = 3)[39] with 2 lag orders (k = 2) for 4 export price series (n = 4), the dynamic relationships in matrices can be shown for the four main rice exporting countries as follows:

$$(6)\qquad \begin{bmatrix} \Delta p_{1t} \\ \Delta p_{2t} \\ \Delta p_{3t} \\ \Delta p_{4t} \end{bmatrix} = \Gamma_1 \begin{bmatrix} \Delta p_{1t-1} \\ \Delta p_{2t-1} \\ \Delta p_{3t-1} \\ \Delta p_{4t-1} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} & \beta_{41} \\ \beta_{12} & \beta_{22} & \beta_{32} & \beta_{42} \\ \beta_{13} & \beta_{23} & \beta_{33} & \beta_{43} \end{bmatrix} \begin{bmatrix} p_{1t-1} \\ p_{2t-1} \\ p_{3t-1} \\ p_{4t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}$$

where p_i is 25% broken rice export price for country i (i= 1,…,4), where p_1 = Thai, p_2 = Vietnam, p_3 = Pakistan and p_4 = India, respectively.

If India is a price leader in this market, then the Indian price series should be non-excludable and weakly exogenous. The first requirement is that the Indian price series (p_{4t-1}) should have a long-run relationship with the other countries' export prices (i.e. reject $H_0 : \beta_{4j} = 0$). In addition, India's price should not respond to previous price deviations from long-run equilibrium in other countries (i.e. fail to reject $H_0 : \alpha_{4j} = 0$). Hence, a price leader in this context is where its own price movements have a long-run relationship with other countries' prices, but it does not strongly respond to other countries' short-run deviations from equilibrium. On the other hand, a price follower also has a long-run relationship with other countries' prices, and it does respond to other countries' short-run price deviations from equilibrium. For the two remaining possible country status (e.g., segmented and regulator),

[39] There exists up to (n-1) cointegrating relations among n variables. Therefore, in our empirical application below with four price series for each low the model has at most 3 cointegrating vectors.

there is no long-run relationship between prices of these country types and the other export prices. A country with segmented status suggest that their export prices also do not respond to short-run price deviations in other countries, while a country in a regulator status do respond.

A likelihood ratio test is used for the procedure described above. Specifically, the likelihood ratio test for coefficient restrictions

($\beta_i = 0$ or $\alpha_i = 0$) can be computed as:

(7) $$LR = N\left[\sum_{i=1}^{r}(\ln(1-\lambda_{unrestricted,i})/\ln(1-\lambda_{restricted,i}))\right]$$

where N is the total number of observations used to estimate $\prod$ matrix, λ are eigenvalues ordered from large to small, *r* is the number of cointegrating vectors. The test statistic is Chi-squared (χ^2) distributed with degrees of freedom equal to the number of zero restrictions on each test. We next compare the likelihood ratio to the critical value, and reject the null hypothesis if this ratio is greater than the critical value.

4.4 Data Description

The data set used in this study includes 902 weekly observations of free on board (FOB) prices from January 1996 through April 2013. These prices are for low quality rice classified as 25% brokens, and data are available for the following countries: Thailand, Vietnam, Pakistan and India. The notations TH, VT, PAK and INDIA used below are logarithmic transformed price series for Thailand, Vietnam, Pakistan and India, and this convention is used throughout the remainder of this paper. The proprietary data were obtained from the International Rice Research Institute (IRRI). IRRI obtained the data set through its collaboration with a rice trading company based in Singapore that monitors weekly rice export prices.

A number of weekly prices are missing for each of the low quality rice exporting countries considered. There are 12 missing observations for the Thai price series, 68 for the Vietnam series and 43 for the Pakistan series accounting for 1.3%, 7.5% and 4.8% of total observations, respectively. As expected, 205 price observations are missing for India (or 22.7% of total observations) from October 2007 to September 2011due to the non-basmati rice export ban in this period.

Therefore, our study divides the data into 2 major cases: Subsample 1(from Jan. 5, 1996 to Oct. 5, 2007), which was the period before Indian rice export ban and Subsample 3 (from Sept. 16, 2011 to April 12, 2013), when India lifted the non-basmati export ban. Analyzing the data based on these 2 sub-periods allows us to more carefully investigate Indian roles and how India's policy affected the price linkages in the low quality rice export market.[40] In order to obtain a smooth data set, the truly missing data (i.e., not due to an actual export ban) are replaced using linear interpolation.[41] To check validity, we found that our interpolated data (when aggregated monthly) is similar to the FAO monthly data (i.e. correlation coefficients are roughly over 90%).

Table 4.1 presents the descriptive statistics for the data considered in our analysis. The mean and standard deviation values of Thailand 25% broken rice export prices are the

[40] Subsample 2 was the period that India excluded the market (from Oct. 12, 2007 to Sept. 9, 2011).
[41] We also interpolate the price series using cubic interpolation and then compared the interpolated data with the FAO monthly data. The finding shows that the linearly interpolated price series is a better fit with the actual data than the alternative cubic interpolation approach.

highest in both Subsample 1 and Subsample 3. The average coefficient of variation of export prices is approximately 20 percent before India's export ban implemented. In the last subsample, when India rejoined the market, mean prices for the 25% broken rice market are still high, but the volatility of prices seems to be lower when we compare with C.V ratios in the period of food price crisis. This implies that India could play role in stabilizing price in the low quality rice export market. In Figure 4.4, the plotting data shows that price movements in this market have similar patterns.

4.5 Empirical Results

4.5.1 Unit roots and Cointegration tests

To assess stationarity in our time series data, we test for unit root with and without structural change(s). We adopt the Clemente-Moñés-Reyes test allowing for a single breakpoint for the full sample with three countries. As we expected, the time of structural changes are detected during the 2008 food crisis for Thailand, Vietnam and Pakistan price series (See Table 4.2, bottom panel).[42] Test statistics suggests that all of the countries' price series are non-stationary in levels. But those series are stationary in the first differenced data. Specifically, the null hypothesis of having a unit root with one break cannot be rejected in levels, but there is evidence that there are no unit roots in the first differenced series.

[42] We also test Clemente-Moñés-Reyes unit root with two breakpoints, but we can detect only one structural change. All countries' price changes were explicitly noticed during food price crisis except for India, because India exited the rice export market.

We also proceeded to test unit root by using the Augmented Dickey-Fuller (ADF)[43] assuming that there are not structural breaks. The test statistics fail to reject the null hypothesis that the rice price series in each country has a unit root when we consider price levels. But the ADF test suggests that this null hypothesis can be rejected at the 5% level for the first differenced prices (i.e., logged price ratios). This implies that all prices are non-stationary in levels, but stationary in the first differences of prices. Therefore, all unit root tests (with or without a structural break) suggest that the price series for all the countries are integrated of order 1.

In this study, the optimal lag selection is based upon the Akaike Information Criterion (AIC).[44] The Johansen's (1995) trace tests are used to determine the number of cointegration ranks for the four price series as reported in Table 4.3.[45] For the bivariate case, we examine each pair of price relationships. Most pairwise prices have one co-integrating equation for Subsample 1, while there is only one long-run price relationship between Pakistan/India for Subsample 3. For the multivariate case, the trace tests show three cointegrating vectors for Subsample 1, and two cointegrating vectors for Subsample 3. In other words, there exist three long run relationships before India's exit and two long run price equilibriums after India's return.

[43] The KPSS test with a null hypothesis of stationarity is conducted as a confirmatory analysis. The hypothesis testing results are consistent with the ADF test, which four export prices are nonstationary in logged levels, but stationary in the first differences of each price series.

[44] The choice of lag length criteria consists of the log of the likelihood function (LL); a likelihood ratio test; Akaike's final prediction error (FPE); Akaike's information criterion (AIC), Hannan and Quinn's information criterion (HQIC), and Schwarz's Bayesian information criterion (SBIC). We apply lag lengths by AIC for the ADF and Johansen cointegration test due to the consistency of criteria and residual autocorrelation test.

[45] For sub-sample 2, none of pairwise shows cointegration relationship in both bivariate case and multivariate case.

Furthermore, we assess the validity of our VAR/VEC model. The misspecification tests of the residuals are presented in Table 4.4. Autocorrelation is tested with a Lagrange multiplier test and we cannot reject the null of no autocorrelation at the 5% level. In addition, we find that the null hypothesis of normality is strongly rejected by the Jarque-Bera test. The mean residuals from estimated VECM are zero with finite variance. According to Gonzalo (1994), the non-normality assumption is not a severe problem that leads to unbiased estimation in Johansen cointegration tests. As long as the errors are independently and identically distributed with zero mean and finite variance, the parameter estimates are still consistent, but they may not be as efficient (StataCorp., 2013).

4.5.2 Market Integration Results

4.5.2.1 Bivariate Cointegration Analysis

According to the Johansen's test results, a VEC model is more appropriate than a VAR model because of the stationarity in the first-differences of nonstationary price series and the existence of cointegration. The VEC estimations for the bivariate case are shown in Table 4.5.1. The bivariate test results reflect the strong interdependence of 25% broken rice prices among four countries. The equilibrium relationship can be written in terms of a linear combination of prices and an equilibrium error term (also called perturbation). This error term is expected to be zero in the long run, because each country's price will revert to the equilibrium level (with the speed of adjustment; $\hat{\alpha}$) in response to any exogenous shocks in the other countries' prices.

For Subsample 1, each pair of price has a single cointegrating vector (i.e., equation 8-13). The long run elasticities ($\hat{\beta}$) above suggest that changes in Thai prices tend to move in the same direction of Vietnam' and Pakistan' prices. For example, the long run elasticity of Thailand and Vietnam is 1.089 implying that a one percent increase in Vietnam price brings about a 1.089 percent increases in Thai price). The magnitude of the long run effect of Pakistani price on Thai price is larger than the effect on Vietnam's price. A one percent increase in Pakistan's price, for example, will lead to price increases in Thailand and Vietnam amounting to 1.093 and 0.973 percent, respectively.

(8) $p_{TH} = 1.089 p_{VT} - 0.425$

(9) $p_{TH} = 1.089 p_{VT} - 0.425$

(10) $p_{TH} = 0.847 p_{INDIA} + 0.821$

(11) $p_{VT} = 0.973 p_{PAK} + 0.146$

(12) $p_{VT} = 0.679 p_{INDIA} + 1.662$

(13) $p_{PAK} = 0.810 p_{INDIA} + 0.959$

(14) $p_{PAK} = -6.257 p_{INDIA} + 43.147$

The speed of adjustment parameters (α) measure the response of prices to deviations from the long-run trend. A slower speed of adjustment (i.e., if the value of the coefficient is close to zero) means that the price series requires a longer time to revert to its long run relationship after the shock. As reported in Table 4.5.1, Thailand has the fastest speed of short-run price adjustment, when the other two countries' prices change. In other words, the time needed to return to one-half of its initial value for Thailand in response to a price change from one country is small. For instance, on average the Thai price adjustment requires 15 weeks to correct 4.6% of any deviation from the long-run trend (i.e. the half-life[46] of a particular shock is nearly four months for Thailand), while Vietnam price needs 17 weeks to adjust 3.9% price deviation from the long run equilibrium.

In addition, we also observe that India's role emerging in this segmented market. That is, all countries have long-run price relationship with India, but their speed of adjustment coefficient ($\hat{\alpha}_1$) is very small and insignificant. For instance, Vietnam's and Pakistan's prices do not adjust to any shocks from India. Although price pairwise of Thailand-India for subsample 1 (in equation 10) and Pakistan-India price for Subsample 3 have a long-run relation (in equation 14), the estimates of α have unexpected signs. Such coefficients (α) show the same direction of adjustment which indicates the presence of explosive equilibrium errors.

Nevertheless, one shortcoming of using a bivariate analysis is that it might provide misleading inferences about price relationships due to high price correlations (particularly in such locations as Thailand and Vietnam) (Yavapolkul, Gopinath and Gulati, 2006). Therefore, examining cointegration using a multivariate model to further investigate the long run price association in the low quality rice market may be useful.

[46] Half-life is the time needed in order to eliminate 50% of the deviation (= $\frac{\ln(0.5)}{\ln(1+\alpha)}$).

4.5.2.2 Multivariate Cointegration Analysis

The analysis of price co-movement is more complex when there are more than one cointegrating vectors because of no unique equilibrium error terms defined. For Subsample 1, the multivariate analysis shows the presence of three cointegrating vectors with the lagged two periods among four countries (in equation 15-17).

(15) $p_{TH} = 0.876p_{INDIA} + 0.66$

(16) $p_{VT} = 0.791p_{INDIA} + 1.063$

(17) $p_{PAK} = 0.9p_{INDIA} + 0.478$

The result shows the positive co-movement of the 25% broken rice prices between each country and India in the long-run equilibrium. The interpretation is that an increase in India's price also increases prices in Thailand, Vietnam and Pakistan in the long-run. For instance, a ten percent price increase in India will lead to price increases of 8.76 percent in Thailand, 7.91 percent in Vietnam, and 9 percent in Pakistan, respectively.

For Subsample 3, there is evidence of two cointegrating vectors with eight lag orders. Normalizing based on Thai export price, the first cointegrating vector indicates a negative relationship between Thai and Indian prices. In the second cointegrating relationship above, Vietnam's long-run price behavior moves in the same direction as Pakistan and India. The cointegrating relationships can be represented as follows:

(18) $p_{TH} = -1.575p_{INDIA} + 15.108$

(19) $p_{VT} = 3.358p_{PAK} + 8.248p_{INDIA} - 63.08$

In Table 4.6.2, we also explore the speed of adjustment (α) parameters for the multivariate case. In Subsample 1, Thailand's speed of adjustment from disequilibrium is faster than the other countries for all three of the speed of adjustment vectors. In the first cointegrating vector, for example, Thailand's coefficient of adjustment is around -0.07. The interpretation is that Thai price will decrease to adjust 7% of any deviation from the long run price equilibrium for all four countries. While, the estimated speed of adjustment indicates that India moves to equilibrium faster when any price shocks of the other three countries occur in Subsample 3.

Overall, the multivariate analysis indicates that Indian prices have long run relationships with rice export prices of Thailand, Vietnam, and Pakistan in both periods we investigated. These relations are consistent with the findings using a bivariate model. This result suggests that Pakistan and India could be long run price leaders because their prices do not respond to disequilibrium in the low quality rice export market. Nevertheless, we need to conduct more formal tests in order to verify whether this finding is true (as seen below).

4.5.2.3 Price Leadership Analysis

Table 4.7 summarizes the results of the long-run exclusion and weak exogeneity tests. Based on the guidelines in Le Goulven (1999), the long-run exclusion tests confirm that each of the four price series is cointegrated in the low quality rice market (i.e., the rejection of the null hypothesis for long run exclusion) in both for Subsamples 1 and 3. This implies that the existence of a long run relationship among these prices. The likelihood ratio tests for weak exogeneity in these two subsamples indicate that the low quality rice prices in India and Pakistan are weakly exogenous. But we fail to reject the null hypothesis for the weak exogeneity test in Vietnam. This suggests that India and Pakistan are clearly defined as long run price leaders in the low quality rice market, while Vietnam is a follower in this market.[47]

Our results also suggest that Thailand was a follower in this market for the earlier 1996 to 2007 period. This finding is not consistent with some previous studies that Thailand is a major price leader in international rice market. However, in the more recent 2011 to 2013 period, the price leader status of Thailand in the low quality rice market re-emerged. However, the result in Subsample 3 seems to counter intuition that Vietnam defined as a price follower does not adjust to any exogenous shocks from other three price leaders. One possible explanation may be due to the small number of observations in this sub-period. Next, we further examine dynamic price relationships in the low quality rice market for all countries in the data, and in particular investigate how each country's low quality rice price reacts to a shock that occurs in other countries (i.e. how Thailand's 25% broken rice prices reacts to shocks in India).

4.5.3 Dynamic price relationship results

As we discussed above, we will examine dynamic price relationships in the low quality rice market by focusing on Subsample 1. To do this, we conducted three more supplementary analyses. Firstly, we explored the contemporaneous correlation coefficients of

[47] The evidence that Pakistan is defined as a long run price leader in the low quality rice export market, while Vietnam is strongly found to be a long run price follower is consistent with the study by Jamora et al. (2012).

residuals from the multivariate VECM estimation to provide inference about short-run causal price relationships (see Table 4.6). Overall, the linear relationships among the residuals of the different countries' price series are generally low (e.g., generally below 0.2, in absolute value). However, the correlation coefficients for Thailand, Vietnam and Pakistan tend to be positive and statistically significant. Only Thailand's price has contemporaneously correlated with India.

Second, we apply the Directed Acyclic Graph (DAG) method to the four price series in order to examine the dynamic sequence of price movements (or the so-called ordering of contemporaneous correlation) This technique allows us to more accurately analyze impulse response functions (IRFs) and forecast error variance (FEV) decompositions, which are sensitive to this ordering (Goodwin, McKenzie and Djunaidi, 2003). Traditionally, the Choleski factorization and Bernanke's structural decomposition are applied to identify contemporaneously causal relationship. However, the limitations of these two approaches are the fact that the first approach is based on recursive structure and the second approach relies on economic theory or knowledge about market, in which we do not know the true ordering. An alternative way, the Directed Acyclic Graph (DAG) is a data-driven method, which helps us to visualize the causal flow of price innovation in contemporaneous time (Awokuse and Bessler, 2003).

Based on the PC algorithm, the directed graph provides the causal relationships among residuals of price series (Sprites et. al., 2000). The idea of this algorithm is that edges between markets are eliminated sequentially if the observed correlation and conditional correlation are zero (see Bessler and Akleman, 1998; Bessler, Wang and Wongcharupan, 2002; Babula, Bessler and Payne, 2004; Saghaian, Maynard and Reed, 2007; Attavanich, McCarl and Bessler, 2011).Using the software TETRAD V, [48] the results show that an external shock affecting Pakistan's and Vietnam's export prices directly impacts Thai prices. In this case, the relationship is uni-directional from Pakistan and Vietnam to Thailand (but not vice-versa), which is consistent with the notion of a price follower in the market.

In general, price movements inferred from the DAG analysis roughly corresponds to the price leadership analysis. In Figure 4.5, we find that Indian rice export price tends to be "exogenous", not being affected by other countries' prices and its own price movements not influencing prices in other countries.[49] Additionally, Thai price is directly affected by Pakistan's price, being a price leader. To some extent, these findings follow the result in the price leadership analysis (See Table 4.5).

According to the inference from the DAG analysis above, we construct impulse response functions (IRFs) which determines how forecast export prices in one country may respond to "shocks." We also conduct forecast error variance (FEV) decomposition analysis, which measures the contribution of each country's "shock" to the price forecast error variance. In Figure 4.6 (See last column of graphs), the estimated IRFs indicate that a one-time shock in Indian rice price in the low quality rice market only has a very small initial positive effect on the price series in other countries, but is not sustained over time.

On the other hand, if we consider the response of rice prices in Thailand, Vietnam, and Pakistan, a shock in any of these countries strongly transmits to the other countries (i.e.,

[48] This causal modeling software is available at http://www.phil.cmu.edu/tetrad/current.html
[49] At the 10 percent level, we fail to reject the null hypothesis that the imposed DAG model is consistent with the data given a Chi square value of 6.062 (4 degree of freedom).

see the upper left hand 3x3 block of graphs in Figure 4.6). This is in contrast to the close to zero Indian rice price response to shocks from Thailand and Vietnam, although there exists the negative response of India to one standard deviation shock in the Pakistan's price (i.e., see last row in Figure 4.6). These IRF results are roughly consistent with previous analysis above (i.e., DAG, contemporaneous correlation analysis and bivariate VECM) where India seems to be exogenous in the low quality rice market.

Results of the forecast error variance (FEV) decompositions are presented in Table 4.7. In general, the FEV decomposition analysis supports previous results that Indian low quality rice prices tend to be a separate market segment. Specifically, more than 85 percent of its forecast error variance is explained by within country shocks. For the FEV of low quality rice prices in Thailand, Vietnam, and Pakistan, each price series seems to be more "endogenous" because its price variation is explained more by shocks in price from the other two countries at the longer-time horizons. For instance, the Thailand's FEV is also largely driven by price shocks in Pakistan (12 to 23 percent) and Vietnam (24 to 34 percent) at the 12-and 24-week horizons.

Third, we examine how export prices in specific countries react to shocks caused by policy changes in other countries. Theoretically, domestic shocks from either the production or consumption side of the market may cause export price response and/or volatility. When an export price series are cointegrated with other export prices from other countries, they should be affected by the other countries' shocks. We further investigate dynamic price linkages when there is a change in the domestic rice policies of India. In line with the previous studies (e.g., Jin, Power and Elbakidze, 2008; Saghaian, Maynard and Reed, 2007), we analyze impacts of policy events on price movements in the low quality rice export market.

Due to the fact that most of the price series has a cointegrating relationship in the low quality rice export market (based on the multivariate analysis), it is suitable to analyze the policy impacts on price movement by VEC estimation. Using all data samples before a policy change, we estimate a multivariate VEC model, and then forecast out of sample for the four price series about six months ahead. The magnitude and persistence of policy impact can be observed by the distance between actual prices and forecasted prices. In addition, the policy event has a statistically significant effect on each price series if its actual price is outside the 90% confidence of forecasted price.

One of interesting cases relating to the rice trade policy change is the 2007 Indian non-basmati rice export ban. For the India's banning export case, we estimate a VECM model (from January 5, 1996, to September 28, 2007), and forecast the export price series starting October 5, 2007 about 24 weeks ahead. The empirical result shows a significant impact on low quality rice export prices, as price series experienced an increase after the policy implemented in September 2007 as shown in Figure 4.7. The impact of export ban was strongest on Pakistan prices, compared to Thai and Vietnam's prices. Thai prices rose after the Indian exclusion, but its policy impact was significantly short-lived (i.e. around 3 weeks) during November 23, 2007 to December 14, 2007.

4.6 Discussion and Conclusions

This study analyzes dynamic price relationships and price leadership in the low quality rice sector, particularly the segment with 25% broken kernels. We focus on four key exporters in this market: Thailand, Vietnam, Pakistan, and India and utilize a rich weekly price data collected by traders from 1996 to 2013. Our study contributes to the literature by focusing on the low quality rice segment and explicitly including India in the analysis (which is important given its status as one of the largest producer and consumer of rice in the world).

Using a VEC model, our bivariate cointegration analysis suggests that there exists interdependence among the 25% broken rice prices of Thailand, Vietnam and Pakistan. Additionally, India does not seem to be strongly cointegrated with the prices of the other countries in the low quality rice market. However, in the multivariate analysis, we find that Indian low quality rice price is cointegrated with low quality rice prices of the other three countries. This empirical finding from the multivariate case provides some evidence about the significant role India in the low quality rice trade and the importance of not omitting India in any analysis of prices and market integration in this low quality rice market.

Assumed parameter restrictions on the VECM, the market price leadership is investigated by using long-run exclusion and weak exogeneity tests. Based on these tests, we find strong evidence (at the 5% level of significance) that Pakistan and India tend to be price leaders in the low quality rice market, while Vietnam tends to be a price follower in both subsamples. This evidence is consistent with previous studies of Jamora and Cramon-Taubadel (2012). In contrast to some of the previous studies on the low quality rice market, we find that Thailand is likely a price follower in this market for the 1996 to 2007 period. Although we provide evidence that Thailand has emerged as a new price leader since late 2011. One explanation may be the recent implementation of Thai mortgage scheme. In particular, farmers received higher rice farm prices than market prices. This price support policy induced a large volume of low quality rice production such that Thailand became a leader in the market. In addition, it could also be that low-quality rice importing countries prefer Thai, Indian, and Pakistani 25% broken rice relative to the Vietnamese low quality rice.

We further investigate the short-run dynamic price relationships among the countries in the low quality rice market using contemporaneous correlation analysis of VEC residuals, directed acyclic graphs (DAG), impulse response functions, and forecast error variance decompositions. Although India serves as a price leader in this market segment, except with Pakistan prices, its price co-movement among other countries is weak in the case of 2007 Indian non-basmati export ban. Moreover, evidence from the additional analysis of dynamic price relationships indicates that there is stronger interdependence of prices among Thailand, Vietnam, and Pakistan, where Thailand and Pakistan tend to be the price leaders and Vietnam is a price follower.

Results from all the analyses conducted above have important implications to countries heavily reliant on imported low quality rice to satisfy domestic demand and wanting to keep domestic prices affordable. In particular, governments of West African countries like Nigeria, Cote d’Ivoire, and Senegal closely monitor and study these low quality rice prices since a significant proportion of the population is still food insecure and these countries consider this type of rice a main staple.

Knowing that Pakistan tends to be the price leader in the 25% broken rice market suggests that these West African countries should consider Pakistan's export price movements when deciding domestic policy regulations. For example, West African countries may consider replenishing local stocks and importing more when Pakistan prices appear to be low (since prices in Thailand and Vietnam would also likely be low). Given that India seems to be a separate segment in the low quality market (and shows less interdependence), West African studies may also benefit from carefully monitoring Indian 25% broken prices because the Indian price movement has high impact to changes in Pakistan's prices based on our results.

Despite the interesting insights generated by this study for the low quality rice market segment, we have to acknowledge certain limitations in the study methods. In particular, our empirical approach assumes a linear price relationship and symmetric price adjustments. According to Enders and Siklos (2001), the standard test for cointegration and its extensions are misspecified when an asymmetric price adjustment process is more appropriate. In addition, the results from conventional VEC model could be questionable if there are asymmetry in the error term distribution and nonlinearity of price dependence. But note that the study by Ghoshray (2008) indicates that there is no strong evidence of asymmetry in the low quality rice market. Nevertheless, we leave for future study the application of models that incorporate asymmetry and nonlinear in the dynamic price relationship analysis, such as copula methods (Goodwin, Holt, Önel and Prestemon, 2014).

Table 4.1. Descriptive Statistics (FOB, USD/ton).

periods	Sample/Statistic	Thailand	Vietnam	Pakistan	India
Full sample					
1996-2013	No. of Observations	890	834	859	697
	Mean	309.58	269.80	273.90	238.09
	Std. Dev.	148.79	110.94	112.01	67.16
	C.V	48%	41%	41%	28%
subsample 1					
1996-2007	No. of Observations	614	571	571	614
	Mean	223.08	206.30	206.61	218.27
	Std. Dev.	48.90	42.77	42.36	42.23
	C.V	22%	21%	21%	19%
subsample 2					
1996-2007	No. of Observations	205	180	205	
	Mean	489.31	407.33	413.77	
	Std. Dev.	126.06	98.04	98.15	
	C.V	26%	25%	24%	
subsample 3					
2011-2013	No. of Observations	71	83	83	83
	Mean	538.69	408.41	391.33	384.71
	Std. Dev.	21.13	47.75	20.90	15.95
	C.V	4%	12%	5%	4%

Table 4.2. Unit Root Tests.

Price	Augmented Dickey-Fuller (ADF) test without structural break	Clemente-Moñés-Reyes tests with one structural break for Full Sample			
		AO		IO	
		Min. t	Optimal breakpoint	Min. t	Optimal breakpoint
Levels					
TH	-1.1	-2.423	5/2/2008	-3.345	10/27/2006
VT	-2.059	-4.185	9/21/2007	-4.443**	6/16/2006
PAK	-1.596	-2.959	6/6/2008	-3.969	1/19/2007
INDIA	-1.791	-0.923	9/21/2007	-2.66	9/28/2007
1st differences					
TH	-8.729***	-8.027**	3/14/2008	-9.523**	3/21/2008
VT	-8.689***	-8.172**	8/29/2008	-9.184**	9/5/2008
PAK	-8.174***	-7.009**	4/4/2008	-14.228**	4/11/2008
INDIA	-8.448***	-30.378**	9/2/2011	-43.359**	9/9/2011

Notes: (1)*, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. (2) TH, VT, PAK and INDIA through this paper stand for price series of Thailand, Vietnam, Pakistan and India in logarithmic transformation. (3) Min. t denotes minimum t-statistics with critical value: -3.56 and -4.27 for AO and IO models at 5% level of significance.

Table 4.3. Johansen Cointegration Test.

Variables	Subsample 1				Subsample 3				
	No. of lag (k)	Null hypothesis	Trace test	No. of cointegration (r)	No. of lag (k)	Null hypothesis	Trace test	No. of cointegration (r)	5% critical value
Bivariate case									
TH-VT	4	$r = 0$	30.721	1	4	$r = 0$	13.489	0	15.41
		$r \leq 1$	2.249**			$r \leq 1$	3.949		3.76
TH-PAK	5	$r = 0$	18.951	1	4	$r = 0$	18.152	0	15.41
		$r \leq 1$	0.954**			$r \leq 1$	4.372		3.76
TH-INDIA	1	$r = 0$	21.051	1	8	$r = 0$	498.677	0	15.41
		$r \leq 1$	3.376**			$r \leq 1$	11.944		3.76
VT-PAK	2	$r = 0$	17.901	1	1	$r = 0$	17.25	0	15.41
		$r \leq 1$	0.680**			$r \leq 1$	6.049		3.76
VT-INDIA	2	$r = 0$	17.17	1	4	$r = 0$	522.695	0	15.41
		$r \leq 1$	1.883**			$r \leq 1$	7.586		3.76
PAK-INDIA	5	$r = 0$	16.136	1	6	$r = 0$	510.444	1	15.41
		$r \leq 1$	1.418**			$r \leq 1$	2.725**		3.76
Multivariate case									
TH-VT-PAK-INDIA	2	$r = 0$	71.869	3	8	$r = 0$	539.193	2	47.21
		$r \leq 1$	35.253			$r \leq 1$	53.251		29.68
		$r \leq 2$	17.192			$r \leq 2$	11.723**		15.41
		$r \leq 3$	1.763**			$r \leq 3$	1.254		3.76

Table 4.4. Misspecification Tests.

	Subsample 1	Subsample 3
Autocorrelation	21.48	16.285
Normality	$8.5e^{+05}$	17.893

Note: Both subsamples fail to reject the null hypotheses of no autocorrelation and normality, which are tested by Lagrange-multiplier and Jarque-Bera tests.

Table 4.5. Parameter estimates from VEC model.
Table 4.5.1. Parameter estimates from Bivariate VEC model.

	Variables	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	Constant
Subsample 1	TH-VT	1	-1.089^{***}	-0.046^{***}	0.039^{***}	0.425
	TH-PAK	1	-1.093^{***}	-0.032^{***}	0.024^{**}	0.435
	TH-INDIA	1	-0.847^{***}	0.0003	0.022^{***}	-0.821
	VT-PAK	1	-0.973^{***}	-0.030^{***}	0.018^{**}	-0.146
	VT-INDIA	1	-0.679^{***}	-0.006	0.019^{***}	-1.662
	PAK-INDIA	1	-0.810^{***}	-0.004	0.023^{***}	-0.959
Subsample 3	PAK-INDIA	1	6.257^{***}	-0.0005	-0.163^{***}	-43.147

Notes: (1) ***, **, * denotes significance at 1%, 5% and 10% level. (2) $\hat{\beta}_2$ and $\hat{\alpha}_2$ stand for a vector of cointegration and speed of adjustment for the second country. (3) $\hat{\beta}_{ji}$ refers to the jth cointegrating vector of country *i*. (4) $\hat{\alpha}_{ij}$ refers to the adjustment speed of country *i* in the jth cointegrating vector.

Table 4.5.2. Parameter estimates from Multivariate VEC model.

	Long-run elasticities (β)	$\hat{\beta}_{1i}$	$\hat{\beta}_{2i}$	$\hat{\beta}_{3i}$	Speed of adjustment (α)	$\hat{\alpha}_{i1}$	$\hat{\alpha}_{i2}$	$\hat{\alpha}_{i3}$
Subsample 1	TH	1	$-1.67e^{-16}$	$1.11\ e^{-16}$	Δ TH	-0.07^{***}	0.051^{***}	0.029^{***}
	VT	0	1	0	Δ VT	0.023^{*}	-0.046^{***}	0.028^{***}
	PAK	0	0	1	Δ PAK	0.013	0.007	-0.021^{**}
	INDIA	-0.876^{***}	-0.791^{***}	-0.9^{***}	Δ INDIA	0.021	0.0006	-0.001
	constant	-0.660	-1.063	-0.478				
Subsample 3	TH	1	0		Δ TH	-0.291^{***}	-0.057^{***}	
	VT	0	1		Δ VT	-0.136	-0.026	
	PAK	-0.09	-3.358^{***}		Δ PAK	-0.124	-0.023	
	INDIA	1.575^{***}	-8.248^{***}		Δ INDIA	0.556^{***}	0.232^{***}	
	constant	-15.108	63.08					

Notes: (1) ***, **, * denotes significance at 1%, 5% and 10% level. (2) $\hat{\beta}_2$ and $\hat{\alpha}_2$ stand for a vector of cointegration and speed of adjustment for the second country. (3) $\hat{\beta}_{ji}$ refers to the jth cointegrating vector of country *i*. (4) $\hat{\alpha}_{ij}$ refers to the adjustment speed of country *i* in the jth cointegrating vector.

Table 4.6. Tests for long-run exclusion and weak exogeneity.

Hypothesis	$\chi^2(1)$	p-value	Hypothesis	$\chi^2(1)$	p-value	**Conclusion**
Subsample 1						
Long-run exclusion			**Weak exogeneity**			
$H_0 : \hat{\beta}_{j1} = 0$	34.5***	0.000	$H_0 : \hat{\alpha}_{1j} = 0$	11.51***	0.009	**Follower**
$H_0 : \hat{\beta}_{j2} = 0$	54.52***	0.000	$H_0 : \hat{\alpha}_{2j} = 0$	7.14*	0.067	**Follower**
$H_0 : \hat{\beta}_{j3} = 0$	22.9***	0.000	$H_0 : \hat{\alpha}_{3j} = 0$	5.88	0.118	**Leader**
$H_0 : \hat{\beta}_{j4} = 0$	6.736*	0.081	$H_0 : \hat{\alpha}_{4j} = 0$	1.6	0.659	**Leader**
Subsample 3						
Long-run exclusion			**Weak exogeneity**			
$H_0 : \hat{\beta}_{j1} = 0$	16.72***	0.000	$H_0 : \hat{\alpha}_{1j} = 0$	2.80	0.246	**Leader**
$H_0 : \hat{\beta}_{j2} = 0$	46.5***	0.000	$H_0 : \hat{\alpha}_{2j} = 0$	7.54**	0.023	**Follower**
$H_0 : \hat{\beta}_{j3} = 0$	29.01***	0.000	$H_0 : \hat{\alpha}_{3j} = 0$	1.81	0.405	**Leader**
$H_0 : \hat{\beta}_{j4} = 0$	5.352*	0.069	$H_0 : \hat{\alpha}_{4j} = 0$	0.23	0.891	**Leader**

Notes: (1) ***, **, * denotes significance at 1%, 5% and 10% level (2) *j* refers to the *j*-th cointegrating vector of country *i* where TH= 1, VT=2, PAK=3 and INDIA=4.

Table 4.7. Contemporaneous correlation coefficients of VEC residuals in Subsample 1.

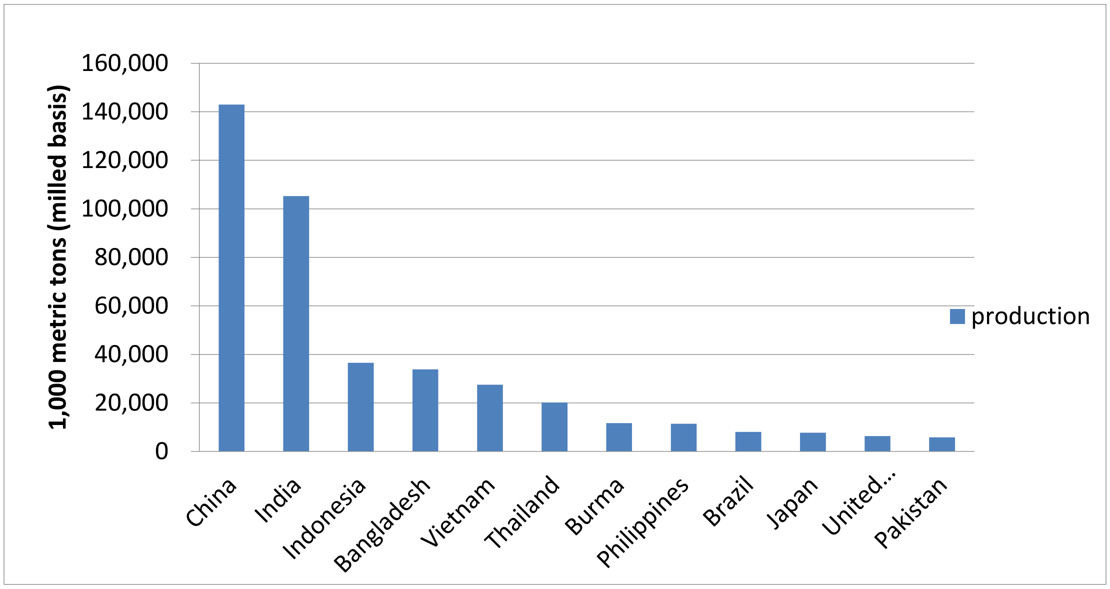
Price series	Thailand	Pakistan	Vietnam	India
Thailand	1			
Pakistan	0.112***	1		
	[0.01]			
Vietnam	0.111***	0.066*	1	
	[0.01]	[0.10]		
India	0.068*	0.0364	0.018	1
	[0.09]	[0.37]	[0.65]	

Notes: (1) ***, **, * denotes significance at 1%, 5% and 10% level. (2) the p-value is reported in the bracket.

Table 4.8. Forecast error variance decomposition of four export prices in Subsample 1.

Variable	weekly horizon	Pakistan	Vietnam	Thailand	India
Pakistan					
	1	100.00	0.00	0.00	0.00
	4	93.20	5.21	1.57	0.02
	8	89.98	7.70	2.30	0.02
	12	88.36	8.78	2.85	0.01
	16	87.13	9.54	3.32	0.01
	20	86.06	10.20	3.73	0.01
	24	85.10	10.80	4.08	0.01
Vietnam	1	0.38	99.62	0.00	0.00
	4	1.33	98.09	0.57	0.01
	8	3.50	94.98	1.45	0.07
	12	6.46	90.95	2.39	0.21
	16	9.92	86.43	3.26	0.40
	20	13.62	81.77	4.00	0.61
	24	17.35	77.23	4.59	0.83
Thailand	1	1.29	1.07	97.64	0.00
	4	4.75	8.46	86.79	0.00
	8	8.05	17.35	74.56	0.04
	12	11.57	24.14	64.16	0.13
	16	15.25	28.88	55.61	0.26
	20	18.96	31.92	48.70	0.42
	24	22.60	33.69	43.13	0.59
India					
	1	0.13	0.03	0.40	99.44
	4	0.81	1.16	1.10	96.94
	8	1.22	1.89	2.21	94.68
	12	1.67	2.46	3.40	92.47
	16	2.23	3.12	4.61	90.03
	20	2.94	3.93	5.79	87.34
	24	3.81	4.89	6.91	84.39

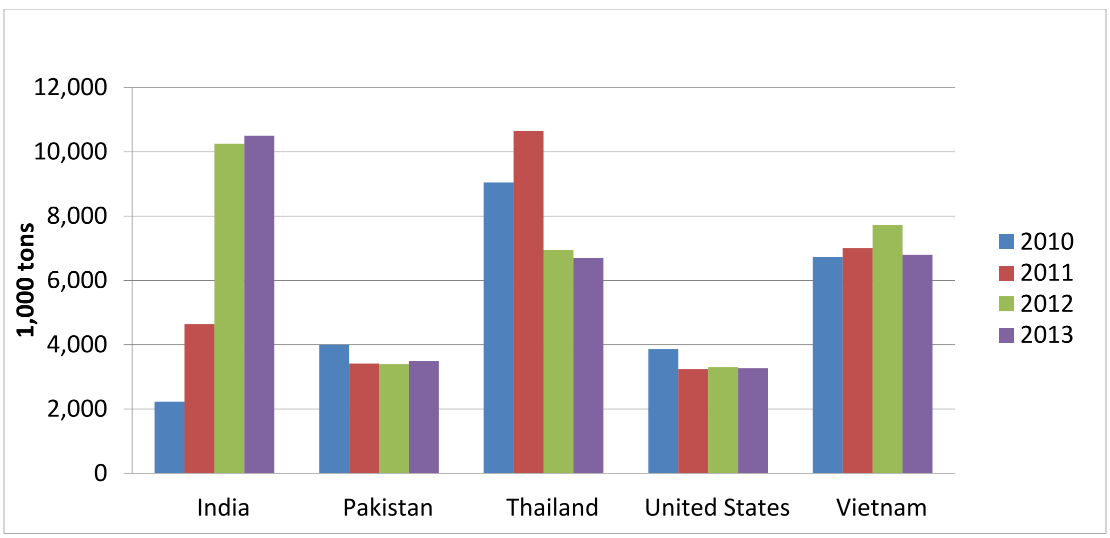
Notes: (1) The values of each row represent percentages of the forecast error of one variable due to the innovation in itself and other price series. At the 16-weeks ahead, for instance, price variation in Vietnam is mainly explained by its own shock (86 percent), Thailand (3 percent) as well as Pakistan and India (10 percent), which all proportions add up to 100 percent in each row. (2) The Choleski decomposition of contemporaneous innovation covariance follows this ordering: PAK, VT, TH and INDIA.



Source: Production, Supply, & Distribution Online Data Base,
FAS/USDA, http://www.fas.usda.gov/psdonline/psdHome.aspx.

Figure 4.1

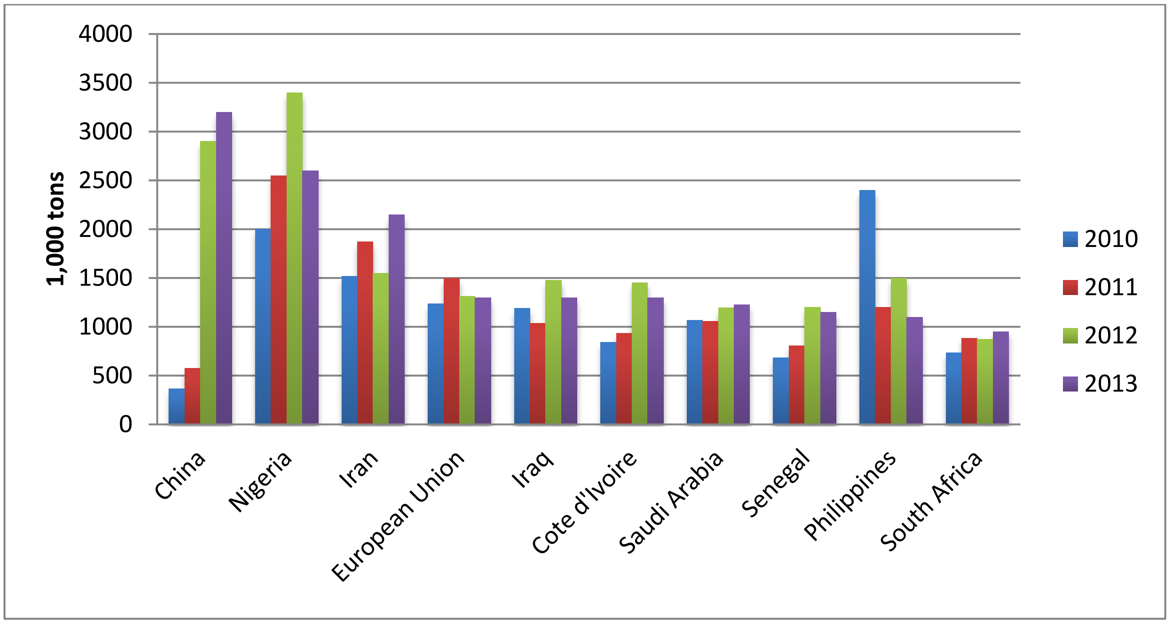
Figure 4.1: Global rice production in 2013 (milled basis) in 1,000 metric tons.



Source: USDA, Foreign Agricultural Service, Production Supply and Distribution (PS&D) and Grain: World Markets and Trade, (Grain Circular).

Figure 4.2

Figure 4.2: Volume of rice exports in major countries (milled basis) in 1,000 metric tons.



Source: USDA, Foreign Agricultural Service, Production Supply and Distribution (PS&D) and Grain: World Markets and Trade, (Grain Circular).

Figure 4.3

Figure 4.3: Volume of rice imports in major countries (milled basis) in 1,000 metric tons.

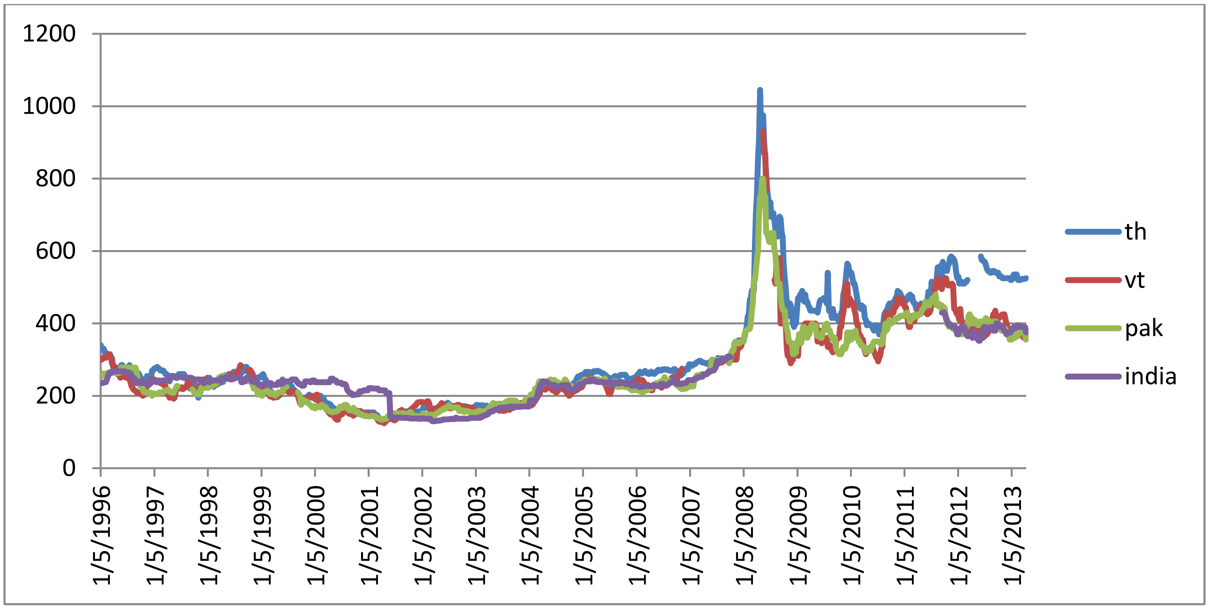


Figure 4.4

Figure 4.4.1: Low quality rice export prices series data plotting.

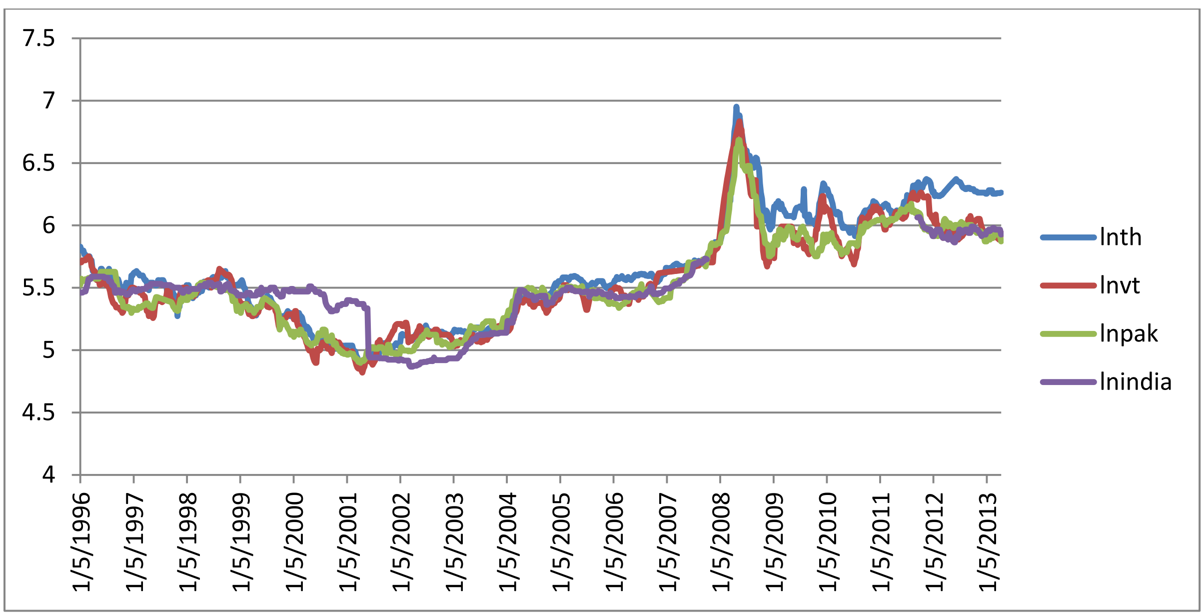


Figure 4.4.2: Logged low quality rice export prices series data plotting.

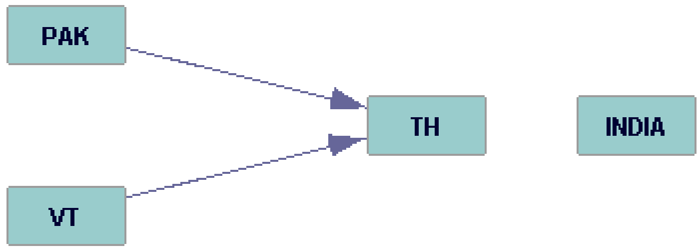


Figure 4.5

Figure 4.5: Price relationship sequence from the Directed Acyclic Graph (DAG) in Subsample 1.

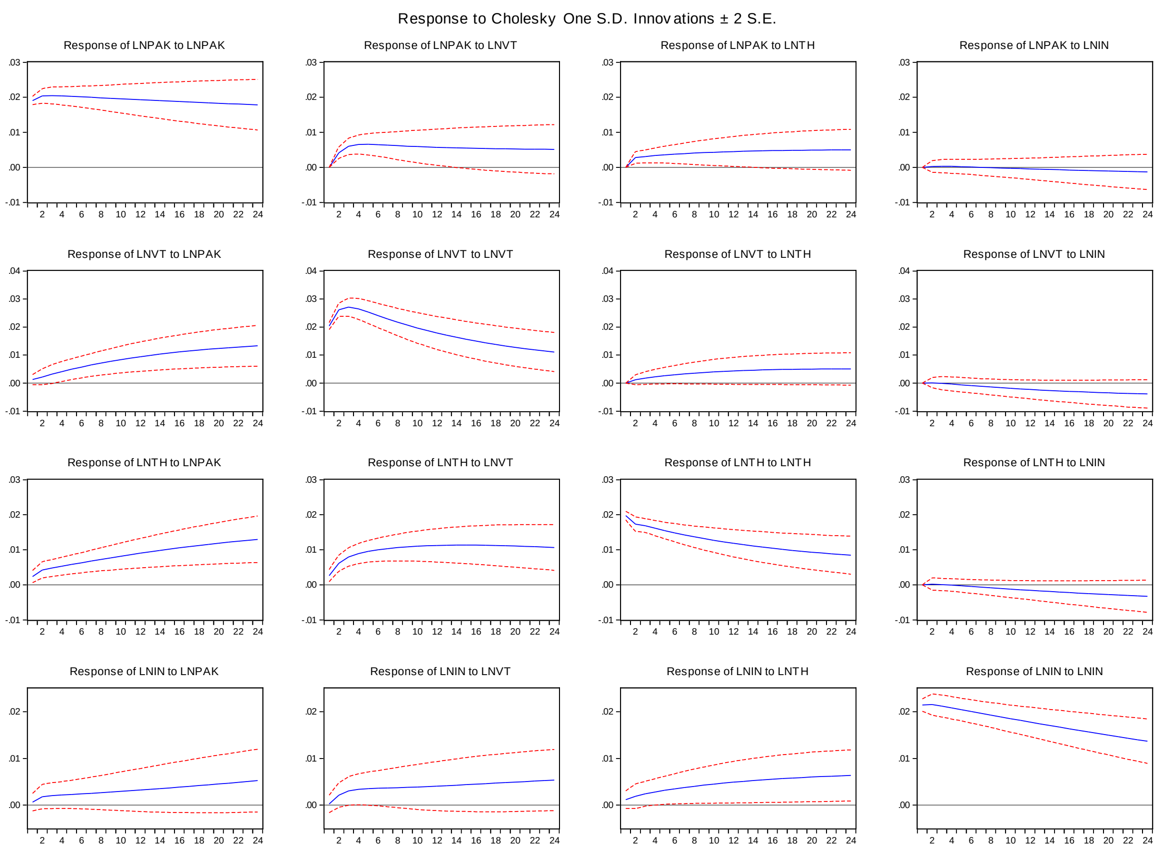
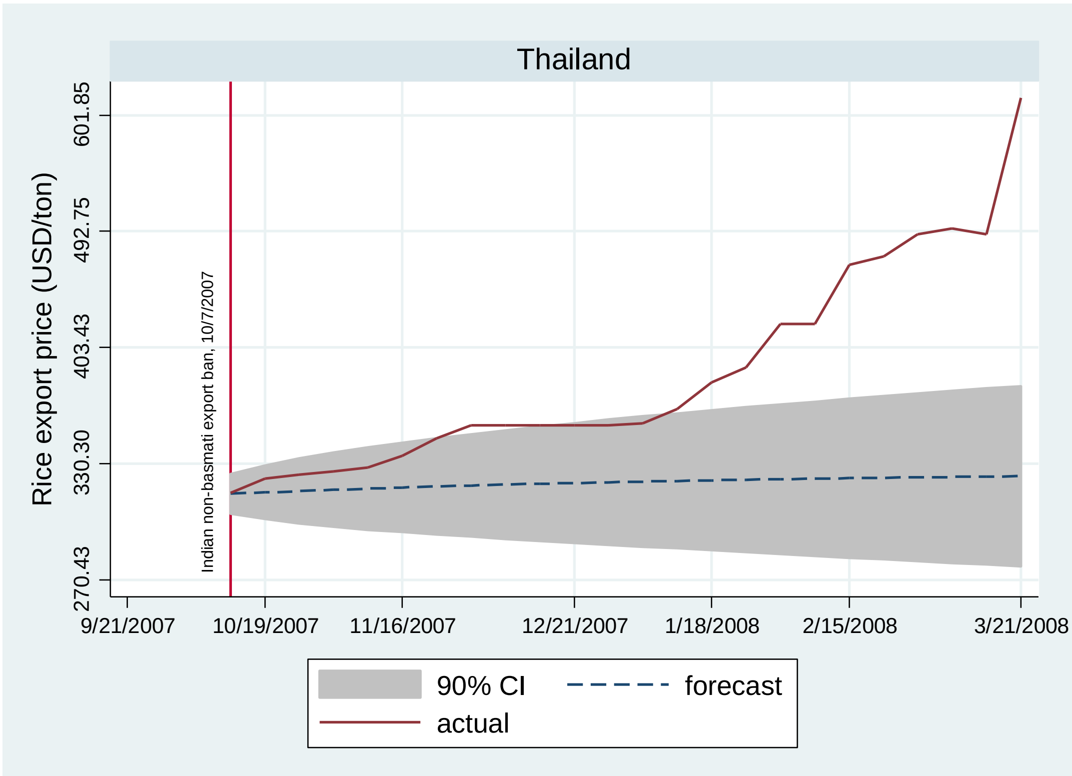
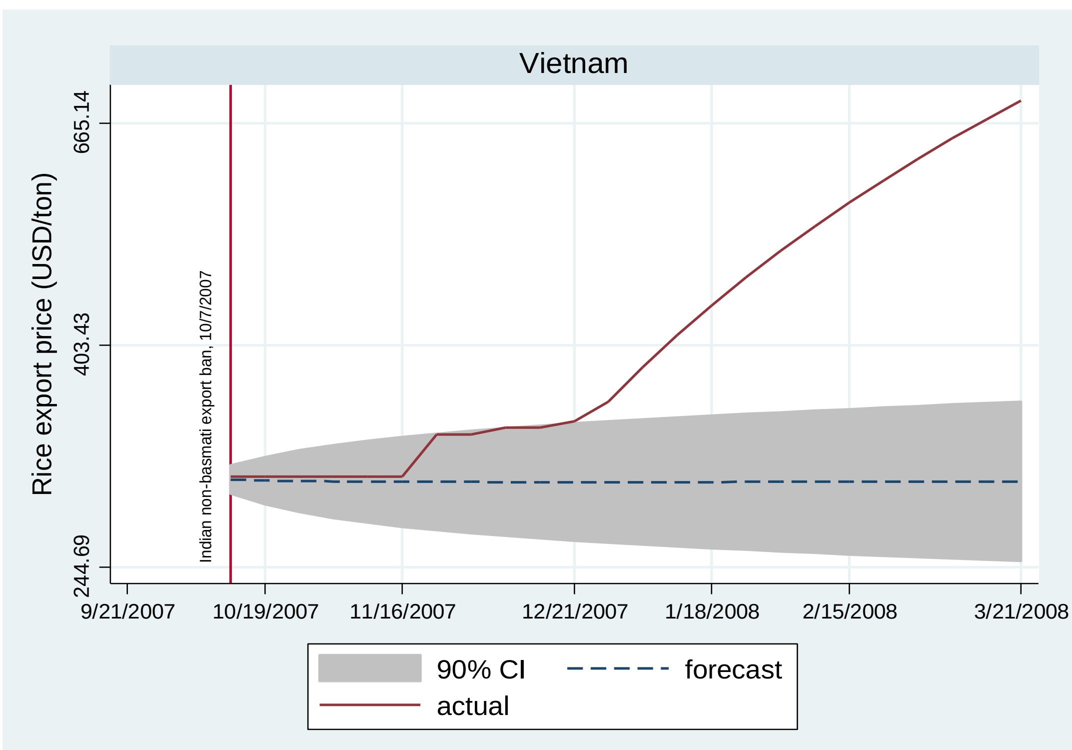


Figure 4.6

Figure 4.6: Impulse response function (IRF) analysis in Subsample 1.


Thailand
Rice export price (USD/ton)
601.85
492.75
403.43
330.30
270.43
Indian non-basmati export ban, 10/7/2007
9/21/2007
10/19/2007
11/16/2007
12/21/2007
1/18/2008
2/15/2008
3/21/2008
90% CI
forecast
actual


Vietnam
Rice export price (USD/ton)
665.14
403.43
244.69
Indian non-basmati export ban, 10/7/2007
9/21/2007
10/19/2007
11/16/2007
12/21/2007
1/18/2008
2/15/2008
3/21/2008
90% CI
forecast
actual

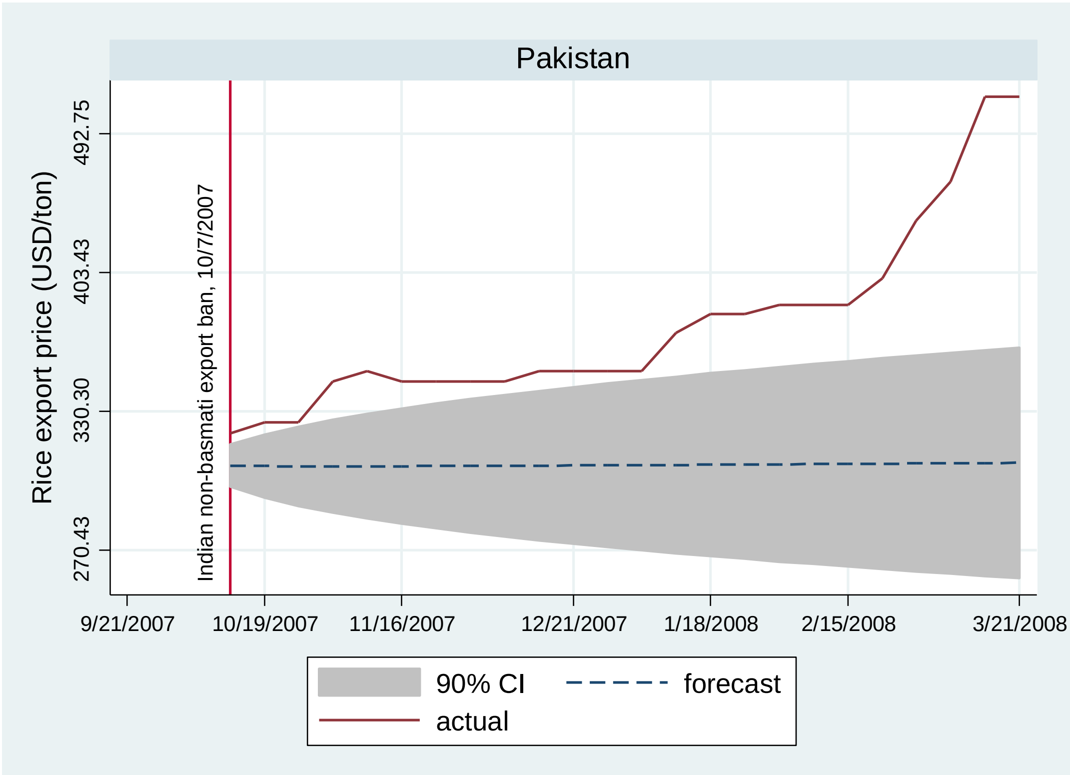


Figure 4.7

Figure 4.7: Impact of Indian non-basmati ban policy on rice export prices.

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APPENDICES

Appendix 2.A.

List of variables.

Variable	Definition	Data source	Data availability
Rice consumption per capita (kilograms/year)	Quantity of rice consumption divided by total population	World Rice Statistic, IRRI website	1961-2011
Real GDP ($)	Gross domestic product at constant 2005 divided by midyear population	World Bank website	1960-2014
Agricultural population share (%)	Rural population divided by total population	World Bank website	1960-2014
Real rice price ($/ ton)	Export price of Thai 5% broken, white rice (WR) adjusted by CPI index 2005 = 100	World Bank website	1961-2013
Real wheat price ($/ ton)	Export price of Wheat (US), no. 2, soft red winter adjusted by CPI index 2005 = 100	Global Economic Monitor (GEM) Commodities, World Bank website	1979-2013

Appendix 2.B.

Descriptive statistics by regions.

Africa

Variable	Obs	Mean	Std. Dev.	Min	Max
rcon	525	19.61	19.60	0.20	73.70
gdp	525	1,626.80	1,834.48	111.79	7,628.72
ruralshare	525	62.47	18.22	13.85	94.01
rrp	525	388.63	149.44	175.38	1,007.45
rwp	525	186.24	59.91	90.17	420.58

America

Variable	Obs	Mean	Std. Dev.	Min	Max
rcon	315	18.33	14.20	1.70	62.70
gdp	315	10,226.22	11,773.77	850.99	45,431.03
ruralshare	315	40.75	20.22	10.85	91.25
rrp	315	376.85	141.15	180.99	963.48
rwp	315	181.02	57.03	102.75	423.84

Asia

Variable	Obs	Mean	Std. Dev.	Min	Max
rcon	294	95.03	41.00	9.50	178.30
gdp	294	4,106.49	7,392.64	241.78	27,392.24
ruralshare	294	59.09	23.33	8.86	90.74
rrp	294	387.71	155.41	170.21	950.58
rwp	294	185.53	62.59	93.53	412.70

Europe

Variable	Obs	Mean	Std. Dev.	Min	Max
rcon	462	4.96	2.96	0.70	17.60
gdp	462	29,783.07	14,628.01	1,131.02	67,804.55
ruralshare	462	26.18	12.88	2.51	63.08
rrp	462	367.71	129.47	178.36	955.56
rwp	462	176.38	49.74	101.98	378.68

Oceania

Variable	Obs	Mean	Std. Dev.	Min	Max
rcon	105	35.21	23.01	4.80	67.40
gdp	105	12,381.61	13,021.03	808.15	36,495.04
agshare	105	48.08	30.39	10.81	86.13
rrp	105	374.13	136.99	186.15	915.90
rwp	105	180.03	56.33	110.24	391.30

Middle-East

Variable	Obs	Mean	Std. Dev.	Min	Max
rcon	84	29.22	16.30	7.40	64.10
gdp	84	16,379.70	10,701.07	1,608.48	36,040.02
agshare	84	12.77	8.03	1.75	26.54
rrp	84	348.78	118.25	175.87	712.39
rwp	84	167.70	45.60	95.89	293.99

Appendix 2.C.

Income elasticity estimates by countries (Model 1).

Estimator	**MG**	**CMG**	**AMG**
With trend			
average coefficients computed as (unweighted) mean	0.666***	0.146	0.576***
no. of positive country-specific coefficients	37 [63.8]	30 [51.7]	36 [62.1]
no. of negative country-specific coefficients	21 [36.2]	28 [48.3]	22 [37.9]
no. of positively significant coefficients	20 [34.5]	12 [20.7]	20 [34.5]
no. of negatively significant coefficients	4 [6.9]	8 [13.8]	5 [8.6]

Notes: (1) total number of significant coefficients is sum of number of significant coefficients at least 10% levels. (2) Values in brackets are percentage of total coefficients and percentage of total significant coefficients.

Income elasticity estimates by regions (Model 1).

Estimator / average coefficients by region	total countries	**MG**		**CMG**		**AMG**	
Africa	15	1.313		0.362		1.162	
America	9	-0.052		-0.786		0.013	
Asia	11	-0.060		-0.065		-0.040	
Europe	17	1.058		0.133		0.817	
Oceania	4	0.670		1.709		0.726	
Middle-east	2	-0.354		0.869		-0.259	
no. of positive region-specific coefficients	Total countries	**MG**		**CMG**		**AMG**	
Africa	15	14	[93.3]	9	[60.0]	13	[86.7]
America	9	4	[44.4]	3	[33.3]	4	[44.4]
Asia	11	7	[63.6]	5	[45.5]	7	[63.6]
Europe	17	10	[58.8]	10	[58.8]	9	[52.9]
Oceania	4	2	[50.0]	2	[50.0]	2	[50.0]
Middle-east	2	0	[0.0]	1	[50.0]	1	[50.0]
no. of negative region-specific coefficients	Total countries	**MG**		**CMG**		**AMG**	
Africa	15	1	[6.7]	6	[40.0]	2	[13.3]
America	9	5	[55.6]	6	[66.7]	5	[55.6]
Asia	11	4	[36.4]	6	[54.5]	4	[36.4]
Europe	17	7	[41.2]	7	[41.2]	8	[47.1]
Oceania	4	2	[50.0]	2	[50.0]	2	[50.0]
Middle-east	2	2	[100.0]	1	[50.0]	1	[50.0]

Income elasticity estimates by regions (Model 1) (continued).

no. of significant region-specific	Total countries	MG		CMG		AMG	
Africa	15	8	[53.3]	6	[40.0]	9	[60.0]
America	9	2	[22.2]	3	[33.3]	1	[11.1]
Asia	11	5	[45.5]	3	[27.3]	5	[45.5]
Europe	17	6	[35.3]	5	[29.4]	7	[41.2]
Oceania	4	2	[50.0]	1	[25.0]	2	[50.0]
Middle-east	2	1	[50.0]	2	[100.0]	1	[50.0]
no. of positively significant coefficients	**Total countries**	**MG**		**CMG**		**AMG**	
Africa	15	8	[53.3]	5	[33.3]	9	[60.0]
America	9	2	[22.2]	0	[0.0]	1	[11.1]
Asia	11	3	[27.3]	3	[27.3]	3	[27.3]
Europe	17	5	[29.4]	2	[11.8]	5	[29.4]
Oceania	4	2	[50.0]	1	[25.0]	2	[50.0]
Middle-east	2	0	[0.0]	1	[50.0]	0	[0.0]
no. of negatively significant coefficients	**Total countries**	**MG**		**CMG**		**AMG**	
Africa	15	0	[0.0]	1	[6.7]	0	[0.0]
America	9	0	[0.0]	3	[33.3]	0	[0.0]
Asia	11	2	[18.2]	0	[0.0]	2	[18.2]
Europe	17	1	[5.9]	3	[17.6]	2	[11.8]
Oceania	4	0	[0.0]	0	[0.0]	0	[0.0]
Middle-east	2	1	[50.0]	1	[50.0]	1	[50.0]

Income elasticity estimates by countries (Model 2).

Estimator	MG	CMG	AMG
With trend			
average coefficients computed as (unweighted) mean	0.489^{**}	0.430	0.366^{*}
no. of positive country-specific coefficients	34 [58.6]	34 [58.6]	34 [58.6]
no. of negative country-specific coefficients	24 [41.4]	24 [41.4]	24 [41.4]
no. of positively significant coefficients	17 [29.3]	13 [22.4]	15 [25.9]
no. of negatively significant coefficients	6 [10.3]	7 [12.1]	6 [10.3]

Notes: (1) total number of significant coefficients is sum of number of significant coefficients at least 10% levels. (2) Values in brackets are percentage of total coefficients and percentage of total significant coefficients.

Income elasticity estimates by regions (Model 2).

Estimator	total	**MG**	**CMG**	**AMG**
average coefficients by region	countries			
Africa	15	1.085	0.558	0.797
America	9	-0.333	-0.327	-0.331
Asia	11	-0.185	-0.244	-0.161
Europe	17	0.766	0.901	0.595
Oceania	4	1.038	1.170	0.986
Middle-east	2	-0.005	1.117	-0.027
no. of positive region-specific coefficients	Total countries	**MG**	**CMG**	**AMG**
Africa	15	10 [66.7]	10 [66.7]	10 [66.7]
America	9	3 [33.3]	4 [44.4]	3 [33.3]
Asia	11	7 [63.6]	6 [54.5]	7 [63.6]
Europe	17	11 [64.7]	11 [64.7]	10 [58.8]
Oceania	4	2 [50.0]	2 [50.0]	3 [75.0]
Middle-east	2	1 [50.0]	1 [50.0]	1 [50.0]
no. of negative region-specific coefficients	Total countries	**MG**	**CMG**	**AMG**
Africa	15	5 [33.3]	5 [33.3]	5 [33.3]
America	9	6 [66.7]	5 [55.6]	6 [66.7]
Asia	11	4 [36.4]	5 [45.5]	4 [36.4]
Europe	17	6 [35.3]	6 [35.3]	7 [41.2]
Oceania	4	2 [50.0]	2 [50.0]	1 [25.0]
Middle-east	2	1 [50.0]	1 [50.0]	1 [50.0]

Income elasticity estimates by regions (Model 2) (continued).

no. of significant region-specific	Total countries	**MG**	**CMG**	**AMG**
Africa	15	6 [40.0]	6 [40.0]	5 [33.3]
America	9	3 [33.3]	2 [22.2]	2 [22.2]
Asia	11	5 [45.5]	4 [36.4]	5 [45.5]
Europe	17	7 [41.2]	6 [35.3]	7 [41.2]
Oceania	4	1 [25.0]	1 [25.0]	1 [25.0]
Middle-east	2	1 [50.0]	1 [50.0]	1 [50.0]
no. of positively significant coefficients	Total countries	**MG**	**CMG**	**AMG**
Africa	15	6 [40.0]	5 [33.3]	5 [33.3]
America	9	2 [22.2]	0 [0.0]	1 [11.1]
Asia	11	4 [36.4]	2 [18.2]	4 [36.4]
Europe	17	4 [23.5]	4 [23.5]	4 [23.5]
Oceania	4	1 [25.0]	1 [25.0]	1 [25.0]
Middle-east	2	0 [0.0]	1 [50.0]	0 [0.0]
no. of negatively significant coefficients	Total countries	**MG**	**CMG**	**AMG**
Africa	15	0 [0.0]	1 [6.7]	0 [0.0]
America	9	1 [11.1]	2 [22.2]	1 [11.1]
Asia	11	1 [9.1]	2 [18.2]	1 [9.1]
Europe	17	3 [17.6]	2 [11.8]	3 [17.6]
Oceania	4	0 [0.0]	0 [0.0]	0 [0.0]
Middle-east	2	1 [50.0]	0 [0.0]	1 [50.0]

Income elasticity estimates by countries (Model 3).

Estimator	MG	CMG	AMG
With trend			
average coefficients computed as (unweighted) mean	0.492***	0.185	0.337*
no. of positive country-specific coefficients	38 [65.5]	32 [55.2]	38 [65.5]
no. of negative country-specific coefficients	20 [34.5]	26 [44.8]	20 [34.5]
no. of positively significant coefficients	18 [31.0]	8 [13.8]	15 [25.9]
no. of negatively significant coefficients	4 [6.9]	5 [8.6]	4 [6.9]

Notes: (1) total number of significant coefficients is sum of number of significant coefficients at least 10% levels. (2) Values in brackets are percentage of total coefficients and percentage of total significant coefficients.

Income elasticity estimates by regions (Model 3).

Estimator / average coefficients by region	total countries	**MG**	**CMG**	**AMG**
Africa	15	1.284	0.300	1.077
America	9	-0.406	-0.744	-0.514
Asia	11	0.005	0.068	-0.027
Europe	17	0.513	0.340	0.267
Oceania	4	1.135	1.271	1.046
Middle-east	2	-0.186	0.663	-0.198
no. of positive region-specific coefficients	Total countries	**MG**	**CMG**	**AMG**
Africa	15	13 [86.7]	8 [53.3]	13 [86.7]
America	9	3 [33.3]	4 [44.4]	4 [44.4]
Asia	11	8 [72.7]	7 [63.6]	8 [72.7]
Europe	17	10 [58.8]	9 [52.9]	9 [52.9]
Oceania	4	3 [75.0]	3 [75.0]	3 [75.0]
Middle-east	2	1 [50.0]	1 [50.0]	1 [50.0]
no. of negative region-specific coefficients	Total countries	**MG**	**CMG**	**AMG**
Africa	15	2 [13.3]	7 [46.7]	2 [13.3]
America	9	6 [66.7]	5 [55.6]	5 [55.6]
Asia	11	3 [27.3]	4 [36.4]	3 [27.3]
Europe	17	7 [41.2]	8 [47.1]	8 [47.1]
Oceania	4	1 [25.0]	1 [25.0]	1 [25.0]
Middle-east	2	1 [50.0]	1 [50.0]	1 [50.0]

Income elasticity estimates by regions (Model 3) (continued).

no. of significant region-specific	Total countries	MG	CMG	AMG
Africa	15	6 [40.0]	4 [26.7]	6 [40.0]
America	9	1 [11.1]	1 [11.1]	1 [11.1]
Asia	11	6 [54.5]	0 [0.0]	6 [54.5]
Europe	17	7 [41.2]	5 [29.4]	4 [23.5]
Oceania	4	1 [25.0]	1 [25.0]	1 [25.0]
Middle-east	2	1 [50.0]	2 [100.0]	1 [50.0]
no. of positively significant coefficients	**Total countries**	**MG**	**CMG**	**AMG**
Africa	15	6 [40.0]	4 [26.7]	6 [40.0]
America	9	1 [11.1]	0 [0.0]	1 [11.1]
Asia	11	5 [45.5]	0 [0.0]	5 [45.5]
Europe	17	5 [29.4]	2 [11.8]	2 [11.8]
Oceania	4	1 [25.0]	1 [25.0]	1 [25.0]
Middle-east	2	0 [0.0]	1 [50.0]	0 [0.0]
no. of negatively significant coefficients	**Total countries**	**MG**	**CMG**	**AMG**
Africa	15	0 [0.0]	0 [0.0]	0 [0.0]
America	9	0 [0.0]	1 [11.1]	0 [0.0]
Asia	11	1 [9.1]	0 [0.0]	1 [9.1]
Europe	17	2 [11.8]	3 [17.6]	2 [11.8]
Oceania	4	0 [0.0]	0 [0.0]	0 [0.0]
Middle-east	2	1 [50.0]	1 [50.0]	1 [50.0]

Appendix 2.D.

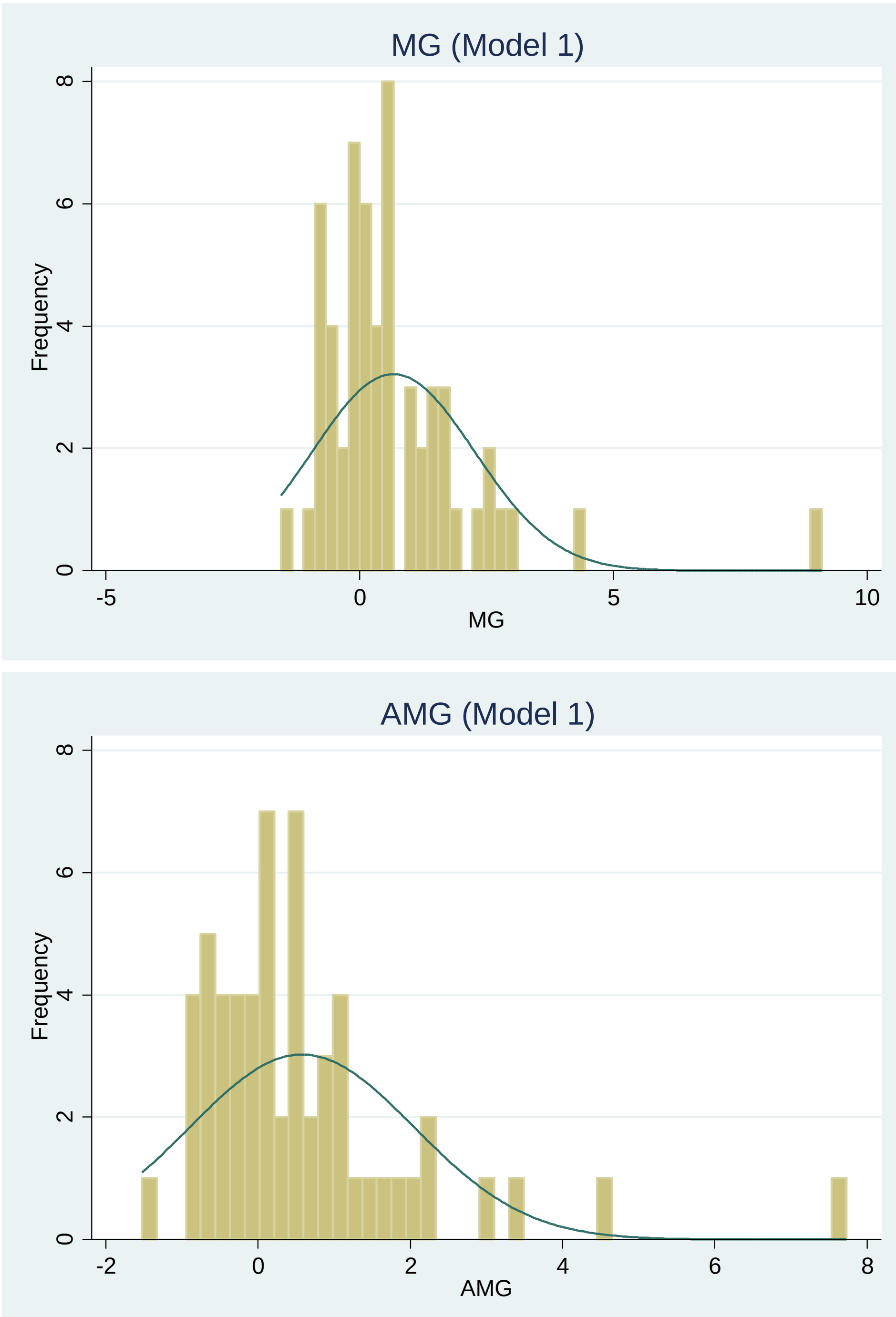

Figure 2.5

Figure 2.5. Histograms of MG and AMG estimated income elasticities (Model 1).

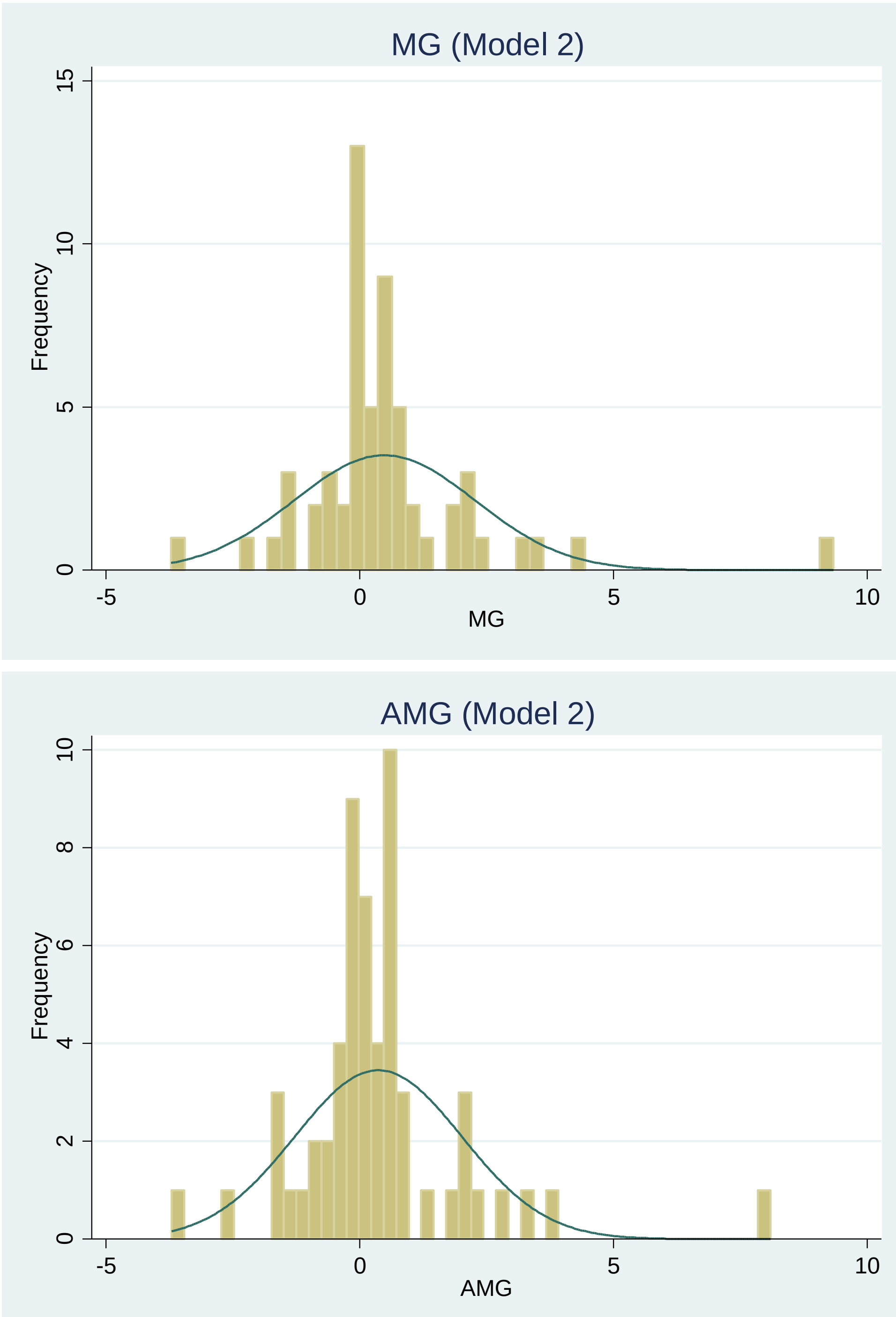

Figure 2.6

Figure 2.6. Histograms of MG and AMG estimated income elasticities (Model 2).

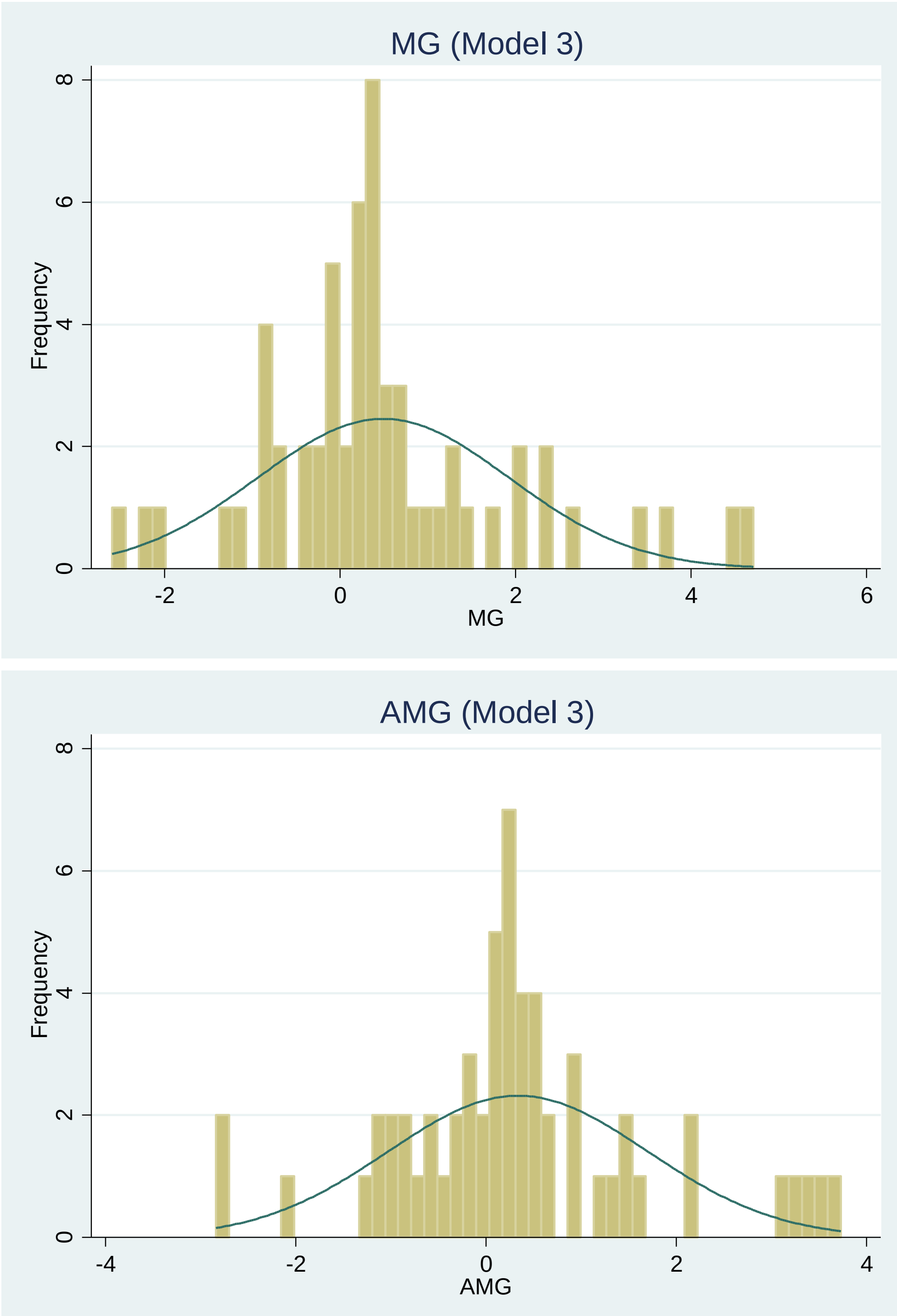

Figure 2.7

Figure 2.7. Histograms of MG and AMG estimated income elasticities (Model 3).

Appendix 2.E.

Income elasticities for individual country (Model 1).

Group	Country	code	Region	MG	CMG	AMG
1	Benin	BEN	Africa	1.447	-5.252^{**}	1.142
2	Burkina Faso	BFA	Africa	0.966	-0.589	0.762
3	Cape Verde	CPV	Africa	0.507^{**}	-0.363	0.485^{**}
4	Cameroon	CMR	Africa	1.173^{***}	1.400^{**}	1.096^{***}
5	Central Africa	CAF	Africa	1.452^{***}	1.498^{*}	1.432^{***}
6	Chad	TCD	Africa	0.499	-0.453	0.472
7	Gabon	GAB	Africa	2.798	2.785	3.039^{*}
8	Mali	MLI	Africa	1.409^{***}	1.099^{***}	1.363^{***}
9	Mauritius	MUS	Africa	0.449	-0.386	0.116
10	Morocco	MAR	Africa	-0.848	1.758^{***}	-0.774
11	Niger	NER	Africa	4.329^{**}	2.038	4.478^{**}
12	Senegal	SEN	Africa	1.854^{**}	1.432	1.800^{**}
13	South Africa	ZAF	Africa	0.453^{*}	0.500	0.454^{*}
14	Togo	TGO	Africa	1.591^{***}	1.475^{**}	1.647^{***}
15	Tunisia	TUN	Africa	1.612	-1.520	-0.083
16	Bahamas	BHS	America	0.428^{*}	0.481	0.332
17	Barbados	BRB	America	-0.229	1.088	-0.265
18	Belize	BLZ	America	0.497^{*}	0.361	0.490^{*}
19	Canada	CAN	America	-0.691	-2.559^{***}	-0.692
20	Dominica	DMA	America	-0.202	-2.735^{**}	-0.200
21	Grenada	GRD	America	0.377	-0.467	0.585
22	Panama	PAN	America	-0.132	-1.053^{*}	-0.040
23	Trinidad And Tobago	TTO	America	-0.622	-0.813	-0.443
24	United States Of America	USA	America	0.108	-1.373	0.352
25	Bangladesh	BGD	Asia	0.165	-0.020	0.108
26	Brunei	BRN	Asia	0.146	-0.169	0.114
27	China	CHN	Asia	0.434^{***}	0.321^{**}	0.460^{***}
28	India	IND	Asia	0.180	0.636^{**}	0.168
29	Japan	JAP	Asia	0.020	0.074	0.021
30	Korea	KOR	Asia	-0.799^{**}	-0.318	-0.629^{*}
31	Malaysia	MYS	Asia	0.446^{***}	0.490^{***}	0.454^{***}
32	Nepal	NPL	Asia	-0.206	-0.028	-0.252
33	Pakistan	PAK	Asia	-1.551^{*}	-1.846	-1.526^{*}
34	Philippines	PHL	Asia	0.567^{***}	0.168	0.685^{***}

Income elasticities for individual country (Model 1).

Group	Country	code	Region	MG	CMG	AMG
35	Thailand	THA	Asia	-0.061	-0.023	-0.043
36	Austria	AUT	Europe	0.542	5.834***	0.886
37	Belgium	BEL	Europe	2.365	-1.456	2.040
38	Cyprus	CYP	Europe	0.496	-0.070	0.110
39	Denmark	DNK	Europe	9.106***	3.511	7.732**
40	Finland	FIN	Europe	0.105	1.932	-0.206
41	France	FRA	Europe	2.514***	1.409	2.224**
42	Germany	DEU	Europe	-0.772***	-1.185***	-0.776**
43	Ireland	IRL	Europe	-0.543	-3.427***	-0.700*
44	Italy	ITA	Europe	-0.961	0.294	-0.858
45	Malta	MLT	Europe	-0.175	-1.105	-0.412
46	Netherlands	NLD	Europe	1.711	-3.264	1.033
47	Norway	NOR	Europe	1.076***	0.873	0.914***
48	Portugal	PRT	Europe	1.160***	1.009*	0.993**
49	Spain	ESP	Europe	-0.324	-3.489***	-0.497
50	Sweden	SWE	Europe	-0.817	0.470	-0.833
51	Switzerland	CHE	Europe	-0.015	0.787	-0.005
52	United Kingdom	GBR	Europe	2.524***	0.140	2.240***
53	Australia	AUS	Oceania	2.974***	6.990***	3.457***
54	Fiji	FJI	Oceania	-0.448	-0.097	-0.736
55	New Zealand	NZL	Oceania	0.992**	0.042	0.796*
56	Vanuatu	VUT	Oceania	-0.719	-0.102	-0.613
57	Jordan	JOR	Middle-East	-0.533*	-0.530*	-0.543*
58	Saudi Arabia	SAU	Middle-East	-0.175	2.268***	0.026

Income elasticities for individual country (Model 2).

Group	Country	code	Region	MG	CMG	AMG
1	Benin	BEN	Africa	-0.835	-4.651**	-0.766
2	Burkina Faso	BFA	Africa	-0.086	-0.513	-1.235
3	Cape Verde	CPV	Africa	0.213	-0.593	0.218
4	Cameroon	CMR	Africa	1.002**	0.291	0.654
5	Central Africa	CAF	Africa	1.733***	2.878***	1.731***
6	Chad	TCD	Africa	-0.066	-0.379	-0.078
7	Gabon	GAB	Africa	3.281	1.351	2.727
8	Mali	MLI	Africa	1.040**	0.810**	0.961**
9	Mauritius	MUS	Africa	-0.162	0.525	-0.265
10	Morocco	MAR	Africa	-0.031	2.161***	-0.035
11	Niger	NER	Africa	4.198	1.934	3.390
12	Senegal	SEN	Africa	1.904**	3.354**	1.980*
13	South Africa	ZAF	Africa	0.607**	0.418	0.621**
14	Togo	TGO	Africa	1.418**	1.720***	1.391**
15	Tunisia	TUN	Africa	2.052	-0.940	0.657
16	Bahamas	BHS	America	-0.007	-0.215	-0.036
17	Barbados	BRB	America	-0.183	1.137	-0.157
18	Belize	BLZ	America	0.502*	0.319	0.516*
19	Canada	CAN	America	-0.713	-2.046*	-0.711
20	Dominica	DMA	America	-2.313	-2.858*	-2.673
21	Grenada	GRD	America	0.831*	0.641	0.789
22	Panama	PAN	America	-0.205	-0.686	-0.140
23	Trinidad And Tobago	TTO	America	-0.931**	-0.459	-0.906**
24	United States Of America	USA	America	0.018	1.224	0.343
25	Bangladesh	BGD	Asia	0.124	0.262	0.024
26	Brunei	BRN	Asia	0.145	0.224	0.130
27	China	CHN	Asia	0.448***	0.259	0.446***
28	India	IND	Asia	0.220	0.552	0.220
29	Japan	JAP	Asia	0.074**	0.132**	0.077**
30	Korea	KOR	Asia	-0.415	-0.546	-0.263
31	Malaysia	MYS	Asia	0.570***	0.703***	0.582***
32	Nepal	NPL	Asia	-0.142	-0.213	-0.117
33	Pakistan	PAK	Asia	-3.719***	-2.934*	-3.706***
34	Philippines	PHL	Asia	0.761*	-1.068*	0.918**
35	Thailand	THA	Asia	-0.101	-0.058	-0.083

Income elasticities for individual country (Model 2).

Group	Country	code	Region	MG	CMG	AMG
36	Austria	AUT	Europe	0.430	6.451^{***}	0.595
37	Belgium	BEL	Europe	2.467	-6.201	2.205
38	Cyprus	CYP	Europe	0.613	-0.059	0.200
39	Denmark	DNK	Europe	9.336^{***}	10.585^{**}	8.098^{***}
40	Finland	FIN	Europe	0.207	1.663	-0.049
41	France	FRA	Europe	2.129^{**}	3.977^{***}	2.014^{**}
42	Germany	DEU	Europe	-0.504	-1.113^{*}	-0.496
43	Ireland	IRL	Europe	-0.142	0.228	-0.174
44	Italy	ITA	Europe	-1.780^{**}	0.735	-1.652^{*}
45	Malta	MLT	Europe	-1.468	-2.136	-1.519
46	Netherlands	NLD	Europe	0.655	-2.156	0.239
47	Norway	NOR	Europe	0.782^{*}	1.426	0.710^{*}
48	Portugal	PRT	Europe	0.425	1.213^{*}	0.390
49	Spain	ESP	Europe	-1.496^{***}	-3.399^{***}	-1.686^{***}
50	Sweden	SWE	Europe	-1.362^{*}	2.718	-1.300^{*}
51	Switzerland	CHE	Europe	0.550	0.235	0.477
52	United Kingdom	GBR	Europe	2.176^{**}	1.148	2.072^{**}
53	Australia	AUS	Oceania	3.589^{***}	5.240^{**}	3.800^{***}
54	Fiji	FJI	Oceania	-0.091	-0.262	-0.451
55	New Zealand	NZL	Oceania	0.659	0.033	0.565
56	Vanuatu	VUT	Oceania	-0.006	-0.331	0.031
57	Jordan	JOR	Middle-East	-0.624^{*}	-0.538	-0.639^{*}
58	Saudi Arabia	SAU	Middle-East	0.614	2.773^{***}	0.585

Income elasticities for individual country (Model 3).

Group	Country	code	Region	MG	CMG	AMG
1	Benin	BEN	Africa	-0.056	-2.321	-0.169
2	Burkina Faso	BFA	Africa	0.368	-1.808	0.197
3	Cape Verde	CPV	Africa	0.198	-0.219	0.219
4	Cameroon	CMR	Africa	1.264^{**}	2.466^{**}	1.221^{**}
5	Central Africa	CAF	Africa	2.064^{***}	2.343^{***}	1.609^{**}
6	Chad	TCD	Africa	-0.079	-0.547	-0.185
7	Gabon	GAB	Africa	2.715	-0.779	3.435^{*}
8	Mali	MLI	Africa	1.311^{**}	1.191^{**}	1.353^{**}
9	Mauritius	MUS	Africa	0.231	0.605	0.012
10	Morocco	MAR	Africa	0.446	2.245^{***}	0.437
11	Niger	NER	Africa	4.712^{*}	1.879	3.154
12	Senegal	SEN	Africa	2.040^{*}	0.497	2.180^{*}
13	South Africa	ZAF	Africa	0.356	0.498	0.360
14	Togo	TGO	Africa	1.378^{**}	-0.367	1.450^{***}
15	Tunisia	TUN	Africa	2.315	-1.189	0.880
16	Bahamas	BHS	America	0.121	0.168	0.044
17	Barbados	BRB	America	-0.697	0.139	-1.089
18	Belize	BLZ	America	0.691^{**}	0.166	0.569^{*}
19	Canada	CAN	America	-0.785	-2.499	-0.790
20	Dominica	DMA	America	-2.054	-2.354^{*}	-2.772
21	Grenada	GRD	America	0.297	-1.408	0.263
22	Panama	PAN	America	-0.451	-1.492	-0.452
23	Trinidad And Tobago	TTO	America	-0.713	1.366	-0.601
24	United States Of America	USA	America	-0.060	-0.784	0.205
25	Bangladesh	BGD	Asia	0.364	0.368	0.236
26	Brunei	BRN	Asia	0.177	0.349	0.189
27	China	CHN	Asia	0.484^{***}	-0.210	0.484^{***}
28	India	IND	Asia	0.510^{**}	0.209	0.510^{**}
29	Japan	JAP	Asia	0.076^{*}	0.070	0.075^{*}
30	Korea	KOR	Asia	-0.317	-0.056	-0.247
31	Malaysia	MYS	Asia	0.322^{*}	0.104	0.319^{*}
32	Nepal	NPL	Asia	0.185	0.185	0.174
33	Pakistan	PAK	Asia	-2.598^{**}	0.251	-2.839^{**}
34	Philippines	PHL	Asia	0.931^{**}	-0.400	0.878^{**}
35	Thailand	THA	Asia	-0.084	-0.121	-0.081

Income elasticities for individual country (Model 3).

Group	Country	code	Region	MG	CMG	AMG
36	Austria	AUT	Europe	0.637	6.684***	0.471
37	Belgium	BEL	Europe	3.774*	1.318	3.300
38	Cyprus	CYP	Europe	0.200	0.025	-0.117
39	Denmark	DNK	Europe	4.493*	4.103	3.732
40	Finland	FIN	Europe	-0.243	-2.732	-0.909
41	France	FRA	Europe	2.336**	3.043*	2.102*
42	Germany	DEU	Europe	-0.919**	-2.324***	-0.934**
43	Ireland	IRL	Europe	-0.107	-3.937*	-0.367
44	Italy	ITA	Europe	-2.159**	2.044	-2.039*
45	Malta	MLT	Europe	-1.237	-0.737	-1.331
46	Netherlands	NLD	Europe	0.452	-3.331	0.050
47	Norway	NOR	Europe	1.098***	1.259	0.985***
48	Portugal	PRT	Europe	0.264	0.128	0.134
49	Spain	ESP	Europe	-0.814	-3.084	-1.007
50	Sweden	SWE	Europe	-1.156	4.481***	-1.176
51	Switzerland	CHE	Europe	0.301	-0.543	0.114
52	United Kingdom	GBR	Europe	1.797*	-0.611	1.529
53	Australia	AUS	Oceania	3.346***	4.959***	3.478***
54	Fiji	FJI	Oceania	-0.210	-0.507	-0.555
55	New Zealand	NZL	Oceania	0.802	0.607	0.657
56	Vanuatu	VUT	Oceania	0.603	0.023	0.603
57	Jordan	JOR	Middle-East	-0.775**	-0.904**	-0.782**
58	Saudi Arabia	SAU	Middle-East	0.404	2.229*	0.387

Appendix 2.F.

Weighted Income elasticities for individual country (Model 1).

Group	Country	code	Region	Weight	MG	CMG	AMG
1	Benin	BEN	Africa	1.443	2.088	-7.579	1.648
2	Burkina Faso	BFA	Africa	1.039	1.004	-0.612	0.792
3	Cape Verde	CPV	Africa	2.114	1.071	-0.768	1.026
4	Cameroon	CMR	Africa	0.790	0.927	1.106	0.866
5	Central Africa	CAF	Africa	0.258	0.375	0.386	0.370
6	Chad	TCD	Africa	0.494	0.247	-0.224	0.233
7	Gabon	GAB	Africa	1.803	5.044	5.021	5.478
8	Mali	MLI	Africa	2.547	3.590	2.800	3.472
9	Mauritius	MUS	Africa	3.478	1.562	-1.343	0.404
10	Morocco	MAR	Africa	0.054	-0.045	0.094	-0.041
11	Niger	NER	Africa	0.739	3.201	1.507	3.311
12	Senegal	SEN	Africa	3.860	7.157	5.528	6.948
13	South Africa	ZAF	Africa	0.683	0.309	0.341	0.310
14	Togo	TGO	Africa	0.994	1.581	1.465	1.637
15	Tunisia	TUN	Africa	0.078	0.125	-0.118	-0.006
16	Bahamas	BHS	America	1.338	0.573	0.643	0.445
17	Barbados	BRB	America	1.048	-0.240	1.140	-0.278
18	Belize	BLZ	America	1.615	0.802	0.583	0.791
19	Canada	CAN	America	0.402	-0.278	-1.028	-0.278
20	Dominica	DMA	America	0.534	-0.108	-1.461	-0.107
21	Grenada	GRD	America	0.725	0.274	-0.339	0.425
22	Panama	PAN	America	3.009	-0.396	-3.168	-0.120
23	Trinidad And Tobago	TTO	America	1.453	-0.904	-1.181	-0.644
24	United States Of America	USA	America	0.405	0.044	-0.556	0.143
25	Bangladesh	BGD	Asia	9.497	1.569	-0.193	1.026
26	Brunei	BRN	Asia	4.149	0.604	-0.701	0.472
27	China	CHN	Asia	4.557	1.977	1.461	2.094
28	India	IND	Asia	4.289	0.771	2.727	0.721
29	Japan	JAP	Asia	2.890	0.056	0.215	0.061
30	Korea	KOR	Asia	5.459	-4.364	-1.738	-3.433
31	Malaysia	MYS	Asia	4.813	2.147	2.357	2.184
32	Nepal	NPL	Asia	5.267	-1.086	-0.146	-1.325
33	Pakistan	PAK	Asia	0.857	-1.329	-1.581	-1.307
34	Philippines	PHL	Asia	6.095	3.457	1.026	4.174

Weighted Income elasticities for individual country (Model 1).

Group	Country	code	Region	Weight	MG	CMG	AMG
35	Thailand	THA	Asia	6.802	-0.412	-0.158	-0.293
36	Austria	AUT	Europe	0.247	0.134	1.443	0.219
37	Belgium	BEL	Europe	0.327	0.774	-0.477	0.668
38	Cyprus	CYP	Europe	0.240	0.119	-0.017	0.026
39	Denmark	DNK	Europe	0.181	1.650	0.636	1.401
40	Finland	FIN	Europe	0.249	0.026	0.481	-0.051
41	France	FRA	Europe	0.264	0.664	0.372	0.587
42	Germany	DEU	Europe	0.144	-0.111	-0.170	-0.111
43	Ireland	IRL	Europe	0.161	-0.087	-0.550	-0.112
44	Italy	ITA	Europe	0.308	-0.296	0.091	-0.265
45	Malta	MLT	Europe	0.241	-0.042	-0.267	-0.099
46	Netherlands	NLD	Europe	0.177	0.303	-0.579	0.183
47	Norway	NOR	Europe	0.208	0.224	0.182	0.190
48	Portugal	PRT	Europe	0.957	1.109	0.965	0.950
49	Spain	ESP	Europe	0.417	-0.135	-1.454	-0.207
50	Sweden	SWE	Europe	0.285	-0.233	0.134	-0.237
51	Switzerland	CHE	Europe	0.274	-0.004	0.216	-0.001
52	United Kingdom	GBR	Europe	0.228	0.576	0.032	0.511
53	Australia	AUS	Oceania	0.486	1.445	3.397	1.680
54	Fiji	FJI	Oceania	2.693	-1.208	-0.260	-1.982
55	New Zealand	NZL	Oceania	0.390	0.387	0.017	0.311
56	Vanuatu	VUT	Oceania	2.904	-2.088	-0.295	-1.780
57	Jordan	JOR	Middle-East	1.261	-0.673	-0.668	-0.685
58	Saudi Arabia	SAU	Middle-East	1.780	-0.312	4.038	0.046
Average share-weighted income elasticities					**0.580**	**0.220**	**0.559**

Weighted Income elasticities for individual country (Model 2).

Group	Country	code	Region	Weight	MG	CMG	AMG
1	Benin	BEN	Africa	1.443	-1.205	-6.711	-1.105
2	Burkina Faso	BFA	Africa	1.039	-0.089	-0.533	-1.284
3	Cape Verde	CPV	Africa	2.114	0.451	-1.252	0.462
4	Cameroon	CMR	Africa	0.790	0.791	0.230	0.517
5	Central Africa	CAF	Africa	0.258	0.447	0.742	0.447
6	Chad	TCD	Africa	0.494	-0.033	-0.187	-0.039
7	Gabon	GAB	Africa	1.803	5.914	2.435	4.915
8	Mali	MLI	Africa	2.547	2.650	2.063	2.448
9	Mauritius	MUS	Africa	3.478	-0.562	1.827	-0.920
10	Morocco	MAR	Africa	0.054	-0.002	0.116	-0.002
11	Niger	NER	Africa	0.739	3.104	1.430	2.507
12	Senegal	SEN	Africa	3.860	7.349	12.944	7.642
13	South Africa	ZAF	Africa	0.683	0.414	0.285	0.424
14	Togo	TGO	Africa	0.994	1.410	1.709	1.382
15	Tunisia	TUN	Africa	0.078	0.159	-0.073	0.051
16	Bahamas	BHS	America	1.338	-0.009	-0.288	-0.048
17	Barbados	BRB	America	1.048	-0.191	1.192	-0.165
18	Belize	BLZ	America	1.615	0.811	0.515	0.833
19	Canada	CAN	America	0.402	-0.286	-0.822	-0.285
20	Dominica	DMA	America	0.534	-1.236	-1.527	-1.428
21	Grenada	GRD	America	0.725	0.603	0.465	0.572
22	Panama	PAN	America	3.009	-0.618	-2.062	-0.422
23	Trinidad And Tobago	TTO	America	1.453	-1.353	-0.666	-1.317
24	United States Of America	USA	America	0.405	0.007	0.496	0.139
25	Bangladesh	BGD	Asia	9.497	1.178	2.484	0.224
26	Brunei	BRN	Asia	4.149	0.602	0.931	0.540
27	China	CHN	Asia	4.557	2.042	1.180	2.034
28	India	IND	Asia	4.289	0.942	2.365	0.946
29	Japan	JAP	Asia	2.890	0.213	0.382	0.223
30	Korea	KOR	Asia	5.459	-2.264	-2.979	-1.435
31	Malaysia	MYS	Asia	4.813	2.741	3.382	2.803
32	Nepal	NPL	Asia	5.267	-0.747	-1.122	-0.614
33	Pakistan	PAK	Asia	0.857	-3.186	-2.513	-3.174
34	Philippines	PHL	Asia	6.095	4.637	-6.509	5.592
35	Thailand	THA	Asia	6.802	-0.686	-0.396	-0.563

Weighted Income elasticities for individual country (Model 2).

Group	Country	code	Region	Weight	MG	CMG	AMG
36	Austria	AUT	Europe	0.247	0.106	1.596	0.147
37	Belgium	BEL	Europe	0.327	0.808	-2.030	0.722
38	Cyprus	CYP	Europe	0.240	0.147	-0.014	0.048
39	Denmark	DNK	Europe	0.181	1.692	1.918	1.468
40	Finland	FIN	Europe	0.249	0.052	0.414	-0.012
41	France	FRA	Europe	0.264	0.562	1.050	0.532
42	Germany	DEU	Europe	0.144	-0.072	-0.160	-0.071
43	Ireland	IRL	Europe	0.161	-0.023	0.037	-0.028
44	Italy	ITA	Europe	0.308	-0.549	0.227	-0.509
45	Malta	MLT	Europe	0.241	-0.355	-0.516	-0.367
46	Netherlands	NLD	Europe	0.177	0.116	-0.382	0.042
47	Norway	NOR	Europe	0.208	0.163	0.297	0.148
48	Portugal	PRT	Europe	0.957	0.406	1.160	0.373
49	Spain	ESP	Europe	0.417	-0.623	-1.416	-0.702
50	Sweden	SWE	Europe	0.285	-0.388	0.775	-0.370
51	Switzerland	CHE	Europe	0.274	0.151	0.065	0.131
52	United Kingdom	GBR	Europe	0.228	0.496	0.262	0.472
53	Australia	AUS	Oceania	0.486	1.744	2.547	1.847
54	Fiji	FJI	Oceania	2.693	-0.245	-0.705	-1.214
55	New Zealand	NZL	Oceania	0.390	0.257	0.013	0.221
56	Vanuatu	VUT	Oceania	2.904	-0.017	-0.960	0.089
57	Jordan	JOR	Middle-East	1.261	-0.787	-0.678	-0.806
58	Saudi Arabia	SAU	Middle-East	1.780	1.093	4.937	1.042
Average share-weighted income elasticities					**0.495**	**0.310**	**0.433**

Weighted Income elasticities for individual country (Model 3).

Group	Country	code	Region	Weight	MG	CMG	AMG
1	Benin	BEN	Africa	1.443	-0.081	-3.350	-0.243
2	Burkina Faso	BFA	Africa	1.039	0.383	-1.879	0.205
3	Cape Verde	CPV	Africa	2.114	0.418	-0.464	0.463
4	Cameroon	CMR	Africa	0.790	0.999	1.948	0.965
5	Central Africa	CAF	Africa	0.258	0.533	0.604	0.415
6	Chad	TCD	Africa	0.494	-0.039	-0.271	-0.092
7	Gabon	GAB	Africa	1.803	4.893	-1.405	6.192
8	Mali	MLI	Africa	2.547	3.341	3.034	3.447
9	Mauritius	MUS	Africa	3.478	0.803	2.103	0.043
10	Morocco	MAR	Africa	0.054	0.024	0.120	0.023
11	Niger	NER	Africa	0.739	3.484	1.390	2.332
12	Senegal	SEN	Africa	3.860	7.872	1.918	8.414
13	South Africa	ZAF	Africa	0.683	0.243	0.340	0.246
14	Togo	TGO	Africa	0.994	1.369	-0.364	1.441
15	Tunisia	TUN	Africa	0.078	0.180	-0.092	0.068
16	Bahamas	BHS	America	1.338	0.162	0.225	0.059
17	Barbados	BRB	America	1.048	-0.730	0.145	-1.142
18	Belize	BLZ	America	1.615	1.116	0.268	0.918
19	Canada	CAN	America	0.402	-0.315	-1.004	-0.317
20	Dominica	DMA	America	0.534	-1.098	-1.258	-1.481
21	Grenada	GRD	America	0.725	0.216	-1.021	0.191
22	Panama	PAN	America	3.009	-1.356	-4.487	-1.360
23	Trinidad And Tobago	TTO	America	1.453	-1.036	1.985	-0.873
24	United States Of America	USA	America	0.405	-0.024	-0.317	0.083
25	Bangladesh	BGD	Asia	9.497	3.457	3.499	2.238
26	Brunei	BRN	Asia	4.149	0.735	1.447	0.783
27	China	CHN	Asia	4.557	2.207	-0.957	2.205
28	India	IND	Asia	4.289	2.188	0.896	2.187
29	Japan	JAP	Asia	2.890	0.219	0.203	0.216
30	Korea	KOR	Asia	5.459	-1.733	-0.308	-1.346
31	Malaysia	MYS	Asia	4.813	1.551	0.501	1.535
32	Nepal	NPL	Asia	5.267	0.975	0.973	0.919
33	Pakistan	PAK	Asia	0.857	-2.226	0.215	-2.432
34	Philippines	PHL	Asia	6.095	5.673	-2.441	5.354
35	Thailand	THA	Asia	6.802	-0.568	-0.822	-0.549

Weighted Income elasticities for individual country (Model 3).

Group	Country	code	Region	Weight	MG	CMG	AMG
36	Austria	AUT	Europe	0.247	0.158	1.653	0.117
37	Belgium	BEL	Europe	0.327	1.236	0.431	1.080
38	Cyprus	CYP	Europe	0.240	0.048	0.006	-0.028
39	Denmark	DNK	Europe	0.181	0.814	0.744	0.676
40	Finland	FIN	Europe	0.249	-0.061	-0.680	-0.227
41	France	FRA	Europe	0.264	0.617	0.804	0.555
42	Germany	DEU	Europe	0.144	-0.132	-0.334	-0.134
43	Ireland	IRL	Europe	0.161	-0.017	-0.632	-0.059
44	Italy	ITA	Europe	0.308	-0.665	0.630	-0.629
45	Malta	MLT	Europe	0.241	-0.299	-0.178	-0.321
46	Netherlands	NLD	Europe	0.177	0.080	-0.591	0.009
47	Norway	NOR	Europe	0.208	0.229	0.262	0.205
48	Portugal	PRT	Europe	0.957	0.252	0.123	0.129
49	Spain	ESP	Europe	0.417	-0.339	-1.285	-0.419
50	Sweden	SWE	Europe	0.285	-0.329	1.277	-0.335
51	Switzerland	CHE	Europe	0.274	0.083	-0.149	0.031
52	United Kingdom	GBR	Europe	0.228	0.410	-0.139	0.349
53	Australia	AUS	Oceania	0.486	1.626	2.410	1.690
54	Fiji	FJI	Oceania	2.693	-0.565	-1.365	-1.494
55	New Zealand	NZL	Oceania	0.390	0.313	0.237	0.257
56	Vanuatu	VUT	Oceania	2.904	1.751	0.068	1.752
57	Jordan	JOR	Middle-East	1.261	-0.978	-1.140	-0.986
58	Saudi Arabia	SAU	Middle-East	1.780	0.720	3.969	0.688
Average share-weighted income elasticities					**0.669**	**0.129**	**0.586**