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THREE ESSAYS ON SAUDI ARABIA AGRICULTURAL MARKETS

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DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Agriculture, Food and Environment at the University of Kentucky

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ABSTRACT OF DISSERTATION

THREE ESSAYS ON SAUDI ARABIA AGRICULTURAL MARKETS

The first essay compares six common models, linear, quadratic, Cobb-Douglas, translog, logarithmic, and transcendental, to estimate wheat yield and area functions for Saudi Arabia. Data cover 1990-2016 for all the variables that affect wheat supply. After testing the models using Box-Cox, multicollinearity, and autocorrelation tests, we decide that the Cobb-Douglas models provide the best fit for both yield and area. We find the price elasticity of wheat is inelastic. Yield price elasticities are more inelastic than area elasticities. The impact of government policy number 335 has a larger effect on area than yield. The cultivated area of wheat, the one-year lag of yield, and the number of machines per hectare are the most influential factors affecting wheat yield. The primary factors influencing the area models are a one-year lag of both cultivated area and yield, as well as the number of machines per hectare.

The second essay estimates the residual demand elasticity that rice exporters face in Saudi Arabia. The inverse residual demand methods, as proposed by Reed and Saghaian 2004, are used for rice exporters to Saudi Arabia during the period 1993-2014. Estimation results of the elasticities of the residual demand indicate that Australia, India, and Pakistan enjoy market power, while Egypt faces a perfectly elastic demand curve. We find Thailand and the US had positive inverse residual demand which means they also have no market power.

The last essay is about the virtual water trade in Saudi Arabia. Using the concept of virtual water introduced by Allan 1994 and developed by Hoekstra and Hung (2002), we estimate virtual water trade for 20 crops of Saudi Arabia during 2000-2016. Our result shows the average virtual water trade was 12.5 billion m^3/year. Saudi has net virtual water imports, with the most significant virtual water imports coming from cereals & alfalfa and vegetables; and there is net virtual water export of fruit. Saudi virtual water trade reduces pressure on water resources by 52%. Distance plays a role in Saudi virtual water export; we found that more than 90% of exports go to neighboring countries, including 45% to GCC countries. More than 30% of virtual water imports come from Europe.

A Gravity model is used to investigate whether water scarcity variables influence trade. We compare the OLS, Fixed effects, Random effects, and PPML estimators to get the best model. The AIC, and tests for multicollinearity, and heteroskedasticity assist in determining estimation procedures and the final models. We cluster the errors by distance to improve the specific country effect variables such as economic mass variables. For the cereals and alfalfa group, we find that water-related variables influence virtual water imports of cereals, millet, sorghum, corn, barley, and sesame. Therefore, we suggest that a basic gravity model be applied to the other crops. In the vegetable group, we find that related water variables impact virtual water trade for all crops except marrow. Dates are the only fruit crop that are not influenced by the water-related variables.

KEYWORDS: Cobb-Douglas, Partial Adjustment, Lerner Index, Inverse Residual Demand, Virtual Water Trade, PPML.

Yosef Abdulrahman Alamri

July 10th, 2019

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Date

DEDICATION

To my patient father: you have done much to help me overcome the difficulties I encountered and the complexities I faced.

To my beloved mother: I will never forget how you stood with me and relieved a lot of my pain and grief.

It is impossible to express how much I thank them for their patience as I lived far from them.

Without my parents, this accomplishment would have no meaning.

To my wife and the most beautiful flowers in my life, Sarah and Reem, and the greatest children, Mohammed and Omar.

To all my brothers and beautiful sisters: I would like to thank you for your incredible support.

If you have such people with you, know that you will never walk alone.

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CHAPTER 1. GENERAL INTRODUCTION

Saudi Arabia relies much more on agricultural imports than agricultural exports. This has been particularly true during the past three decades. In 2016, agricultural production accounted for only 2% of total GDP. Despite agriculture's small share, the Saudi Arabia GDP was raising throughout the period. Agriculture in Saudi Arabia faces huge limitations of the water resources. These water limitations have led to changes in production and trade policies from times to time.

The Saudi Arabia government has not ignored the agricultural sector. The history of its support to the sector began in the early 1980s. However, sometimes the support of agriculture ignored the limitation of Saudi Arabia's natural resources, particularly water. Decision makers have recently realized that they must reconsider their ideas on food self-sufficiency to promote food security. Imports play an important role because of problems with water scarcity.

The study of agricultural trade markets (exports and imports) in Saudi Arabia is one of the most critical determinants of the development of foreign trade. It helps to provide an integrated picture of the market needs, the consumer's preferences, and the competing between goods, including international trade. Since a comprehensive study of the various aspects of foreign trade with the outside world in its different and varied markets is too large an undertaking, this analysis focuses on studying the effect of agricultural policies on the yield and area of wheat. Saudi Arabia was one of the top exporting countries in the 1990s but is now one of the top importing countries. Therefore, the first essay investigates the factors that influence wheat area and yield for Saudi Arabia from 1990 to 2016. A partial adjustment model is used with linear, quadratic, Cobb-Douglas, translog, logarithmic, and transcendental models to investigate the impact of policy number 335 on yield and area model. We start by checking the correlation matrix between variables. After that, we used the Box-Cox test to select the preferred forms. The preferred function, then, is checked for multicollinearity and autocorrelation. We found that the Cobb-Douglas model was found to represent both yield and area models best. The price elasticity of wheat was found to be inelastic in both models. The results indicate that the cultivated area of wheat, one-year lagged yield, and the number of machines per hectare affect wheat yield model. On the other hand, the one-year lag of cultivated area, one-year lagged of yield, and the number of machines per hectare affect cultivated area of wheat model. The policy change was found to have a significant influence on the wheat area models.

Rice production takes a tremendous amount of water, so it is logical that Saudi Arabia is a major rice importer. The second essay examined the Saudi Arabian rice market. Due to water scarcity and climate conditions, Saudi Arabia imports all its rice from abroad. During the 2009-2013, the quality of rice required for consumer preference led Saudi Arabia to be the second-ranked importer of rice in value. This results in intense competition among exporters to obtain a larger share of Saudi rice. Therefore, this essay examines the intensity of competition among these countries using an inverse residual demand function, as used by Reed and Saghaian (2004), which was estimated using annual data from 1993 to 2014. The results indicate that Australia, India, and Pakistan enjoy a markup of price over marginal cost in the Saudi rice market. India had the highest rice mark up and Australia had the lowest. Egypt, Thailand, and the US were found to be price takers in the market.

The last essay integrated water scarcity and foreign trade by studying the determinants of international trade of crops using the concept of virtual water for Saudi

Arabia. The agriculture sector accounted for 83% of the total water used in Saudi Arabia in 2016, with more than 90% of this coming from nonrenewable groundwater (MEWA, 2017). There were two objectives for this essay: first, to present the benefits of using the concept of virtual water trade as a bridge to overcome the gap between local water sources and food demand in Saudi Arabia. Second, to investigate whether water scarcity variables influence agricultural trade between Saudi Arabia and its commercial partners. Virtual water trade is calculated for twenty crops and three groups during 2000-2016. The results show that domestic consumption of water has decreased for Cereals and fruit and increased for vegetable and alfalfa. The results indicate higher virtual water imports from Europe compared to other continents. Yet Ukraine was the top exporter of virtual water to Saudi Arabia while Kuwait was the top importer of virtual water from Saudi Arabia.

A gravity model of virtual water was used to achieve the second objective. An AIC forward or backward criterion was used to select the variables for each crop model. OLS, fixed effect, and random effect were compared according to the F-test, Breusch and Pagan LM test, and Hausman test. A PPML model was also fitted for each crop to solve issues of zero trade and heteroscedasticity. Our results indicate that alfalfa, wheat, marrow, and date imports were not influenced by water-related variables. We found more than 60% of the significant coefficients for water-related variables did not support Allan's ideas for importing virtual water from water-abundant countries.

CHAPTER 2. THE WHEAT YIELD AND AREA OF FUNCTIONS FORM IN SAUDI ARABIA[1]

2.1 Abstract:

The primary purpose of this paper is comparing six common models, which were linear, quadratic, Cobb-Douglas, translog, logarithmic, and transcendental, to estimate the yield and area functions for Saudi Arabian wheat. Data cover 1990-2016 for all the variables used in the wheat models. After testing the models using Box-Cox, multicollinearity, and autocorrelation, we came up with the fact that the Cobb-Douglas methods were the best models to show the relationship between variables in both yield and area models. We found the elasticity of wheat was inelastic. The yield function was more inelastic than the area function. The impact of government policy number 335 shows a significant impact in the area compared to the yield model. Cultivated area of wheat, the one-year lag of yield, and the number of machines per hectare were the most influence factors affecting the yield model. While, the influence factors in the area models were a one-year lag of both cultivated area and yield, as well as the number of machines per hectare.

2.2 Introduction

The primary purpose of this investigation is to determine the factors that affected the yield and area of Saudi Arabia's wheat crop over the past three decades. This information will be useful to policymakers in the development of future agricultural policies, as agricultural policies are very important to the agricultural sector. To assist in

[1] Based upon Alamri, Yosef, and Tyler Mark (2018) "Functions of Wheat Supply and Demand in Saudi Arabia" *Journal of Agricultural Economics and Rural Development* Vol. 4(1), pp. 372-380.

accomplishing the investigation's goal, the introduction will provide a detailed historical account of Saudi Arabia's wheat crops.

Wheat production has been an important part of Saudi Arabia's agricultural production history for many decades. From the early 1980 to 2007, the government provided support to farmers to produce wheat (Al-Saffy and Mousa 2010). Due to the government's support, approximately 524.6 thousand hectares of land, on average, was dedicated to wheat production between 1990–2008, resulting in the production of 2.5 million tons of wheat annually.

In 2008, Saudi Arabia decided to change its wheat policies due to water shortages. As a result, they developed Resolution 335. This resolution stated that the Saudi Grains Organization (SAGO) was required to stop purchasing locally produced wheat for up to eight years, at an annually declining rate of 12.5% starting from 2008. The resolution also continuos prohibited the export of domestically produced wheat. The Ministry of Agriculture also continuos stopped issuing licenses to produce wheat, barley, and fodder. These agricultural policy changes resulted in some wheat farmers becoming reluctant to grow wheat in Saudi Arabia, due to higher input costs and lower revenues (Al-Nashwan, 2010; ADF, 2017; SAGO, 2017). Consequently, between 2009 and 2016, wheat was only cultivated on approximately 152.7 thousand hectares annually, resulting in the production of 0.93 million tons of wheat, on average, as opposed to the 2.5 million tons produced annually in the previous two decades (; MEWA, 2017).

Table 2.1 illustrates that the average area of wheat cultivation and average wheat production in Saudi Arabia, from 1990 to 2016, was 414.4 thousand hectares and 2.04 million tons, but there was an annual rate of decline of about 0.03% and 0.02% annually, respectively. Wheat accounted for about 38% of the total grain area and 42% of the total grain production in 2016 (MEWA, 2017). Total wheat production in 2016 was estimated at 765.8 thousand tons, a decline of about 79% when compared to 1990.

From 1990 to 2016, the average wheat yield per hectare was about 5.21 tons per hectare, with a growth rate of about 0.007% per year. Wheat yield in 2016 was about 6.26 tons per hectare, which was 35% more than that in 1990 (4.65 tons per hectare). Producer prices ranged from $445.8 (2016) to $252.9 (1998) per ton, while the average producer's wheat price was about $329.3 (1990-2016) per ton.

The average import quantity and value of wheat during the period 1990–2016 in Saudi Arabia accounted for 612.9 thousand tons or $189.06 million, with an annual growth rate of about 0.12% and 0.12%, respectively. When compared to 1990, the Saudi import quantity of wheat was 732% higher in 2008 and 1311% higher in 2016. The average wheat import price during the period of 1990–2016 was about $346.6 per ton, with an annual decline of about 0.002% during that same period (figure 2.1).

During the study period, the average annual domestic consumption of wheat was about 2.45 million tons, while the average per capita consumption of wheat in Saudi Arabia was about 104 kg per year.

The research problem arose when the gap between the local production and domestic consumption of wheat encouraged local studies to focus on the most critical factors that led to the growth of this gap. These studies focused on agricultural policies, as well as supply shifters, which did not provide a complete picture of this crop.

The rest of this paper is organized as follows. The next section focuses on developing yield and area models. The estimation results follow that section. In the final section, we discuss our conclusions and elaborate upon our policy implications. We also provide recommendations for future research.

Table 2.1 Wheat area, production, yield, producer and import prices, import quantity and value, and domestic consumption in Saudi Arabia during the period (1990-2016).

Year	Area	Production	Yield	Producer Price	Import Quantity	Import Value	Price Import	Domestic Consumption
	1000Ha	1000Ton	Ton/Ha	($/ton)	1000Ton	1000 US$	$/ton	1000Ton
Average	414.4	2041.2	5.21	329.30	612.92	189063.66	346.62	2450.37
Max	924.4	4123.7	6.43	445.8	3236.9	1023599	696.36	4100
Min	102.6	660.1	4.25	252.9	0.047	13	155.599	1550
% change	-84%	-79%	35%	11%	1311%	1119%	-14%	137%

Source:
** Ministry of Environment Water & Agriculture. Saudi Arabia.*
** General Authority for statistics (GASTAT). Saudi Arabia.*
** FOASTAT, the Food and Agriculture Organization of the United Nations (FAO).*
** The United States Department of Agriculture (USDA), PSD and GATS.*

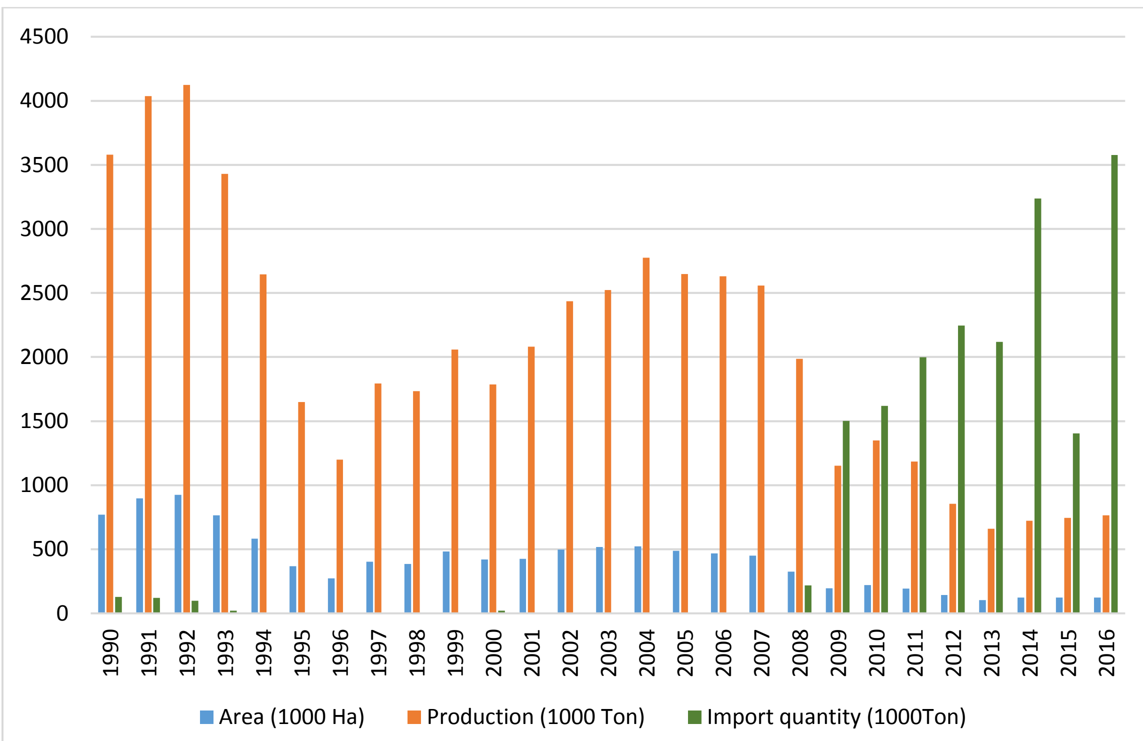

Figure 2.1 Area, production and import quantity of wheat in Saudi Arabia during the period 1990-2016.

2.3 Literature review:

This research is a continuation of the research efforts that preceded it on the response of wheat supply in Saudi Arabia. Despite these significant efforts, the published studies on the wheat supply response are still limited, and their focus has been on studying the effect of independent variables on the supply using linear, logarithmic and quadratic models.

Al-Turkey (1991) used variations of the production model of wheat and concluded that the best model was the quadratic model. While Khalifa and Taj Eddin (1993) estimate the production function of wheat in Saudi Arabia using a linear model. AlSultan, (2005) used linear and quadratic trend model, simple and double moving average, and simple and double Exponential smoothing to predict the yield of wheat in Saudi Arabia.

The implications of supporting program were discussed by AL-Kahtani (1994), Al-Hadithi (2002), and Al-Nashwan (2010). AL-Kahtani (1994) estimates the optimal level of wheat production under the price support program in Saudi Arabia. He found that the producer benefits more from this program than the consumer. Al-Hadithi, (2002) showed that the rise in the cultivated area and quantity of wheat production in Saudi Arabia was a result of the government supporting program during the period 1982-1992. Likewise, as a result of the changes in the agricultural policy of reducing the prices and encouraging diversification away from subsidized crops, the area and production of wheat fell in 1997. However, Al-Nashwan (2010) conducted an economic estimation of the impact of government decision number 335 on wheat. He found there was a positive effect of the government decision that reduces the consumption of scarce water due to the reduced cultivate area of 56.42 thousand hectares annually for eight years. He expected the increase for savings in water resources from 2009 through 2016 by 800%. On the other hand, he showed that the adverse effect of the government decision was the reduction of domestic wheat production by 314.96 thousand tons per year for eight years.

2.4 Methodology:

2.4.1 Conceptual model

Agricultural product markets are influenced by external factors that affect the supply to the market. The supply of agricultural produce is affected by natural and disaster factors, such as floods, rainfall, soil fertility, and high or low temperature, among others (Debertin, 2012). In this study, we used widely different functions, described by Griffin et al. (1987), Anderson et al. (1996) and Debertin (2012), to estimate the yield and area function of wheat, as represented in Table 2.2. Non-linear transformations made the distribution of the residuals more normal and reduced the multicollinearity and heteroskedastic problems (Wooldridge, 2009).

Our model depends on using a lag for some of the price and non-price variables, because of farmer habits, and the delay in response (partial adjustment) of yield and area (it takes time to adjust to new conditions).

Therefore, the partial adjustment model (Nerlove model) is a common approach applied to investigate the response of crops supply (Braulke, 1982; Leaver, 2004). The Nerlove model estimates long and short-run elasticities, so it is a dynamic model. The area or yield of crops is a function of the expected price of that crop, the previous period's area or yield, as well as other explanatory variables (non-price factors) (Kabubo, 1991; Leaver, 2004).

Table 2.2 Model Specification for yield and area function.

Type	Transform to linear
$linear$ $y = a + \sum_i \beta_i x_i$	$y = a + \beta_1 x_i + \beta_2 x_j + \varepsilon$
$Quadratic$ $y = a + \sum_i \beta_i x_i + \sum_i \sum_j \delta_i x_i x_j$	$y = a + \beta_1 x_i + \beta_2 x_j + \beta_3 x_i^2 + \beta_4 x_j^2 + 2\delta_1 x_i x_j + \varepsilon$
$Cobb - Douglas$ $y = A \prod_i x_i^{\beta i}$	$ln\, y = lnA + \beta_1 lnx_i + \beta_2 lnx_j + \varepsilon$
$Translog$ $y = a + \sum_i \beta_i ln\, x_i$	$y = a + \beta_1 lnx_i + \beta_2 lnx_j + \varepsilon$
$Logarithmic$ $lny = a + \sum_i \beta_i lnx_i + \sum_i \sum_j \delta_{ij}(lnx_i)(lnx_j)$	$lny = a + \beta_1 lnx_i + \beta_2 lnx_j + \delta_1 (lnx_i)(lnx_j) + \varepsilon$
$Transcendental$ $y = A \prod_i x_i^{B_i}(\exp(\delta_i x_i))$	$y = Ax_i^{\beta 1} x_j^{\beta 2} e^{\delta_1 x_i + \delta_2 x_j}$ Rewrite as linear: $lny = lnA + \beta_1 lnx_i + \beta_2 lnx_j + \delta_1 x_i + \delta_2 x_j + \varepsilon$

Source: Griffin et al. (1987), Anderson et al. (1996), and Debertin (2012)
Where y is the dependent variables, x's are independent variables, and $a, \beta,$ and δ are parameters to be estimated.

Therefore, in our study, the optimum level of the area cultivated of wheat at time t ($Area_t^*$) is a function of the expected price of wheat (P_t^*) and other exogenous variables (X_t) (such as technology, rainfall, and fertilizer). We follow Braulke, 1982; Kabubo, 1991; Leaver, 2004; Riaz et al. 2014; and Khan et al. 2018:

$$Area_t^* = \beta_0 + \beta_1 P_t^* + \beta_2 X_t + e_t \tag{2.1}$$

Where e_t is the error term. Due to partial adjustments, one cannot observe the optimal level, so we assume:

$$Area_t - Area_{t-1} = \delta(Area_t^* - Area_{t-1}), \qquad where\ 0 < \delta < 1 \tag{2.2}$$

Which means that the actual change in the cultivated area is related to the change in the expected optimal area. δ is the partial adjustment parameter; when it is equal to zero there is no change between area level during the period time ($Area_t = Area_{t-1}$). When it is equal to one, there is an instanteous adjustment to the optimal level ($Area_t = Area_t^*$).

We can rewrite equation (2.2) as:

$$Area_t = \delta Area_t^* + (1-\delta)Area_{t-1} \tag{2.3}$$

According to the Nerlove model, the farmer corrects or adapts their expected price based on the actual price from the previous period.

$$P_t^* = \gamma P_{t-1} + (1-\gamma)P_{t-1}^* \tag{2.4}$$

Equation (2.4) describes the expected price at time t as a weighted average of the actual and expected price at time t-1. It has two unobservable expected prices. Therefore, we could decrease the unobserved prices in equation (2.4) by assume:

$$P_t^* = \gamma P_{t-1} + \gamma(1-\gamma)P_{t-1} + \cdots + \gamma(1-\gamma)^n P_{t-(1-n)} \tag{2.5}$$

Where γ is the adjustment coefficient.

Braulke (1982) eliminates the unobserved prices in equations (2.1) through (2.3). Using the reduced form, we substitute equation (2.1) into equation (2.3):

$$Area_t = \delta(\beta_0 + \beta_1 P_t^* + \beta_2 X_t + e_t) + (1-\delta)Area_{t-1}$$

$$Area_t = \delta\beta_0 + \delta\beta_1 P_t^* + \delta\beta_2 X_t + (1-\delta)Area_{t-1} + \delta e_t \tag{2.6}$$

Then equation (2.4) is substituted into equation (2.6) (we could also use a Koyck transformation by substituting equation (2.5) into equation (2.6)):

$$Area_t = \delta\beta_0 + \delta\beta_1\gamma P_{t-1} + \delta\beta_1(1-\gamma)P_{t-1}^* + \delta\beta_2 X_t + (1-\delta)Area_{t-1} + \delta e_t \quad (2.7)$$

Lagging equation (2.6) and multiply by $(1-\delta)$ (using the Koyck transformation), then subtracting this lagged equation from the unlagged equation (2.7) results in:

$$\begin{aligned} Area_t = {} & \delta\beta_0\gamma + \delta\beta_1\gamma P_{t-1} + (1-\gamma)Area_{t-1} + (1-\delta)Area_{t-1} \\ & - (1-\gamma)(1-\delta)Area_{t-2} + \delta\beta_2 X_t - \delta\beta_2(1-\gamma)X_{t-1} + \delta e_t \\ & - (1-\gamma)\delta e_{t-1} \end{aligned} \quad (2.8)$$

Equation (2.8) can be written as:

$$Area_t = \varphi_0 + \varphi_1 P_{t-1} + \varphi_2 Area_{t-1} + \varphi_3 Area_{t-2} + \varphi_4 X_t + \varphi_5 X_{t-1} + u_t \quad (2.9)$$

Where $\varphi_0 = \delta\beta_0\gamma$, $\varphi_1 = \delta\beta_1\gamma$, $\varphi_2 = (1-\gamma) + (1-\delta)$, $\varphi_3 = -(1-\gamma)(1-\delta)$, $\varphi_4 = \delta\beta_2$, $\varphi_5 = -\delta\beta_2(1-\gamma)$, and $u_t = \delta e_t - (1-\gamma)\delta e_{t-1}$

A similar procedure with the yield model obtains:

$$Yield_t = \mu_0 + \mu_1 P_{t-1} + \mu_2 Yield_{t-1} + \mu_3 Yield_{t-2} + \mu_4 X_t + \mu_5 X_{t-1} + \omega_t \quad (2.10)$$

Where parameters have similar interpretations as the area parameters in equation (2.9).

2.4.2 Estimation Short and Long run elasticities:

The short and long-run elasticities can be driven from equation (2.9) and (2.10). Assuming a linear function, the short-run elasticities for Area $= \varphi_1 \frac{\bar{P}_{t-1}}{\overline{Area}}$ and the long run elasticity $= \frac{\varphi_1}{1-\varphi_2-\varphi_3} \frac{\bar{P}_{t-1}}{\overline{Area}}$, where $\bar{P}_{t-1}$ is the average of the one year lag wheat price and $\overline{Area}$ is the average area of wheat cultivated during the study period. The short-run elasticities for Yield $=\mu_1 \frac{\bar{P}_{t-1}}{\overline{Yield}}$, and the long run elasticity $= \frac{\mu_1}{1-\mu_2-\mu_3} \frac{\bar{P}_{t-1}}{\overline{Yield}}$, where $\overline{Yield}$ is the average of wheat yield.

2.4.3 Model Specification

When we look at previous studies estimating yield and area of different crops (Kabubo, 1991; Mushtaq and Dawson, 2003; Leaver, 2004; Nosheen and Iqbal 2008; Riaz et al. 2014; Khan et al. 2018, Sumathi et al., 2019), we focused on the most common explanatory variables used to examine the yield and area functions.

To estimate the yield function for the wheat crop in Saudi Arabia during the study period, yield of wheat was adopted as the dependent variable (Yield in ton/hectare). While one-year lag producer wheat price (P_{w-1} in \$/Ton), the area cultivated by wheat ($Area$ in 1000Ha), one year lag yield ($Yield_{t-1}$), the amount of rainfall ($RainFall$ in mm), and the number of machines (a proxy for capitalization) per hectare (a variable that reflects the use of technology, Tec) were adopted as independent variables. Dummy variables were also used (0 before 2008; 1 after 2008) to show the impact of government policy number 335 (D). However, some argument can be made for using a time trend rather than the Tec variable. The problem we face with a time trend is the high collinearity with other variables. Therefore, the Yield function is as follows:

$$Yield_t = f(P_{w-1}, Area_t, Yield_{t-1}, RainFall_t , Tec_t, D) \quad (2.11)$$

The area model has cultivated area of wheat as the dependent variable and explanatory variables of one-year lag producer wheat price, one year lag of area, one-year lag yield, a proxy for capitalization, and a dummy variable to represent the impact of the policy. The Area function is as follows:

$$Area_t = f(P_{w-1}, Area_{t-1}, Yield_{t-1}, Tec_t, D) \quad (2.12)$$

2.4.4 Data:

The models were estimated using time series data from 1990–2016. We used various data sources for the variables. Data on area and production came from the Open Source library at the Ministry of Environment, Water and Agriculture; and the General Authority for Statistics (GASTAT) in Saudi Arabia, the Food and Agriculture Organization of the United Nations (FAO) and the United States Department of Agriculture (USDA). The producer wheat price came from FAO.

The number of machines is collected from FAO as well as the Statistical, Economic and Social Research and Training Centre for Islamic Countries (SESRIC) and the Arab Organization for Agricultural Development (AOAD). The amount of rainfall is collected from available secondary data from the World Development Indicators - World Data Bank.

2.5 Result and Discussion:

To estimate the yield and area function, we used six common models, linear, quadratic, Cobb-Douglas, translog, logarithmic, and transcendental. After choosing the explanatory variables, we checked the correlation matrix between the independent and dependent variables. The yield variables, $Yield_{t-1}$, $Area_t$, and Tec_t were highly correlated with yield, whereas $P_{w-1}$and $RainFall_t$ were weakly correlated to yield. The one-year lag for both yield and area were highly correlated with area, while other variables were weakly correlation.

An important point for estimating the best model is how to choose among function forms, meaning what kind of relationship exists between the dependent and independent variables, whether linear or non-linear. Yield and area models were tested for the best function forms using the Box-Cox test. The Box-Cox transformation makes the residuals more normally distributed and less heteroscedasticity (Andrew et al. 2013). Our results for yield show that we fail to reject the null hypothesis for linear and log forms. We did find that log forms were preferred since they had a lower log likelihood ratio. The log function forms were also preferred for the area model. However, other function forms were also estimated (table 2.3 to 2.6). The Cobb-Douglas, which results from the Box-Cox tests, provided a result which was consistent with economic logical.

When the regression models are estimated, we anticipate some multicollinearity issues. We used robust S.E for all models to control for the correlation between the variation between the dependent variable and independent variables. Yet for the Cobb-Douglas estimations, we had no evidence of multicollinearity problems among variables.

The coefficient for technology was negative in area models because of the rapid decrease in production after 2008 due to government policy number 335, while the number of machines in Saudi Arabia increased. The machine data does not distinguish its use, so the number of machines in Saudi Arabia increased, but they were not likely used on wheat. In fact, they might be new machines needed for other agricultural products. The policy dummy variable was negative in area models, which indicates that area were negitively influenced by the policy.

2.5.1 Detecting autocorrelation:

We first estimate the Yield and Area model using the ordinary least square methods from 1990 through 2016 (results in tables 2.3 to 2.6). We used the last year's price as the expectation for product price. One of the problems of the Nerlovian model is serial correlation. We test for serial correlation using the Breusch-Godfrey test. Autocorrelation is a result of the wrong functional form, missing variables, or correlation between residuals (Wooldridge, 2009). Our results indicate that the best models to represent the yield functions were Translog and Cobb-Douglas, while the linear, translog, and Cobb-Douglas were best for the area function. The chosen forms were chosen depending on the number of significant coefficients, the conformity to economic logic, and the adjusted R squared. The result of the LM test shows that both area and yield had no autocorrelation issues (we fail to reject the null hypothesis of no serial correlation). However, we found that the translog forms in the area function suffered from serial correlation. For that reason, we ignore the translog function from our explanation below since we assume the issues came from an incorrect function form.

2.5.2 Estimate of supply response of wheat:

We first estimated area and yield models which included a trend. We found that the area was decreasing with time and yield was increasing with time. This shows the impact of the policy change where the government decreased the incentive for cultivating wheat.

2.5.3 Yield equation for wheat:

Table 2.3 and 2.4 presents the results from estimating equation (2.11). We choose the Translog and Cobb-Douglas models (columns 6 and 12) as the best models describing the wheat yields in Saudi Arabia. The sign for output price is positive but not significant, which means there is no relationship with yield. The sign for all other coefficients was as expected, but some of these coefficients were not significantly different from zero. Therefore, we tested for multicollinearity issues and found the model does not suffer from it. We found that lagged yield, area cultivated, and capitalization proxy (the number of machines) were the most important factors that influence wheat yield. The short-run elasticity of output price for the translog model was 0.03, and the long run elasticity was -0.02 (partial adjustment coefficient was -1.303). While the short-run elasticity for the Cobb-Douglas model was 0.02 and the long run elasticity was 0.04. Raising the producer price by 10% leads to output changes of 3% and -2% with a translog model in short and long-run elasticities, respectively, while with Cobb Douglas model, it will increase by 2% and 4%, respectively. The negative long-run elasticity of price with the translog model shows that increasing the output price will lead to decreasing in wheat yield, which is contrary to supply theory. However, when the short-run elasticity is less than the long–run (as in the Cobb-Douglas result), the properties of the production are upheld when there are several input factors which are fixed in the short run and variable in the long run (Leaver, 2004). This shows the importance of including economic logic when choosing the preferred model. Both translog and Cobb Douglas functions were chosen by Box-Cox, but Cobb-Douglas is preferred because of economic theory.

Comparing our result to the previous studies, Mushtaq and Dawson (2003) and Nosheen and Iqbal (2008) found that the range for the short run elasticity was 0.155-0.164 and the long run 0.37-0.693 which is much higher than our result. This could be due to the policy impact in our model, which resulted in very high prices for many years, but lower prices later. This policy likely influences the price elasticities from this study.

2.5.4 Acreage response for wheat:

Table 2.5 and 2.6 show the six function forms for the area of wheat cultivation. We found that the linear and Cobb-Douglas were the preferred functions for the area model.

We ignore the results of the translog since we found that model suffers from autocorrelation issues. All the coefficient signs were consistent with economic theory, but some were not significant. We found that lagged area and yield, as well as the capitalization proxy, were the most important factors affecting the wheat area.

We choose models that include the policy dummy variable because ignoring that policy leads to bias in our estimation. For the linear model (column 2) the short and long-run elasticity for the wheat price was 0.24 and 0.47, respectively. While the Cobb-Douglas equation (column 12) has a short-run elasticity of 0.23 and a long-run elasticity of 0.48.

In conclusion, the result shows that the short run and long run elasticities are inelastic in both area and yield models. This means that shifts in the demand curve will have larger impacts on the price of output. Our elasticities falls within the range of previous studies, such as Kabubo (1991), Abebe (2001), and Nosheen and Iqbal (2008), who found the short run elasticity was from 0.045-0.34, and the long run elasticity was from 0.105-0.79. Again, this is likely due to the high wheat price for many years and the government's policy to support its production in the early years.

Table 2.3 Function Form of Linear, Quadratic, and Translog of the Yield of Wheat in Saudi Arabia during 1990-2016.

Variables	**Linear**		**Quadratic**		**Translog**	
	(2)	(1)	(3)	(4)	(5)	(6)
P_{w-1}	0.000217 (0.000576)	0.000462 (0.000990)	-0.0254 (0.0628)	0.0221 (0.117)		
$Area$	-0.00146*** (0.000377)	-0.00153*** (0.000408)	-0.0767* (0.0394)	-0.0695 (0.0521)		
$Yield_{t-1}$	0.324* (0.180)	0.355 (0.208)	-15.34 (15.52)	-16.10 (15.86)		
Tec	-28.50*** (6.145)	-28.21*** (6.330)	-1,092** (351.7)	-990.4* (456.9)		
$RainFall$	-0.0201 (0.0295)	-0.0232 (0.0303)	-0.514 (1.915)	-0.0388 (2.746)		
P_{w-1}^2			-7.90e-05** (2.56e-05)	-7.41e-05* (3.46e-05)		
$Area^2$			9.76e-06 (6.86e-06)	1.14e-05 (6.64e-06)		
$Yield_{t-1}^2$			0.568 (1.253)	0.905 (1.213)		
Tec^2			3,562** (1,199)	3,265** (1,256)		
$Yield_{t-1} * Area$			0.00839 (0.00614)	0.00830 (0.00671)		
$Yield_{t-1} * P_{w-1}$			0.0125 (0.00801)	0.00497 (0.0186)		
$Yield_{t-1} * RainFall$			0.0957 (0.240)	0.0140 (0.383)		
$Yield_{t-1} * Tec$			127.9** (50.75)	130.8** (49.01)		
$P_{w-1} * Area$			3.31e-05 (2.62e-05)	1.24e-05 (5.09e-05)		
$P_{w-1} * RainFall$			-0.00130** (0.000502)	-0.00112* (0.000476)		
$P_{w-1} * Tec$			0.630* (0.294)	0.309 (0.783)		
$Area * RainFall$			0.00109 (0.00101)	0.000838 (0.00146)		
$Area * Tec$			0.390** (0.135)	0.357* (0.155)		
$RainFall$ *Tec			-7.594 (9.250)	-8.176 (9.581)		
lnP_{w-1}					0.0522 (0.179)	0.155 (0.278)
$lnArea$					-0.448** (0.167)	-0.507** (0.200)
$lnYield_{t-1}$					2.123** (0.985)	2.303** (1.070)
$lnRainFall$					-0.330 (0.255)	-0.365 (0.271)
$lnTec$					-0.258*** (0.0680)	-0.256*** (0.0709)
D		-0.0935 (0.260)		-0.335 (0.697)		-0.158 (0.243)
$Constant$	4.642*** (1.169)	4.378*** (1.494)	73.92 (49.02)	65.02 (65.28)	3.477 (2.454)	2.896 (2.843)
Observations	26	26	26	26	26	26
R-squared	0.928	0.928	0.976	0.977	0.928	0.929

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4 Function Form of Logarithmic, Transcendental, and Cobb Douglas of the Yield of Wheat in Saudi Arabia during 1990-2016.

Variables	**logarithmic**		**Transcendental**		**Cobb Douglas**	
	(7)	(8)	(9)	(10)	(11)	(12)
P_{w-1}			-0.00668** (0.00313)	-0.00741** (0.00308)		
$Area$			3.14e-05 (0.000116)	4.90e-05 (0.000134)		
$Yield_{t-1}$			-0.756* (0.371)	-0.637 (0.402)		
$lnTec$			-3.843* (1.951)	-4.433** (1.870)		
$RainFall$			0.0444 (0.0376)	0.0478 (0.0295)		
lnP_{w-1}	3.199* (1.523)	2.976* (1.588)	2.171* (1.034)	2.436** (1.025)	-0.000354 (0.0352)	0.0229 (0.0527)
$lnArea$	2.107 (1.493)	1.854 (1.561)	-0.149** (0.0550)	-0.179** (0.0719)	-0.0752** (0.0332)	-0.0886** (0.0382)
$lnYield_{t-1}$	0.759 (1.254)	0.855 (1.247)	4.068* (2.058)	3.490 (2.243)	0.461** (0.203)	0.502** (0.221)
$lnRainFall$	-0.540 (0.949)	-1.128 (1.229)	-0.343 (0.270)	-0.375 (0.218)	-0.0619 (0.0505)	-0.0700 (0.0523)
$lnTec$	-1.159 (0.536)	-1.361** (0.568)	-0.0185 (0.0207)	-0.0145 (0.0203)	-0.0469*** (0.0137)	-0.0464*** (0.0142)
$lnYield_{t-1} * lnP_{w-1}$	-0.000760** (0.000262)	-0.000727** (0.000276)				
$lnYield_{t-1} * lnArea$	0.000156** (6.03e-05)	0.000136** (5.40e-05)				
$lnYield_{t-1} * lnRainFall$	0.00834 (0.0250)	0.00410 (0.0234)				
$lnYield_{t-1} * lnTec$	-0.340 (0.632)	-0.0684 (0.822)				
$lnP_{w-1} * lnArea$	-0.340 (0.210)	-0.307 (0.217)				
$lnP_{w-1} * lnRainFall$	0.167 (0.214)	0.254 (0.219)				
$lnP_{w-1} * lnTec$	0.0833 (0.0605)	0.130* (0.0707)				
$lnArea * lnRainFall$	-0.0864 (0.116)	-0.0473 (0.126)				
$lnArea * lnTec$	0.0944* (0.0440)	0.0791 (0.0501)				
$lnRainFall * lnTec$	0.0430 (0.0801)	0.0540 (0.0883)				
D		0.0768 (0.113)		-0.0581 (0.0456)		-0.0357 (0.0438)
Constant	-18.24 (12.28)	-16.86 (13.10)	-10.26* (5.056)	-11.03** (4.708)	1.227** (0.512)	1.096* (0.593)
Observations	26	26	26	26	26	26
R-squared	0.959	0.960	0.957	0.960	0.923	0.925

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.5 Function Form of Linear, Quadratic, and Translog of the Area of Wheat in Saudi Arabia during 1990-2016

Variables	**Linear**		**Quadratic**		**Translog**	
	(1)	(2)	(3)	(4)	(5)	(6)
P_{w-1}	0.149 (0.297)	0.303 (0.385)	-1.825 (8.285)	1.843 (8.842)		
$Area_{t-1}$	0.542*** (0.131)	0.491*** (0.126)	-4.217 (4.095)	-1.946 (4.433)		
$Yield_{t-1}$	-174.4*** (58.74)	-158.3** (69.87)	-2,551 (2,210)	-1,787 (1,944)		
Tec	-6,889** (2,596)	-6,859** (2,643)	-68,452 (83,557)	-50,303 (73,210)		
P_{w-1}^2			0.00247 (0.00602)	0.00470 (0.00556)		
$Area_{t-1}^2$			-0.000384 (0.000786)	-0.000602 (0.000780)		
$Yield_{t-1}^2$			169.4 (178.8)	143.7 (143.4)		
Tec^2			33,133 (277,232)	-11,120 (233,128)		
$Yield_{t-1} * Area_{t-1}$			0.934 (0.745)	0.463 (0.831)		
$Yield_{t-1} * P_{w-1}$			0.320 (1.209)	-0.601 (1.636)		
$Yield_{t-1} * Tec$			18,641 (13,136)	16,605 (11,301)		
$P_{w-1} * Area_{t-1}$			0.00203 (0.00373)	0.00191 (0.00354)		
$P_{w-1} * Tec$			-97.69*** (30.04)	-121.4** (40.53)		
$Area_{t-1} * Tec$			-1.284 (25.99)	-2.196 (22.42)		
lnP_{w-1}					257.7* (136.6)	329.3* (158.3)
$lnArea_{t-1}$					250.4*** (62.55)	213.2*** (48.89)
$lnYield_{t-1}$					-555.8* (309.7)	-349.3 (391.7)
$lnTec$					-38.10 (33.22)	-32.98 (33.30)
D		-56.58 (88.65)		-143.7 (157.7)		-120.5 (97.97)
Constant	1,135*** (348.9)	983.9* (487.3)	8,542 (6,571)	5,411 (6,370)	-1,823* (1,054)	-2,414* (1,367)
Observations	26	26	26	26	26	26
R-squared	0.901	0.902	0.978	0.981	0.828	0.835

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.6 Function Form of Logarithmic, Transcendental, and Cobb Douglas of the Area of Wheat in Saudi Arabia during 1990-2016.

Variables	**logarithmic**		**Transcendental**		**Cobb Douglas**	
	(7)	(8)	(9)	(10)	(11)	(12)
P_{w-1}			0.00221	-0.000930		
			(0.0140)	(0.0130)		
$Area_{t-1}$			0.000881	0.000142		
			(0.00116)	(0.000960)		
$Yield_{t-1}$			-1.472	-0.253		
			(2.040)	(2.110)		
Tec			-19.27*	-26.40***		
			(9.485)	(7.959)		
lnP_{w-1}	-11.47*	-9.531*	-1.108	0.293	0.0110	0.229
	(5.847)	(5.409)	(4.498)	(4.168)	(0.231)	(0.245)
$lnArea_{t-1}$	-6.625	-5.325	0.168	0.323	0.637***	0.524***
	(4.847)	(4.276)	(0.462)	(0.377)	(0.133)	(0.107)
$lnYield_{t-1}$	-6.273***	-2.987	4.759	-0.899	-2.145**	-1.516
	(1.969)	(2.871)	(10.41)	(10.56)	(0.813)	(0.911)
$lnTec$	-1.669	-0.678	0.00366	0.0832	-0.159**	-0.144*
	(1.777)	(1.370)	(0.107)	(0.107)	(0.0744)	(0.0747)
$lnYield_{t-1} * lnP_{w-1}$	0.00243**	0.00164				
	(0.00106)	(0.00112)				
$lnYield_{t-1} * lnArea_{t-1}$	0.000591	0.000163				
	(0.000440)	(0.000393)				
$lnYield_{t-1} * lnTec$	-5.114**	-6.442**				
	(1.770)	(2.314)				
$lnP_{w-1} * lnArea_{t-1}$	1.169	1.084				
	(0.770)	(0.693)				
$lnP_{w-1} * lnTec$	0.168	-0.0997				
	(0.103)	(0.152)				
$lnArea_{t-1} * lnTec$	0.136	0.240				
	(0.235)	(0.188)				
D		-1.130		-0.437		-0.367*
		(0.686)		(0.296)		(0.199)
Constant	77.06*	57.52	10.28	5.736	4.786**	2.984
	(36.83)	(34.49)	(23.21)	(21.13)	(1.801)	(2.313)
Observations	26	26	26	26	26	26
R-squared	0.950	0.964	0.944	0.952	0.922	0.930

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

2.6 Conclusion:

In 2008, Saudi Arabia decided to implement government policy number 335, which changed the incentives for wheat cultivation and production significantly. Government programs had been instrumental in supporting wheat cultivation, but then this support stopped, which led to a rapid decrease in the area used for wheat cultivation and domestic production.

The purpose of this research was to estimate yield and area functions for Saudi Arabian wheat. The results showed that the most important factors for wheat yield were cultivated area of wheat, one-year lagged yield, and the number of machines per hectare. For the wheat area, the one-year lag of both cultivated area and yield, and the number of machines per hectare were the factors that impact the cultivated area of wheat.

We found government policy number 335 had a strong effect on the area wheat producers in Saudi Arabia. This show that policy was influence the cultivated area and not influence the yield of wheat. We concluded that the farmer increases the efficiencies of the productivity per hectare. The Cobb-Douglas model was found to represent both yield and area models best. The yield model was less responsive to wheat prices than area function. The influence of resolution 335 had a higher impact on the yield model than the area model. We found that the price elasticity of wheat was inelastic in both models. Mushtaq and Dawson (2003) found the short and long run elasticity for wheat supply was inelastic.

The study recommends reviewing the government's resolution 335 by presenting the benefits and costs carried by society. This future study would focus on the impact of resolution 335 in saving water. The orientation of foreign investment in wheat cultivation is a solution in case of stability of that country.

CHAPTER 3. COMPETITION IN THE SAUDI ARABIAN RICE MARKET[2]

3.1 Abstract

The objective of this research is to estimate the residual demand elasticity that rice exporters face in Saudi Arabia. The inverse residual demand methods, as proposed by Reed and Saghaian 2004, are used for rice exporters to Saudi Arabia during the period 1993-2014. Estimation results of the elasticities of the residual demand indicate that Australia, India, and Pakistan enjoy market power, while Egypt faces a perfectly elastic demand curve. We found Thailand and the US had positive inverse residual demand which means no market power.

3.2 Introduction:

Rice is one of the main crops in the world; it is estimated that more than 470 million tons of rice were consumed in 2015, where it ranked third in importance regarding area planted and production after wheat and corn crops (USDA, 2016). The most important countries of the world in rice production are China, India, and Indonesia, as they accounted for 59% of the global rice production in 2014. Global rice production increased by 7.9% during the period 2009-2014, from 686.9 million tons to 740.96 million tons (FAO, 2016).

Rice exports are concentrated with five exporting countries, India, Thailand, Vietnam, Pakistan and the United States, accounting for more than 70% of the world's rice exportation in 2013. From 2009 to 2013, global rice exports increased by 23% from 30.2 million tons to 37.1 million tons (FAO, 2016). Moreover, global rice imports also increased by 29% from 29.3 million tons in 2009 to 37.8 Million tons in 2013.

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[2] Based upon Alamri, Yosef and Saghaian, Sayed (2018); "Measuring the Intensity of Competition Among Rice Exporters to Saudi Arabia"; *Int J Sci Res Publ* 8(1) (ISSN: 2250-3153).

Saudi Arabia was the seventh leading destination of rice imports in the world (accounting for 3%) with 1.26 million tons in 2013 (FAO, 2016). Rice cultivation is unsuitable in Saudi Arabia because of the climate, and this has necessitated the import of all its rice from abroad (Baazeem, 2007; Ahmed and Mousa 2014 and 2015). Its imports accounted for almost 4% of the total world imports (1.6 million tons) in 2015 (USDA, 2016). For the period 2009-2013, Saudi Arabia ranked fourth among the global rice importers (4%) and was ranked second for the value of the world rice imports (5%). This demonstrates the high-quality rice required for consumption in Saudi Arabia; it had the second highest price for rice imports over the same period compared to other countries in the world.

Rice is the primary food in Saudi Arabia, and its consumption level is affected by culture and traditions. “Kabsah” is the traditional dish in Saudi Arabia, which contains rice and meat (Al-Saffy and Mousa 2012). Rice accounted for 8% (1.6 million tons) of the total grain crop consumption in Saudi Arabia in 2015 (USDA, 2016). In the Saudi market, the aromatic thin, long-grained product, which is known as Basmati, is the most popular rice variety. The American long-grain parboiled grain rice, imported from the U.S., and medium-grain Calrose rice, imported from the U.S. and Australia, come in second and third, respectively (Ahmed and Mousa 2014 and 2015). There were also several industries based on rice products, such as rice oil used in the manufacture of cosmetics and the lubrication of leather, in addition to baby food using short or medium grain rice (Baazeem, 2007).

Saudi Arabia is forced to import rice from abroad, given the importance of the rice crop in providing the food needs of the population and in the absence of water and other resources needed for significant rice cultivation. Therefore, the countries exporting to Saudi market face intense competition to obtain a larger share of rice exports, which suggests a study of the competitiveness of the most important rice exports to identify the competitive situation that helps foreign policymakers to make appropriate decision on the import of rice from these countries. The objective of this study is to analyze the intensity of competition among the leading rice exporting countries to Saudi Arabia.

3.2.1 The Saudi Arabian Rice Market

In 2014, total rice consumption in Saudi Arabia reached 47kg per capita. On average, each Saudi consumed 11 kg more compared to 1995 (USDA PSD 2016; GASTAT 2016). Table 3.1 shows that the volume and value of rice imports were, on average, around 952.47 thousand tons and 2752.18 million Saudi Riyals (approximately $733.9 million) during 1993-2014 and have at an annual growth rate of 0.04% and 0.09%, respectively. The volume and value of rice imports increased annually by an estimated 41.41 thousand tons and 235.25 million Saudi Riyals ($62.73 million) (figure 3.1).

Imported rice prices increased fluctuated during the study period, on average around 2664.15 Saudi Riyals/ton ($710.44/ton), having an annual growth rate of 0.039%. The price of rice imports also increased annually by an estimated 115.69 Saudi Riyals/ton ($30.85/ton) (Figure 3.1).

Table 3.1 Rice imports for Saudi Arabia, 1993 -2014.

	Quantity 1000 Ton	Value Million Saudi Riyals	Price Saudi Riyals/Ton
Average	952.47	2752.18	2664.15
Annual growth rate[1]	0.043	0.086	0.039
Annual change rate[2]	4%	9%	4%

[1] $Anuual\ growth\ rate = \left(\frac{Ending\ value}{Begining\ value}\right)^{\frac{1}{\#of\ year}} - 1$

[2] $Anuual\ change\ rate = \frac{Trend\ coefficient}{Average\ period}$

Source: Central Department of Statistics & Information (CDSI). Ministry of Economy and Planning Annual Statistics Book. General Authority for statistical (GASTAT) in Saudi Arabia

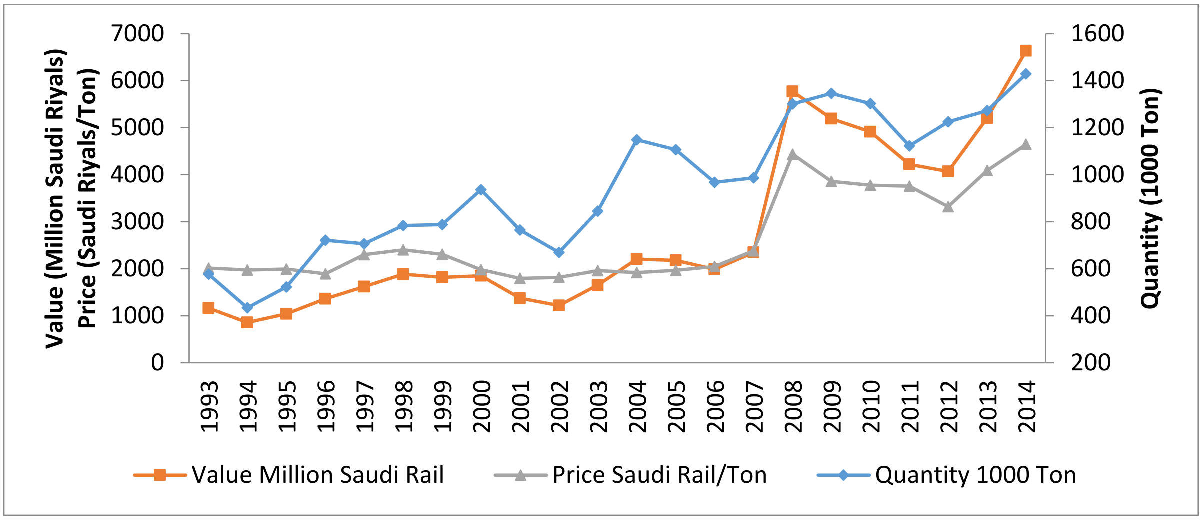

Figure 3.1 Import quantity, value, and price for Rice in Saudi Arabia, 1993-2014

Saudi Arabia's rice imports from India, the U.S., Pakistan, Thailand, Australia, and Eygpt for the period 1993 -2014 are shown in table 3.2. India accounted for about 66% of the rice imports in quantity terms and 71% in value terms, with the US (11.4% and 11%), Pakistan (10.8% and 9%), Thailand (8% and 6%), Australia (2% and 2%), and Egypt (1% and 1%) accounting for the rest. India was also the fastest growing supplier during the period, with rice imports growing by 6.4% annually in volume and 10% in value.

Rice prices jumped during the period from 2007- 2008 (due to the world crisis) to around 6824 Saudi Riyals per ton ($1819.7/ton). All exporters raised their prices during this period. The highest average prices were from India, and they rose from 2454.7 Saudi Riyals per ton in 1993 ($654.6/ton) to around 5301.7 Saudi Riyals per ton in 2014 ($1413.8/ton). However, The US prices had the second highest average price during the period, followed by Australia (table 3.2).

India's share of rice imports reached 73.6% in volume in 2014. Pakistani rice ranked second with 10.6%, and the U.S. had 7.3% (GASTAT, 2016).

Table 3.2 Saudi Arabia imports of rice from the leading countries during 1993-2014

Average rice import	India	US	Pakistan	Thailand	Australia	Egypt
Quantity (1000 Ton)	625.9	108.1	104.5	78.7	18.3	9.73
%	66	11.4	10.8	8	2	1
Annual Growth	6.41	0.85	0.71	0.29	1.64	-6.65
Value (Million Saudi Riyals)	1952.53	293.6	252.6	169.4	46.7	19.7
%	71	11	9	6	2	1
Annual Growth	9.96	3.98	4.3	4.43	5.86	-3.79
Price (Saudi Riyals/ton)	2861.7	2645.96	2241.1	1943.3	2602.3	1901.4

Sources:

- Central Department of Statistics & Information (CDSI). Ministry of Economy and Planning Annual Statistics Book
- General Authority for statistical (GASTAT) in Saudi Arabia.
- United States Department of Agriculture (USDA).
- UN Comtrade Database from the United Nations Statistics Division.
- Food and Agriculture Organization (FAO) of the United Nations-Statistics Division websites.

3.2.2 Rice Varieties:

There are more than 1500 type of rice in the world (Baazeem, 2007). However, there are three main groups of preferred rice varieties in Saudi Arabia: Basmati, Parboiled, and Round grain (Ismaiel and Al-rwis, 2009; Baazeem, 2007). In 2003, the Saudi Central Department of Statistics and Information changed the old classification of rice, to new classifications, which are Rice in the husk (paddy or rough), Husked (brown) rice, Semi-milled or wholly milled rice whether polished or glazed, and Broken Rice (Consulate General of Pakistan, 2013; CDSI, 2016; GASTAT, 2015).

In this paper, we choose the six largest rice exporting countries to Saudi Arabia during the period 2009 to 2013 for the analysis. These countries represent 99% of all rice imported by Saudi Arabia (Table 3.3). During the period of 2012 through 2014, India was the dominant rice exporter to Saudi Arabia. It was the leading supplier for all types of rice (Husk 73%, Brown 65%, Semi-milled or wholly milled 70%, Broken 45%). The USA was the second leading supplier for Husk (13%), Brown (22%), and Broken (39%). However, Pakistan was competitive with India in Semi-milled or wholly milled rice, accounting for 11% of imports. India dominates the Saudi rice market because of consumer preferences shifting toward "Muzza Basmati Rice" (Al-Saffy and Mousa 2012).

Table 3.3 Geographical distribution of imports of rice, the most important import markets during the period (2009 - 2013)

Row Labels	Import quantity in Ton	Relative important %	Import Value ($ 1000US)	Relative important %	import price $/ Ton
India	805,866.4	65%	888,710.8	71%	1102.8
Pakistan	155,982	13%	123,178.2	10%	789.7
Thailand	122,574.8	10%	94094.8	7%	767.65
USA	117,230	9%	118,729.6	9%	1012.79
Australia	17169.25	1%	18518.5	1%	1078.59
Egypt	16310.5	1%	14139.25	1%	866.88
Total import	1,237,196	--	1,257,319	--	1016.27

Source: compiled and calculated from:
FAO website: http://faostat3.fao.org/download/T/TP/E
UK Comtrade Website: http://comtrade.un.org/data/

3.3 Literature review

Ismaiel and Al-Zaagi, 1991, demonstrated that real national income increases, from 17 billion riyals in 1971 to 305 billion riyals in 1985 (aproxmatly from $4.5 to $81.3 billion), were a significant factor in the rise of imported food commodities, including rice. The study concluded that changes in the real price of imported rice, real national income, and population explained 86% of the variation in annual rice imports for Saudi Arabia. The demand and income elasticity on rice imports were -0.35 and 0.49, respectively.

Al-Rwis (2004) studied and analyzed rice imports of Saudi Arabia during 1992-1998 using AIDS model. The results explained that the demand for rice imports from India was price inelastic. While Pakistan, the US, and Thailand were price elastic and rice was a necessary commodity for India, Pakistan, and Thailand while complements for the US. The study shows there was a competitive relationship between the rice imports from India and the rice imported from the US and between the rice imports from Pakistan and the US. He also found that there was competition between rice imports from the US and Pakistan, but no competition with rice imports from Thailand.

Baazeem (2007) studied market power among rice exporters to Saudi Arabia. He described the Saudi rice market as controlled by a few importing companies. He suggested that they determine their marketing strategies, the quality of imported rice, and the sources of importation to maximize profits. He found that rice imports were concentrated in six rice-exporting countries, India, Pakistan, the US, Thailand, Australia, and Egypt. Also, rice imports are concentrated in the following varieties, Basmati, American, and Egyptian. The results of the residual demand models for rice exporters to Saudi Arabia indicate that both India and Pakistan enjoy market power in the Saudi rice importing market. The residual inverse demand elasticities for both countries was estimated at -0.13 and was statistically significant at the 0.05 level

Ismaiel and Al-Rwis (2009) also estimated the inverse residual demand for rice exporters to Saudi Arabia to analyze market power. The results showed that both India and Pakistan enjoy market power in the export of rice to Saudi Arabia because these countries concentrate on the export of Basmati rice.

Through previous studies, there were no studies using market power in Saudi Arabia through the new rice classification. Therefore, this study is based on the use of inverse residual demand to demonstrate the factors that influence rice imports from major exporting countries.

3.4 Research Method

3.4.1 Conceptual Framework

Many studies measure market power for different countries in both domestic and global markets as shown in table 3.4. The residual demand model for each exporter country could be described as (Baker and Bresnahan, 1988; Goldberg and Knetter, 1999; and Zhang, Reed, and Saghaian 2007):

$$P_i = P_i(Q_i, Q_{i-1}, Q_{i-2}, Q_{i-3}, Q_{i-4}, Q_{i-5}, X) \quad (3.1)$$

$$and\ P_{i-1} = P_{i-1}(Q_{i-1}, Q_i, Q_{i-2}, Q_{i-3}, Q_{i-4}, Q_{i-5}, X) \quad (3.2)$$

Where P_i is the import price from country i (i= Australia, Egypt, India, Pakistan, Thailand, or the US), Q_i is the import quantity from country i, and X represent the explanatory variables effecting the demand model.

We obtain the inverse residual demand function for each exporter country by profit maximization:

$$\pi_i = P_i(Q_i, \dots, Q_{i-5}, X)Q_i - C_i(Q_i, W_i) * ER_i \quad (3.3)$$

Where C_i indicates the cost of exporter country i, W_i is the cost shifters for country i, and ER_i is the bilateral exchange rate between Saudi Arabia and country i. All exchange rates are converted to Saudi Arabia currency. Exchange rate movements offer ideal cost shifters in international markets because they move the relative costs of the exporting countries (Reed and Saghaian, 2004).

Because of the imperfectly competitive market, Reed and Saghaian explained “the extent of competition is expressed as the relative markup of price over marginal cost or the Lerner index” (P.g:115).

Table 3.4 Literature review focus on the inverse residual demand

Author name	Market	Import country	Export country	Data	Methods	Markup result
Evans & Ballen 2015	Green Skin Avocado	The USA	The Dominican Republic	Monthly Jan 2004 - Dec 2013	IVGMM Instrumental Variable Generalized Method of Moments	–0.245
Pall et al. 2014	Wheat	Albania Azerbaijan Egypt Georgia Greece Lebanon Mongolia Syria	Russia	Quarterly 2002-2009	IVPLM Instrumental Variable Poisson Pseudo Maximum-Likelihood Estimator	-0.06 -0.16 -0.02 -0.06 -0.07 -0.06 (No Market power) -0.25 (No Market power) -0.05 (No Market power)
Tasdogan et al. 2005	Olive Oil	EU	Greece Italy Spain	Annually 1970-2001	2SLS Two-Stage Least Square	-0.079 -0.36 -0.157
Reed and Saghaian 2004	Beef segmented by (chuck, loin, and ribs), and each cut is separately analyzed on a chilled and frozen basis	Japan	Australia Canada New Zealand The USA	Monthly Feb 2002-Aug 2000	2SLS	The highest belongs to U.S. frozen ribs. Canada has limited market power. Australia and New Zealand enjoy some market power, including five chilled beef categories.
Goldberg and Knetter 1999	Beer	Canada France UK The U.S	Germany	Annually 1975-1993	3SLS	-0.14 -0.44 -0.21 -0.07
Baker and Bresnahan 1988	Beer	France Domestic- three firms: 1. Anheuser-Busch 2. Coors 3. Pabst		Annually 1962-1982	3SLS	-0.31 -0.31 -0.06 (No Market power)

To maximize profit, $\pi_i = TR_i - TC_i$ (3.4)

$$\frac{\partial \pi_i}{\partial Q_i} = MR_i(Q_i, \dots, Q_{i-5}, X) - MC_i(Q_i, W_i) * ER_i \tag{3.5}$$

The monopolist i sets the output where the marginal revenue (MR) equals marginal cost (MC):

$$MR_i(Q_i, \dots, Q_{i-5}, X) = MC_i(Q_i, W_i) * ER_i \tag{3.6}$$

We know that MR is equal to

$$\begin{aligned} MR_i(Q_i, \dots, Q_{i-4}, X) \\ &= P_i \\ &+ Q_i \left[\frac{\partial P_i(Q_i, \dots, Q_{i-5}, X)}{\partial Q_{i-1}} + \frac{\partial P_i(Q_i, \dots, Q_{i-5}, X)}{\partial Q_{i-1}} \frac{\partial Q_{i-1}}{\partial Q_i} + \cdots \right. \\ &\left. + \frac{\partial P_i(Q_i, \dots, Q_{i-5}, X)}{\partial Q_{i-5}} + \frac{\partial P_i(Q_i, \dots, Q_{i-5}, X)}{\partial Q_{i-5}} \frac{\partial Q_{i-5}}{\partial Q_i} \right] \end{aligned} \tag{3.7}$$

Then,

$$\begin{aligned} P_i + Q_i \left[\frac{\partial P_i(\dots)}{\partial Q_{i-1}} + \frac{\partial P_i(\dots)}{\partial Q_{i-1}} \frac{\partial Q_{i-1}}{\partial Q_i} + \cdots + \frac{\partial P_i(\dots)}{\partial Q_{i-5}} + \frac{\partial P_i(\dots)}{\partial Q_{i-5}} \frac{\partial Q_{i-5}}{\partial Q_i} \right] \\ = MC_i(Q_i, W_i) * ER_i \end{aligned} \tag{3.8}$$

Moreover, for the competitors (i-1):

$$\begin{aligned} P_{i-1} + Q_{i-1} \left[\frac{\partial P_{i-1}(\dots)}{\partial Q_i} + \frac{\partial P_{i-1}(\dots)}{\partial Q_i} \frac{\partial Q_i}{\partial Q_{i-1}} + \cdots + \frac{\partial P_{i-1}(\dots)}{\partial Q_{i-5}} + \frac{\partial P_{i-1}(\dots)}{\partial Q_{i-5}} \frac{\partial Q_{i-5}}{\partial Q_{i-1}} \right] \\ = MC_{i-1}(Q_{i-1}, W_{i-1}) * ER_i \end{aligned} \tag{3.9}$$

The perfectly competitive situation results when the expression within the parenthesis is equal to zero, which means price equals marginal cost. Thus, the Lerner index follows (Lerner, 1934):

$$\frac{P(Q) - MC(Q)}{P(Q)} = -\frac{\partial P(Q)}{\partial Q}\frac{Q}{P(Q)}$$

$$\frac{P(Q) - MC(Q)}{P(Q)} = -\frac{1}{E} \tag{3.10}$$

Where E is price elasticity. The Lerner index is equal to zero in the case of perfect competition, varies inversely with the elasticity of demand, and increases with increased market power.

Therefore, the residual demand function of countries (i-1) is obtained when equation (3.2) and (3.6 after converted to i-1) is solved for exporter quantity (i-1):

$$Q_{i-1} = Q_{i-1}(Q_i, \dots, Q_{i-5}, X, W_i ER_i) \tag{3.11}$$

The inverse residual demand for competitive (P_i) country by substituting equation (3.11) in equation (3.1):

$$P_i = P_i[Q_i, Q_{i-1}(Q_i, \dots, Q_{i-5}, X, W_i ER_i), Q_{i-2}(Q_i, \dots, Q_{i-5}, X, W_{i-2} ER_{i-2}),$$

$$Q_{i-3}(Q_i, \dots, Q_{i-5}, X, W_{i-3} ER_{i-3}), \dots., \; Q_{i-5}(Q_i, \dots, Q_{i-4}, X, W_{i-5} ER_{i-5}), X]$$

$$P_i = P_i[Q_i, X, W_i ER_i] \tag{3.12}$$

The inverse residual demand function for other competitors is similar to equation (3.12).

Goldberg and Knetter (1999) developed a method that solves the problem of calculating the unknown marginal costs by measuring market power in the international market for an exporter. They used a double log inverse residual demand (the difference between the market demand and the competitive fringe's supply curves) to capture the exporter's market power through the elasticity (Evans & Ballen 2015). The double-log inverse residual demand function developed by Goldberg and Knetter (1999) is:

$$lnP_{mt}^{ex} = \lambda_m + \eta_m ln\hat{Q}_{mt}^{ex} + \alpha'_m lnY_{mt} + \beta' lnW_{mt}^{N} + \varepsilon_{mt} \tag{3.13}$$

Where $P^{ex}{}_m$ is the price charged by the supplier group, m denotes a specific destination market, and t indicates the number of competitors an exporter faces in that market. The vector Y_{mt} denotes the demand shifters. $W^{N}{}_{mt}$ indicates the cost shifters for the N export competitors in a specific destination market (the measures of input prices). The exporter prices of rice and the demand shifters are expressed in the destination market currency (Evans & Ballen 2015). The coefficient η_m is interpreted as the residual demand elasticity. Therefore, the residual demand is considered perfectly elastic when η_m is not significantly different from zero (perfectly competitive market), and considered under imperfect competition when η_m is negative and significant. The error term is assumed independent and identically distributed (Reed and Saghaian 2004; Evans & Ballen 2015).

$\hat{Q}$ (Import quantity) is endogenous because it is determined with the import price and correlated with error term ε because of the simultaneity between price and quantity (endogeneity bias $E(\hat{\beta}) \neq \beta$), so these variables need to be instrumented as suggested by Goldberg and Knetter (1999). An instrumental variable is used to determine the endogenous regressor (Q), but it only affects the dependent variable through its effect on the independent variables (Reed and Saghaian, 2004; Evans and Ballen, 2015).

So, we will regress Q on all the exogenous variables

$$Q = \alpha_0 + \alpha_1 Z + \alpha_2 W + \alpha_3 Y + u \tag{3.14}$$

Where Z is the instrumental variables. W denotes cost shifters such as exchange rates. Y is the vector of exogenous variables affecting the demand, such as time trend, real income, the price level for the destination market. We can apply IV estimations to break the correlation between the error term and independent variables. The endogenous variables are just identified when we have the same number of endogenous and IV's. However, the endogenous variables are over-identified, when we have more IV's than endogenous variables. We test the efficacy of the instrumental variables using the F-test. The null hypothesis that the coefficients on the Z in the first stage are zero. After the IV technique, we use $\hat{Q}$ in place of Q because it is uncorrelated with ε_t. Then we plug $\hat{Q}$ into the model and we obtain $\hat{\eta}$ as an unbiased estimate (Wooldridge, 2009).

3.4.2 The Empirical Model

This paper estimates a residual demand model for rice exports into Saudi Arabia as used by Reed and Saghaian (2004) as follows:

$$LnP_t^i = \lambda \quad + \eta Ln\hat{Q}_t^i + \alpha \quad T_t + \beta \quad Ln\left(\frac{DY_t}{CPI_t}\right) + \sum_{j\neq i} \delta^j \, Lne_t^j + \varepsilon_t \tag{3.15}$$

Where *Ln is* natural logarithm, *P* is imported price measured by Saudi Riyals, η is the residual demand elasticity, Q is the quantity of rice imports, *t* indexes time, *i* and *j* indexes countries that Saudi Arabia imported from, *T* is a time trend, *DY* is Saudi Arabia nominal disposable income, CPI is the cost of living index, and *e* is the bilateral exchange rate. Saudi Arabia's currency is fixed with the US dollar ($1=3.75 SR), so we converted all the exporter country prices to US dollars and divide by 3.75 to convert to the Saudi currency market. In our model, we omit the US exchange rate due to perfect collinearity.

In this study, we assume (similar to Reed and Saghaian, 2004) that the Saudi Arabia rice market is differentiated by country of origin. Further, each exporting country faces a residual demand curve from Saudi Arabia that is downward sloping. The main parameter of interest is the coefficient on quantity imported, which represents the inverse of the residual demand elasticity. The null hypothesis is that each country that exports rice to Saudi Arabia faces a perfectly elastic residual demand.

Two-Stage Least Squares (2SLS) were used to estimate the model, after testing for heteroskedasticity and autocorrelation. Note that "whereas asymptotic theory gave the result that the 2SLS is (asymptotically) unbiased, small-sample theory indicates that it is biased. This bias decreases as the sample size increases, but increases as the number of excluded exogenous variables increases" (Bowden and Darrel, 1984, pg:139).

3.4.3 Data:

The inverse residual demand model was estimated using annual data from 1993 to 2014. The primary challenge of this paper was the lack of data for Saudi Arabia. We used different sources to fix this problem. Data on Saudi rice imports were collected from:

1- Central Department of Statistics & Information (CDSI) and General Authority for statistical (GASTAT) in Saudi Arabia.

2- United States Department of Agriculture (USDA), UN Comtrade Database from the United Nations Statistics Division, and Food and Agriculture Organization (FAO) of the United Nations-Statistics Division websites.

The population, gross domestic product (GDP), and cost of living indices for Saudi Arabia came from the General Authority for Statistics. Producer price index came from FAO, while Production of rice came from FAO and USDA. GDP and exchange rate data for the competitors were from the World Development Indicators.

3.5 Results and Discussion

The objective of this study is to examine the market power of rice exporters to Saudi Arabia, so an inverse residual demand was estimated to determine which countries have market power. Tables 3.5 and 3.6 displays the estimated parameters for the residual demand model from the leading exporting countries to Saudi Arabia in the double logarithmic form. We applied instrumental variable (IV) estimation because it eliminates the correlation between the error term and independent variables. We used the one-year lagged import quantity, the country's GDP and production from the competitor country as instrumental variables (Angrist and Alan, 2001; Páll, 2015). Lagged quantity variables are less likely to be affected by the current price ($Cov(lnQ_{t-1}, \varepsilon_t) = 0$) (Angrist and Alan, 2001). We checked for multicollinearity problems and found that some variables suffer from high collinearity. We dropped variables with high collinearity from the models. We then tested for heteroscedasticity and autocorrelation for all models. The Pagan- Hall test shows that we fail to reject the null hypothesis of homoscedasticity for all models. While the Cumby-Huizinga test results indicate that we fail to reject the null hypothesis that the error term has no first order serial correlation for all models except for Pakistan and Thailand. Therefore, to solve both issues we used robust standard errors in our estimation. After those adjustments, we found that the model had no problems with heteroscedasticity and autocorrelation.

We tested for the endogeneity of the variable Q using the Hausman test. The result showed that we failed to reject the null hypothesis for all exporting countries at the 5% level of significance, except India (at 5%), the US, and Australia (at 10%). Thus, OLS estimation can be applied to estimate the residual demand equation for all rice exporting countries except India, the US, and Australia. Yet for comparison purposes, we use

Table 3.5 The OLS demand model

VARIABLES	Australia	Egypt	India	Pakistan	Thailand	US
lnQ	-0.0103	-0.0335	-0.510**	-0.104	0.140	0.186
	(0.0397)	(0.0916)	(0.191)	(0.127)	(0.103)	(0.207)
Exchange rate						
Australia		0.880	-0.236	1.497	-1.482***	
		(1.271)	(1.031)	(2.083)	(0.460)	
Egypt	-0.410			-0.873		
	(0.344)			(0.805)		
India	-0.217	-0.234		0.447	0.885*	-1.410**
	(0.683)	(1.098)		(0.749)	(0.468)	(0.469)
Pakistan	0.598	2.439	1.301**			0.201
	(0.426)	(3.366)	(0.537)			(0.698)
Thailand	-0.283	-1.944		-0.516		
	(0.294)	(1.305)		(0.807)		
Per capita Saudi GDP	0.491	0.331	0.00723	0.468	-0.0777	-0.675
	(0.306)	(1.139)	(0.462)	(1.116)	(0.258)	(0.483)
Producer price index						
Australia		0.996	0.229	0.155	0.125	0.181
		(0.730)	(0.263)	(0.192)	(0.127)	(0.209)
Egypt	0.527		0.127	1.015	-0.789**	-0.598
	(0.308)		(0.537)	(1.341)	(0.279)	(0.584)
India	-0.268	-0.557	-0.0602	-0.0638	0.0511	0.243
	(0.163)	(1.141)	(0.390)	(0.192)	(0.121)	(0.354)
Pakistan	0.0894	0.294	-0.363		-0.174	-0.149
	(0.172)	(0.832)	(0.365)		(0.133)	(0.302)
Thailand	-0.316	0.155		-0.265		0.224
	(0.261)	(0.747)		(0.278)		(0.384)
US	-0.0610	0.471	0.443*	0.402*	0.369**	
	(0.158)	(0.590)	(0.226)	(0.217)	(0.128)	
Non-Saudi POP		-0.907		-0.165	1.123*	3.116**
		(2.381)		(2.143)	(0.534)	(1.253)
Time	-0.0415				0.0440	
	(0.106)				(0.0828)	
Constant	7.823***	2.931	5.484***	4.684**	2.829***	4.201***
	(1.852)	(4.423)	(1.763)	(2.039)	(0.882)	(1.255)
Observations	22	22	22	22	22	22
R-squared	0.954	0.586	0.791	0.876	0.978	0.896

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.6 The Inverse residual demand model

Variables	Australia	Egypt	India	Pakistan	Thailand	US
lnQ	-0.0604*	-0.353	-0.933**	-0.446*	0.632*	0.480*
	(0.0304)	(0.511)	(0.357)	(0.214)	(0.311)	(0.243)
Exchange rate						
Australia		-0.135	-0.662	0.841	-0.160	
		(2.546)	(1.084)	(2.106)	(0.980)	
Egypt	-0.332			-1.410*		
	(0.461)			(0.731)		
India	0.403	1.069		1.481	2.484**	-0.579
	(0.693)	(3.019)		(1.146)	(1.096)	(0.782)
Pakistan	0.554	0.566	2.031***			-0.494
	(0.559)	(4.372)	(0.619)			(0.975)
Thailand	-0.148	-1.103		-0.551		
	(0.386)	(1.682)		(0.800)		
Per capita Saudi GDP	0.757	1.004	-0.0369	0.975	1.320*	-0.397
	(0.488)	(1.843)	(0.529)	(1.127)	(0.702)	(0.514)
Producer price index						
Australia		1.799	0.577	0.571	-0.179	0.356
		(1.279)	(0.323)	(0.341)	(0.318)	(0.249)
Egypt	0.439		0.0696	1.194	0.316	-0.664
	(0.301)		(0.619)	(1.231)	(0.770)	(0.649)
India	-0.351	-1.082	-0.156	-0.0198	-0.303	0.193
	(0.216)	(1.109)	(0.424)	(0.174)	(0.301)	(0.371)
Pakistan	0.106	0.536	-0.410		0.00844	-0.0396
	(0.159)	(0.852)	(0.325)		(0.240)	(0.308)
Thailand	-0.114	1.346		-0.332		0.220
	(0.205)	(1.797)		(0.335)		(0.365)
US	-0.0881	-0.0617	0.276	0.204	0.389**	
	(0.155)	(1.142)	(0.279)	(0.227)	(0.157)	
Non-Saudi POP		-2.921		-1.121	-1.684	3.026*
		(4.587)		(2.166)	(1.722)	(1.366)
Time	-0.323				-0.555*	
	(0.312)				(0.270)	
Constant	6.894**	0.169	5.750**	3.549	2.385	2.273
	(2.244)	(5.926)	(2.429)	(2.210)	(1.784)	(2.248)
Observations	21	21	21	21	21	21
R-squared	0.941	0.395	0.830	0.883	0.955	0.864
Pagan-Hall	0.95	0.99	0.75	0.71	0.99	0.90
Cumby-Huizinga	0.02**	0.17	0.11	0.03**	0.08	0.70
Wu-Hausman	0.09*	0.45	0.02**	0.21	0.11	0.09*
Sargan test	0.14	0.10	0.12	0.22	0.07*	0.13

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

instrumental variable estimations for all countries in order to compare the results with OLS. We used two-stage least squares (2SLS) estimation rather than OLS for the other exporters (Wooldridge, 2009). After we tested for whether India, the US, and Australia models were over-identified using the Sargan test, we failed to reject the null hypothesis; so we have good instrumental variables. The Sargan test statistic is significant for Thailand, indicating that the IVs are not as strong.

Both OLS and IV results are shown for comparisons. Table 3.5 shows the result of the OLS models for all competitors. None of the quantity coefficients were significantly different from zero except for India. When we compare the OLS results with inverse residual demand in table 3.6, we find that the OLS results for quantity had lower standard errors, but some coefficients also had unexpected signs. However, if endogeneity is present then standard errors are not valid (Wooldridge, 2009).

The inverse residual demand equations in table 3.6 show the signs and significance of the quantity coefficients differ by country. The residual demand coefficients were significant at 10% level for Australia, Pakistan, Thailand, and the US; and significant at 5% level for India. All F- tests are significant at the 1% level. A negative sign for the coefficient on quantity is consistent with economic logic and the existence of market power. This was the case for Australia, India, and Pakistan with coefficients of -0.06, -0.93, -0.45, respectively. The high elasticity for India is related to the type of rice it produces and its preference among Saudi consumers. Egypt also had a negative sign, but it was not significantly different from zero, suggesting a perfectly elastic demand and no market power. Results show that Australia had small markups over marginal costs, while India had large markups due to the preferred type of “Basmati rice.” Ismaiel and

Al-Rwis (2009), and Baazeem (2007) showed that India and Pakistan had market power in their rice export to Saudi Arabia, while the US, Australia, Thailand, and Egypt faced a perfectly elastic demand.

The inverse residual demand coefficient was the only significant coefficient for the Australian price export model while the other variables had no impact. The statistically significant inverse residual demand coefficient indicates that Australia had market power in the Saudi rice market, but it was very small.

In the Egypt model, none of the explanatory variables had significant coefficients, so they did not influence the Egypt price. The sign of the inverse residual demand coefficient was negative but not statistically different from zero, indicating that Egyptian rice faces a perfectly elastic demand in Saudi Arabia. Egypt cannot increase the price of its exports without losing its market to competitors.

In the India model, the quantity coefficient and the exchange rate of Pakistan were the important factors affecting the export price. Other variables had no evidence of influence on the model. The inverse residual demand coefficient had the expected negative sign, and it was statistically significant. The coefficient indicates that India had a large mark-up over marginal cost, approximately -0.93. This result is consistent with Al-Rwis's study in 2004, which found that Saudi demand for imported rice from India was price inelastic. The exchange rate coefficient had a positive sign, as expected from theory. India's price is sensitive to the exchange rate of Pakistan because both produce the same variety of rice, "Basmati".

The Pakistan model shows that the amount of rice exports and the exchange rate of Egypt were the only variables significantly affecting price in the model. The quantity of export was negative, as expected, and statistically significant — it shows a 0.45 mark-up over marginal cost. The exchange rate of Egypt was statistically significant but had a negative sign, which was not expected. This could be caused by the Egyptian pound depreciating more than the US dollar. Therefore, Pakistan modified their rice prices to compensate for the change in the Egyptian exchange rate.

The model for Thailand had a higher number of significant coefficients on explanatory variables. The important variables in the Thailand model were export quantity, the exchange rate of India, per capita Saudi GDP, producer price index of the US, and time trend. The positive inverse residual demand indicates that as Thai rice prices increase, their exports to Saudi Arabia grow. This is contrary to expectations. Thailand prices do rise as the exchange rate from India increases. The results also suggest that Thailand can increase its price as the producer price index in the US increases. Surprisingly, the coefficient on real per capita income for Saudi citizens was positive and significantly different from zero for Thailand only. Thailand is the largest rice exporter, so income increases for Saudi Arabia and worldwide demand for rice increases (as measured by world rice price) might force Saudi Arabia to import rice from Thailand. This also might be related to the increase in the number of workers who came from South Asia during the study period. An increase in per capita GDP by 1% leads to a 1.32% increase in the Thailand price in Saudi Arabia. The time trend sign indicates that Thailand export prices are falling during the study period. Saudi Arabian income and consumption of Thailand rice are increasing (annual growth by 0.29 during the study period table 3.2), so it might be difficult for the model to apportion variation in Thai rice prices to these correlated variables.

In the US model, the export quantity and the non-Saudi citizen population were the important variables that influence the US export price. The positive sign for the inverse residual demand was contrary to economic logic and demonstrated that the US had no market power in their rice shipments. As the US increases its rice price to Sudia Arabia, it sells more. This positive sign is similar to the finding of Zhang, Reed, and Saghaian, 2007, who found that the US and Brazil export of soybeans were competitive and had a positive sign on residual demand. They argued that the positive coefficient was related to the growth of the world soybean demand. The number of non-Saudi residents had a positive coefficient, which shows that increased non-Saudi residents lead to an increase in the export price. Al-Saffy and Mousa (2012) and Ahmed and Mousa (2014) show the rice of demand in Saudi Arabia will grow as the population growth and the number of visitors increase.

3.6 Conclusion and Recommendation

Saudi Arabia rice imports increased annually by 41 thousand ton from 1993 to 2014. These rice imports are concentrated among six rice-supplying countries: India, Pakistan, the US, Thailand, Australia, and Egypt. These exporters accounted for about 65%, 13%, 10%, 9%, 1%, and 1%, respectively, of Saudi rice imports during the period 2009 to 2013.

The objective of this study is to analyze the intensity of competition among the main rice exporting countries to Saudi Arabia. Therefore, the inverse residual demand facing rice exporters to Saudi was estimated using annual data from 1993 to 2014 to estimate the extent of market power.

Data on imported quantity and import value from each country was collected from various sources such as Central Department of Statistics and Information in Saudi Arabia, General Authority for statistical in Saudi Arabia, USDA, UN Comtrade Database from United Nations Statistics Division and Food and Agriculture Organization of the United Nations-Statistics Division websites. Nominal disposable income, CPI, and the number of the population for Saudi came from the General Authority for statistical in Saudi Arabia. Producer price index came from FAO, while rice production came from FAO and USDA. Competitor exchange rates and GDP came from the World Development Indicators (WDI).

The study results show that India received the highest growth among supplying countries in quantity, value, and import price. The results of the residual-demand models for rice exporters to Saudi Arabia approximates the markup of price over marginal cost or Lerner index. The results indicate that Australia, India, and Pakistan enjoy market power in Saudi rice importing market. The inverse residual demand for these countries was estimated as -0.06, -0.93 and -0.45, respectively, and these coefficients were statistically significant at the 0.05 level. Egypt, Thailand and the US had no market power.

Saudi Arabia appears to be paying more for its rice imports from some suppliers due to their markup policies. Rice imports from India seem to have a particularly high markup. This could be due to the unique characteristics of India’s rice, being long-grained, Basmati rice. Saudi consumers seem to prefer this type of rice (Ahmed and Mousa, 2014 and 2015). An analysis which uses data on rice characteristics might verify these ideas. This is certainly an area of future research but it requires more detailed data than we have available. Nonetheless, Saudi Arabia should consider diversifying its suppliers of rice to reduce its reliance on some suppliers, especially India (Baazeem, 2007; Ahmed and Mousa 2014). Egypt seems a reasonable supplier since it is a price taker.

CHAPTER 4. An Examination of Saudi Arabia's Virtual Water Trade in crops[3]

4.1 Abstract

Using the concept of virtual water introduced by Allan 1994 and developed by Hoekstra and Hung (2002), we estimate virtual water trade for 20 crops of Saudi Arabia during 2000-2016. Our result shows the average virtual water trade was 12.5 billion m^3/year. Saudi had net virtual water imports, with the most significant virtual water import for cereals & alfalfa and vegetables; and there is net virtual water export of fruit. Saudi virtual water trade reduced pressure on water resources by 52%. Distance plays a role in Saudi virtual water export; we found that more than 90% of exports go to neighboring countries, including 45% to GCC countries. On the other hand, more than 30% of virtual water imports came from Europe. A Gravity model is used to investigate whether water scarcity variables influence trade. We compare the OLS, Fixed effects, Random effects, and PPML estimators to get the best model. The AIC, and tests for multicollinearity, and heteroskedasticity assist in determining estimation procedures and the final models. We cluster the errors by distance to improve the specific country effect variables such as economic mass variables. For the cereals and alfalfa group, we find that water-related variables influence virtual water imports of Cereals, Millet, Sorghum, Corn, Barely, and Sesame. Therefore, we suggest that a basic gravity model be applied to the other crops. In the vegetable group, we find that related water variables impact virtual water trade for all crops except marrow. Dates are the only crop from fruit group that are not influenced by the water related variables.

[3] Based upon Alamri, Yosef, & Reed, M. (2019). "Estimating Virtual Water Trade in Crops for Saudi Arabia." *American Journal of Water Resources*, 7(1), 16-22.

4.2 Introduction:

Saudi Arabia has a subtropical desert climate with warm temperatures and scant rainfall. The wind is dry and rainfall was only 62.2 mm in 2017 (GASTAT, 2018). Water supply and consumption are huge issues in Saudi Arabia. Per capita renewable water is very low (78 m^3 in 2014) compared to global levels (5920.5 m^3) (World Bank, 2019), while the storage capacity of dams does not exceed 0.84 cubic kilometers (Alqahtani et al., 2017). In order to supply its water needs, Alqahtani et al., (2017) estimate that Saudi Arabia annually withdraws large quantities of deep groundwater at a rate that is more than nine times the amount of the availability of renewable water (936%).

Water requirements have increased steadily as the population has increased by 23% between 2007 and 2017 (FAO, 2018). Saudi Arabia counts on three primary sources of water: groundwater, desalinated seawater, and recycled water (usually used for power generation). It is estimated that total withdrawals in 2016 were 23.9 billion cubic meters, an increase of 37% over 2010. This total is distributed among different sectors as follows: agriculture 83%, municipal 13%, industry 4% (GASTAT, 2016[b]; MEWA, 2018). Saudi Arabia relies almost entirely on groundwater for irrigating crops; 83% of crop irrigation came from groundwater. The irrigated of non-groundwater totaled 17.82 billion cubic meters in 2016[4]. Groundwater resources in Saudi Arabia are being depleted at a very rapid rate. Most of the water withdrawals come from deep fossil aquifers, and some predictions suggest that these resources may not last more than 12 years (MEWA, 2018; Alqahtani et al., 2017; Odhiambo, 2016).

[4] It came from the that total agriculture sector used equal to 19.8 billion cubic meters and MEWA (2017) mention that 90% of that used came from nonrenewable ground water.

The liberalization of world trade has led to the fluid movement of goods and services among countries. This more open trading environment has encouraged countries to seek gains from trade, which is good, but it sometimes leads to difficulties when resources are not priced efficiently. The mispricing of water is a huge issue throughout the world, so open trade sometimes neglects the optimal use of water resources, especially for those countries that suffer from a scarcity of these resources. Furthermore, Saudi government intervention in agricultural policies has supported many crop farmers, but this support has led to distorted agricultural prices where private prices are above social prices. The lack of control over the use of groundwater and the fact that water is essentially free (even groundwater resources) has helped lead to exhaustion of groundwater. Water management policies in Saudi Arabia have taken a back seat to supply side policies that increase self-sufficiency in some crops, ignoring the importance of depleting water resource. All of this leads to the conclusion that Saudi Arabia has not benefited as much from foreign trade because it has squandered its meager groundwater supplies.

Many studies have called for the government to stop subsidies for the cultivation of crops that use water intensively. The lack of effective water policies that reflect shortages, legislation to promote agricultural production of water-intensive crops, and general inefficiencies in use of water within the agriculture sector have led to an increase in water consumption[5] from nonrenewable groundwater (MEWA, 2018; Alqahtani et al., 2017). Recently, government initiatives focused at rationalizing Saudi Arabia's water supplies and uses. In 2008, the government issued a policy to reduce wheat cultivation by

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[5] *Water consumption* is the amount of fresh water used from the surface and groundwater and then evaporated or incorporated into the product (which equal to water withdrawal subtract from return flow) (Alqahtani et al., 2017).

stopping subsidies to farmers gradually. In 2010, the government supported investors interested in agricultural investment outside the Kingdom of Saudi Arabia. In 2018, a new government resolution was proposed to stop cultivation of alfalfa (MEWA, 2018). In the long term, these policies will help the agricultural sector move towards the cultivation of high-value products through rationalization of water consumption (MEWA, 2018; Alqahtani et al., 2017; Odhiambo, 2016).

Water problems are not going to go away for Saudi Arabia. The country must find ways to rationalize its water use so that it can deal with its limited amount of renewable water. Saudi Arabia, as one of the water-scarce countries, faces challenges related to its water resources from population growth, climate change, pollution and degradation of water quality. Because water is consistently mispriced, Allan (1994) developed the concept of virtual water to address the water gap and analyze ways to achieve water security[6]. Allan discussed the idea that water-scarce countries can import high water consumption crops from countries that have abundant water resources, creating a virtual water market through trade in agricultural and food crops (Hamouda & El-Sadek 2007; Hoekstra and Chapagain 2007[a]; Al Otaibi et al., 2013[a]). Saudi Arabia should consider importing crops (importing virtual water) instead of using scarce local water. The virtual water trade could be a key to improving water security.

Virtual water is defined as the amount of water needed to produce a good (Hoekstra and Chapagain, 2007[a]). Virtual water trade calculates the amount of virtual water imported

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6 *Water security* is defined by UN-Water member (2013) as "the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability." Where available water resources are higher than demand, the level of water security is high; when the water supply cannot meet the demand for water, the level of water security is low (UN-Water, 2013).

or exported through goods. For example, when Saudi Arabia imports a ton of rice, it saves the water needed to produce this ton of rice locally. The idea of virtual water trade is to transform the production of agricultural commodities into the corresponding quantity of water consumed to produce these agricultural commodities.

Saudi Arabia's previous development plans ignored the indirect impacts of foreign trade in agricultural products on local water uses (sometimes called the closed water balance) (Alqahtani et al., 2017). The authorities only looked at how to distribute local water to domestic uses. Virtual water trade allows Saudi Arabia to increase its water supplies through trade. The objective of this research is to present the benefits of using the concept of virtual water trade as a bridge to overcome the gap between local water sources and food demand in Saudi Arabia. The study also investigates whether water scarcity variables influence agricultural trade between Saudi Arabia and its commercial partners.

Research on the virtual water content of various agriculture crops increases the awareness of the impact of producing these products with local water resources. This encourages the reduction of water use on the cultivation of crop products that are heavy consumers of water and importing those crops from water-abundant countries. For example, to produce a kilogram of wheat requires about 1000 liters of water in many countries, so the virtual water of this kilogram of wheat is 1000 liters (Heokestra and Hung, 2002). Knowing the virtual water content of each agricultural enterprise and determining how much virtual water is traded can help countries know their net import balance for virtual water and help them assess ways to use water more efficiently in the agricultural sector. It also gives a clearer picture of ways to track and increase virtual water availability when developing future development plans.

4.2.1 *Agriculture Sector and Water Use of Saudi Arabia:*

Saudi Arabia seeks to achieve food security by focusing on the development of its agricultural sector. However, this sector faces many environmental and regulatory constraints, especially water availability. Saudi Arabia is trying to address these problems by diversifying agricultural enterprises and moving away from certain water-intensive crops, for instance they have moved away from cereals and alfalfa toward fruit and vegetable crops. The agricultural sector represents a small percentage of GDP, but it is increasing, especially in recent years (figure 4.1).

Saudi Arabia saw growth in demand for food products, driven by high standards of living, and per capita income as well as population growth. Figure (4.2) shows the volume and value of agricultural imports and exports. Imports are much higher than exports with a ratio of 511% during 2016.

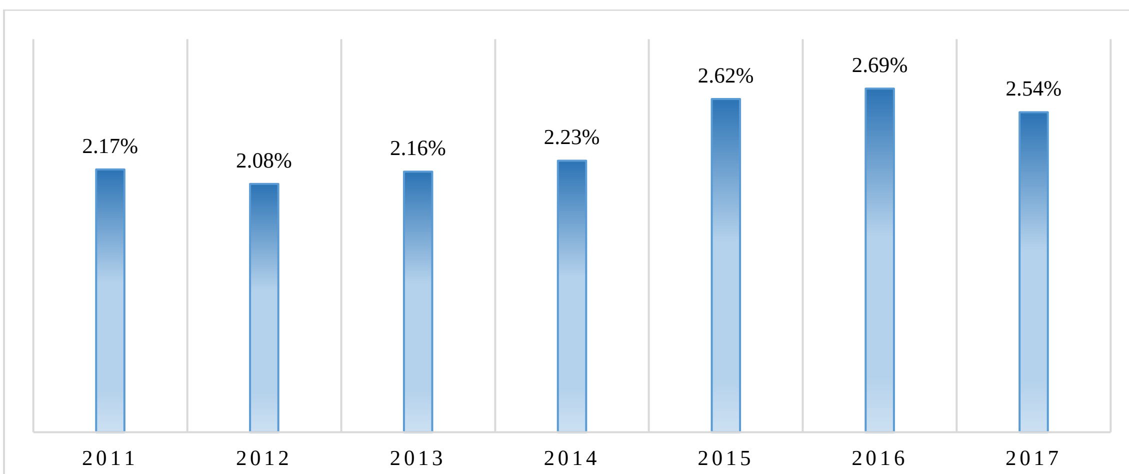

Figure 4.1 Contribution of the agricultural sector to GDP (%) during 2011-2016

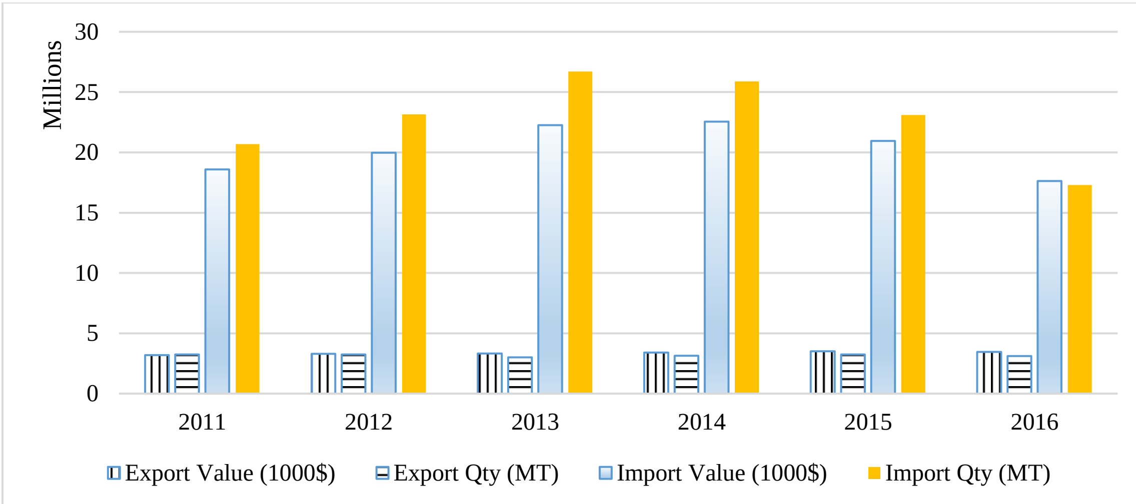

Figure 4.2 Saudi Arabia Import and Export of Agricultural Products during 2011-2016

4.2.2 *Water use in the agricultural sector:*

Water demand for agricultural production is influenced by various factors such as cultivated area, climatic conditions, crop type, irrigation method, and soil quality. Saudi Arabia has problems with almost all these factors.

To understand the effect of virtual water on Saudi Arabia groundwater, we use the idea of consumption water from Pindyck and Rubinfeld (1995); Harris (2006); Job (2009); Whittington (2011); and Arfanuzzaman and Rahman (2017). Figure (4.3) shows the supply and demand for groundwater in Saudi Arabia. For the supply curve, the part from 0 to Q_1 represents the yearly recharge of groundwater (which is priced at zero). S^c is the highest amount of renewable water available for agricultural use (it will vary by year, but we assume it constant and non-responsive to water price). If water is withdrawn from the ground at more than the recharge rate, there is no price charged in Saudi Arabia, but there is an opportunity cost because the water is not available for future use. The supply curve (a+bQ) represents increasing opportunity cost as more water is withdrawn. The demand curve (for instance c-dQ) is the marginal benefit to farmers from using the water.

Two types of equilibrium can emerge from figure (4.3): one is where the demand for water falls within the renewable water constraint (S^c); the other is where nonrenewable groundwater is used to meet water demands. Net social welfare is the area of consumer and producer surplus from using groundwater:

$$SW = \int (c - dQ)dQ - \int (a + bQ)dQ$$

Social welfare is maximized where $\frac{\partial SW}{\partial Q} = 0 \rightarrow (c - dQ) - (a + bQ) = 0$ which is at $P_d = P_s \rightarrow P^*$. The supply curve represents the marginal cost of extraction plus the marginal cost of consuming the water today rather than in the future. Fluctuations in the supply of water depend on physical storage availability and yearly recharge amounts. Q_c represent the total amount of renewable and nonrenewable groundwater. At a price of P_1 farmers increase their water use from the optimum to Q_2. Current farmers gain from this low price for water, but social welfare is lost because future water users value this extra water more than current water users.

At P* and Q* the marginal benefit is equal to marginal cost in the domestic market and social welfare is maximized. Yet in most situations, water is not priced at the socially optimum level, but instead is much lower priced (UN water, 2013). This encourages current use and delays issues with future water shortages. However, virtual water imports can mitigate this situation if policies encourage such imports (UN water, 2013). Virtual water imports shift the water demand curve to the left (D` for instance). In the case of Saudi Arabia where increasing consumption of crops can increase water demand, shifting production from Saudi Arabia to other countries (through crop imports) can help improve the situation.

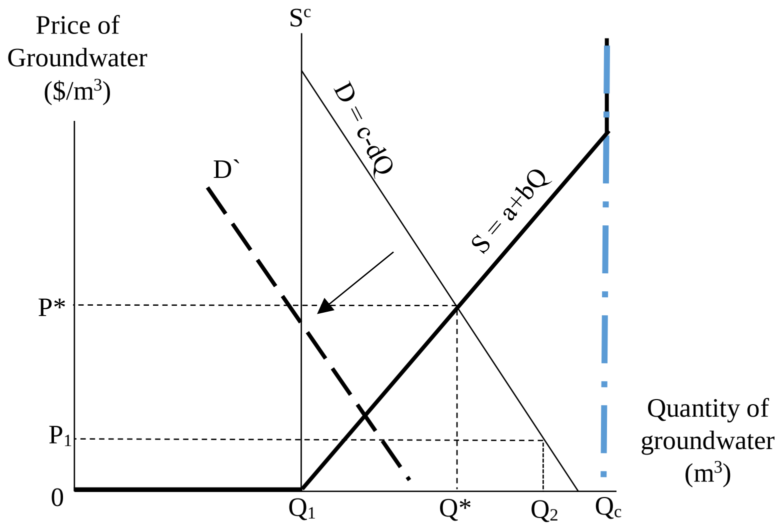

Figure 4.3 Demand and Supply of groundwater use

Table 4.1 shows that Saudi Arabia's water consumption increased by 37.1% from 2010 to 2016. The agricultural sector was the largest consumer, accounting more than 80% of the total water consumption in Saudi Arabia. This proportion is significantly higher than in the world, where the agriculture sector accounts for 65% of freshwater use (World Bank, 2018). The agricultural sector is also the fastest growing segment for water use in Saudi Arabia compared to other sectors; municipal use increased by 37% and industrial use increased by 35% (figure 4.4).

Table 4.1 The water consumption by sectors (Municipal, Industrial, and Agricultural) in Saudi Arabia during 2010-2016

Sector	2010	2011	2012	2013	2014	2015	2016
Municipal	13%	13%	12%	12%	12%	12%	13%
Industrial	4%	4%	4%	4%	4%	4%	4%
Agricultural	83%	83%	84%	84%	84%	84%	83%
Total	17,447	19,193	20,884	22,260	23,416	24,833	23,933

Source: MEWA, 2018, and GASTAT, 2016[b]

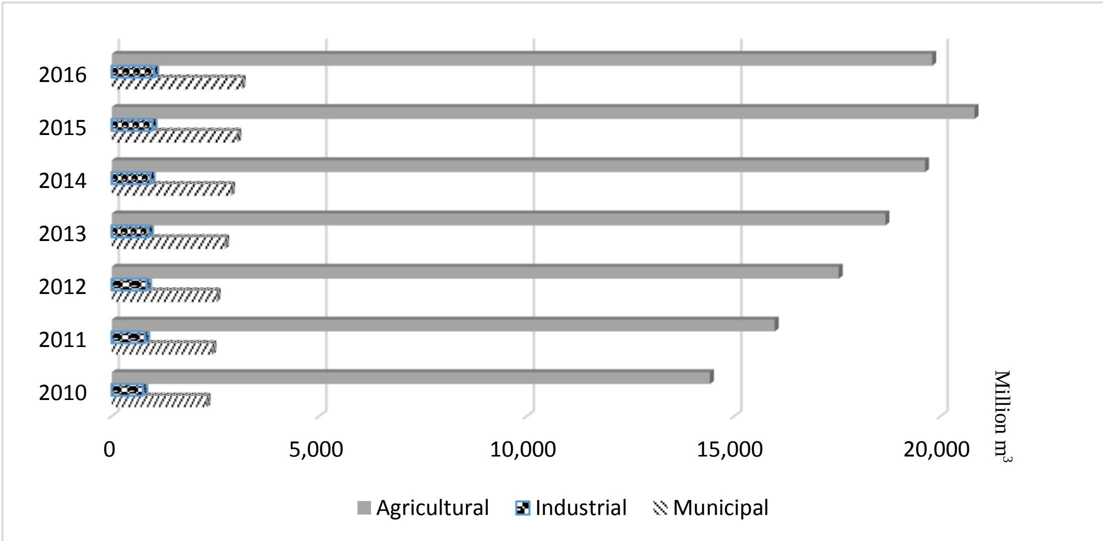

Figure 4.4 Water consumption by sector from 2010 to 2016

Climate conditions in Saudi Arabia are among the most severe in the world. Surface water resources are severely limited and rechargeable ground water is scarce (Alqahtani et al., 2017). Table (4.2) shows that per capita use of non-renewable groundwater has increased from 291.7 m^3 in 2014 to 639.8 m^3 in 2016. The per capita use of renewable water declined from 149.4 m^3 in 2014 to 71.4 m^3 in 2016. Average per hectare use of non-renewable water increased from 51.7 m^3 in 2014 to 118.6 m^3 in 2016. Average per hectare use of renewable water declined from 26.5 m^3 in 2014 to 13.2 m^3 in 2016. These numbers clearly show the importance of this study, because Saudi Arabia is increasingly consuming non-renewable compared to renewable groundwater.

Table 4.2 Per capita and hectare use of renewable and non-renewable groundwater in 2014 and 2016

Year	Population	Agriculture	Nonrenewable groundwater	Renewable groundwater	Nonrenewable Groundwater		Renewable Groundwater	
	(Million)	(Million Ha)	(Billion m^3)	(Billion m^3)	per Capita m^3	hectare m^3	per Capita m^3	hectare m^3
2014	30.78	173.58	8.98	4.6	291.7	51.7	149.4	26.5
2016	32.2	173.62	20.6	2.3	639.8	118.6	71.4	13.2

Note: Renewable water is a natural water resource where seawater desalination and reuse of treated wastewater has not been included.
Source: alqahtani. et al., 2017; MEWA,2018 and FAO, 2018

As mentioned before, the agricultural sector relies heavily on non-renewable groundwater. Water needs per hectare vary widely by crop in Saudi Arabia. The main concern is that most crops produced by Saudi Arabia, such as wheat, barley, and alfalfa, consume large amounts of this water (MEWA, 2018). Cucumbers need 8.39 thousand m^3/ha (the lowest) while alfalfa needs 45.97 thousand m^3/ha (the highest) on traditional farms (Alqahtani et al., 2017). Hoekstra and Hung (2002) show 3,000 to 5,000 kg of water is needed for every kg of grain produced. So, it is very important for Saudi Arabia to follow policies that use its scarce water on water efficient crops.

4.3 Literature Review

Allan described his concept of virtual water in 1994. He refers to the situation in the Middle East where there is potential for water wars. He discussed the suffering of the water scarce countries from their shortage of freshwater as well as the depletion of their water resources to meet the needs of domestic and industrial use. That water can become available through the concept of virtual water trade to avoid the consumption of rare domestic freshwater (Allan, 2003; Hoekstra and Chapagain 2007[a]; Alqahtani et al., 2017). Several studies have focused on estimating virtual water trade for the world using the methods developed by Allan (Alqahtani et al., 2017), but not many have focused on the virtual water trade for Saudi Arabia.

4.3.1 *Global virtual water studies:*

The first comprehensive study calculating the total amount of virtual water accumulated for the world was presented by Hoekstra and Hung (2002). They suggest that water-scarce countries should import crops and food instead of seeking self-sufficiency to alleviate their water scarcity. The water needs of different crops were calculated, and virtual water was estimated from imports and exports in order to obtain the world's virtual water trade.

Zimmer and Renault (2002) address methodological problems and provide preliminary results of virtual water trade. Their main objective was to map the world's virtual water balance[7]. To do this, they address three aspects of the methodology: processes and products, flow-charting, and estimation of water requirements and virtual water for food. They include crops and animal products together. The results show that virtual water accounted for one-quarter of the global water budget for food (the estimated amount of water required to maintain global food consumption) in 2000. They recommend more research by region and that virtual water broken into blue, green and gray[8].

Yang et al. (2006) show that the increase in population growth and economic growth rates led to higher per capita water rates. These factors are resulting in the growing problem of water scarcity in many parts of the world. This led to the expansion of the concept of virtual water trade. They argue that policy instruments must be developed along with practical means to balance national water needs with available supplies. A key new idea within this discussion is the possibility of increasing the efficiency of water use through virtual water trade. They found that "a global water saving results from international food trade due to the generally high crop water productivity in the food exporting countries compared with the food importing countries" (p.g 453).

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[7] *Virtual-water balance* is the net import of virtual water over a specified period between two countries, which is equal to the total imports of virtual water minus total exports of virtual water (Alqahtani et al., 2017).
[8] *Blue water* is the total amount of fresh water used in the production of the commodity. *Green water* is the volume of rainwater that is used during the production process to produce a good. *Gray water* is the amount of fresh water needed to reduce pollution to the point where contaminated water becomes freshwater (Hoekstra and Hung, 2002; Mekonnen and Hoekstra, 2010[a]; Alqahtani et al., 2017).

Hoekstra and Chapagain (2007[b]) estimate the water footprint[9] of Morocco and the Netherlands. Both countries import more virtual water than they export. They find that 14% of Morocco's water footprint is from external water resources, while 95% is from external sources for the Netherlands. This means that international trade can save water when water-intensive goods are exported from water-surplus countries. If Morocco produced what it imports from the Netherlands, it would need 780 million m^3 of water each year, but the Netherlands needed only 140 million m^3 of water per year to produce them. This saves the world 640 million m^3 of water per year. International agricultural trade can dramatically affect local water demand and hence local water scarcity, so the formulation of international agricultural trade policy should include an analysis of its water effects.

Mekonnen and Hoekstra, (2010[a]) show that water is virtual because when the product is already produced, the water used in its production is no longer in the commodity. They show that production of one kilogram of wheat and rice requires 1,300 liters and 3,400 liters of water, respectively. They break down virtual water use of crops by blue, green and gray water worldwide during the period 1996-2005. Using data from the FAO, they calculate the water footprint of 126 crops through the CROPWAT[10] program. The water footprint varies by crop and production area. The global water footprint for crop production was estimated at 7,404 billion m^3/year (78% green, 12% blue, 10% gray). Wheat and rice account for 45% of the world’s blue water. The total water footprint was highest for India, followed by China and the United States of America.

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9 *The water footprint of a country* refers to the amount of fresh water consumed or contaminated within the country’s water balance (the process of balancing the water supply with the total water demand within a specified period). It is an indicator of water used directly and indirectly by that country (the sum of water used to produce goods and services consumed by citizens of the country) (Alqahtani et al., 2017).

10 There is more information about this program in the appendix 1.

Mekonnen and Hoekstra (2010[b] and 2011) estimated wheat's water footprint broken into three components, green, blue and gray water. The results show that wheat used 1,088 billion cubic meters of virtual water per year during the period 1996-2005. Green water accounts for 70% of the total, blue water 19%, and gray water 11%. They also found that 18% of the virtual wheat water is used for export, with about 55% from wheat exports of the United States, Canada, and Australia. The amount of water saved from the international wheat trade was about 65 billion cubic meters/year because water-abundant countries exported to water-scarce countries. The study showed that countries such as Italy and Japan rely on other countries to supply their wheat, putting pressure on the water resources of their trading partners such as the US, Canada, Australia, and France.

4.3.2 *Saudi Arabia virtual water studies:*

Hamouda and El-Sadek (2007) show that food imports are necessary to compensate for Saudi Arabia's lack of water resources. Hoekstra and Hung (2002) found that Saudi Arabia is among the top 30 countries importing virtual water and its virtual water imports supply 50-80% of its water supplies. Both studies suggest that cultural and behavioral changes are necessary for Saudi Arabia to adapt to the current scarce water situation. Hamouda and El-Sadek (2007) show that the total water savings of Saudi Arabia through the import of commodities totaled 15.7 billion m^3 for 2003. They concluded that Saudi Arabia needed to consider reducing the production of millet, fruit, and beans in order to save water.

Multsch et al. (2013) estimate the water footprint for crops in each region of Saudi Arabia using SPARE:WATER[11]. The study separates green, blue and gray virtual water needs for each crop. The total footprint estimate was 6% larger than the findings of Mekonnen and Hoekstra (2010[b]). They found the total water footprint of the agricultural sector in Saudi Arabia at 17 km^3/year with the percentage of blue water at 86%, gray water 9% and green water 5%.

Al Otaibi al et, (2013[b]) discuss the challenges faced by the GCC (Gulf Cooperation Council) countries related to the scarcity of water and its impact on the economics and abundance of food. Virtual water for agricultural and livestock are estimated for the GCC countries. They also estimate virtual water trade between GCC countries to illustrate the close relationship between dependence on food imports and water scarcity. The study concludes that virtual water trade for the GCC countries is necessary to bridge the gap between domestic production and demand for food. They argue that there needs to be a change in the culture of water resource management and more regional integration among GCC countries to reduce the fears and risks that can result from virtual water trade. They show that Saudi Arabia is the largest supplier and importer of virtual water[12] among GCC countries and that imports have increased by 214.5% from 2000 to 2007. They found that Saudi Arabian virtual water exports increased by 216% during the period, especially in the categories of cereals, vegetables, eggs, and milk.

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[11] SPARE:WATER and CROPWAT were the programming calculate the crop water requirement (More about these two programs in the appendix 1 & 2).

[12] *Virtual-water exports* are the amount of virtual water associated with the product or item being exported and transported from one country to another. *Virtual-water imports* are the amount of virtual water associated with the product or item being imported and transported to a country. Thus, this water is used as an additional source of water for the country (Mekonnen and Hoekstra, 2010 [a]; Alqahtani et al., 2017)

Alqahtani et al., (2017) argue that development plans in Saudi Arabia are based on the concept of a closed water management system, which depends on domestic sources of water and allocates it to local uses. It estimates the individual and total water footprint of Saudi Arabia and differentiates virtual water use between green, blue, and gray water. The results show that Saudi Arabia receives virtual water imports from agricultural and food commodities totaling 55 billion m^3/year. Bluewater represents about 41% of this total. Saudi Arabian exports of agricultural and food products represent 6.1 billion m^3/year of virtual water, but only 13% of blue water. The net foreign trade of grain and feed products played an active role in the provision of water, with a net virtual water trade of 171 billion m^3. Finally, the study recommends Saudi Arabia should reduce its water footprint by rationalizing water consumption in the agricultural sector and adjusting the structure of foreign trade by increasing imports of products that provide virtual blue water. Finally, they recommend that Saudi Arabia modify its dietary pattern by reducing the consumption of products that use much water (meat) and increasing consumption of products that use less water (vegetables and fish).

4.3.3 *Studies on a Gravity model of virtual water trade:*

There have been studies of virtual water trade using the Gravity model recently. Fracasso (2014), Duarte et al., (2016), and Chen and Wilson, (2017), used panel data to explain virtual water trade with OLS and Poisson Pseudo-Maximum Likelihood (PPML) methods. Fracasso (2014) used panel data in one analysis and only cross-section data in another analysis. He found that water endowment (per capita water availability) and pressure on water resources (the ratio of freshwater withdrawn to total renewable water) had a definite impact on bilateral flows. To investigate the virtual water trade of agriculture exchange between countries, Duarte et al., (2016) amended the Gravity model to include the availability of renewable water as measured by precipitation and total renewable water, and agricultural land by cultivated area. They found that the economic variables were significant factors on virtual water flows, but water variables were not. Following the model developed by Fracasso in 2014, Chen and Wilson, (2017) investigate the impact of trade policy on virtual water trade across countries by adding ad valorem tariff equivalents to a model that included the water variables. They found a negative correlation between imports of crops with high water consumption and bilateral tariffs.

Fracasso et al. (2016) complemented the study of Fracasso (2014) by using cross-section data to determinate the factors affecting the virtual water trade among Mediterranean basin countries. They conclude that countries with greater water endowments do not necessarily export more virtual water. Tamea et al. (2014) estimated two gravity models (for imports and exports), to examine the factors which affect virtual water trade. They found that economic variables drive virtual water trade, rather than dietary demand. GDP, population, and virtual water production of exporting countries were the drivers of virtual water trade. Delbourg and Dinar (2016) also examined the impact of water endowment on virtual water trade and found a positive effect between virtual water imports and lower water endowment.

4.4 Methodology

4.4.1 Calculation Virtual water trade and water index

Our research methodology is divided into two parts:

First, the data were classified into general categories such as Cereals & alfalfa, Vegetables, and Fruits taking into account the classification of GASTAT (General Authority for Statistics in Saudi Arabia) and Alqahtani et al., (2017). The categories are then classified into specific products: Wheat, Millet, Sorghum, Corn, Barley, Sesame, Alfalfa, Tomato, Potato, Marrow (a type of squash), Eggplant, Okra, Carrot, Dry Onion, Cucumber, Melon, Watermelon, Dates, Citrus, and Grapes. Further, products were classified as either exports or imports.

Second, using the methods developed by Hoekstra and Hung (2002), we calculate total virtual water trade using the following stages (Figure 4.5):

Stage1: Estimate total net virtual water trade:

1. Estimating virtual water of the crop (VWC) per ton using crop water requirements[13]:

$$VWC_{ct} = \frac{CWR_c}{YE_{ct}}$$

Where the subscript *ct* is crop c in year *t*, CWR is crop water requirement, and *YE* is the crop yield.

2. Estimating virtual water trade (VWT):

$$VWT_{emct} = CT_{emct} \times VWC_{ec}$$

Where CT_{emct} denotes the crop *c* trade from e exporting country to m importing country in year *t*. VWC_{ec} is the virtual water of the crop c for the exporting country.

[13] *Crop water requirement* is the total amount of water used from the beginning of crop cultivation until harvesting, in a specific climatic system. CWR calculations require converting the agricultural products to virtual water. Because the product data varies by country, we use the Mekonnen and Hoekstra (2010[a]) and Multsch et al., (2013) results to estimate the virtual water.

3. Net virtual water trade of a country (NVW):

To calculate the NVW, we need to calculate gross virtual water imports and exports for Saudi Arabia, as follow:

$$GVWI_{mt} = \sum_{mt} [CT_{mct} \times VWC_{e_i c}]$$

Gross virtual water import (GVWI) is the sum of CT_{mct} , the crop *c* import from m country in year *t*, times VWD_{ec} the virtual water of the crop *c* in the exporting country *i*.

$$GVWE_{et} = \sum_{et} [CT_{ect} \times VWC_{ec}]$$

Gross virtual water export (GVWE) is the sum of CT_{ect} , the crop c export from e country in year *t*, times VWD_{ec} the virtual water of the crop c in the exporting country e (here represent Saudi Arabia).

The net virtual water trade of a country, NVW, is:

$$NVW = GVWI - GVWE$$

Stage 2: Estimate the water footprint of a country (WF):

$$WF = WU + (GVWI - GVWE)$$
$$= WU + NVW$$

WF is total domestic water use WU, plus the difference between gross virtual water imports and exports. To find total domestic water use, we include the water used by the agricultural, industrial, and municipal sectors. We recalculated the amount of virtual water using the water requirements for each crop under Mekonnen and Hoekstra (2010[b]) and Multsch, et al., (2013).

Stage 3: Estimate water index:

1. Virtual water dependency (WD):

$$WD = \frac{NVW}{WU + NVW} \times 100$$

The WD reflects the country dependence on international water resources. A value of zero mean *GVWI* is equal to *GVWE* (virtual water trade is in balance); a value of one hundred percent means the country totally depends on virtual water imports.

2. Water Self-Sufficiency (WSS):

$$WSS = \frac{WU}{WU + NVW} = \frac{WF}{WU + NVW} - \frac{NVW}{WU + NVW} = \frac{(WU + NVW)}{WU + NVW} - \frac{NVW}{WU + NVW} = 1 - WD$$

The WSS reflects the country's ability to provide the water required for domestic production. Values closer to zero mean the country depends greatly on importing virtual water, while values closer to one hundred mean the country provides its water requirements domestically.

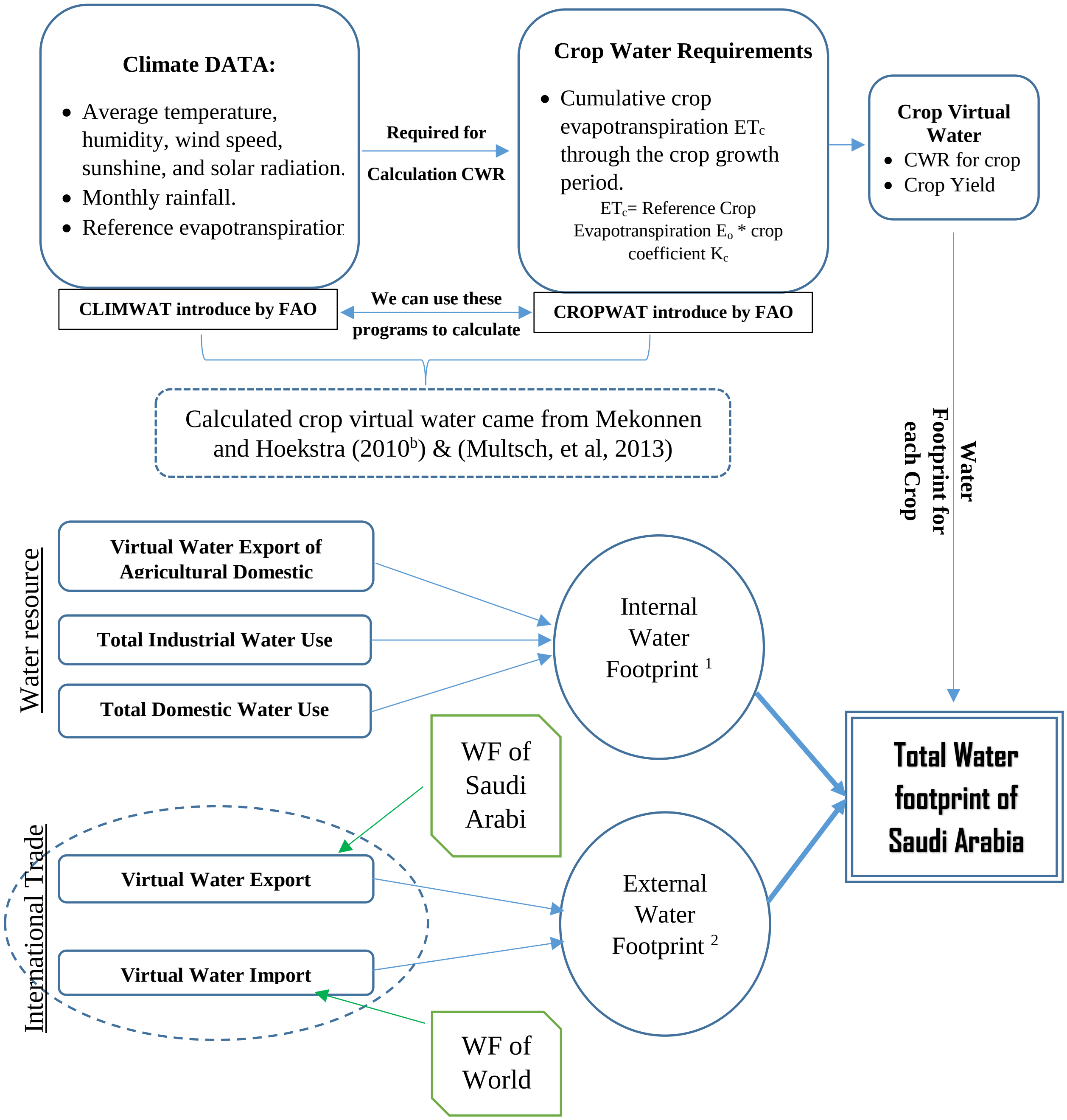

Figure 4.5 Analysis the Virtual Water for Crops in Saudi Arabia

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[1&2] The Water Footprint of a country is divided into two parts (Hoekstra and Hung, 2002; Alqahtani et al., 2017):

1- *The country's internal water footprint* is the water used annually within the country to produce water-consuming goods and services.
2- *The country's external water footprint* is defined as the water used annually to produce imported agricultural, food, and services consumed by the citizens of that country.

4.4.2 *Conceptual framework of Gravity model*

Stage 4: Using water availability and scarcity data with a Gravity model to explain the virtual water trade flows between Saudi Arabia and trading blocs.

Many economic studies have attempted to describe foreign trade flows and their causes. Some of these studies used the Gravity Model to analyze trends in bilateral trade between different countries and to analyze the determinants of crops trade (using the concept of virtual water). According to the Gravity model, the volume of the bilateral trade between two countries is described by economic, demographic, and geographic variables.

The gravity model is commonly used in statistical analysis of bilateral flows between countries (Head, 2003). Newton's law, which is the beginning point for the gravity model, is used in methodologies in many different sciences and it has had a high impact in economic science. The first gravity application was developed by Carey in 1865 to explain the interactions of human group activities, particularly in the field of social economy. Ravenstein in 1865 applied the concept of gravity to the study of population migrations. The model has long been used in the social sciences in the field of social interactions, which address concerns such as immigration, tourism, direct foreign investment, and transportation. Reilly in 1931 used the law of gravity in the analysis of patterns of shopping trips and retail trade in order to identify commercial areas for some US cities; he called it the "Reilly Model" (El-Nader et al., 2010; Yotov et al, 2017).

The first applications of the model to economics and international commerce came in the 1960s. Jan Tinbergen in 1962 applied Newton's law to the field of economics and earned a Nobel Prize in 1969. Then Poyhonen in 1963 developed a standard form of

Newton's law to measure the volume of two-way bilateral trade and to explain trade flows between countries. The model became widely used in international trade to explain bilateral trade between countries. It was found that the trade volume between the two countries depends on their GDPs and is inversely related to the distance between them (Matyas, 1998; El-Nader et al., 2010; Bacchetta et al, 2012; Yotov et al, 2017).

The Gravity model begins with a CES utility function for country i, which is the importer (consumer) country. The problem is to maximize utility subject to a budget constraint:

$$\left.\begin{aligned} &max\left(\sum_j \beta_{jt}^{\frac{1-\sigma}{\sigma}}\, q_{jit}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{1-\sigma}} \\ &s.t. budget\ constraint \sum_j P_{jit} q_{jit} = y_{it} \end{aligned}\right\} \quad (4.1)$$

Where B_{jt} is the share parameter, q_{jit} is the consumed crops from country j to country i in time t (the aggregate of q_{jit} will be X_{jit}), σ elasticity of substitution between all crops, p_{jit} country j export price to country i of crops at time t, and y_{it} nominal income of country i at time t.

Solving for equation (4.1), we end with the basic Gravity model:

$$X_{jit} = \frac{y_{jt} y_{it}}{y_{wt}} \left(\frac{\tau_{jit}}{P_{jt} P_{it}}\right)^{1-\sigma} \quad (4.2)$$

Where the P_{jt}, and P_{it} (price index for country i) are multilateral trade resistance factors, y_{wt} is world income, and τ_{jit} is the trade cost.

Depken and Sonara (2005) depict the basic gravity model from equation (4.2) as:

$$A_{ij} = \beta_0 \frac{GDP_i^{\beta_1} GDP_j^{\beta_2}}{Dist_{ij}^{\beta_3}} \tag{4.3}$$

Where A_{ij} is Trade (exports or imports) from country i to/from the country j, *GDP* is the gross domestic product for each country, $Dist_{ij}$ is the distance between the two locations, and β_0 is the gravitational constant.

Taking the logarithm of both sides will convert equation (4.3) into a linear function of parameters (a double logarithmic form). This equation is called the Basic Gravity Model (BGM):

$$lnA_{ij} = \beta_0 + \beta_1 lnGDP_i + \beta_2 lnGDP_j - \beta_3 lnDist_{ij} + \varepsilon_{ij} \tag{4.4}$$

Where ε_{ij} represents the random error in a linear equation (since we can estimate it by OLS). However, the error term may be correlated with A_{ij} since specific country characteristics related to trade are omitted.

Thus, we augment the basic Gravity model (equation 4.4) in a fashion similar to Ruiz, Juan and Vilarrubia (2007), Bacchetta et al, (2012), Fracasso (2014), and Yotov et al, (2017) to include both year fixed effects and country pair fixed effects as follow:

$$lnA_{ijt} = \beta_0 + \beta_1 lnY_{it} + \beta_1 lnY_{jt} + \beta_2 lnPOP_{it} + \beta_2 lnPOP_{jt} + \sum_{j=1}^{S} \propto_{ij} D_{ij} + \gamma_t + \varepsilon_{ijt} \tag{4.5}$$

Where Y is GDP in the countries *i* or *j*; POP is the population in countries *i* or *j*; D_{ij} is a set of Dummy Variables which represent country pair fixed effects (which control for invariant characteristics such as Border, Geographic Distance, Language, and Trade

Agreements); γ_t are year fixed effects; and ε_{ijt} is the error term. The intercept term represents the average virtual water trade in the base year holding other variables constant.

Because the gravity model is a double logarithmic model, the regression coefficients are elasticities. We expect the sign on the coefficient for GDP to be positive and the coefficient for distance to be negative. Since our interest is focused on estimating the effect of a country-specific variable on trade, we include exporter by importer fixed effects to help control for the effect of distance, common language, common culture, or contiguity. This solves bias problems from omitted multilateral trade resistance. These dummy variables also reduce the error term from time-varying effects (from unobservable characteristics that vary over time).

There is often concern about Omitted Variable Bias (Cov (X_i, OV_i) $\neq 0$, then Cov (X_i, ε_i) $\neq 0$) in Gravity models related to the difficulty in accounting for unobservable country-pair characteristics. To solve that issue, we will use panel data with fixed effects to allow us to control for time-varying unobserved country heterogeneity and time-invariant country pair unobserved characteristics.

Another issue with gravity models involves endogeneity. This issue could come from measurement error (correlation between explanatory variables and the error term), autocorrelation (errors are correlated serially), or reverse casualty between member countries of RTAs and the size of virtual water trade. Water-scarce countries may want to have an RTA with abundant water countries. In order to control for endogeneity, country-pair-fixed effects are used to account for unobservable time-invariant covariates (Shahid, 2011; Martínez-Zarzoso, 2018).

4.4.3 *Model Specification:*

The emergence of the virtual water concept by Allan in 1994 helped people understand some of the water scarcity problems and how they can be overcome through trade between two countries. Virtual water quantifies ways of reducing water scarcity through production changes and international trade (Hamouda and El-Sadek, 2007; Hoekstra and Chapagain 2007[a]). Allan's idea about virtual water is consistent with international trade theory. Countries with a comparative advantage in water (they are water abundant), could transfer their virtual water to water-scarce countries through trade of water-using crops. This idea represents a rendition of the Ricardian and Heschker-Ohlin-Vanek (HOV) model. Taking into account Allan's ideas and following the HOV model about comparative advantage between two countries, we formulate a gravity model of virtual water trade. The Gravity model is the result from production using endowments from an HOV trade model and consumption from CES utility (Fracasso, 2014; Delbourg and Dinar, 2016; Chen and Wilson, (2017)).

The main point here is whether crops, which are water-intensive in production, are exported from countries that have abundant water resources to water-scarce countries. Saudi Arabia is considered a water scarce country, and it is reasonable that it benefits by importing crops (importing virtual water) instead of using scarce local water on agricultural production. Therefore, we use a gravity model to test whether the volume of virtual water trade between Saudi Arabia and the rest of the world is influenced by relative water scarcity.

From the above explanation, we add exporter fixed effects to solve the omitted variable bias which comes from multilateral resistance trade and misspecification (Ruiz, Juan and Vilarrubia, 2008; Bacchetta et al, 2012; Fracasso (2014); and Yotov et al, 2017). However, from equation (4.2) P_{jt} and P_{it} are not observable and omitting them introduces bias. Thus, we control for unobserved exporter and importer time fixed effects, and time-variant country-specific effects (Wooldridge, 2009). However, Fracasso (2014) shows that including time-varying country fixed effects force all country specifics to drop out the model (GDP and population). Therefore, we build our related water variables, in the next section, as a ratio to keep these variables in the model (Fracasso, 2014). We ignore tariffs variables due to data availability and Saudi Arabia was not a colony of any country, so that variable is excluded too.

We include five bloc dummy variables, each dummy represents the time in force for a Regional Trade Agreements with Saudi Arabia. D98 identifies the agreement for the Pan-Arab Free Trade Area (PAFTA) (the number indicates the year the agreement began), D03 identifies the agreement with the Gulf Cooperation Council (GCC), D05 identifies the agreement with the WTO, D13 identifies the agreement with Singapore, and D14 identifies the agreement with the European Free Trade Association (EFTA).

In addition to the above-mentioned explanatory variables, we include variables related to water. Other studies have used total renewable water, average annual precipitation and virtual water used in agricultural production for water endowment or availability, and arable land as a measure of land endowment (Sartori et al. (2017); Fracasso (2014); Duarte et al, (2016); Fracasso et al, (2014); and Tamea et al (2014)). Among these variables, we introduce three variables describing Allan's idea of water scarce countries (such as Saudi Arabia) importing crops from abundant countries. First, the Water Dependency Ratio (WDR) is a country's WD divided by Saudi Arabia's WD. If the ratio is greater than one the country is more dependent on virtual water inflows than Saudi Arabia. We expect the coefficient on WDR to be negative in the import equation if Allan's hypothesis is correct. Second, the Water Footprint ratio (WFR) for each product is the other country's water footprint divided by the water footprint of Saudi Arabia. A higher WFR means that the country consumes more water resources per ton produced than Saudi Arabia. If Allan's hypothesis holds, then the WFR should have a negative sign in the import equation. Third, the Relative Renewable Water to Arable Land Ratio (RRWALR) represents the m^3 of renewable water per hectare. The RRWALR is RWALR for the other country divided by the RWALR for Saudi Arabia. An RRWALR greater than one means the country has more abundant water resources relative to Saudi Arabia. Allan's hypothesis is that the coefficient on RRWALR is positive for the import equation.

We used panel data rather than purely cross-section data. Cross-sectional data could lead to bias in our results because the error terms reflect omitted variables that are correlated with trade and GDP. Also, cross-sectional data cannot estimate both GDP and country fixed effects due to multicollinearity. Panel data is preferred because it has observations over time that help control for an unobserved country specific heterogeneity, control for time-invariant effects that lead to omitted variables bias, and provide more degree of freedom (Wooldridge, 2009; Bacchetta et al, 2012). Panel data accounts for the issues of varying multilateral resistance terms (MRT) over time by using importer/exporter time fixed effects (Yotov et al, 2017).

Finally, we also applied a Poisson Pseudo Maximum Likelihood (PPML) estimator (log-linearized) to solve the issue of zero trade flows, multilateral resistance terms (MRT), and inconsistency and bias (heteroscedasticity) when estimating trade costs and policy.

PPML leads to perfect compatibility between fixed effects and the unobserved multilateral resistance trade (Fracasso (2014); Duarte et al., (2016); Chen and Wilson, (2017); Blanke and Fischer (2017)). However, our estimations were different from previous studies. First, we applied our model to 20 crops and 3 commodity groups, rather than on aggregate data. Second, we calculated the VWT so that it more accurately reflected water scarcity. Third, we used a specific country (Saudi Arabia) in the analysis to gauge the influence of water-related variables on VWT. Fourth, we used different variables related to water scarcity relative to Saudi Arabia in order to capture ideas from Allan. Fifth, we include the effects of different trading blocs on virtual water trade. Finally, we conduct more diagnostic tests related to data and the model. Therefore, our final gravity model specification with PPML for import virtual water is:

$$VWT_{it} = \exp[\alpha_0 + \beta_1 lnY_{it} + \beta_1 lnY_{jt} + \beta_2 lnPOP_{it} + \beta_2 lnPOP_{jt} + \mu_{it} + D_{year} + D_{ij} + \pi_1 WDR + \pi_2 WFR + \pi_3 RRWALR + \epsilon_{ijt}] \quad (4.6)$$

Where

- VWT is virtual water import.
- μ_{it} are exporter time fixed effects
- D_{year} are dummies for the RTA member and non-member
- D_{ij} is a set of Dummy Variables which represent country pair fixed effects
- *WDR, WFR,* and *RRWALR* are the related water variables
- ϵ_{ijt} is the error term.

4.4.4 *Data:*

We estimate virtual water flows from 2000 through 2016. Production data came from General Authority for Statistics (GASTAT) in Saudi Arabia. However, most of the trade data came from GATS: Global agricultural trade system online from the United States Department of Agriculture (USDA). Marrow and watermelon trade data came from General Authority for Statistics (GASTAT) in Saudi Arabia and the Food and Agriculture Organization of the United Nations (FAO) (Table 4.3). We used Harmonized codes for Sorghum, Barley, Tomato, Potato, Eggplant, Dry Onion, Cucumber, Dates, Alfalfa, Citrus, and Grapes. We are using BICO codes for Wheat, Millet, Corn, Sesame, and Marrow. We used the World Trade Organization codes for Okra, Carrot, Melon, and Watermelon.

The amount of virtual water for crops (the water footprint) calculated from Mekonnen and Hoekstra (2010[b]) is more comprehensive, detailed, and accurate than other studies. Multsch et al., (2013) has data on Saudi Arabia's water footprint that is newer based on an approach similar to Mekonnen and Hoekstra, (2010[b]). It uses the SPARE: WATER rather than the CropWat program[15] (Table 4.4). We rely on Multsch et al., 2013 for Saudi Arabia, but Mekonnen and Hoekstra for the rest of the world. The water footprint for Alfalfa for the rest of the world came from Chapagain and Hoekstra (2004). If the data are not available for the country from Mekonnen and Hoekstra (2010[b]), we take the average global water footprint.

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[15] Multsch et al. (2013) used 55% of irrigation efficiency while Mekonnen and Hoekstra used 100% (no losses with irrigation). As we mention in the beginning of this study, Saudi Arabia uses a great deal of nonrenewable ground water. Multsch et al. modified the calculation for the blue water footprint with the low efficiency and methods of irrigation (surface and sprinkler irrigation), For more details about the program see appendix 1 & 2).

In order to obtain the water needs for heterogeneous groups of agricultural products (Cereals, Vegetables, and Fruits); we take the average of the water footprint for each category for each country. We omit Hong Kong, Gibraltar, Eswatini and Taiwan because the water footprint is not available from Mekonnen and Hoekstra (2010[b]). We add these countries to the Areas not Elsewhere Specified.

For explanatory variables, country-specific characteristic data came from World Bank's World Development Indicators, such as *GDP* and *POP*, except GDP for Korea which came from the OECD (Organization for Economic Co-operation and Development). Distance (*Dist)* came from the time and date website (https://www.timeanddate.com/worldclock/distance.html), which specializes in measuring the distance between cities. Total renewable water and arable land came from AQUASTAT. The water footprint variable came from Mekonnen and Hoekstra (2010[b]) while water dependency variables came from Hoekstra and Hung (2002) (see figure 4.5 for calculations). RTA dummies variable came from Regional Trade Agreements Information System (RTA-IS) of The World Trade Organization (WTO) website.

Table 4.3 Data Sources for Various Crops.

Crops	Import and export	HS Code
Wheat	Import: USDA using BICO-HS6 Export: USDA using BICO-HS6 and FAO	1001
Millet	USDA using BICO-HS4	1008
Sorghum	USDA using Harmonized: HS-4	1007
Corn	USDA using BICO-HS6	1005
Barley	USDA using Harmonized: HS-4	100300
Sesame	USDA using BICO-HS6, as well as FAO	120740
Tomato	USDA using Harmonized: HS-4	702
Potato	USDA using Harmonized: HS-4	701
Marrow	Import: USDA using WTO- Agricultural Total, as well as FAO Export: GASTAT	70993
Eggplant	USDA using Harmonized: HS-4	70930
Okra	USDA using WTO- Agricultural Total	70990
Carrot	USDA using WTO- Agricultural Total	70610
Dry Onion	USDA using Harmonized: HS-6	71220
Cucumber	USDA using Harmonized: HS-4	707
Melon	USDA using WTO- Agricultural Total	80719
Watermelon	USDA using WTO- Agricultural Total	80711
Alfalfa	USDA using Harmonized: HS-6, as well as FAO	121410
Dates	USDA using Harmonized: HS-6	80410
Citrus	USDA using Harmonized: HS-6	80590
Grapes	USDA using Harmonized: HS-6	80610

Table 4.4 Average water footprint of crops, Saudi Arabia and World (m^3/ton)

Crop	World	Saudi Arabia	Saudi Arabia
Wheat	1827	1516	2462
Millet	4478	2785	5199
Sorghum	3048	3358	3842
Corn	1222	1637	4751
Barley	1423	1220	1701
Sesame	9371	5498	7026
Tomato	214	469	393
Potato	287	363	651
Marrow	336	--	759
Eggplant	362	618	762
Okra	576	788	496
Carrot	195	806	517
Dry Onion	345	615	299
Cucumber	353	199	167
Melon	221	256	664
Watermelon	238	361	497
Alfalfa	--	--	2634
Dates	2277	3648	3439
Citrus	1242	1429	5263
Grapes	608	933	1861
Source	Mekonnen & Hoekstra, (2010[b])		Multsch, et al, (2013)

4.5 Result and Discussion

4.5.1 *Saudi Arabia production using the concept of virtual water:*

Agricultural policies played an important role in the growth of crop production in Saudi Arabia. The government has provided subsidies, soft loans, and various services for the sector. In recent years, however, these policies have changed to incorporate water preservation policies, moving the country to import crops that are intensive users of water. Production of cereals, vegetables, and fruit crops decreased by 55%, 34%, and 10%, respectively, from 2000 to 2017 (GASTAT, 2018). Alfalfa production increased by 71% during the same period because many wheat farms turned to alfalfa after government support for wheat fell in 2008.

Virtual water consumption for agriculture increased by 38% between 2000 and 2017. Virtual water consumption for cereals and fruit decreased by 111% and 18%, respectively, during this period, but virtual water consumption for vegetables and alfalfa increased by 9% and 78%, respectively. Saudi farmers moved to more water-intensive vegetable crops during the period. Wheat has the highest consumption of virtual water among cereals, potatoes have the highest water consumption among vegetables, and dates have the highest water consumption among fruit crops.

4.5.2 *Virtual water trade of crops*

The water footprint of Saudi Arabia (WFSA) was 500.99 billion m^3 during the study period (which is 289.2 billion m^3 of WU and 211.8 billion m^3 in net virtual water trade). The average WFSA was 29.5 billion m^3/year (17.01 billion m^3/year as WU +12.46 billion m^3/year for NVW), this result was higher than Hoekstra and Hung (2002) found.

The water dependency statistic for Saudi Arabia is equal to 42.27% =[211.8/(211.8+289.2)], which means that 42% of Saudi Arabia's water comes from virtual net imports (notice that we only calculate the virtual water for crops). We found that Saudi Arabia was heavily dependent on virtual water import for all cereals. The self-sufficiency ratio of water was 57.7 %, which shows the problem of using scarce domestic water resources rather than import (higher than Hoekstra and Hung (2002) found which was 33.2%).

Figures 4.6, 4.7, and 4.8 and appendix 3 & 4 show virtual water imports and exports of crops between Saudi Arabia and the world during the period 2000 to 2016. In 2013, Saudi Arabia's imports of virtual water peaked at 21.57 billion m^3, which is the last year before the Saudi Arabia government issued the policy to stop exporting dairy products. Increasing virtual water imports was related to the government's tendency to import cereals and alfalfa (these products had high water consumption) instead of relying on local production to save water. The results show that annual average net virtual water for Saudi Arabia are 12.5 billion m^3/year.

The cereal and alfalfa group accounted for a significant percentage of gross virtual water imports, followed by vegetables and fruit. The fruit group was the highest for gross virtual water export, followed by vegetables and then cereals and alfalfa. Saudi Arabia was a positive net importer of virtual water over the entire period. Net imports totaled 21.6 billion m^3 in 2013 but fell to 8.9 billion m^3 in 2016. This fall was due to a drop in grain exports from Australia, Canada, Germany, Russia and Ukraine to Saudi Arabia due to lower prices and lower production in these countries. Also, political problems between Russia and Ukraine during that period (both account for 28% of total virtual water imports of Saudi Arabia) also depressed exports to Saudi Arabia. These figures are higher than Alqahtani et al., (2017), but they studied a different period and used the Mekonnen & Hoekstra, (2010[b]) method to calculate the virtual water.

Total virtual water imports of Saudi Arabia increased from 7.5 billion m^3 in 2000 to 8.9 billion m^3 in 2016. Much of the virtual water imports come from cereals and alfalfa. These imports increased from 7.45 to 7.98 billion m^3 during the study period. Vegetables were the second-leading group for virtual water imports, increasing from 28 million m^3 to 845 million m^3 over the period to reflect the impact of declining domestic production of vegetables and increasing consumption. Virtual water from fruit imports increased from 13 million m^3 to 43 million m^3 during the study period. The slower (but still high) growth reflects the impact of increased domestic production as a result of government support for fruit crops, especially dates.

There is a tendency for the Saudi government to enact agricultural policies to limit exports of intensive-water using crops, which lessens the pressure on non-renewable water resources, such as the decision to ban the export of alfalfa and the gradual lifting of subsidies for wheat producers in Saudi Arabia. Fruit exports continue, and their virtual water content increased from 88 million m^3 in 2000 to 475 million m^3 in 2016.

Kuwait, UAE, Yemen, Bahrain, and Qatar were the top five countries importing virtual water from Saudi Arabia during the study period, accounting for almost 70% of Saudi Arabia’s virtual water exports (figure 4.9). Ukraine, Russia, Australia, Argentina, and India were the top five countries exporting virtual water to Saudi Arabia, accounting 58% of the total Saudi Arabia imports (figure 4.10 and appendix 5).

Saudi Arabia received 212.4, 2.8, and 3.4 billion m^3 of virtual water through cereal & alfalfa, vegetable, and fruit trade, respectively, during the study period. It is clear from figure 4.3 that Saudi Arabia's policies to stop exports of some agricultural products have produced remarkable water-saving results so that there are almost no exports of virtual water for the cereal and alfalfa group.

Wheat imports were where much of the virtual water was obtained for cereal & alfalfa, while tomato was the leading source of virtual water for vegetables, and grapes were the leading virtual water source for fruit.

Most of the virtual water exports from vegetables were from potatoes, and most of the virtual water exports from fruit were from dates. The government's support for dates is the major reason that there is a net export of virtual water for fruits.

Overall, Saudi Arabia relies on agricultural imports to provide virtual water to overcome its scarcity. If Saudi Arabia did not import these crops during the study period and relied exclusively on local production (using the concept of virtual water), it would require an average of 12.5 billion m^3 of additional local virtual water, which is equivalent to 52% of the total local water resources (estimated at 23.9 billion m^3 in 2016).

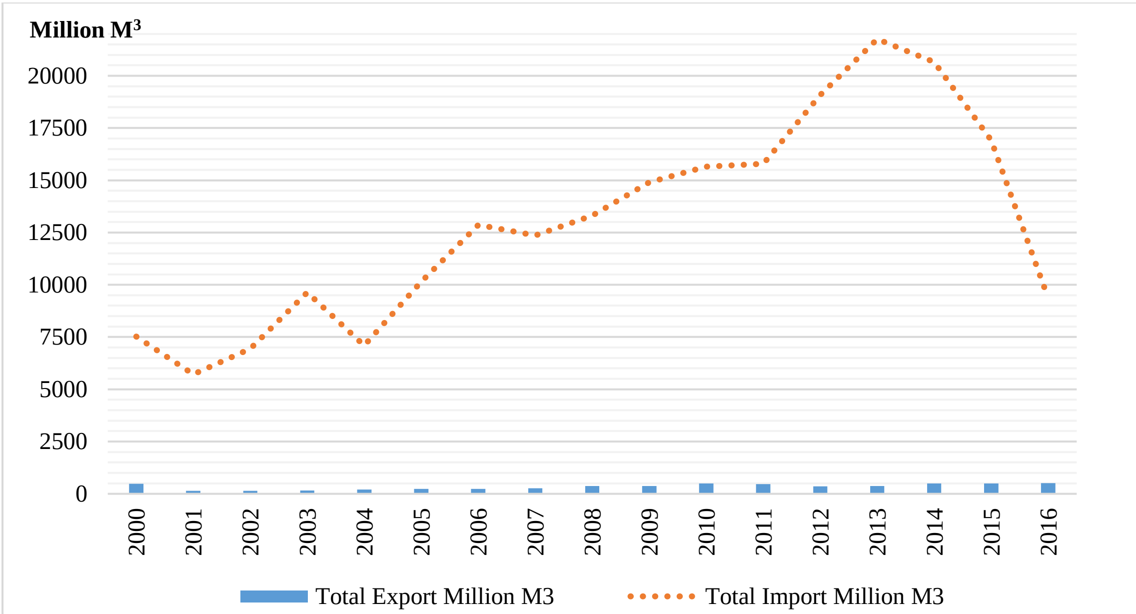

Figure 4.6 Total Virtual Water Trade for Saudi Arabia during the period 2000 to 2016

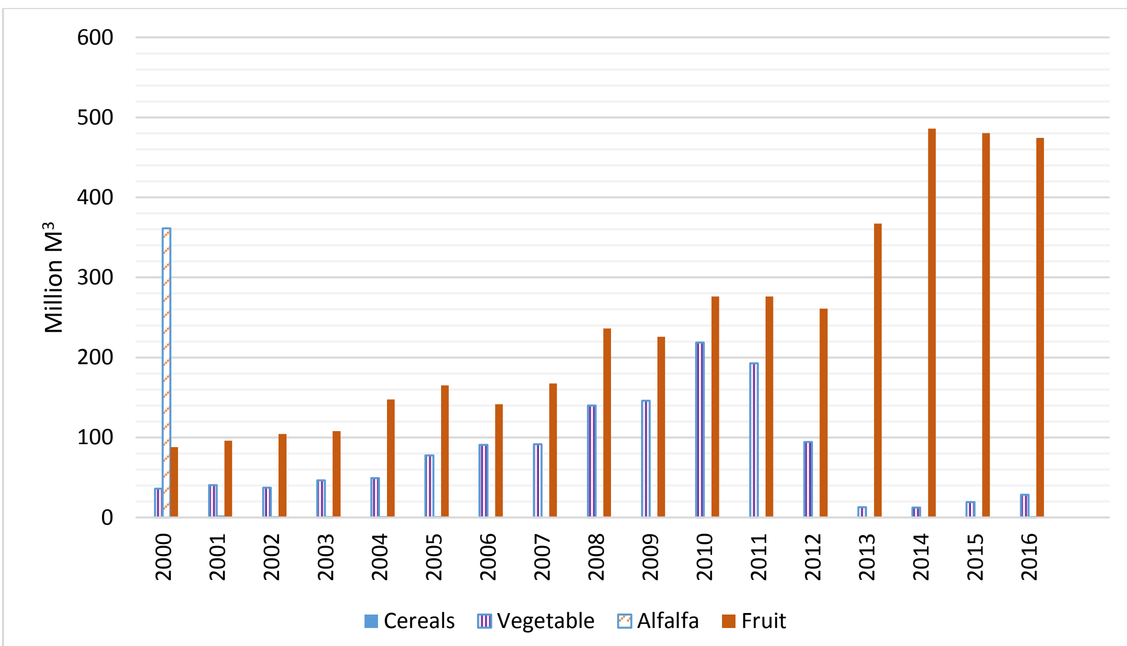

Figure 4.7 Total Virtual Water Exports from groups in Saudi Arabia during the period 2000 to 2016

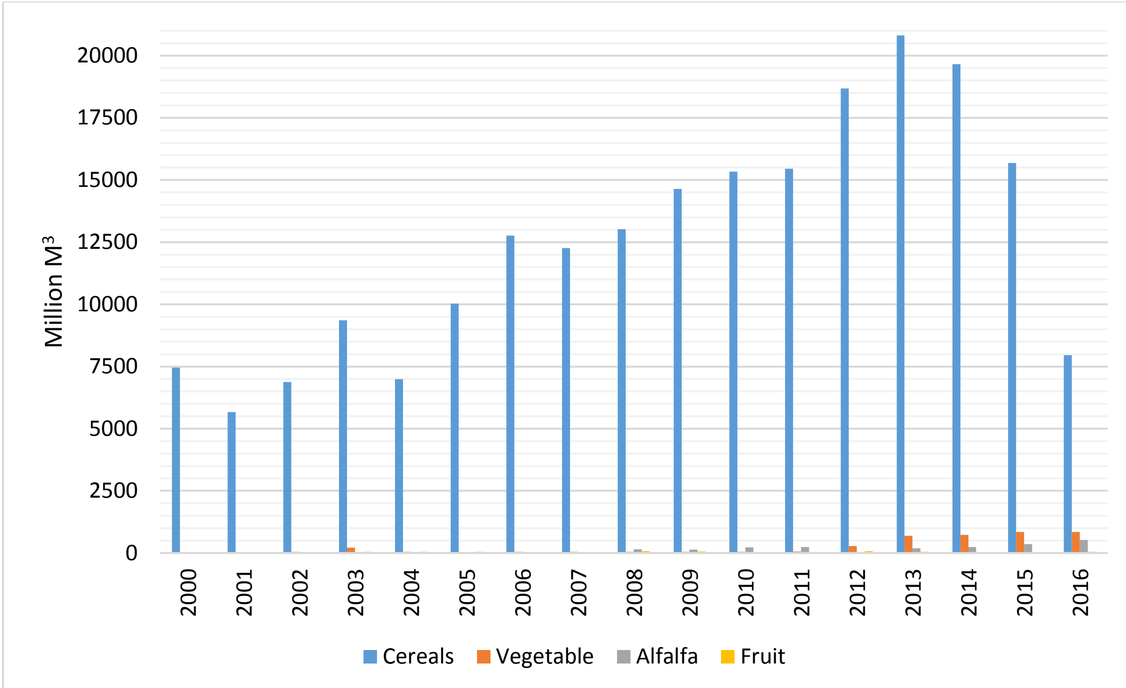

Figure 4.8 Total Virtual Water Imports of groups in Saudi Arabia from 2000 to 2016

Figure 4.9 Saudi Arabia virtual water export map (million m^3)

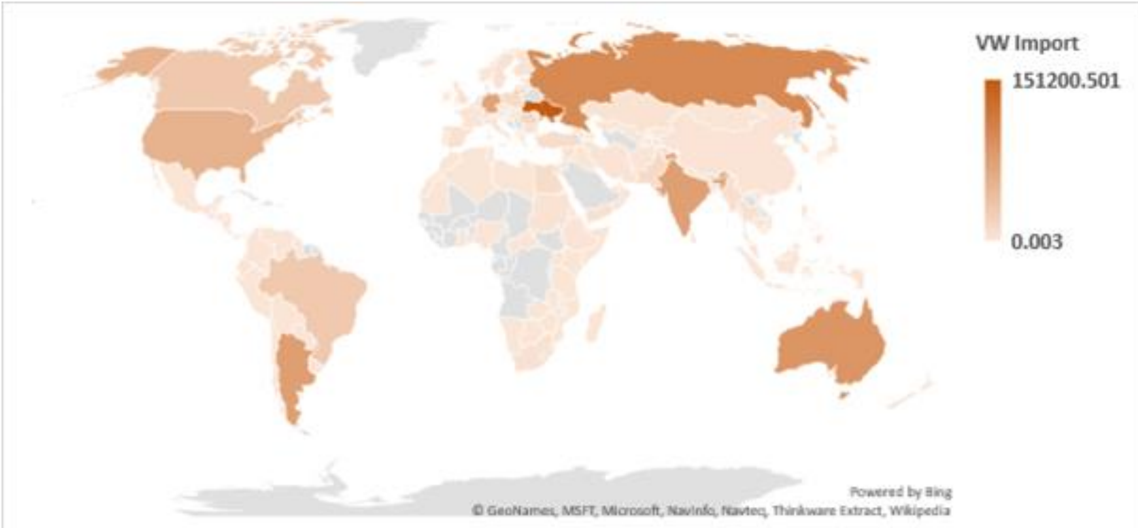

Figure 4.10 Saudi Arabia virtual water import map (million m^3)

4.5.3 *The Gravity model of VWT:*

The panel data used in the gravity model were balanced; all countries (cross-section) had the same years (time series). Use of panel data presents some problems such as Heteroscedasticity and Autocorrelation. In this study, we only concentrated on the import side, since Saudi Arabia is a water scarce country. In addition, our VWT results indicated that virtual water imports are much greater than virtual water exports.

Table 4.5 presents the variables definition included in the gravity model. To account for unobservable trade costs, we include dummies variables such as whether the countries share a common religion, common border, and RTA membership as well as geographical distance. These variables were invariant with time. The economic mass variables included the size of the supply of country i represented as GDP, the GDP of Saudi Arabia as GDPSA; and the population of both country i and Saudi Arabia as POP and POPSA, respectively. There are three water-related variables included: WDR and WFR, which should be negatively related to imports, and RRWALR, which should be positively related to imports.

For each crop, we compare the OLS, Fixed effect, Random effect, and PPML estimators to obtain the best model. The chosen result is accomplished through tests designed to choose between models. The tests were the F-test (the data fit the model well if the F value is high to compared to least square dummy variable (LSDV) and fixed effect)), Variance Inflation Factor (which shows collinearity between explanatory variables), Breusch and Pagan LM test (which compares Pooled OLS and random effects), Hausman (which compares fixed and random effects)[16], and Wald test (which compares the stability of the variance).

We start by including all the variables in the model. We use a forward or backward stepwise procedure for final variable inclusion (Lindsey and Sheather (2010)) which involves the Akaike Information Criteria (AIC) (Figure 4.11). We tend to pick the procedure that includes more water-related variables.

We drop the common language dummy since it perfectly correlated with the PAFTA member dummy. We also drop the culture dummy variable that is perfectly correlated with the GCC dummy variable. The D05 dummy (WTO member) was omitted because non-members had a tiny amount of virtual water trade with Saudi Arabia. Some of the variables were dropped from the model when using fixed effect because they are time-invariant. Because some of these time-invariant variables are interesting for our purposes, we tended not to include country fixed effects in our analysis.

Heteroscedasticity is a common problem with panel data, so we used robust standard errors with OLS estimators to reduce bias (Woolridge, 2009). We also cluster the errors by the distance to improve the specific country effect variables such as the economic mass variables.

Finally, we handle zero trade observations and the resulting heteroscedasticity issues by using a PPML estimator. Dropping zero trade flows leads to loss of useful information.

[16] The null hypothesis says that using RE is the better (efficient and consistent), while the alternative hypothesis FE is the better.

Table 4.5 Variable Definitions

Variable	Define
lnALFALFA	Log of virtual water trade from country i for Alfalfa
lnCEREALS	Log of virtual water trade from country i for Cereals
lnWHEAT	Log of virtual water trade from country i for Wheat
lnMILLET	Log of virtual water trade from country i for Millet
lnSORGHUM	Log of virtual water trade from country i for Sorghum
lnCORN	Log of virtual water trade from country i for Corn
lnBARLEY	Log of virtual water trade from country i for Barley
lnSESAME	Log of virtual water trade from country i for Sesame
lnVEGETABLE	Log of virtual water trade from country i for Vegetable
lnTOMATO	Log of virtual water trade from country i for Tomato
lnPOTATO	Log of virtual water trade from country i for Potato
lnMARROW	Log of virtual water trade from country i for Marrow
lnEGGPLANT	Log of virtual water trade from country i for Eggplant
lnOKRA	Log of virtual water trade from country i for Okra
lnCARROT	Log of virtual water trade from country i for Carrot
lnDRYONION	Log of virtual water trade from country i for Dry Onion
lnCUCUMBER	Log of virtual water trade from country i for Cucumber
lnMELON	Log of virtual water trade from country i for Melon
lnWATERM	Log of virtual water trade from country i for Watermelon
lnFRUIT	Log of virtual water trade from country i for Fruit
lnDATES	Log of virtual water trade from country i for Dates
lnCITRUS	Log of virtual water trade from country i for Citrus
lnGRAPES	Log of virtual water trade from country i for Grapes
Dummy Variables	
Drelg	1 for common religion; 0 otherwise
Dcong	1 for common contiguity; 0 otherwise
D98	1 for a member of regional trade with PAFTA starting at 2000; 0 otherwise.
D03	1 for a member of GCC starting at 2003; 0 otherwise.
D13	1 for a member of regional trade with Singapore starting at 2013; 0 otherwise.
D14	1 for a member of regional trade with EFTA starting at 2014; 0 otherwise.
Basic Gravity model Variables	
lnDis	Log Distance between Saudi Arabia and country i
lnGDPi	Log GDP of country i
lnGDPSA	Log GDP of Saudi Arabia
lnPOPi	Log of the population of country i
lnPOPSA	Log of the population of Saudi Arabia

Table 4.5 (continued)

Variable	Def.
Water-related variables	
lnRRWALR	Log of Relative Renewable Water to Arable Land Ratio between Saudi Arabia and country i
lnWDR	Log of water dependency ratio between Saudi Arabia and country i
lnWFRAL	Log water footprint ratio for Alfalfa
lnWFRBA	Log water footprint ratio for Barley
lnWFRCA	Log water footprint ratio for Carrot
lnWFRCI	Log water footprint ratio for Citrus
lnWFRCR	Log water footprint ratio for Corn
lnWFRCU	Log water footprint ratio for Cucumber
lnWFRDA	Log water footprint ratio for Dates
lnWFRDR	Log water footprint ratio for Dry Onion
lnWFREG	Log water footprint ratio for Eggplant
lnWFRGR	Log water footprint ratio for Grapes
lnWFRMA	Log water footprint ratio for Marrow
lnWFRME	Log water footprint ratio for Melon
lnWFRMI	Log water footprint ratio for Millet
lnWFROK	Log water footprint ratio for Okra
lnWFRPO	Log water footprint ratio for Potato
lnWFRSE	Log water footprint ratio for sesame
lnWFRSO	Log water footprint ratio for Sorghums
lnWFRTO	Log water footprint ratio for Tomato
lnWFRWA	Log water footprint ratio for Watermelon
lnWFRWH	Log water footprint ratio for Wheat
lnWFRCER	Log water footprint ratio for Cereals
lnWFRFRU	Log water footprint ratio for Fruit
lnWFRVEG	Log water footprint ratio for Vegetable

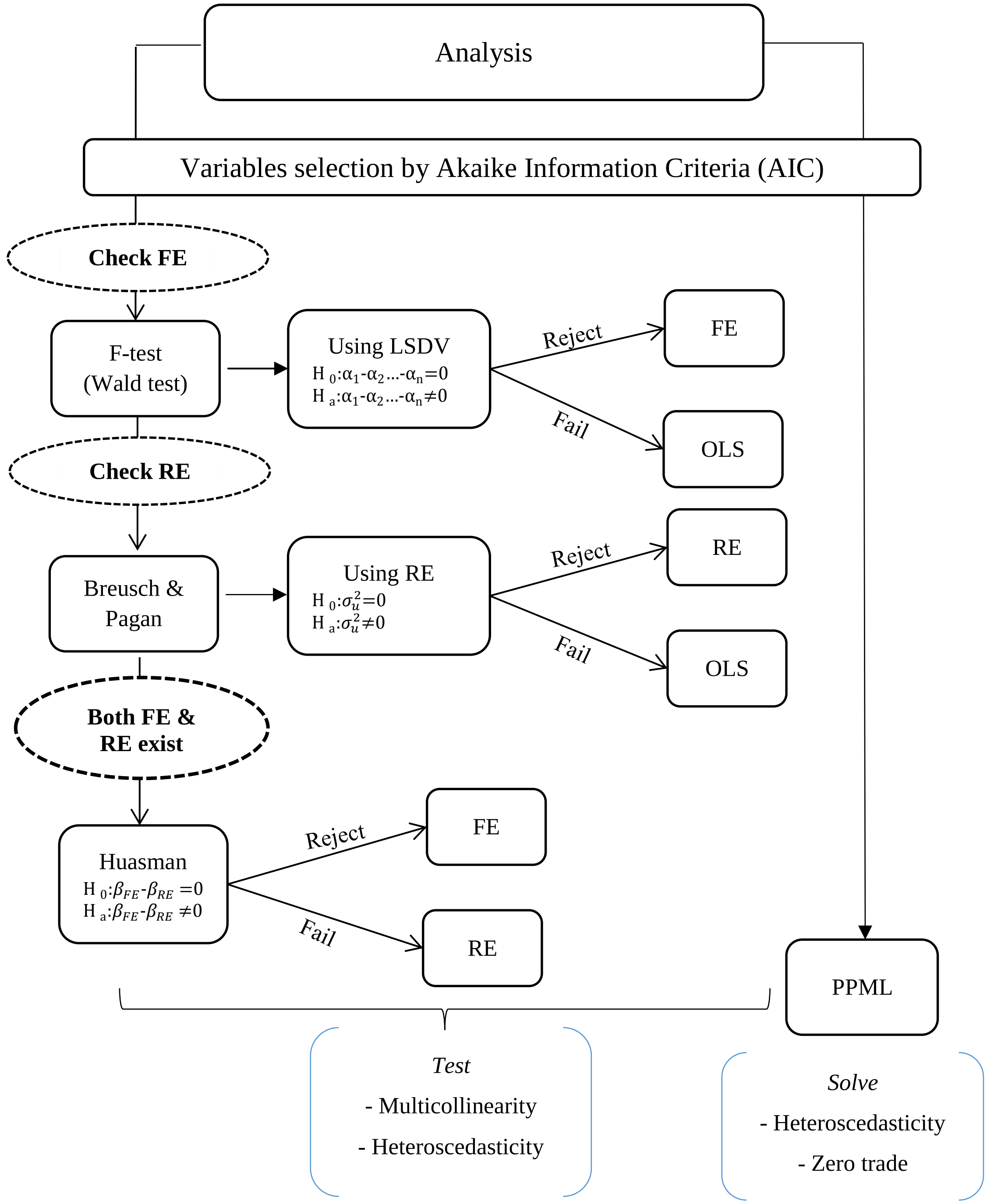

Figure 4.11 Design of the analysis

4.5.3.1 Virtual water import of Cereals and Alfalfa group:

Cereals crops receive 97.8% of the total VWT of Saudi Arabia compared to 1.9% with vegetables and 0.3% with fruit crops. Our general criteria for choosing the gravity model of crops between OLS, fixed effect, and random effect, is shown in table 4.6. Only results for the selected model are shown. All models are fitted with the PPML estimators because of the zero trade observations, and the results from PPML are compared with the chosen model from table 4.6. Zero trade observations are common; more than 55% of the observations in the Cereals and Alfalfa groups are zero. We found that water-related variables significantly influence the virtual water imports for Cereals, Millet, Sorghum, Corn, Barely, and Sesame. All other crop models had all water-related coefficients that were not significantly different from zero. However, we omit the Sorghum results since it was not consistency with economic logic and had high collinearity between variables.

Table 4.6 Selecting models of Cereals and Alfalfa crops

Crop	FE vs. OLS (F-test)	RE vs. OLS (Breusch and Pagan LM)	Preferred model
Alfalfa	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS
Cereals	Pooled OLS	*H_0: Rejected* RE	*RE*
Wheat	Pooled OLS	*H_0: Rejected* RE	*RE*
Millet	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS
Sorghum	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS
Corn	FE	*H_0: Rejected* RE	*Hausman test* *H_0: fail to reject* *RE*
Barley	Pooled OLS	*H_0: Rejected* RE	*RE*
Sesame	Pooled OLS	*H_0: Rejected* RE	*RE*

4.5.3.1.1 Results of the gravity model of virtual water import for alfalfa crop:

Table (4.7) shows the results of the gravity model with OLS and PPML model estimations of the virtual water trade for Alfalfa during 2000-2016. There are eleven countries in the sample. The selection procedures were followed (we found no collinearity, but there was heteroscedasticity), so we used clustering with robust standard error methods to control for heteroscedasticity. The OLS model was preferred according to both the F-test and the Breusch and Pagan LM test. Both preferred models had the same sign and significance for explanatory variables, except OLS, which had one more significant variable (distance). The GDP of Saudi Arabia and distance coefficients had expected signs while the dummy for common religion had an adverse sign. The coefficient for renewable water per hectare ratio was also of the wrong sign, but it was not significant.

The largest positive impact on virtual water trade came from the GDP of Saudi Arabia, while the largest negative coefficient was for the religion dummy. GDP of Saudi Arabia had a strongly significant coefficient in both OLS and PPML models, and the OLS elasticities had a higher impact than PPML. The sign of religion dummy likely is because Saudi Arabia imported alfalfa from only one Muslim country (Egypt) and it was a small amount. Saudi Arabia simply gets the lion's share of its alfalfa from non-Muslim countries. The RRWALR coefficient was negative but not significant. This result contrasts with Fracasso (2014) who found that the amount of arable land was positively correlated with virtual water trade for exporting countries.

4.5.3.1.2 Results of the Gravity model of virtual water import for Cereals aggregate:

Cereals crops are water-intensive compared to other crops. Earlier results show that these crops account for more than 90% of Saudi Arabia's total virtual water imports during 2000-2016. There were 1224 observations from 72 countries over the period 2000-2016 for cereals. Nine PAFTA member countries and four GCC countries exported cereals to Saudi Arabia accounting for 0.5% and 0.02%, respectively, of the total virtual water trade of Saudi Arabia. The water footprint ratio for cereals (WFR) was calculated by taking the average of wheat, barley, corn, millet, sorghum, and sesame water footprint for each country as a ratio of Saudi Arabia.

We found that the AIC forward process is preferred for the cereals gravity model and the resulting model is random effects based on its high F-value and the result of the Breusch and Pagan LM test (table 4.6 & 4.7). The religion dummy, GCC member dummy, and the population had unexpected signs while others were mostly as expected. The results show diversion of trade to non-GCC members. The sign of population of other countries was somewhat reasonable, as the population in other countries rise; it will increase the consumption of domestic cereals and results in less exports.

The coefficient for WDR was significant for cereals in the PPML estimation, which is consistent with Allan's idea. The negative sign on the coefficient for WDR suggests that Saudi Arabia imports more cereals from countries that have lower external water dependency (which makes sense). The positive sign on WFR was not consistent with Allan's hypotheses because it means that countries with a larger water footprint for cereals (meaning they have a greater water shortage than Saudi Arabia) export more cereals to

Saudi Arabia. The coefficient is expected to have a negative sign, but it was positive for cereals. The RRWALR also had a negative sign (which was not expected) but it was not significant. Fracasso (2014) mentioned that there might be a relation between arable land and population after including arable land in his models.

4.5.3.1.3 Results of the Gravity model of virtual water import for Wheat:

We chose backward AIC for the wheat models because the forward criteria only resulted in variables which were time-invariant (table 4.7). The VIF shows no problem with collinearity between the variables. OLS was preferred by the F-test, but the random effect is efficient under the Breusch and Pagan LM. As the population in Saudi Arabia increases, there are more imports of wheat. However, since 2008 the government established the policy to reduce support for wheat farmers, which lead to a decrease in production and a gap to fill by imports (Alamri and Mark, 2018). The random effects model provides little explanation for wheat imports since there is only one significant coefficient, a religion dummy variable, which implies that Saudi Arabia gets the vast majority of its wheat from non-Muslim countries. This negative coefficient on religion is significant in both models.

The results from the PPML model explain more variation in VWT for wheat. There are more significant coefficients in this model; for instance, GDP, POP, POP of Saudi Arabia, and the religion dummy. However, none of the coefficients on water variables were significantly different from zero. Thus, relative water scarcity does not seem to affect VWT for wheat.

4.5.3.1.4 Results of the Gravity model of virtual water import for Millet:

For the VWT model for millet, GDP and POP of Saudi Arabia, WDR, and PAFTA membership had coefficients that were significantly different from zero according to the forward AIC information (table 4.7). The VIF test shows no problem with collinearity between these variables. The Wald test indicates a problem with heteroscedasticity. The Breusch and Pagan LM test points to pooled OLS as the preferred model.

The coefficients for PAFTA and WDR had expected signs, indicating that trade creation for millet occurred with PAFTA member. Allan's idea holds through the WDR coefficient as a lower water dependency ratio leads to rising VWT trade with Saudi Arabia in millet. The PPML model had more economic mass variables, such as GDP and POP of Saudi Arabia, as significantly different from zero but not much change in the other coefficients.

4.5.3.1.5 Results of the Gravity model of virtual water import for Corn:

The AIC forward procedure was used to pick to variables in the model for corn (Table 4.8). The fixed effects model was preferred according to F-test, while the Bresuch and Pagan LM and Hausman test show that the random effects model is preferred. The random effects model is reported.

The coefficient for GCC membership and distance were both significantly different from zero and of an unexpected sign in the PPML estimation. Saudi Arabia imports little corn from GCC member countries. Most of Saudi Arabia's corn suppliers are a long way from the Kingdom (Argentina, Brazil, the US, and Ukraine), so this might be why the distance coefficient is positive.

The random effects model had different significant coefficients than the PPML model. Saudi Arabia's GDP positively influenced corn imports while the relative water footprint ratio had a positive effect. The WFR signs are not consistent with expectations, suggesting that Saudi Arabia imports more corn from countries with a larger footprint per ton for corn.

4.5.3.1.6 Results of the Gravity model of virtual water import for Barley:

The backward AIC procedure resulted in the random effect model being selected for barley. Barley is the leading cereal imported by Saudi Arabia, and it accounts for more virtual water import than any other crop. Barley imports came from thirty-nine countries, but only one was a GCC member and only four members of the PAFTA. The F-test shows that OLS was preferred while the Breusch and Pagan LM test show that Random effects were preferred.

The coefficients for WDR was consistent with Allan idea while WFR was not consistent. The WDR variables show that Saudi Arabia, as the water-scarce country, imports barley from countries with more abundant water, but the WFR coefficient indicates that Saudi Arabia imports barley from water-scarce countries. The RRWALR coefficient was negative but not significantly different from zero. Overall, there is some evidence that barley imports are coming from water-scarce countries.

The contiguous dummy variable had the opposite sign; countries that share a border with Saudi Arabia supply less barley. This is reasonable since almost all the border countries have the same water problems. There is a high correlation between contiguous countries and GCC member too. The PAFTA trade agreement coefficient was negative and significant, meaning that virtual water barley imports were larger from non-members. PAFTA member countries export less than 1% of Saudi Arabia's barley imports. We conclude that countries who share a border with Saudi Arabia or are members of the PAFTA agreement are not important barley suppliers.

4.5.3.1.7 Results of the Gravity model of virtual water import for Sesame:

The forward AIC procedure was used to determine the reported model for sesame (the random effects model, table 4.8). The basic gravity variables were included in the final model, as well as PAFTA membership, WFR, RRWALR, and a dummy for religion. These variables did not have high multicollinearity according to the VIF test. Two GCC members and eight PAFTA members exported sesame to Saudi Arabia.

The result for the relative water footprint of sesame does not support the Allan idea (it is positively related to virtual water imports in both models). The RRWALR coefficient was negative but not significant in the random effect models while it was negative and significant with the PPML model. The sign of the coefficient for RRWALR does not support Allan's idea either; countries with less renewable water per hectare tended to export more sesame to Saudi Arabia.

The religion dummy coefficients were negative but not significant. The GDP of other countries was negatively related to Saudi Arabia's virtual water imports of sesame. Saudi Arabia imports sesame from poorer countries; more than 78% of their total sesame imports come from countries with a lower GDP than Saudi Arabia.

Table 4.7 Gravity model of virtual water import of Alfalfa, Cereals, Wheat, and Millet

Variables	Alfalfa		Cereals		Wheat		Millet	
	OLS	PPML	RE	PPML	RE	PPML	OLS	PPML
lGDP	0.289	0.964	0.169	1.442***	0.594	0.812***		
	(-0.261)	(-0.678)	(-0.169)	(-0.339)	(-0.717)	(-0.263)		
lGDPSA	3.111***	1.825***					-0.687	-0.729**
	(-0.761)	(-0.667)					(-1.19)	(-0.33)
lPOP			-0.277	-0.694*	-0.765	-0.679**		
			(-0.387)	(-0.382)	(-0.749)	(-0.274)		
lPOPSA					4.165	6.492***	3.365	3.678***
					(-3.274)	(-1.177)	(-4.174)	(-1.309)
lDis	-1.756**	-1.914	-1.475	-1.870**			-0.659	-2.408
	(-0.68)	(-1.808)	(-1.084)	(-0.773)			(-0.427)	(-1.889)
Drelg	-4.499**	-4.621***	-0.389	-3.165***	-3.738***	-2.536***		
	(-1.913)	(-0.804)	(-0.991)	(-0.894)	(-1.437)	(-0.947)		
Dcong					-2.384	-1.618		
					(-1.836)	(-1.356)		
D98			-0.306	0.696			1.893**	1.74
			(-1.682)	(-1.422)			(-0.838)	(-1.864)
D03			-3.435**	-6.567***				
			(-1.574)	(-1.705)				
lRRWALR	-0.337	-1.67	-0.129	-0.33				
	(-0.483)	(-1.045)	(-0.343)	(-0.276)				
lWDR			-0.698	-0.723**			-0.455*	0.177
			(-0.599)	(-0.292)			(-0.236)	(-1.144)
lWFR			0.577	3.215**	3.785	0.164		
			(-1.547)	(-1.39)	(-2.307)	(-0.53)		
Constant	-70.47***	-48.97***	20.25***	1.72	-62.63	-110.5***	-29.17	-21.19
	(-20.82)	(-17.34)	(-6.879)	(-6.934)	(-60.73)	(-18.5)	(-42.92)	(-16.93)
Observations	54	187	313	731	124	510	45	221
R-squared	0.363	0.285	0.219	0.584	0.307	0.142	0.543	0.539
AIC	Forward		Forward		Backward		Forward	
VIF	No collinearity		No collinearity		No collinearity		No collinearity	
Breusch and Pagan (Prob > chibar2)	0.1329		0.0000		0.0002		1.0000	
Hausman (Prob > chi2)	--		--		--		--	
Wald test (Prob > chi2)	0.0005		0.0000		0.0000		0.0000	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.8 Gravity model of virtual water import of Sorghum, Corn, Barley, and Sesame

Variables	Sorghum		Corn		Barley		Sesame	
	OLS	PPML	RE	PPML	RE	PPML	RE	PPML
lGDP	-0.665	0.14			0.380***	0.817***	-0.86***	-2.95***
	(-0.464)	(-1.362)			(-0.135)	(-0.195)	(-0.167)	(-0.808)
lGDPSA	2.046**	1.09	0.768**	0.65			0.611	2.801***
	(-0.73)	(-1.001)	(-0.338)	(-0.412)			(-0.943)	(-1.015)
lPOP	-0.404	-0.645					1.060***	3.945***
	(-0.591)	(-1.303)					(-0.255)	(-1.001)
lPOPSA							3.271	-2.27
							(-3.595)	(-6.697)
lDis	-5.797*	-6.482	0.475	2.149***			0.232	1.7
	(-2.881)	(-4.149)	(-0.835)	(-0.537)			(-0.651)	(-1.274)
Drelg	-12.41**	-13.48***					-0.616	0.147
	(-4.392)	(-4.535)					(-0.745)	(-0.674)
Dcong	omitted		0.378	4.503**	-6.437***	-6.876***		
			(-0.347)	(-2.086)	(-1.091)	(-1.306)		
D98	omitted				-4.295***	-5.448***	1.916	1.291
					(-0.645)	(-1.797)	(-1.417)	(-2.532)
D03			-1.269	-6.422***	7.552***	5.312**		
			(-1.352)	(-1.452)	(-0.961)	(-2.459)		
lRRWALR	-2.974**	-3.443***			-0.462	-0.231	-0.09	-3.360***
	(-1.036)	(-0.931)			(-0.34)	(-0.257)	(-0.288)	(-1.272)
lWDR					-0.563***	0.199		
					(-0.191)	(-0.376)		
lWFR	-3.546**	-3.044**	2.192**	-0.373	4.264***	6.256***	1.589***	3.919***
	(-1.592)	(-1.476)	(-1.01)	(-1.049)	(-0.703)	(-2.078)	(-0.435)	(-1.289)
Constant	32.69	46.58	-15.2	-25.23**	2.627	-8.505*	-65.00*	-32.23
	(-37.36)	(-47.09)	(-10.87)	(-9.946)	(-3.549)	(-4.906)	(-39.09)	(-93.15)
Observations	22	119	180	493	124	340	172	629
R-squared	0.865	0.224	0.057	0.086	0.576	0.686	0.596	0.623
AIC	Backward		Forward		Backward		Forward	
VIF	Collinearity		No collinearity		No collinearity		No collinearity	
Breusch and Pagan (Prob > chibar2)	1.0000		0.0000		0.0019		0.0000	
Hausman (Prob > chi2)	--		0.7200		--		--	
Wald test (Prob > chi2)	0.0000		0.0000		0.0000		0.0000	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5.3.2 Virtual water imports of the Vegetable group:

Vegetables account for almost 2% of Saudi Arabia's virtual water imports from crops. We thought including vegetables in the analysis would be interesting because they have a short storage life. More than 50% of the observations were zero for the chosen countries exporting vegetables to Saudi Arabia, so the importance of the PPML model is enhanced. Table 4.9 shows the selected models for various vegetables according to the criteria described in Figure 4.11. The test for collinearity shows that it is a problem with the economics mass variables in the tomato and carrot models. Also, we had collinearity between the variables in the Tomato, marrow, eggplant, carrot, dry onion, and watermelon models.

The negative coefficient on the RTA dummy variables suggests that Saudi Arabia had more trade with a non-member of RTA countries. The most interesting coefficients for our purposes are for the water-related variables. We found that water-related variables had a significant impact on virtual water imports for all crop models except marrow (Tables 4.10 and 4.11). The sample size for marrow was small, so this could be the reason no water-related coefficient was significant. There were 25 water-related coefficients, which were significantly different from zero, but only six of these coefficients had the expected sign. These unexpected results could be due to two data-related problems with the sample. First, the sample size is small in many cases and it may not reflect the current influence on virtual water imports. Second, some data are not available for all countries.

Yet the results strongly suggest that Saudi Arabia imports vegetables from countries that are more water scarce. This implies that water and trade policies of Saudi Arabia and its trading partners might not be reflecting the relative scarcity of water. This is a concern in an increasingly water-short world.

Table 4.9 Selecting models of Vegetable Crops

Crop	FE vs. OLS (F-test)	RE vs. OLS (Breusch and Pagan LM)	Preferred model
Vegetable	Pooled OLS	*H_0: Rejected* RE	*RE*
Tomato	Pooled OLS	*H_0: Rejected* RE	*RE*
Potato	Pooled OLS	*H_0: Rejected* RE	*RE*
Marrow	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS
Eggplant	FE	*H_0: Fail to reject* Pooled OLS	*FE*
Okra	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS
Carrot	FE	*H_0: Rejected* RE	*Hausman test* *H_0: Rejected* *FE*
Dry onion	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS
Cucumber	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS
Melon	Pooled OLS	*H_0: Rejected* RE	*RE*
Watermelon	Pooled OLS	*H_0: Fail to reject* Pooled OLS	Pooled OLS

The results for the gravity variables in table 4.10 and 4.11 show that most coefficients are significantly different from zero and of the expected sign. The only exception came from the fixed effects for eggplant. Almost all significant coefficients in the Eggplant model (which was with fixed effects) were contrary to expectations. The small sample size and large number of years with no trade could be a reason for this result. Furthermore, many variables were very close to linear combinations of each other. When the PPML estimation was used, the number of observations increased, and the model performed better.

Surprising, the distance coefficients for the tomato and dry onion models were positive. There was a small sample size for dry onions. Furthermore, more than 71% of the virtual water imports from dry onions came from Yemen and Egypt, which are quite close to Saudi Arabia.

Table 4.10 Gravity model of virtual water import of Vegetable, Tomato, Potato, Marrow, Eggplant, and Okra

	Vegetable		Tomato		Potato		Marrow		Eggplant		Okra	
	RE	PPML	RE	PPML	RE	PPML	OLS	PPML	FE	PPML	OLS	PPML
lGDP	0.443***	0.398***	-0.266	-1.870					-12.90***	-0.193	-0.824***	-1.142***
	(0.159)	(0.123)	(0.735)	(1.842)					(0.0980)	(4.012)	(0.183)	(0.230)
lGDPSA			-2.638***	0.169	1.013**	0.366	5.374*	6.859***	-7.585***	-5.774**	-0.731*	-1.330**
			(0.825)	(0.661)	(0.416)	(0.222)	(2.526)	(1.025)	(0.158)	(2.679)	(0.426)	(0.536)
lPOP	0.552**	0.366**	-0.0103	10.43**			-16.15	8.963	-1.873***	-0.124	0.697***	0.925***
	(0.266)	(0.162)	(0.460)	(4.410)			(15.10)	(11.09)	(0.269)	(2.499)	(0.240)	(0.229)
lPOPSA			11.15***	0.512			29.01*	17.33**	50.37***	18.18		
			(3.941)	(2.845)			(12.12)	(8.800)	(0.337)	(15.74)		
lDis	-0.724	-1.088**	-1.266	15.77**								
	(0.506)	(0.533)	(1.003)	(6.394)								
Drelg			-0.0783	49.88***			12.50	2.634			1.003**	-0.367
			(1.188)	(18.33)			(10.33)	(12.63)			(0.478)	(0.469)
Dcong	0.747	-0.594	1.216	7.069**	-1.224	-5.754***	-203.6	89.46				
	(0.719)	(0.867)	(1.528)	(2.932)	(0.913)	(1.019)	(182.3)	(142.6)				
D98	2.725***	2.752***			3.787**	9.153***			Omitted	-10.44***	-1.389***	-2.318***
	(0.973)	(0.467)			(1.592)	(2.645)				(2.015)	(0.461)	(0.638)
D03	-2.587*	-2.838**	-4.186***	27.76**			omitted					
	(1.501)	(1.108)	(1.421)	(13.12)								
lRRWALR	0.349*	-0.0433	0.397	-2.498***	0.292	1.077**	-3.320	-0.337	-30.86***	-1.200		
	(0.188)	(0.155)	(0.455)	(0.939)	(0.216)	(0.503)	(2.901)	(3.500)	(0.497)	(1.772)		
lWDR			-0.670	-0.484	-0.0522	-0.672					0.686*	1.051***
			(1.426)	(1.033)	(0.460)	(0.877)					(0.402)	(0.347)
lWFR			1.179***	5.015***	-1.588*	-6.634***	335.0	-139.8	Omitted	12.10***		
			(0.410)	(1.651)	(0.831)	(2.422)	(296.4)	(232.3)		(2.032)		
Constant	-11.49**	-1.008	-99.68**	-295.6***	-26.35**	-19.21**	-102.4	-747.1***	-209.1***	-126.1	33.17***	54.31***
	(5.387)	(5.031)	(48.45)	(64.67)	(10.57)	(8.652)	(329.0)	(238.5)	(2.141)	(149.2)	(10.06)	(11.54)
Observations	691	1,275	113	272	110	289	14	68	11	85	66	221
R-squared	0.298	0.403	0.63	0.936	0.377	0.810	0.941	0.918	1.000	0.090	0.582	0.598
AIC	Forward		Backward		Forward		Backward		Forward		Backward	
VIF	No collinearity		Collinearity		No collinearity		Collinearity		Collinearity		No collinearity	
Breusch and Pagan LM (Prob > chibar2)	0.0000		0.0000		0.0000		1.0000		1.0000		0.1987	
Hausman (Prob > chi2)												
Wald test (Prob > chi2)	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.11 Gravity model of virtual water import of Carrot, Dry onion, Cucumber, Melon, and Watermelon

	Carrot			Dry onion		Cucumber		Melon		Watermelon	
	FE	FE	PPML	OLS	PPML	OLS	PPML	RE	PPML	OLS	PPML
lGDP	0.643	0.720	0.837	3.533***	3.332***			-0.234	0.842	4.132***	2.334*
	(0.492)	(0.491)	(0.590)	(1.191)	(0.955)			(0.201)	(0.576)	(1.450)	(1.284)
lGDPSA	-1.342**	1.690	-0.414							-2.939***	-0.768
	(0.616)	(1.201)	(0.861)							(0.937)	(1.460)
lPOP	0.179	-0.452	-0.589	-5.731***	-11.74***			0.352*	-0.125	-6.424**	-7.588**
	(5.768)	(5.602)	(0.469)	(1.589)	(2.626)			(0.184)	(0.400)	(2.492)	(3.464)
lPOPSA	7.533**	Omitted	5.139***	-14.66***	-9.091***	-8.262**	1.332	2.384	-3.888		
	(2.991)		(1.366)	(4.092)	(2.160)	(3.078)	(0.858)	(1.841)	(2.414)		
lDis	Omitted	Omitted	0.174	11.86***	32.46***					-4.511***	-5.077***
			(1.199)	(3.321)	(6.857)					(0.668)	(1.295)
Drelg				12.03***	30.64***			1.614***	2.076***		
				(3.567)	(6.554)			(0.356)	(0.737)		
Dcong	-0.535	-2.051***	-1.522								
	(0.699)	(0.627)	(1.839)								
D98				-8.482***	-19.37***			-0.184	1.461	5.401*	27.55
				(1.906)	(4.316)			(0.588)	(1.332)	(2.806)	(18.19)
D03				Omitted						-13.58***	-5.476
										(4.529)	(5.085)
lRRWALR				1.377**	6.243***			-0.377*	-1.186***		
				(0.499)	(1.542)			(0.203)	(0.417)		
lWDR				5.347***	8.799***	1.242*	2.465***			-2.848	-16.87
				(1.331)	(1.697)	(0.636)	(0.931)			(1.960)	(13.49)
lWFR	Omitted	Omitted	2.896***	23.97***	52.31***	3.200***	2.340	2.483***	4.529***	5.069***	-3.988
			(0.890)	(5.217)	(10.69)	(0.801)	(1.481)	(0.647)	(0.650)	(1.047)	(8.510)
Constant	-107.7	-51.41	-82.22***	175.6***	25.93	143.7**	-21.91	-34.20	55.60*	121.1***	97.28***
	(63.60)	(79.64)	(18.42)	(50.45)	(33.84)	(52.74)	(15.03)	(30.26)	(32.85)	(29.60)	(21.31)
Observations	96	96	221	35	153	16	102	96	289	41	119
R-squared	0.409	0.525	0.816	0.828	0.303	0.659	0.110	0.72	0.806	0.827	0.675
Country effect	Yes	Yes									
Time Effect	No	Yes									
AIC		Backward		Backward		Forward		Backward		Backward	
VIF	Collinearity			No collinearity		No collinearity		No collinearity		Collinearity	
Breusch and Pagan LM (Prob > chibar2)	0.0000			1.0000		1.0000		0.0000		1.0000	
Hausman (Prob > chi2)				0.8109							
Wald test (Prob > chi2)	0.0000			0.0000		0.6375		0.0000		0.0019	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.5.3.3 Virtual water imports of the fruit group:

Fruit accounts for only 0.3% of total virtual water imports from crops. The PPML model is important for fruits because more than 35% of observations are zero. Grapes accounted for more virtual water imports than any other fruit, followed by dates and citrus. Table 4.12 shows the criteria for selecting the fruit models.

The D13 and D14 of RTA variables were dropped from the fruit models because they were a linear combination of other time-invariant variables. Furthermore, virtual water imports of fruit from these countries were very small. In general, we found OLS elasticities had much better significance levels than PPML elasticities in all models due to the small standard errors.

The coefficient on distance was positive for all virtual water import models. This was surprising because nearby countries accounted for more than 41% of the total virtual water imports for fruits. This surprising result for distance could be because of the co-linearity with time-invariant variables. We did not drop these variables because they are the focus for the study (table 4.13).

There were eleven coefficients for water-related variables that were significantly different from zero, and seven had the expected sign. The unexpected positive coefficients for WFR and the negative coefficients for RRWALR are not consistent with Allan's ideas. Saudi Arabia imports much of its fruits from nearby countries that have a similar climate and have water issues.

There is no evidence that water-related variables influence date imports of Saudi Arabia. The OLS model had no significant coefficients. The coefficient for the Saudi population was negative, which is surprising. This could be due to the low quality of imported dates compared to the domestic product. Saudi Arabia does export dates.

Table 4.12 Selecting models of fruit crops:

Crop	FE vs. OLS (F-test)	RE vs. OLS (Breusch and Pagan LM)	Preferred model
Fruit	Pooled OLS	*H_0: fail to reject* Pooled OLS	Pooled OLS
Dates	Pooled OLS	*H_0: fail to reject* Pooled OLS	Pooled OLS
Citrus	Pooled OLS	*H_0: fail to reject* Pooled OLS	Pooled OLS
Grapes	FE	*H_0: Rejected* RE	*Hausman test H_0: Rejected FE*

Table 4.13 Gravity model of virtual water import of Fruit, Dates, Citrus, and Grapes

	Fruit		Dates		Citrus		Grapes		
	OLS	PPML	OLS	PPML	OLS	PPML	FE	FE	PPML
lGDP	0.159	0.214	0.222	4.171***			-0.304	-0.129	1.156***
	(0.104)	(0.139)	(0.939)	(0.845)			(0.505)	(0.608)	(0.255)
lGDPSA					-1.197	0.949	-1.088*	2.226***	-1.817***
					(0.809)	(0.658)	(0.568)	(0.542)	(0.569)
lPOP	0.580***	-0.171	0.913	1.372	-0.300*	-0.193	-4.130*	-4.648*	-1.835***
	(0.134)	(0.225)	(1.582)	(1.290)	(0.154)	(0.208)	(2.016)	(2.240)	(0.361)
lPOPSA			-5.276	-15.42***	4.469	-3.372	10.25***	Omitted	6.243**
			(4.719)	(1.182)	(2.913)	(3.685)	(2.313)		(2.453)
lDis	-1.042***	1.082*	1.378	16.50***	1.876***	4.347***	Omitted	Omitted	1.464**
	(0.301)	(0.632)	(5.977)	(3.402)	(0.571)	(1.683)			(0.726)
Drelg	-1.033***	0.574	1.097	12.81***	3.867***	8.131***	-0.718	-1.125*	1.860
	(0.360)	(0.619)	(3.643)	(1.744)	(0.848)	(2.614)	(0.431)	(0.622)	(1.242)
Dcong	1.129**	0.549	2.441	16.38***	-2.824***	-3.752***	Omitted	Omitted	-2.606***
	(0.535)	(0.914)	(3.171)	(1.549)	(0.513)	(0.944)			(0.650)
D98	3.686***	4.199***	1.841	11.31***	1.174**	0.951	Omitted	Omitted	3.390**
	(0.422)	(0.836)	(5.204)	(3.269)	(0.528)	(1.334)			(1.381)
D03	-3.604***	-2.971**	3.796	2.826					
	(0.674)	(1.423)	(4.035)	(3.746)					
lRRWALR	0.395***	-0.421*	0.00150	-0.417	-0.812***	-0.959***	-0.924	-1.261	-1.029***
	(0.107)	(0.223)	(0.713)	(0.633)	(0.139)	(0.336)	(1.994)	(2.869)	(0.269)
lWDR	-0.623***	-1.053***			-0.544**	-0.106	Omitted	Omitted	-1.217
	(0.125)	(0.359)			(0.254)	(0.999)			(0.768)
lWFR	-1.423**	-9.081***	Omitted				Omitted	Omitted	-2.727***
	(0.660)	(2.810)							(0.628)
Constant	-1.209	-10.08	61.06	-2.889	-47.27	6.907	-57.02**	34.86	-63.67**
	(2.987)	(6.444)	(54.24)	(26.04)	(31.04)	(47.47)	(26.69)	(29.32)	(29.90)
Observations	477	714	39	170	96	289	164	164	289
R-squared	0.300	0.583	0.687	0.727	0.604	0.389	0.341	0.394	0.621
Country effect							Yes	Yes	
Time Effect							No	Yes	
AIC	Backward		Backward		Backward			Backward	
VIF	Collinearity		Collinearity		Collinearity		Collinearity		
Breusch and Pagan LM (Prob > chibar2)	1.0000		1.0000		0.3991		0.0001		
Hausman (Prob > chi2)							0.0481		
Wald test (Prob > chi2)	0.0000		0.9985		0.0000		0.0000		

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.6 Conclusion and Recommendation

This study calculates virtual water movements between Saudi Arabia and the world. The study compares the quantity of water consumed in three crop categories, cereals & alfalfa, vegetables, and fruits, by calculating the quantities of exports and imports for 20 crops and calculating the trade in virtual water. The investigate whether Saudi Arabia is using trade in virtual water as a means to bridge the shortage of local water sources for food demand in Saudi Arabia.

The results show that virtual water consumption by crops increased by 38% during 2000-2017. We found that consumption by cereals and fruit decreased by 111% and 18%, respectively, using the concept of virtual water, while consumption increased by 9% and 78% for vegetables and alfalfa, respectively, during the period. Wheat, potatoes, and dates were found to have the highest consumption of virtual water for these groups. The annual average of the virtual water received from crop imports by Saudi Arabia is 12.5 billion m^3/year. Cereals and alfalfa obtained the most significant percentage of gross virtual water from imports, and fruits accounted for the most virtual water from exports. Net virtual water imports reached 211.8 billion m^3 during the study period, and Saudi Arabia benefited by receiving 52% of its virtual water from outside the country, thus conserving local water resources.

The results of the study show that Saudi Arabia virtual water exports of fruits exceeded its imports. We also found that 1.4% of the virtual water production was used for exports, not used for domestic consumption. Ukraine is the top exporter of crops to Saudi Arabia, accounting for 18% of the total average Saudi Arabia imports of virtual water during the study period. On the other hand, Kuwait is the top beneficiary of Saudi Arabia's virtual water exports, accounting for 20%. The water footprint of Saudi Arabia (WFSA) totals 500.99 billion m^3 from 2000 through 2016. Saudi Arabia was 42.3% dependent on virtual water imports. However, the water self-sufficiency was high, which reflects that Saudi Arabia provides much of its water requirements domestically.

We fitted a gravity model and used either a forward or backward AIC to select the variables for each crop. We chose the OLS, fixed effect, or random effect model based on the F-test, Breusch and Pagan LM test, and Hausman test. We also check the models for heteroskedasticity. The PPML model was estimated to solve the issues of zero trade and heteroskedasticity. This was important because more than a third of the trade observations were zero.

Our results indicate that the water-related variables influence each crop model except alfalfa, wheat, marrow, and dates. Yet more than 60% of the significant coefficients for water-related variables had an adverse sign (not supporting Allan's ideas). Therefore, our results indicate that Saudi Arabia's crop imports often do not involve importing crops from water abundant countries. Instead, the country is getting much of its imports from water-scarce countries, exacerbating world water problems. This is likely related to the mispricing of water in many countries and the lack of other policies that could overcoming this mispricing.

We found that Saudi Arabia's membership in various RTAs did not have a positive influence on its virtual water trade. Most of the coefficients for the RTA dummies were negative and many were significantly different from zero. This likely reflects the fact that many RTAs are with similarly water-constrained countries surrounding Saudi Arabia, so their water issues likely had a more dominant impact than the free trade agreement.

In the end, we recommend that the external agricultural investment activity needs to be directed towards some strategic commodities needed by Saudi Arabia, which are challenging to produce domestically because of water scarcity, such as cereals and alfalfa products. The structure of foreign trade must be reconsidered so that goods with high water needs are imported, and limited water resources are used to provide fresh produce, such as vegetables. This study is just the beginning. More research on Saudi Arabia should focus on the impact of many factors on virtual water trade, including relative water abundance, distance, free trade agreements, and other trade and water variables.

CHAPTER 5. **GENERAL CONCLUSION**

Saudi Arabia saw growth in demand for food products, driven by high standards of living, and per capita income as well as population growth over the last two decades. As a percentage of GDP, the volume of agricultural imports are much higher than exports with a ratio of 511% during 2016. The cost of agricultural imports to Saudi Arabia increased from $3.5 billion in 1990 to $17.9 billion in 2016 (FAO, 2016).

Saudi Arabia's situation of scarce water and difficult climate conditions lead the Saudi government to depend heavily on agricultural import. However, government programs have contributed to agricultural development, including the concessional and non-interest loan financing program and other support and technology services to achieve diversity and high efficiency.

This study is examines possible ways for Saudi Arabia to develop its agricultural market by identifying the factors affecting the volume of market flows. The study focuses on ways to achieve food security while using its limited resources, especially natural resources. The focus of this study is on the factors affecting Saudi Arabia's changing agricultural market domestically and globally.

The first essay examined the factors that affect wheat yield and area of Saudi Arabia as well as the impact of policy number 335 on the wheat supply. A Nerlove model with six common function forms was specified to explore the most critical factors affecting the wheat supply during 1990-2016. We found that cultivated area of wheat, one-year lagged yield, and the number of machines per hectare were the most important factors for wheat yield, while the factors that impact the cultivated area were the one-year lag of both cultivated area and yield, and the number of machines per hectare. Our results show that government policy had a negative impact on wheat area in Saudi Arabia. Comparing the six common functions, we determined that the Cobb-Douglas model was preferred to represent both yield and area models. Finally, the price elasticity of wheat was found to be inelastic in both models.

The second essay investigated the competition of rice exporter to Saudi Arabia market. The inverse residual demand model was estimated during the period 1993-2014, to determine the extent of market power. We found that Australia, India, and Pakistan enjoy market power in Saudi Arabian rice market. While Egypt, Thailand, and the US had no market power. However, Thailand and the US had a positive sign and significant.

The third essay discovered whether water scarcity variables are affecting international agricultural trade between Saudi Arabia and commercial partners during the study period 2000-2016. To achieve that, we first calculated virtual water trade for 20 crops and three groups, and then we estimate the gravity model using the concept of virtual water. We found that domestic virtual water consumption by crops increased by 38% during 2000-2017. On the side, we found that cereals and alfalfa had a high ratio of gross virtual water from imports, while fruits had the highest of total virtual water from exports. Our results indicate that Saudi Arabia was 42.3% dependent on virtual water imports. In the second part of this essay, we examined the determinants of Saudi virtual water trade flows by applying the gravity model using the concept of virtual water in 20 crops and three groups. We found more than a third of the trade observations were zero. To solve these issues, we used the PPML model. Also, we compared the OLS, fixed effect, or random effect model to choose the preferred model. We used AIC forward or backward to select the best variables. Then, we performed the F-test to choose between OLS and fixed effect. After that, we test whether the OLS preferred or random effect by Breusch and Pagan test. If the fixed and random effect were present, then the Hausman test would be used. We found that the water-related variables had an influence for most of the crops model, but most of these significant coefficients had an unexpected sign. We, therefore, conclude that Saudi Arabia virtual water imports have not supported Allan's idea. Saudi Arabia imports much of its crops from other water scarce countries. Finally, the RTA results indicate that Saudi Arabia imports many of its products from nonmember countries. However, the D98 and D03 member countries have similar water condition to Saudi Arabia.

APPENDICES

APPENDIX 1. CROPWAT Program

A decision support tool developed by the Land and Water Development Division of FAO.

CROPWAT is a computer program for the calculation of crop water requirements and irrigation requirements[17] based on soil, climate and crop data. In addition, the program allows the development of irrigation schedules for different management conditions and the calculation of scheme water supply for varying crop patterns. CROPWAT can also be used to evaluate farmers' irrigation practices and to estimate crop performance under both rainfed and irrigated conditions. CROPWAT is a Windows program based on the previous DOS versions. Apart from a completely redesigned user interface, CROPWAT for Windows includes a host of updated and new features, including:

- Monthly, decade and daily input of climatic data for calculation of reference evapotranspiration (ETo)
- Backward compatibility to allow use of data from CLIMWAT database
- Possibility to estimate climatic data in the absence of measured values
- Decade and daily calculation of crop water requirements based on updated calculation algorithms including adjustment of crop-coefficient values
- Calculation of crop water requirements and irrigation scheduling for paddy & upland rice, using a newly developed procedure to calculate water requirements including the land preparation period
- Interactive user adjustable irrigation schedules
- Daily soil water balance output tables
- Easy saving and retrieval of sessions and of user-defined irrigation schedules
- Graphical presentations of input data, crop water requirements and irrigation schedules
- Easy import/export of data and graphics through clipboard or ASCII text files

This information from:
http://www.fao.org/land-water/databases-and-software/cropwat/en/

[17] *Irrigation requirements* are the amount of water required for the natural growth of the plant and include evaporation from the surface of the soil and some losses that are difficult to avoid under normal circumstances (Mekonnen and Hoekstra, 2010[a]; Alqahtani et al., 2017).

APPENDIX 2. A Site-sPecific Agricultural water Requirement and footprint Estimator (SPARE:WATER)

A tool for estimating the fate of water use in agricultural production systems. SPARE:WATER enables the spatial explicit calculation of the crop specific water footprint, the national water footprint and alternative production scenarios, considering all water resources required to produce food and feed, including green (precipitation), blue (irrigation) and grey (de-salinization) water. SPARE:WATER is based on the virtual water concept originally introduced by Allan in the 1990s, and further developed to the water footprint concept by Hoekstra in the past years. Equipped with a graphical user interface SPARE:WATER calculates crop water requirement according to the Food and Agricultural Organization FAO56 crop water guidelines. User defined parameters allow to set crop types, irrigation efficiencies, salinity of irrigation water or depression of yields due to salinization. A SPARE:WATER scenario manager allows to rapidly investigate the effect of introducing different cropping regimes on site specific water resources. All model data are saved in the working directory of the session, including soil and climate information as well as data on yields to calculate crop water requirements for each spatial entity.

Multsch et al. calculated the gray water footprint for crops from the amount of “leaching requirement has been estimated for desalinization in irrigation agriculture” while Mekonnen[a] and Hoekstra from “the volume of freshwater that is required to assimilate the load of pollutants based on existing ambient water quality standards”

This information from:
https://www.geosci-model-dev.net/6/1043/2013/gmd-6-1043-2013-discussion.html

APPENDIX 3. Total Saudi Arabia's Virtual Water trade from 2000 through 2016 (million m^3)

Year	Total			Cereal and Alfalfa			Vegetable			Fruit		
	Import	Export	NVW	Import	Export	NVW	Import	Export	NVW	Import	Export	NVW
2000	7493.95	485.15	7008.81	7453.25	361.16	7092.09	27.51	36.17	-8.66	13.20	87.82	-74.63
2001	5717.68	137.94	5579.74	5673.44	1.36	5672.09	30.78	40.57	-9.80	13.46	96.01	-82.55
2002	6948.05	141.82	6806.22	6875.96	0.14	6875.82	51.11	37.38	13.72	20.98	104.30	-83.32
2003	9617.95	154.64	9463.31	9356.65	0.17	9356.48	216.05	46.56	169.49	45.25	107.92	-62.67
2004	7095.56	196.86	6898.71	6996.40	0.20	6996.20	47.62	49.13	-1.52	51.54	147.52	-95.98
2005	10122.20	242.65	9879.55	10033.62	0.14	10033.48	41.39	77.49	-36.10	47.20	165.03	-117.83
2006	12846.12	232.09	12614.02	12760.52	0.00	12760.52	46.61	90.72	-44.11	38.99	141.37	-102.38
2007	12336.75	259.08	12077.67	12260.35	0.00	12260.35	45.62	91.56	-45.94	30.78	167.52	-136.74
2008	13154.20	376.30	12777.90	13036.01	0.00	13036.01	43.83	139.98	-96.14	74.35	236.33	-161.97
2009	14765.46	371.89	14393.56	14652.89	0.00	14652.89	46.60	145.87	-99.27	65.96	226.02	-160.06
2010	15436.52	494.82	14941.70	15351.61	0.00	15351.61	49.76	218.80	-169.03	35.14	276.02	-240.88
2011	15558.63	469.09	15089.54	15463.75	0.00	15463.75	56.14	192.70	-136.56	38.74	276.38	-237.65
2012	19041.78	355.05	18686.74	18687.32	0.00	18687.32	283.45	94.24	189.21	71.02	260.81	-189.79
2013	21568.41	380.30	21188.11	20830.56	0.00	20830.56	691.50	12.92	678.58	46.35	367.38	-321.03
2014	20427.20	498.44	19928.76	19667.00	0.00	19667.00	728.02	12.51	715.51	32.18	485.93	-453.75
2015	16580.71	499.42	16081.29	15697.53	0.00	15697.53	845.73	19.13	826.60	37.46	480.29	-442.83
2016	8866.74	503.23	8363.51	7979.08	0.27	7978.81	845.03	28.49	816.54	42.63	474.47	-431.84
SUM	217577.92	5798.78	211779.14	212775.94	363.43	212412.51	4096.74	1334.22	2762.52	705.24	4101.13	-3395.89
Average	12798.70	341.10	12457.60	12516.23	21.38	12494.85	240.98	78.48	162.50	41.48	241.24	-199.76
Max	21568.41	503.23	21188.11	20830.56	361.16	20830.56	845.73	218.80	826.60	74.35	485.93	-62.67
Min	5717.68	137.94	5579.74	5673.44	0.00	5672.09	27.51	12.51	-169.03	13.20	87.82	-453.75

APPENDIX 4. Net virtual water, water dependency, and self-sufficiency water of crops in Saudi Arabia during the period 2000 to 2016 (Million m^3)

Groups	Crop	VWTi	VWTe	NVW
Cereals & Alfalfa	Wheat	21875.71	0	21875.71
	Millet	558.90	0	558.90
	Sorghum	12.54	0	12.54
	Corn	31296.24	0	31296.24
	Barley	155165.26	0	155165.26
	Sesame	3754.40	0	3754.40
	Alfalfa	112.88	363.43	250.55
Vegetable	Tomato	3726.92	34.50	3692.42
	Potato	162.68	511.77	-349.09
	Marrow	2.38	15.35	-12.97
	Eggplant	0.35	40.77	-40.42
	Okra	36.98	452.21	-415.23
	Carrot	84.10	49.02	35.07
	Dry Onion	7.17	2.76	4.41
	Cucumber	2.14	12.91	-10.77
	Melon	51.24	32.72	18.51
	Watermelon	22.79	182.21	-159.42
Fruit	Dates	220.99	3622.65	-3401.66
	Grapes	338.57	71.95	266.62
	Citrus	145.67	406.52	-260.85
Total		217577.92	5798.78	211779.14

APPENDIX 5. Top-five list of total virtual water import countries to Saudi Arabia for each group and crops during the period 2000-2016

1- Cereals & Alfalfa

Rank	Cereals	Wheat	Millet	Sorghum	Corn	Barley	Sesame	Alfalfa
1	Ukraine	Canada	India	India	Argentina	Ukraine	Sudan	Spain
2	India	Poland	Yemen	Sudan	Brazil	Russia	India	USA
3	Russia	Germany	Australia	Australia	USA	Australia	Ethiopia	Italy
4	Australia	Australia	USA	China	Yemen	Germany	Yemen	Argentina
5	Argentina	USA	China	Thailand	Sudan	Argentina	Somalia	South Africa

2- Vegetable

Rank	Vegetable	Tomato	Potato	Marrow	Eggplant	Okra	Carrot	Dry Onion	Cucumber	Melon	Watermelon
1	Egypt	Jordan	Lebanon	India	Jordan	India	Australia	Yemen	Jordan	Syria	Yemen
2	Syria	Syria	Netherlands	Bangladesh	Egypt	Bangladesh	China	India	India	Yemen	Syria
3	Jordan	Turkey	Syria	Oman	Lebanon	Yemen	Turkey	Egypt	Yemen	Egypt	Oman
4	Yemen	Egypt	UK	Lebanon	Syria	Spain	Yemen	China	Bangladesh	Turkey	Egypt
5	Turkey	Yemen	China	--	Iran	Syria	Oman	Iran	Lebanon	Iran	Iran

3- Fruit

Rank	Fruit	Dates	Citrus	Grapes
1	Egypt	UAE	Turkey	Lebanon
2	Philippines	Oman	Egypt	Turkey
3	South Africa	Jordan	Lebanon	India
4	Yemen	Egypt	South Africa	Syria
5	Ecuador	Yemen	Philippines	South Africa

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