Three Essays on Climate Change Impacts on Agriculture

by

Trang Thi Huyen Le

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Approved by

Dr. Curtis M. Jolly, chair, Alumni Professor of Agric. Economics
Dr. Denis A. Nadolnyak, Co-chair, Professor of Agric. Economics
Dr. Henry W. Kinnucan, Alumni Professor of Agric. Economics
Dr. Asheber Abebe, Professor of Mathematics and Statistics

Abstract

In the first chapter, we evaluate the effects of climate change on Vietnam's rice market. Results suggest that under a low-emission scenario and without interventions, rice production would drop by as much as 18% by 2030 relative to the 1980–1999 average. Farm and wholesale prices would increase by 1.86%, causing domestic demand to fall by 0.38%. The export sector would experience a rise of 6.94% in export free-on-board prices and a drop of 55.36% in export quantities. Farmers would experience a sales loss of 16.02%, whereas wholesalers would see a sales gain of 1.48%. For exporters, their sales loss would amount to 48.42%.

The second chapter examined the impact of changing climate on profit efficiency of rice farming in Ben Tre province, Vietnam. Using the stochastic profit frontier function, the study found that the profit efficiency score of rice farmers is as low as 59% on average. This implies that farmers could improve their profit by about 40%. Rice farmers in the area with rainfall anomaly of +185mm are found to have profit efficiency as low as 37.1%. On average, their profit efficiency scores are lower than those of rice farmers in the same district by 22 percentage points. Rice farmers would suffer worse loss of profit from increasing abnormal rainfall trigged by changing climate.

The third chapter evaluated impact of climate change on peanut and peanut butter market. The results suggested that an increase of 1% in average maximum temperature may raise peanut price and peanut butter price by 4.88% and 0.72% respectively, resulting in a fall of 0.14% in demand for peanut butter. Rainfall during the harvesting period has a modest effect on peanut and peanut butter market. Peanut price and peanut butter price may increase by 0.16% and 0.02% respectively in response to 1% increase in rainfall during the harvesting period. On the other hand, average maximum temperature during the harvesting period has a positive effect on peanut

supply. This effect brings a fall in peanut price and peanut butter price. 1% increase in average maximum temperature during the harvesting period may reduce peanut price and peanut butter price by 2.46% and 0.36% respectively, causing demand for peanut butter to increase 0.07%.

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Chapter 1

Effects of Climate Change on Rice Yield and Rice Market in Vietnam

1.1. Introduction

Climate change is no longer a concept but reality. Confronting Southeast Asia where millions of residents earn their livelihoods through agriculture, it is among the greatest challenges threatening development and poverty eradication (Asian Development Bank, 2009). Vietnam is among the countries to be worst affected (Dasgupta et al., 2007). Engendering increased temperatures, rainfall fluctuations, and increased weather extremes, climate change poses huge threats to the agricultural sector because of its direct exposure and reliance on weather conditions. Paddy rice, of course, is not an exception.

Paddy rice plays a crucial role in the nation's economy in that it sustains food security, creates rural employment, and serves as a source of export revenues. Rice farming is at least one source of income, if not the only, for more than 75% of poor households and 48% of non-poor households (Yu et al., 2010). As the second-largest shipper, Vietnam alone accounts for approximately 20% (by quantity) of the total world rice trade[1]. Its economic significance and climatic vulnerability have urged researchers to study how changes in climate would affect rice yield/production. A question that is of at least equal importance but has not received sufficient attention is how potential yield impacts affect the rice market. This study was purposely conducted in an attempt to answer that question. We first determine the long-run effects of climate change on rice yield using the co-integration framework. Estimated parameters are then plugged into an equilibrium displacement model (EDM) to simulate impacts of climate change on Vietnam's rice

[1] The biggest exporters of rice include Thailand (30% of total exports), Vietnam (20%), India (11%), and the United States (10%) (http://www.tradingeconomics.com/commodity/rice).

market. In determining the effects of climate change on rice yields, we focus on temperatures and precipitation as they are most likely to be altered under climate change.

The remainder of the article begins with a brief literature review of relevant studies (Section 2). This is followed by sections on data and variables (Section 3) and co-integration tests to determine yield impacts of temperatures and precipitation (Section 4). In Section 5, a model is built for Vietnam's rice market, on which simulations are performed (Sections 6 and 7). The article concludes with a summary of key findings (Section 8).

1.2. Literature Review

As for many other regions throughout the world, temperatures and precipitation play a crucial role in the production potential of major crops in Southeast Asia. The effects of these factors are, however, highly country specific because one country is distinguishable from others with regard to its sensitivity to weather conditions.

Using data from farmer-managed irrigated rice fields in six important rice-producing countries in tropical/subtropical Asia, Welch et al. (2010) reached the conclusion that rice yields plummet as nighttime temperatures are higher. Daytime temperatures up to a point are found to enhance yields. That being said, they cautioned that any gains caused by higher daytime temperatures are likely to be outweighed by losses resulting from higher nighttime temperatures as temperatures are rising faster at nights. Additionally, if daytime temperatures become too high, this will impede rice yields, inflicting more loss. In Malaysia, Alam et al. (2014) reported that rice yields plunge by 3.44% in the current season and 0.03% in the next season in response to a 1% increase in temperature. Utilizing the crop model ORYZA 2000, Vaghefi et al. (2011) predicted a decline of 0.36 t/ha in rice yield under the scenario of a 2°C increase in temperature at a CO2 concentration of 383 ppm. If the level of CO2 concentration rises to 574 ppm, the loss is 0.69 t/ha. In the Philippines, Peng et al. (2004) reported a drop of 10% in rice yields for every 1°C increase in minimum temperature during the dry cropping season (January to April), whereas maximum temperatures were insignificant. In the Mekong Delta in Vietnam, it is estimated for dry-season crops that if temperatures in January fall below 19°C, every 1°C drop would cause a loss of 0.12 t/ha. For wet-season crops, each 1°C increase beyond 35°C would lead to a plunge of 0.38 t/ha (Nhan, Trung, and Sanh, 2011).

Regarding precipitation, it is reported that rice yields in Malaysia plunge by 0.12% in current season and 0.21% in the following season as a result of 1% increase in precipitation (Alam et al., 2014). In Indonesia, the Philippines, and Laos, the 2009–2010 El Nino[2], for instance, caused rice yields to drop, respectively, 3%, 6.6%, and 6.74% relative to 2008–2009 (Shean, 2014). Naylor et al. (2007) estimated that a 1-month delay in the onset of the rainy season during El Nino years would upset rice production in the wet season (January–April) in ˜ Indonesia in that production in West/Central Java would fall by approximately 6.5% and in East Java/Bali by 11.0%. In the Mekong Delta, wet-season rice production would lose 0.2 t/ha for each 100 mm increase in precipitation beyond 250 mm, and 0.6 t/ha for each 100 mm decrease below 50 mm (Nhan, Trung, and Sanh, 2011).

Although studies that evaluate climate change impacts on rice production are plenty, studies that go further to assess impacts on rice market are few. Particularly for Vietnam, the study by Furuya, Kobayashi, and Yamauchi (2014) is, to the best of my knowledge, the first and only one that touches on how the rice market would react in response to changes in climate. The variable of interest in their study is, however, not temperature nor precipitation but evapotranspiration (ET).

[2] El Nino is a climate phenomenon in the western Pacific region that results in a drier-than-normal rainfall pattern over parts of Southeast Asia, with Indonesia and the Philippines suffering the most (Shean, 2014).

The reasoning behind the study is as simple as this: Climate change leads to changes in ET. Changes in ET in turn result in changes in rice yields and farming areas. At the end of the day, climate change would shock the rice market through changes in the rice supply. The following two simulations were conducted in the study: (a) the baseline, which assumes that ET after 2000 is the average of ET from 1995 to 1999; and (b) the CC-B2, in which ET is presumed to accord with the Intergovernmental Panel on Climate Change (IPCC) B2 scenario. By contrasting the CC-B2–simulated results with those of the baseline, the authors ended up with effects of climate change on the rice market. It is reported that in the Mekong Delta climate change would depress rice production in the wet and dry seasons, respectively, by 1.76% and 2.19% between 2026 and 2030 relative to the baseline. Consequently, farm prices in the CC-B2 simulation are 8.31% higher. For the country as a whole, the 2026–2030 average farm price in the CC-B2 is 415,000 dong/t higher than that in the baseline because climate change is expected to decrease the total production of rice. In spite of higher forecasted rice prices, the CC-B2 yields an almost identical projection of rice demand to that in the baseline. Per capita rice consumption would step up steadily from 229.2 kg in 2010 to 258.6 kg in 2030. There is no apparent difference in the 2026–2030 average per capita rice consumption between the two simulations. Such likeness can be explained as follows: The surge in per capita consumption is the net outcome of the positive effect of income growth and the negative effect of rice price increase. The two simulations make use of the same projections of income growth (provided in the IPCC's special report on emissions scenarios B2; see Gaffin et al., 2004) but differ in their own projections of rice prices. Because the effect of income overwhelmingly outweighs that of price, both simulations end up with nearly identical projections of per capita rice consumption.

1.3. Data and Variables

Vietnamese farmers, as a general practice, cultivate three rice crops a year, which are traditionally named spring, autumn, and winter[3]. Yield data measured in metric tons per hectare are available for each cropping season on a yearly basis from 1975 to 2014 collected by the General Statistics Office of Vietnam. Although crop lengths vary over years, the spring crop across the country starts and finishes roughly between January and April, the autumn crop between May and September, and the winter crop between September and December. We also see this “grouping” adopted in Furuya et al. (2010), which they note is based on the cropping calendars of the U.S. Department of Agriculture (1994). Figure 1.1 provides a snapshot of rice yields of each of the three cropping seasons. In all three seasons, yields have been soaring since 1975 with the spring crop being notably more productive than the other two.

Data on maximum and minimum temperatures and precipitation are obtained from the Climatic Research Unit (University of East Anglia) and are 0.5° × 0.5° gridded station data. Available from 1975 to 2014 on a monthly basis, maximum and minimum temperatures (°C) are monthly averages, and precipitation is the total amount per month (millimeters per month). In the forthcoming analysis, months are grouped according to the length of each cropping season. After being grouped, maximum/minimum temperatures and precipitation are seasonal averages. The spring cropping season is characterized by the lowest maximum/minimum temperatures and precipitation (Figures 1.2, 1.3, and 1.4). The autumn cropping season is hottest and receives the highest amount of precipitation. The temperature gap between the spring and autumn cropping seasons is roughly 5°C.

[3] The names of the cropping seasons do not necessarily reflect the four climatic seasons in a year. In most parts of Vietnam, there are not four distinguished seasons. For instance, in southern parts of Vietnam, there are two seasons in a year—namely, dry and wet seasons.

Yield and weather variables enter the empirical analysis in logarithms. We use a double-log specification in order to obtain the elasticities of yields with respect to temperatures and precipitation, which are ultimately used to simulate the economic model for Vietnam's rice market.

1.4. Empirical Analysis

Unit Root Tests

Times series are prone to be nonstationary, which renders usual regressions spurious. The co-integration concept (Granger, 1981) provides a framework to deal with nonstationary time series. A co-integrated relationship implies that the two series have a long-run equilibrium, and therefore, they cannot drift too far away from each other (Ender, 2004). A co-integration test demands that the series be integrated to the same order. The first step is therefore to check for unit roots in all variables at their levels and first differences. Table 1.1 presents the τ -statistics of the unit root tests (Dickey and Fuller, 1979). At 5% level of significance, all variables are integrated to order 1.

Co-integration Tests

Engle and Granger (1987) were the first to devise a method to test for co-integration. This two-step method is, however, suitable when the test involves two variables (Kennedy, 2008). For three or more variables, the Johansen method (Johansen, 1988) is preferred. Prior to the tests, the choice of the number of lags in the underlying vector autoregressive (VAR) is made; in this article, the choice is guided by the Akaike information criteria. Table 1.2 presents the Johansen's trace statistics for each of the three cropping seasons. For the spring crop, the trace statistic at rank = 1 is 23.52, which is smaller than the 1% critical value. We therefore cannot reject the null hypothesis that there is one co-integrating vector among interested variables. In the same manner for the autumn crop, the trace statistic at rank = 2 fails to exceed the critical value, implying two co-integrating vectors. Multiple co-integrating vectors do not imply multiple long-run equilibria, but rather multiple sector equilibria in a long-run equilibrium (Kennedy, 2008). Researchers often discard those vectors that make no economic sense. For the winter crop, the trace test gives the conclusion that there exists no integration among interested variables.

For the spring and autumn crops, the long-run relationships between yields and weather variables are presented in Table 1.3. Maximum temperatures have negative effects on yields of both spring and autumn crops, whereas minimum temperatures have a positive effect on the spring crop but a negative effect on the autumn crop. In response to a 1% increase in maximum temperatures, spring crop yield would reduce by 28.8% and autumn crop yield 43.87%. A 1% increase in minimum temperatures would boost spring crop yield by 17.12% but reduce autumn crop yield by 0.32%. As it is remarkably warmer in the autumn cropping season, temperatures inflict greater harm and precipitation yields greater benefit to the autumn crop than they do to the spring crop. In both cropping seasons, precipitation is positively linked to yields. A 1% increase in precipitation would ramp up spring crop yield by 1.81% and autumn crop yield by 4.31%.

Gonzalo (1994) indicates that underspecifying the number of lags in the underlying VAR can significantly increase the finite-sample bias in the parameter estimates and lead to autocorrelation. We therefore perform Lagrange-multiplier tests to check for autocorrelation up to 10 lags. The tests fail to reject the null hypothesis of no autocorrelation, which implies that the number of lags is correctly specified. We also test the normality of the residuals using the Jarque-

Bera tests. The tests conclude that the null hypothesis of normally distributed errors cannot be rejected[4].

1.5. Vietnam Rice Market Model

Here we specify a structural model for the Vietnam rice market that is built on Wailes and Chavez's (2011) work. The model consists of the supply sector, the demand sector (domestic demand and export), stocks, and price linkage equations:

(1)	$Y_S = f_S(T_{SMin}, T_{SMax}, R_S)$	Spring yield
(2)	$Y_A = f_A(T_{AMin}, T_{AMax}, R_A)$	Autumn yield
(3)	$Y_W = f_W(T_{WMin}, T_{WMax}, R_W)$	Winter yield
(4)	$A_S = A_S(P_F)$	Spring farming area
(5)	$A_A = A_A(P_F)$	Autumn farming area
(6)	$A_W = A_W(P_F)$	Winter farming area
(7)	$Q = 0.667(Y_S A_S + Y_A A_A + Y_W A_W)$	Total milled rice production
(8)	$D = D(P)$	Domestic demand
(9)	$E = E(FOB)$	Export demand
(10)	$EST = g(Q, FOB)$	Ending stock
(11)	$P_F = f(P)$	Wholesale-farm price linkage
(12)	$P = f(FOB)$	FOB-wholesale price linkage
(13)	$EST = Q + BST - D - E$	Market clearing

[4] We also conduct stability tests to check whether we have correctly specified the number of co-integrating vectors. Test results show that all eigenvalues lie strictly in the unit circle, which implies that the process is stable.

where Y_S, Y_A, Y_W are respectively yields in spring, autumn and winter crops[5]; A_S, A_A, A_W are farming areas; T_{SMin}, T_{AMin}, T_{WMin}, T_{SMax}, T_{AMax}, T_{WMax}, R_S, R_A, and R_W represent minimum, maximum temperatures and precipitation; *Q* is total milled rice production in three seasons; *EST* and *BST* represent milled rice ending and beginning stocks; *D* and *E* are respectively domestic and foreign demand; *P*, P_F and FOB are wholesale, farm and export prices, respectively.

Equations (1)-(7) characterize the supply sector. Yields are specified as functions of temperatures and precipitation. Farming areas are predicated upon farm prices. We assume that harvested areas equal farming areas. Total milled rice production is the sum of the products of yields and farming areas scaled down by the paddy-milled rice conversion rate (0.667)[6]. Equations (8)-(9) model the demand sector in which the domestic demand responds to wholesale prices, and the export demand to FOB prices. Ending stock (10) is a function of total milled rice and export prices. Farm price is linked to wholesale price (11), while wholesale price is modeled as a function of FOB price (12). Market clearing condition (13) requires that ending stocks be the residual of total milled rice plus beginning stocks net of demand and export. Beginning stocks are simply ending stocks of the previous year. The model contains 13 endogenous variables (Y_S, Y_A, Y_W, A_S, A_A, A_W, *Q, D, E, EST, FOB*, P_F, and *P*) and 10 exogenous variables (T_{SMin}, T_{AMin}, T_{WMin}, T_{SMax}, T_{AMax}, T_{WMax}, R_S, R_A, R_W, and *BST*). All other exogenous variables that affect rice yields and supply and demand of rice are not in the scope of this study, and therefore suppressed.

Climate change is associated with fluctuations in temperatures and precipitation. In order to simulate the impacts of climate change on the rice market, the structural model is first expressed in the equilibrium displacement form as follows:

[5] S, A, and W are abbreviations for spring, autumn, and winter, respectively

[6] The conversion rate is calculated based on the FAO database for Vietnam's rice production.

(1') $$Y_S^* = \alpha_1 T_{SMin}^* + \beta_1 T_{SMax}^* + \gamma_1 R_S^*$$

(2') $$Y_A^* = \alpha_2 T_{AMin}^* + \beta_2 T_{AMax}^* + \gamma_2 R_A^*$$

(3') $$Y_W^* = \alpha_3 T_{WMin}^* + \beta_3 T_{WMax}^* + \gamma_3 R_W^*$$

(4') $$A_S^* = \varphi P_F^*$$

(5') $$A_A^* = \varphi P_F^*$$

(6') $$A_W^* = \varphi P_F^*$$

(7') $$Q^* = 0.667(h_S(Y_S^* + A_S^*) + h_A(Y_A^* + A_A^*) + h_W(Y_W^* + A_W^*))$$

(8') $$D^* = \eta P^*$$

(9') $$E^* = \eta_E FOB^*$$

(10') $$EST^* = \delta_1 Q^* + \delta_2 FOB^*$$

(11') $$P_F^* = \theta_1 P^*$$

(12') $$P^* = \theta_2 FOB^*$$

(13') $$EST^* = k_Q Q^* + k_{BST} BST^* - k_D D^* - k_E E^*$$

where the asterisked variables indicate percentage changes ($X^* = dlnX = dX/X$); α_i, β_i, and γ_i i = 1, 2, 3 are the elasticities of yields with respect to minimum temperatures, maximum temperatures, and precipitation in each cropping season, respectively; φ is the elasticity that reflects farmers' sensitivity to farm prices in their decisions on farming areas. Here, we assume that farmers are equally price sensitive across three cropping seasons; $h_j = (Y_j * A_j)/Q$ j = S, A, W, are the quantity shares of spring, autumn, and winter rice production in total milled rice; δ_1 and δ_2 are respectively the elasticities of ending stocks with respect to total milled rice and FOB prices; η and η_E are price elasticities of domestic and export demand, respectively; $\theta_1$and θ_2 are respectively the wholesale-farm and FOB-wholesale price transmission elasticities; $k_Q = Q/EST$,

$k_{BST} = BST/EST$, $k_D = D/EST$, and $k_E = E/EST$ are respectively the ratios of total milled rice, beginning stock, domestic demand, and export to the ending stock.

1.6. Parameterization

Our study benefits from Wailes and Chavez's (2011) in the sense that most of the key elasticities are retrieved from their study. Specifically, the elasticities of ending stocks with respect to milled rice (δ_1), and FOB prices (δ_2) are respectively 2.386 and -1.178[7]. The domestic demand price elasticity (η) is set to -0.2. The price elasticity of farming areas (φ) is 0.007. The price transmission elasticities (θ_1, θ_2) are, however, not readily available. Wailes and Chavez (2011) estimated that $P^* = 0.987P_F^*$, and $P_F^* = 0.541FOB^*$. Thus, the value of θ_1 is simply equal to 1/0.987 = 1.013 while θ_2 is 0.987 x 0.541 = 0.534.

The elasticities of yields with respect to temperatures and precipitation (α_i, β_i, γ_i) are set to the estimated parameters in table 1.3[8]. The quantity shares of spring, autumn, and winter rice production in total milled rice (h_j) are set to their 2009-2013 averages as given in table 1.4. The export demand elasticity (η_E) is -30 taken from Minot and Goletti (2000). k_Q, k_{BST}, k_D, and k_E take on their 2008-2012 mean values (table 1.4).

1.7. Simulation

The EDM model (equation (1')-(13')) can be equivalently expressed in matrix form as **XY = Z** where **Y** is the column vector of percentage changes in endogenous variables relative to an

[7] Wailes and Chavez (2011) actually used Thailand FOB export prices instead of Vietnam FOB because of the unavailability of the latter. However, because Vietnam and Thailand are rivals (the top two rice exporters by quantity), their export prices should be close.

[8] The parameters $\alpha3$, $\beta3$, and $\gamma3$ are set to 0 as there exists no co-integration among yields, temperatures, and precipitation in winter crops.

initial equilibrium; **X** is the matrix of parameters corresponding to endogenous variables; and **Z** is the column vector of zeros and percentage change in exogenous variables along with their parameters. The percentage changes in endogenous variables in response to a 1% change in exogenous variables can be obtained by $\mathbf{Y} = \mathbf{X}^{-1}\mathbf{Z}$.

Table 1.5 presents the effects of spring temperatures and precipitation on the rice market. It is no surprise that the effects of maximum temperatures outweigh those of minimum temperatures and precipitation. For instance, a 1% increase in maximum temperatures in the spring cropping season, viewed in isolation, would reduce total milled rice by 9.02%. In contrast, every 1% increase in minimum temperatures and precipitation would increase total milled rice by 5.36% and 0.57%, respectively. The variable that boosts/shrinks total milled rice would depress/increase prices. The price effects at farm and wholesale levels are almost identical, which is explained by the price transmission elasticity of 1.013. The overall impression is that effects on the export market overwhelmingly exceed those on the domestic market. For instance, every 1% increase in maximum temperatures, viewed in isolation, would increase domestic prices (farm and wholesale prices) by 0.94% while increasing FOB prices by 3.51%. Consequently, domestic consumption would fall by 0.19% compared with a drop of 27.95% in exports. That domestic consumption falls far less than exports is partially ascribed to the magnitudes of the corresponding price elasticities. While that of the domestic demand is −0.3, that of the export demand is −30.

Similar analysis applies to the effects of autumn temperatures and precipitation on the rice market (table 1.6). In order to determine effects of climate change on the rice market, we utilize projected changes in temperatures and precipitation under the low emission scenario (B1) compiled by the Vietnamese Ministry of Natural Resources and Environment (2009). The report, however, provides projected changes for mean temperatures, not maximum or minimum temperatures (table 1.7). We, therefore, assume that maximum and minimum temperatures would increase by the same Celsius degrees as mean temperatures. This might be a very strong assumption, but these are the best-bet projected changes for maximum and minimum temperatures. Percentage changes are then computed by dividing absolute change (°C) by the corresponding 1980–1999 baseline values. For precipitation, projected changes are already expressed in percentage changes in the report. Table 1.8 summarizes projected changes in temperatures and precipitation.

Projected changes (%) in temperatures and precipitation in each cropping season are multiplied by their corresponding 1%-change effects (tables 1.5 and 1.6). Intermediate results are summed across weather variables and then across cropping seasons. The final results that reflect the effects of climate change on the rice market are summarized in table 1.9[9]. Thus, without the application of interventions and new cropping advancements, results suggest a plunge of 17.89% in total milled rice by 2030. In response, farm and wholesale prices each increase by 1.86%. Being price inelastic (−0.2), domestic demand consequently falls by 0.38%. The export sector would experience a rise of 6.94% in export prices and a drop of 55.36% in export quantities. Farmers would suffer from a sales loss of 16.02%, whereas wholesalers would see a sales gain of 1.48%[10]. For exporters, their sales loss would amount to 48.42%.

The effects on the export sector are quite substantial partly because of the large price elasticity of export demand (−30). This parameter value is taken from Minot and Goletti's study

[9] Because we use 1980–1999 as the baseline for projected changes in temperatures and precipitation, changes in the rice market are also viewed in relative to their 1980–1999 corresponding averages.

[10] Let sales (S) be defined as the product of prices (P) and quantities (Q) sold. Percentage changes in sales ($S*$) would therefore be the sum of $P*$ and $Q*$. This way, farmers' sales would change by (−17.89% + 1.87% = −16.02%). Similarly, sales at the wholesale level would change by (−0.38% + 1.86% = 1.48%). Exporters' sales would changes by (−55.36% + 6.94% = −48.42%).

that dated back to 2000. As we do not want to overestimate the effects of climate change on this sector, a naturally arising question would be how these effects will alter if the export demand happens to be more/less price elastic. Basic microeconomic theory advises that as demand becomes less price elastic, a shift in the supply curve would lead to greater change in price but smaller change in quantity. Here, we therefore expect that a less price elastic export demand would amplify the effects on FOB prices while rendering the effects on export quantities less pronounced. Additionally, sales loss would become less severe. In an attempt to check our economic intuition, we experimentally set the export demand price elasticity alternatively to -20, -10, and -5 and redo the simulation. For simplicity, we only report changes by 2030 (table 1.10). Toward the decline of η_E (in absolute terms), the effects on FOB prices are enhanced, indicating greater increase in prices. In contrast, the effects on exports are less pronounced, indicating less reduction in quantities exported. Finally, less negative effects on exporters' sales imply that exporters experience fewer losses.

1. 8. Conclusion

This study aims to quantify effects of climate change on rice yield and, more importantly, the rice market in Vietnam. We approach the research objective by first determining yield effects of maximum/minimum temperatures and precipitation. Given the estimated parameters, we simulate an EDM for Vietnam's rice market to obtain effects of a 1% change in temperatures and precipitation on rice market. Finally, by combining these 1%-change effects with projected changes in temperatures and precipitation under the low emission scenario (B1), we are able to quantify effects of climate change on the rice market.

Results suggest that temperatures and precipitation are tied to rice yields in the spring and autumn crops. In the event of climate change, these two climatic elements can probably wreak havoc on Vietnam's rice economy if no interventions or improvements in growing techniques are put in place. Rice production would drop by as much as 18% by 2030. The largest loss is accrued to exporters as they see their export quantities and sales drop by a half by 2030. In the domestic market, because of a plunge in rice production, consumers would have to pay more. For farmers, increase in farm prices is not sufficient to neutralize reduction in production, resulting in a loss of sales. Only wholesalers benefit as they would see a rise in sales. This gain is, however, far too modest compared with losses that accrued to farmers and exporters. Interventions and/or advancements in growing techniques are, therefore, a must in order to mitigate these adverse effects.

It is well known that temperatures (and perhaps precipitation) affect rice yields differently in different growth stages. Thus, a potential extension to this study is to include as explanatory variables temperatures and precipitation of each of every month during the crop length instead of seasonal averages. This way, one could achieve more precise and detailed insights of the effects of these weather factors on rice yields. This approach, however, demands a longer time series to compensate for the increase in the number of regressors.

Another issue that should be addressed in future studies is the use of aggregated data (country averages). As Vietnam straddles a wide range of latitudes (8° to 23° north of the equator), the northern parts are distinguishable from the southern parts in terms of climate conditions. Southern Vietnam experiences a tropical climate with two distinguished seasons—namely, the dry and wet seasons—whereas the northern parts enjoy a subtropical climate with more distinct seasonal variations. Thus, the use of aggregated data has blurred climatic distinctions among regions of the country. Although acknowledging the disadvantage of using aggregated data, we are unable to tackle the issue in the current study because regional yield data are available only for 1991–2014, which does not provide sufficient observations for the co-integration analysis

Table 1.1. Unit Root Tests

Variable	Spring crop		Autumn crop		Winter crop	
	Level	F.D	Level	F.D	Level	F.D
Max temperature	-2.369	-4.007	-1.982	-5.539	-1.558	-5.018
Min temperature	-2.615	-3.719	-1.550	-4.551	-1.842	-4.229
Precipitation	-2.373	-3.415	-2.808	-4.327	-2.041	-4.556
Yield	-1.884	-3.578	-2.314	-3.458	-1.148	-3.475

Note: Critical values for unit roots tests with constant at 5% level is -2.893 (MacKinnon 1991)

Table 1.2. Johansen Trace Tests for Co-integration[a]

H_0: rank = r	Spring crop	Autumn crop	Winter crop	1% critical
	Trace statistic	Trace statistic	Trace statistic	value
0	68.18	138.50	51.38	54.46
1	23.52*	46.23	23.79	35.65
2	8.27	14.87*	5.99	20.04
3	2.61	1.21	1.01	6.65

[a] 5 lags are used in the test for spring crop, 6 lags for autumn crop, and 3 lags for winter crop.

Note: Asterisks (*) indicate the number of co-integrating vectors among variables at 1% level of significance.

Table 1.3. Effects of Temperatures and Precipitation on Rice Yields

RHS variable: Yield	Spring crop	Autumn crop
LHS variables	Estimate	Estimate
Max temperature	-28.80	-43.87
Min temperature	17.12	-0.32
Precipitation	1.81	4.31
Constant	39.77	129.83
LM test[a]	7.99 (0.948)	19.23 (0.256)
Jarque-Bera test	3.59 (0.892)	3.93 (0.863)

[a] Lagrange-multiplier test for serial correlation up to 10 lags.

Note: P-values are in the parentheses.

Table 1.4. Definitions and Baseline Values for Model Parameter

Items	Definitions	Value
α_1	Minimum temperature elasticity of rice yield in spring	17.120
α_2	Minimum temperature elasticity of rice yield in autumn	-0.320
α_3	Minimum temperature elasticity of rice yield in winter	0
β_1	Maximum temperature elasticity of rice yield in spring	-28.800
β_2	Maximum temperature elasticity of rice yield in autumn	-43.870
β_3	Maximum temperature elasticity of rice yield in winter	0
γ_1	Precipitation elasticity of rice yield in spring	1.810
γ_2	Precipitation elasticity of rice yield in autumn	4.310
γ_3	Precipitation elasticity of rice yield in winter	0
φ_1	Price elasticity of harvested rice area in spring	0.007
φ_2	Price elasticity of harvested rice area in autumn	0.007
φ_3	Price elasticity of harvested rice area in winter	0.007
δ_1	Production elasticity of ending stocks	2.386
δ_2	Price elasticity of ending stocks	-1.178
η	Price elasticity of domestic demand	-0.200
η_E	Price elasticity of export demand	-30.000
θ_1	Wholesale-farm price transmission elasticity	1.013
θ_2	FOB-wholesale price transmission elasticity	0.534
h_S	Share of spring rice production from total rice production	0.470[a]
h_A	Share of autumn rice production from total rice production	0.309[a]

Table 1.4. Definitions and Baseline Values for Model Parameters (*continued*)

Items	Definitions	Value
h_W	Share of winter rice production from total rice production	0.221[a]
k_Q	Ratios of total production to the ending stock	17.616[b]
k_{BST}	Ratios of beginning stock to the ending stock	1.257[b]
k_D	Ratios of domestic demand to the ending stock	13.187[b]
k_E	Ratios of export to the ending stock	4.688[b]

[a] These are 2009-2013 mean values computed from data provided by the Vietnamese General Statistics Office.

[b] These are 2008-2012 mean values computed from data obtained from the U.S Department of Agriculture.

Table 1.5. Effects of 1% Change in Spring Temperatures and Precipitation on Rice Market

Variables	Max temperature	Min temperature	Precipitation
Farm price	0.94	-0.56	-0.06
Wholesale price	0.93	-0.55	-0.06
FOB price	3.51	-2.09	-0.22
Total milled rice	-9.02	5.36	0.57
Domestic consumption	-0.19	0.11	0.01
Export	-27.95	16.61	1.76

Table 1.6. Effects of 1% Change in Autumn Temperatures and Precipitation on Rice Market

Variables	Max temperature	Min temperature	Precipitation
Farm price	0.94	0.01	-0.09
Wholesale price	0.93	0.01	-0.09
FOB price	3.52	0.03	-0.35
Total milled rice	-9.04	-0.07	0.89
Domestic consumption	-0.19	0.00	0.02
Export	-27.99	-0.20	2.75

Table 1.7. Projected Changes (^{0}C) in Mean Temperatures 2020-2040[a]

	2020	2030	2040
Spring cropping season	0.50	0.74	0.99
Autumn cropping season	0.36	0.53	0.69

[a] These changes are under the B1 emission scenario compared to the 1980-1999 baseline.

Source: Author's calculations based on MONRE 2009.

Table 1.8. Projected Changes (%) in Max and Min Temperatures and Precipitation 2020-2040[a]

		2020	2030	2040
Spring cropping season	*Max temperature*	1.86	2.77	3.67
	Min temperature	2.70	4.01	5.32
	Precipitation	-1.30	-1.95	-2.78
Autumn cropping season	*Max temperature*	1.15	1.70	2.21
	Min temperature	1.51	2.23	2.90
	Precipitation	1.70	2.50	3.46

[a] For spring, the 1980-1999 baseline values for max and min temperatures are 26.86^{0}C and 18.53^{0}C, respectively. For autumn, these figures are 31.05^{0}C and 23.67^{0}C.

Source: Author's calculations based on MONRE 2009.

Table 1.9. Effects of Climate Change on Rice Market 2020-2040 (% change)

Variables	2020	2030	2040
Farm price	1.26	1.87	2.43
Wholesale price	1.26	1.86	2.43
FOB price	4.68	6.94	9.03
Total milled rice	-12.06	-17.89	-23.26
Domestic consumption	-0.25	-0.38	-0.49
Exports	-37.32	-55.36	-71.99
Farmers' sales	-10.8	-16.02	-20.83
Wholesalers' sales	1.01	1.48	1.94
Exporters' sales	-32.64	-48.42	-62.96

Table 1.10. Climate Change Effects on Exports with Various Export Demand Price Elasticities[a]

Variables	Export demand price elasticity, η_E =			
	-30	-20	-10	-5
FOB price	6.94	10.18	19.03	33.65
Exports	-55.36	-54.09	-50.47	-44.58
Exporters' sales	-48.42	-43.91	-31.44	-10.93

[*] These are projected percentage changes by 2030.

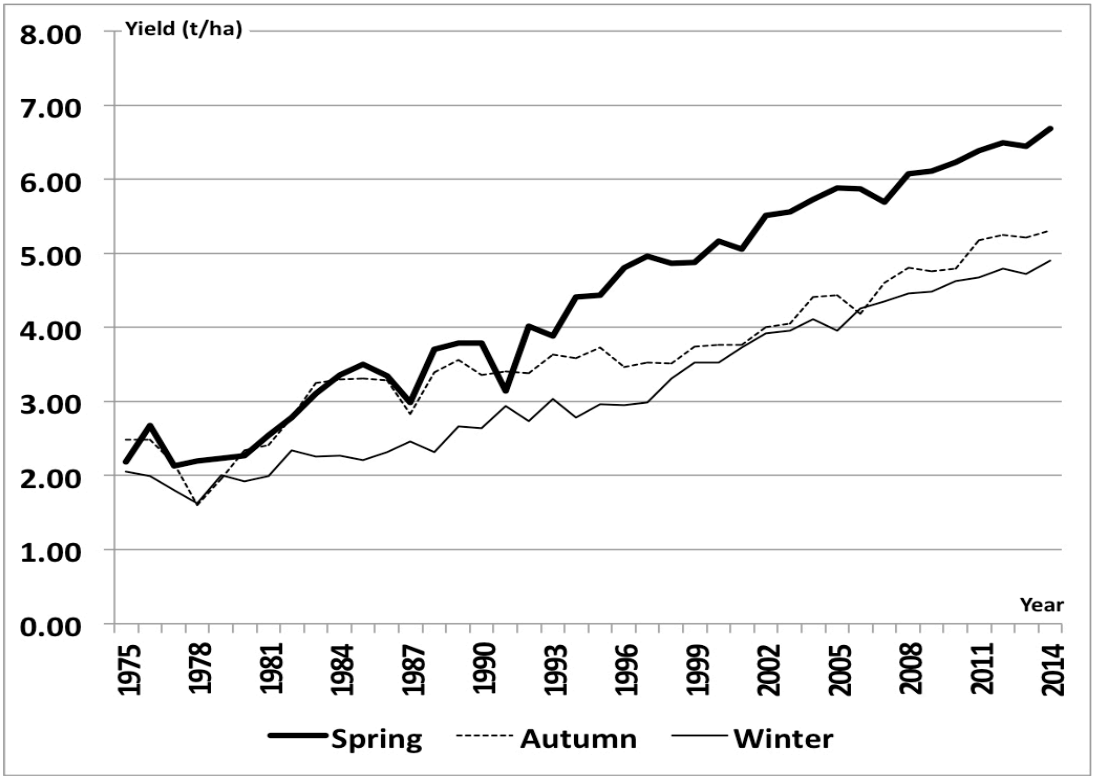

Figure 1.1. Rice Yields (MT/ha) in Three Cropping Seasons in Vietnam 1975-2014

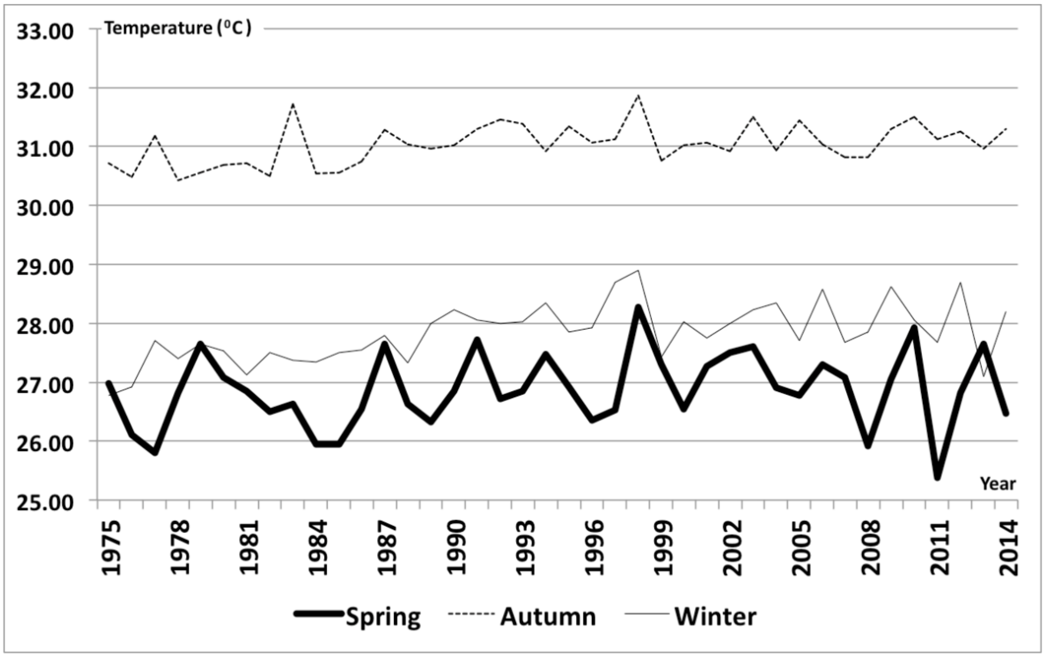

Figure 1.2. Maximum Temperatures (^{0}C) in Three Cropping Seasons in Vietnam

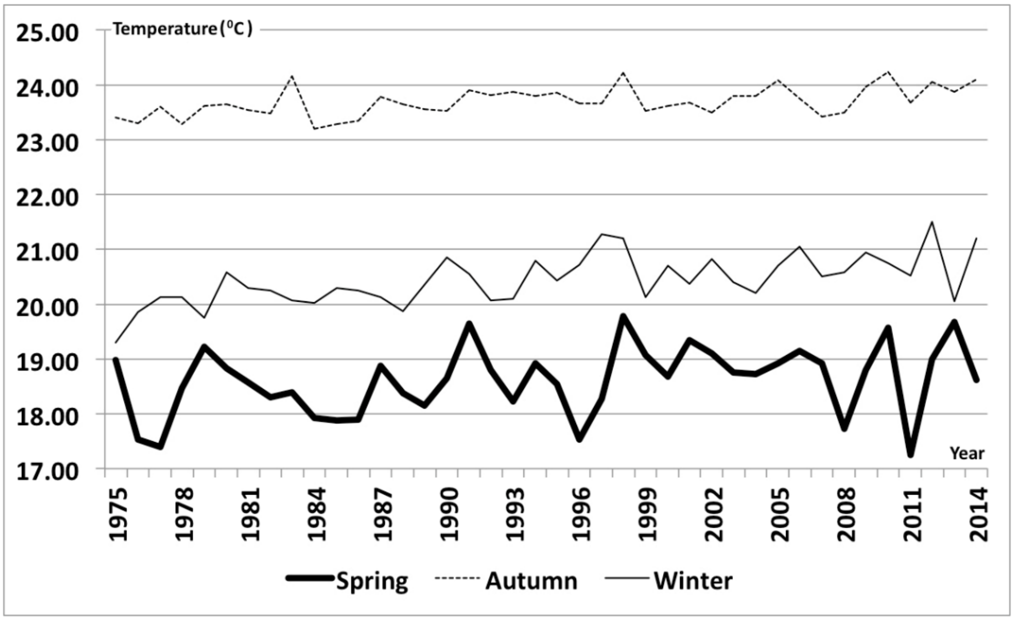

Figure 1.3. Minimum Temperatures (^{0}C) in Three Cropping Seasons in Vietnam

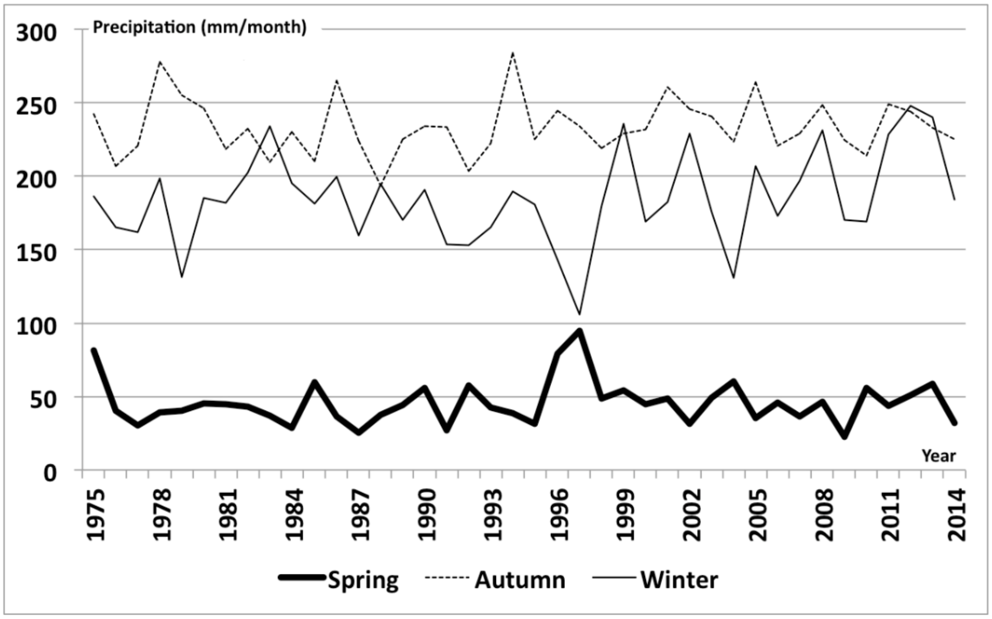

Figure 1.4. Precipitation (Mm/Month) in Three Cropping Seasons in Vietnam

Chapter 2

Climate Condition and Rice Profit Inefficiency in Ben Tre Province, Vietnam

2.1. Introduction

Climate change has become an increasingly troublesome threat faced by humankind. Among its many potential disastrous effects, climate change endangers food security through its negative impacts on agriculture. A report from the Food and Agriculture Organization (FAO) indicated that global warming would cast adverse effects on four key components of food security – food availability, food accessibility, food utilization and food system stability (FAO, 2008). Among agricultural and developing economies, Vietnam is one of the worst affected by climate change events (Dasgupta et al. 2007). According to the Ministry of Natural Resources and Environment of Vietnam (MONRE, 2016) temperature in Vietnam has increased by 0.62^0C on average in the period 1958-2014. Rainfall has increased slightly in amount, but more important, changed in pattern. It has increased in the winter and spring and reduced in the autumn over the whole country. But in the South, where Ben Tre province is located, rainfall has increased in all four seasons. The largest increase occurred in the winter (85%) and the smallest increase occurred in the autumn (4.7%) over the past 57 years (1958-2014). Droughts and abnormal rainfall have occurred more frequently in recent years. Climate change triggered events are expected to have negative impacts on the environment and crop production in Mekong Delta (Padilla, 2011). Rice yield is expected to decline by 20% due to saltwater intrusion which is resulted from a change in fresh water and saltwater pressure gradients trigged by warming global temperature. Rice production relies on favorable weather conditions to thrive and it is sensitive to climate change. Consequently, increased temperatures and changing rainfall patterns induced by climate change pose a risk to its production. Injurious effects of climate change on rice production and rice yield have been well documented in a number of studies (Naylor et al., 2007; Nhan et al., 2011; Alam et al., 2014; Shean, 2014; and Le, 2016).

Rice is a stable food for many Vietnamese households and it also plays an important role in the economic growth of the country. Vietnam alone accounts for approximately 20% (quantity) of the total world rice trade. It is, therefore, understandable that a vast amount of effort has been put forth to measure the efficiency of rice farming in Vietnam on both the national scale (Kompas, 2004; Khai and Yabe, 2011; Linh, 2012; Tu and Trang, 2016) and the regional scale (Mekong Delta: Hien et al. 2003 and Huy, 2009; Red River Delta: Hoang and Yabe 2012; Central Vietnam: Trong and Napasintuwong, 2015). Stochastic frontier method is the common approach used to measure production inefficiency. These studies indicated that rice farming in Vietnam has not been efficient in all aspects, production, cost, and profit. It is, therefore, crucial that rice farmers have to improve their performance especially in the wake of climate change. Under changing climate, even for good managers, random shocks may lower productivity and profits. Despite the documented effects of climate conditions on rice productivity (Naylor et al., 2007; Nhan et al., 2011; Alam et al., 2014; Shean, 2014; and Le, 2016), a literature review on Vietnam rice production inefficiency has shown no study that establishes a link between climate conditions and (in)efficiency. In light of this, first, we set off to measure profit efficiency (defined as the ability of a farm to achieve the possible highest profit given input prices and a level of fixed factors (Ali and Flinn, 1989)) of individual rice farmers located in Ben Tre province, one of the most vulnerable areas to climate change in Mekong Delta Vietnam, by using stochastic frontier function. Second, we isolate factors contributing to profit inefficiency, taking into consideration climate conditions.

The stochastic profit frontier function and profit inefficiency model is simultaneously estimated using a two-stage estimation method and the computer program Frontier 4.1 (Coelli, 1996).

The remainder of this article begins with a brief review on related literature. In the next section, we present the analytical framework followed by the description of the empirical model and the data. Discussion is to follow the estimation of results. The paper ends with a conclusion, and recommendations.

2.2. Literature Review

The stochastic production frontier approach is commonly employed to assess rice production efficiency in Vietnam. On the national scale, Kompas (2004) found that average production efficiency was 59% during 1991-1999. In a recent study, Linh (2012) estimate an efficiency of 63.4% and Khai and Yabe (2011) 82.6%[11]. Confined to Mekong Delta, Hien et al. (2003) estimated that technical efficiency for the winter-spring, spring-summer and summer-autumn seasons were 86.23, 79.55, and 80.24%, respectively.

Although the stochastic production frontier is a well-known method used for measuring efficiency level, Ali and Flinn (1989) noted that it might not be an appropriate approach since farmers are likely to face different prices and possess distinctive levels of endowments. Ali et al. (1994) argued that the profit frontier approach combined all three concepts of technical, allocative, and scale efficiency in the profit relationship, and any errors in the production decisions would be reflected in lower profit or revenue for the producers (Technical efficiency measures the farm's ability to produce on the output frontier (the maximum achievable output). If the farm's output lies

[11] Both studies used data from the Vietnam Household Living Standard Survey 2003-2004. In addition to the production frontier approach, Linh (2012) made use of Data Envelopment Analysis. Average efficiency score is roughly 70%.

below the frontier output given a set of inputs, it is said to be technically inefficient. Allocative efficiency measures the farm's ability to make the best decisions on product mix and resource allocation. It is determined by comparing the marginal products of inputs with their normalized prices. If a farm is not using inputs by equating marginal products of inputs with their normalized prices given input prices and output level, it is said to be inefficiently allocated. Scale efficiency measures the farm's optimal size. If a farm is not producing outputs by equating marginal cost and product price, it is said to be scale inefficient (Kumbhakar et al., 1989)). Upon this criticism, the stochastic profit frontier emerged as an alternative and has been well applied in a number of studies to estimate economic efficiency of individual farms (Ali and Flinn, 1989; Ali et al., 1994; Rahman, 2003; Ohajianya et al. 2006). Utilizing this approach, Trong and Napasintuwong (2015) found that profit efficiency for hybrid farmers in Central Vietnam was on average as low as 63%.

Whether one utilizes the profit or production frontier approach, climate and environmental condition should be incorporated. For example, Demir and Mahmud (2002), who included agro-climatic variables such as rainfall anomalies and soil quality, emphasized that omission of climate variables could lead to inaccurate interregional technical efficiency comparisons among 67 provinces of Turkish agriculture. In Mukherjee et al. (2012) where heat stress was incorporated to measure technical efficiency of dairy farms located in Georgia and Florida, the variable absorbed some of output shortfall that otherwise would have been attributed to inefficiency. In a study by Hoang and Yabe (2012), environmental factors such as plant disease, soil fertility, irrigation and water pollution were added as potential determinants of inefficiency of rice production in Vietnam Red River Delta. They found that the average profit efficiency was 75% and significantly impacted by such environmental factors.

2.3. Analytical Framework

Suppose that the profit function for a farm is given by $f(P_i, Z_i)$. Farm i would achieve profit:

$$\pi_i = f(P_i, Z_i) \tag{1}$$

where π_i is the restricted normalized profit of farm *i,* here defined as gross revenue less variable costs divided by output price received by farm *i*; P_i is the vector of input prices faced by farm *i* divided by output price; and Z_i is the vector of fixed factors utilized by farm *i.* Stochastic profit frontier analysis assumes that a farm potentially obtains less than maximum profit due to a degree of inefficiency. According to Ali and Flinn (1989), profit efficiency is defined as the ability of a farm to achieve the possible highest profit (which is the profit frontier) given prices and a level of fixed factors. Profit inefficiency is the loss of profit from not being on the frontier. Specifically,

$$\pi_i = f(P_i, Z_i)\xi_i \tag{2}$$

where ξ_i is the level of efficiency for farm *i* which lies strictly between zero and one. If ξ_i =1, farm *i* achieves the possible highest profit. When ξ_i <1, farm i is not making the most from inputs used. Let the profit be subject to random shocks $exp(v_i)$, and u_i be defined as $u_i = -ln(\xi_i)$ or equivalently $exp(-u_i) = \xi_i$, the stochastic profit frontier that takes into account inefficiency is given by:

$$\pi_i = f(P_i, Z_i)exp(v_i - u_i) \tag{3}$$

where v_i is assumed to be independently and identically normally distributed $N \sim (0, \sigma_v^2)$ and is independent of u_i; and u_i is the non-negative random errors independently $N^+ \sim (\mu, \sigma_u^2)$ distributed with truncation point at 0 with mean $\mu_i = \delta_0 + \sum_d \delta_d W_{di}$ and variance $\sigma_u^2(|N(\mu_i, \sigma_u^2)|)$ (Battese and Coelli, 1995), where W_i is the set of explanatory variables associated with profit inefficiency on farm *i*. Within this context, profit efficiency is estimated by:

$$EF_i = E[exp(-u_i)|e_i] \tag{4}$$

The stochastic profit frontier and profit efficiency are estimated simultaneously by maximum likelihood estimation. The log likelihood function is expressed in terms of the total variance $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2/\sigma^2$. γ is bounded between 0 and 1. A value of γ close to 1 suggests the existence of inefficiency while a value close to 0 indicates the absence of inefficiency[12]. (For simplicity, we do not present the expression for the log likelihood function here.)

2.4. Empirical Model

We utilize the translog profit function expressed as follows with subscript *i* dropped for convenience:

$$\begin{aligned}\ln \pi = \alpha_0 &+ \sum_{i=1}^{4} \alpha_i \ln P_i \\ &+ \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4} \alpha_{ij} \ln P_i \ln P_j + \sum_{i=1}^{4} \gamma_i \ln P_i \ln Z \\ &+ \frac{1}{2}\beta_{11} \ln Z \ln Z + \beta_1 \ln Z + h_1 + h_2 + h_3 + v - u \end{aligned} \tag{5}$$

where all variables are defined above; i = 1, 2, 3, 4 where (1) is fertilizer, (2) is insecticide, (3) is seed, and (4) is harvesting labor; h_1 is insecticide dummy (=1 if farmer uses insecticides, = 0 if not); h_2 is seed dummy(=1 if farmer buys seeds, =0 if not); h_3 is dummy variable for harvesting labor use(=1 if farmer hires labor for harvesting, =0 if not) Z is the stock of agricultural assets (hoe, axe, sickle, ox-cart, wheelbarrow…).

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[12] If γ is not significantly different from zero, σ_u^2 is 0, and the model reduces to a mean response function in which the inefficiency term enters directly (Battese and Coelli, 1995).

The mean μ of the random error u_i representing profit inefficiency is expressed as a linear function of explanatory variables, W_d:

$$\mu = \delta_0 + \sum_{d=1}^{7} \delta_d W_d \tag{6}$$

where W_d includes: (1) age of farmer (years); (2) farmer's education (1: high school, 0: less than high school)[13]; (3) family size (0: up to 5 persons, 1: more than 5 persons); (4) main occupation (=1 if main occupation is farming, =0 if not); (5) number of crops per year (=1 if farmer had 1 crop per year, =0 if farmer had more than 1 crop per year); (6) land preparation (dummy: =1 if farmer outsourced land preparation, =0 if not); and (7) absolute value of rainfall anomaly defined as a departure of the observed average monthly rainfall from the respective 1990-2010 average: -90mm, +45mm, and +185mm. Rainfall anomaly is incorporated to inefficiency function to identify the impacts of changing climate on profit inefficiency of rice farmers in Bentre Province. This method was employed by Demir and Mahmud (2002) to demonstrate the impact of climate factor on technical efficiency comparisons among 67 provinces of Turkish agriculture.

In the sample, there are farmers who did not use insecticides on their last rice crop, and/or did not hire labor for harvesting. For those farmers, input prices were not available. Our approach is to assign the value of zero for the input prices and add two dummies in the profit function to indicate such behaviors. These dummies are to account for farmers who have a different relationship between profit and input prices. The dummies will take on the value of 1 if farmers use insecticides/hire labor for harvesting.

Similarly, there are 32 farmers who did not buy seed from nursery companies. They used their own stored seeds from the previous crop. For these farmers, we assigned the value of rice

[13] No farmers have education higher than high school in the sample.

price for the seed price. Besides, one dummy variable (=1 if farmer purchased seed and 0 if farmer used stored seed) was also added in the translog profit function to indicate the different relationship between profit and purchased/stored seed.

2.5. Data

Farm-specific data used in the study were obtained from person to person survey in Thanh Phu district, Ben Tre province (Vietnam) for winter-spring season of 2011[14]. In this district, rice is the dominant crop and shrimp is the dominant farmed animal species. Farmers can choose on their own whether to do rice farming or shrimp culture or both. For farmers who only do rice farming, the maximum number of crops per year is 3. Substituting rice for shrimp would reduce the number of crops per year. Underlying their choice is their anticipated benefit (efficiency) of the chosen option. Our sample includes only farmers who farm rice at least once during the prior 12 months. One hundred and fifty rice farmers were randomly chosen, out of which 83 farmers fully completed the survey.

Table 2.1 provides measurements and statistics of selected variables. Age of farm household is 47 years old with 5 years of schooling on average. Most of the rice farmers in the study consider farming as their primary occupation. Fundamental inputs for producing rice are fertilizer, insecticide, seed and harvesting labor. Thirty two farms did not buy seed and 68 farms did not use insecticide whereas fertilizer is utilized by all farmers. Since farming is considered as primary occupation, farmers do almost all of farming work. They only hired labor for harvesting period. Fifty seven out of 83 farms hired harvesting labor in the sample.

[14] The data used in this study was extracted from a larger survey dataset which was used for a research project during 2011-2013 on climate change impacts. The survey was made possible with help from local officials.

For those farmers who use all 4 inputs, fertilizer accounts for the largest share of total input expenditure. Specifically, farmers spend 3200.89 thousand VND (43% of total input expenditure) for fertilizer, but only 1348.50 thousand VND (18%), 1231.48 thousand VND (17%), and 1615.24 thousand VND (22%) for insecticide, seed, and harvesting labor, respectively, for 1.0 hectare of rice. Average rice yield in the study area is 3.68 ton/ha, lower than the average rice yield for the whole province (4.71 ton/ha)[15]. The huge range of yield (0.6 ton/ha – 6.0 ton/ha) indicates that there may be possibility to increase rice yield.

Rainfall in the studied area is collected through three weather stations. We matched surveyed farms to the weather stations based on their proximity to the stations. Rainfall anomaly is -90mm (rainfall during the crop was 90mm lower than the average monthly rainfall from the respective 1990-2010 average in that area), +45mm (rainfall during the crop was 45mm higher than the average monthly rainfall from the respective 1990-2010 average in that area), and +185mm (rainfall during the crop was 185mm higher than the average monthly rainfall from the respective 1990-2010 average in that area).

2.6. Results and Discussions

The maximum likelihood estimates of the stochastic profit frontier and profit inefficiency are presented in table 2.2. The upper part of the table displays estimates for the translog normalized profit function while the lower part lists estimates for profit inefficiency.

We test for the existence of the inefficiency term. The null hypothesis of no inefficiency component is rejected at 1%[16] (table 2.2). This is confirmed by the estimated value of γ which is

[15] Data from the General Statistics Office of Vietnam

[16] The test is derived in Coelli (1995). The null hypothesis is that $\mu = \sigma_u^2$. Under the null hypothesis, the truncated-normal model reduces to a linear regression model with normally distributed errors.

close to one ($\gamma = 0.999$) and statistically significant at 1%, establishing the fact that a high level of inefficiency exists among rice farmers in Ben Tre province, Vietnam.

Profit efficiency scores

The distribution of profit efficiency scores for each farmer is presented in figure 2.1. The average score is as low as 59.7%, meaning that actual profit of rice farmers in the study is about half of maximum profit that they would achieve. This implies that on average farmers could increase their profit by about 40% by improving their technical, allocative, and scale efficiency. Our estimate is smaller than those in Hoang and Yabe (2012) for Red Rive Delta (75%) and in Trong and Napasintuwong (2015) for Central Vietnam (63%). This number is much lower compared to other rice farming Asian countries. Such as, average technical efficiency of rice farmer in Indonesia is 0.77 (Haryanto et al., 2015), the mean level of profit efficiency is 0.68 for the Northeast and Northern Thailand (Rahman, 1994). The results from either pool or separate estimation demonstrated that the average efficiency scores are larger than 0.83 for Cambodia (Khoy et al., 2016) (table 2.3).

In comparison with these countries, Vietnam has the highest yield, almost two times higher than that of Thanland and Combodia[17]. However, the fertilizer consumption per ton of rice of Vietnam is roughly 15 times (in 2010) and 10 times (in 2015) higher than that of Cambodia and almost two times higher than that of Indonesia[18]. This partly explains that such low profit efficiency of rice farmers in Ben Tre Province particularly and Vietnam in general.

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[17] Rice yield is 5.34, 2.97, 5.02, and 2.99 ton/ha in 2010 and 5.58, 3.43, 5.41, and 2.91 ton/ha in 2015 for Vietnam, Cambodia, Indonesia, and Thailand respectively (FAO).

[18] Fertilizer consumption per ton of rice is 60.55, 4.08, 36.16, and 54.23 kg/ton in 2010 and 76.20, 7.72, 41.76, and 55.14 kg/ton in 2015 for Vietnam, Cambodia, Indonesia, and Thailand respectively (computed based on data from FAO).

Farmers exhibit a wide spectrum of profit efficiency score, ranging from 3% to 99% (figure 2.1). Moreover, it is notable that the scores are split at the value of 60%. Fifty percent of farmers operate at the level of profit efficiency less than 60%. The remaining fifty percent of rice farmers show their efficiency higher than 60%.

Factors explaining inefficiency

As can be seen from the lower part of the table 2.2, farmer's age, main occupation, numbers of rice crops per year, and land preparation have negative impact on profit inefficiency. While the impact of rainfall anomaly on profit inefficiency is positive.

The positive impact of rainfall anomaly on profit inefficiency indicates that a rise in absolute value of rainfall anomaly may cause profit inefficiency to increase. In other words, the larger the rainfall anomaly is, the lower profit efficiency of rice framers in that area is.

The quantile plot of profit efficiency scores by rainfall anomaly is presented in figure 2.2. The purpose of the presentation of these plots is to give a hint on the relative "strength" of the effects of rainfall anomaly on profit inefficiency. As such, rainfall anomaly (of +185mm) remarkably shifts the whisker box (figure 2.2).

Compared to (+45mm) and (-90mm), rainfall anomaly of +185mm significantly increases profit inefficiency. Specifically, profit efficiency score of farmers who operate in area with rainfall anomaly of (+45mm) and (-90mm) are 0.639 and 0.627, respectively, whereas that of farmers who operate in area with rainfall anomaly of +185mm is as low as 0.371. In other words, those who farm rice in area where rainfall during the crop is 185mm higher than the average monthly rainfall would see their profit efficiency score reduced by 30 percentage points on average and such reduction is statistically significant (table 2.4).

Farmer’s growing concern about higher temperature and saline intrusion trigged by climate change has induced a gradual shift from intensive rice farming to rotation with shrimp culture in Thanh Phu district (IFAD, 2014). So, a dummy variable for numbers of *rice crops* per year was incorporated in the profit inefficiency function to discover the effect of rotation on rice farming efficiency. As shown in table 2.2, the dummy variable for numbers of *rice crops* per year affects negatively on rice profit inefficiency, implying that those who farm only one crop of rice per year perform better than those who farm more than one crop. Thus, crop rotation plays an important role in raising profit and reducing inefficiency for rice farmers in Ben Tre province.

Land preparation is one of the key determinants of rice yield. But only half of farmers in the sample did land preparation. As expected, the result reveals that outsourcing *land preparation*, while adding cost, turns out to be helpful in terms of reducing profit inefficiency (table 2.2).

The variable *main occupation* is added to reflect the relative importance of agricultural work in households' income. To our expectation, the coefficient on "*main occupation*" is negative and significant (table 2.2). So, being farmer as the main occupation reduces profit inefficiency. This implies that if household’s income comes primarily from rice farming, farmers pay more attention to their crops and have incentives to invest more in terms of land preparation and crop rotation.

2.7. Conclusion and Recommendations

Climate change has posed a serious threat to agriculture around the world. Among agriculture dependent countries, Vietnam is severely impacted by climate change. However, studies on profit efficiency of agricultural production commonly ignored climate effect. This study examined the impact of changing climate on profit efficiency of rice farming in Ben Tre province, Vietnam. Using the stochastic profit frontier function, the study found that the profit efficiency score of rice farmers is as low as 59% on average. This implies that farmers could improve their profit by about 40%. This score is much smaller than those of other rice farming Asian countries, such as Thailand (68%) and Cambodia (83%). Rice farmers in the area with rainfall anomaly of +185mm are found to have profit efficiency as low as 37.1%. On average, their profit efficiency scores are lower than those of rice farmers in the same district by 22 percentage points. According to the climate change scenarios for Vietnam from MONRE 2016, by the end of the 21st century, extreme rainfall would rise over the whole country with the greatest increase in the South where Mekong Delta, known as "rice bowl" of Vietnam, is located. The average maximum 1-day rainfall and maximum 5-day rainfall would likely increase 10% - 70% and 10% - 50%, respectively, for the whole country. Under such scenarios, rice farmers would suffer worse loss of profit from increasing abnormal rainfall. Climate change is uncontrolled, so the government should invest on rice seed technology to create seed that can tolerate severe weather. Besides, a good weather forecast to which a suitable and specific sewing calendar for each area is established would lessen the impact of anomaly climate. The results reveal that doing land preparation and rotating rice farming with shrimp culture lower rice profit inefficiency. In addition, IFAD (2014) reported that crop rotation can reduce exposures to climate change while also improve nutrition for farmers. So, the local government should pay more attention on providing documents and training on rice farming to help famers improve rice production as well as clearly guiding farmers through crop rotation.

Table 2.1. Measurements and Summary Statistics of Selected Variables

Variables	Measurement	Mean	Min	Max
Age of farmer	Years	46.79	27	73
Schooling	Years	5.04	0	11
Family size	Number	4.31	2	9
Primary occupation	Index (1=farming; 0=non farming)	0.92	0	1
Land preparation	Index (1=do land preparation ; 0=do not do land preparation)	0.53	0	1
Area	Hectare	0.91	0.05	4
Rice price	Thousand VND*/kg	6.77	5.30	8.000
Fertilizer price	Thousand VND /ha	3200.89	600	10000
Insecticide price				
Buy insecticide (15 farms)	Thousand VND /ha	1348.50	100	3000
Did not buy insecticide (68 farms)				
Seed price				
Buy seed (51 farms)	Thousand VND /ha	1231.48	110	5000
Did not buy seed (32 farms)				
Wage				
Hire labor (57 farms)	Thousand VND /ha	1615.24	400	3600
Did not hire labor (26 farms)				
Farmer's asset value	Thousand VND	454.04	0	3050
Yield	Ton/ha	3.68	0.60	6

*Exchange rate of USD 1.00 = Thousand VND 16.119 in 2011

Table 2.2. Maximum Likelihood Estimates of Profit Frontier Function

Variables	Coefficients	t ratios
Profit function		
Constant	3.323	4.709***
$ln\, P_F$	3.288	13.135***
$ln\, P_I$	4.135	4.162***
$ln\, P_S$	-2.366	-19.803***
$ln\, P_L$	5.494	27.705***
$ln\, Z$	-0.224	-8.875***
$\frac{1}{2}(ln\, P_F \times ln\, P_F)$	-1.159	-31.513***
$\frac{1}{2}(ln\, P_I \times ln\, P_I)$	-0.351	-1.288
$\frac{1}{2}(ln\, P_S \times ln\, P_S)$	-0.031	-1.302
$\frac{1}{2}(ln\, P_L \times ln\, P_L)$	-1.105	-33.161***
$\frac{1}{2}(ln\, Z \times ln\, Z)$	0.070	28.384***
$ln\, P_F \times ln\, P_I$	0.018	0.192
$ln\, P_F \times ln\, P_S$	0.553	31.263***
$ln\, P_F \times ln\, P_L$	0.127	20.874***
$ln\, P_I \times ln\, P_S$	-0.097	-0.931
$ln\, P_I \times ln\, P_L$	-0.032	-1.599
$ln\, P_S \times ln\, P_L$	-0.059	-7.608***
$ln\, P_F \times ln\, Z$	0.033	14.286***
$ln\, P_I \times ln\, Z$	-0.145	-7.820***
$ln\, P_S \times ln\, Z$	-0.069	-36.993***
$ln\, P_L \times ln\, Z$	-0.011	-6.120***
h_1	-3.534	-3.091***
h_2	0.591	14.851***
h_3	-14.883	-30.592***
Profit inefficiency		
Constant	2.245	2.131**
Farmer's age	-0.041	-2.151**
Farmer's education	0.171	0.411
Family size	0.887	1.346
Main occupation	-2.472	-4.580***

Table 2.2. Maximum Likelihood Estimates of Profit Frontier Function (continued)

Variables	**Coefficients**	**t ratios**
Number of crops per year	-2.826	-2.473**
Land preparation	-1.090	-2.110**
Rainfall anomaly	0.015	2.538**
Variance parameters		
$\sigma^2 = (\sigma_u^2 + \sigma_V^2)$	3.164	4.934***
$\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_V^2)$	0.999	103246.060***
No inefficiency component [a]	46.57 (p < .0000)	
Observations	83	

Note: P_F, P_I , P_S and P_L are normalized variable input prices; subscripts F = fertilizer, I = insecticides, S = seed and L = labor; Z = value of farmer's assets

[a] The test is based on Coelli (1995)'s one-sided test.

* Significant at 10% level ($p < .10$).

** Significant at 5% level ($p < .05$).

*** Significant at 1% level ($p < .01$).

Table 2.3. Efficiency Scores of Rice Farmers in Asian Countries

	Efficiency scores	Authors
Red River Delta of Vietnam	0.75	Hoang and Yabe (2012)
Central of Vietnam	0.63	Trong and Napasintuwong (2015)
Indonesia	0.77	Haryanto et al., 2015
Northeast and Northern Thailand	0.68	Rahman, 1994
Cambodia	0.83	Khoy et al., 2016

Table 2.4. Unpaired T-Tests For Mean Comparison

Rainfall anomaly	**Profit efficiency score**
Rainfall anomaly	
-90 mm	0.627
+ 45 mm	0.639
+ 185 mm	0.371
t-ratio	
+45 mm vs. + 185 mm	2.76^{**}
-90 mm vs. + 185 mm	2.78^{**}

** Significant at 5% level ($p < .05$).

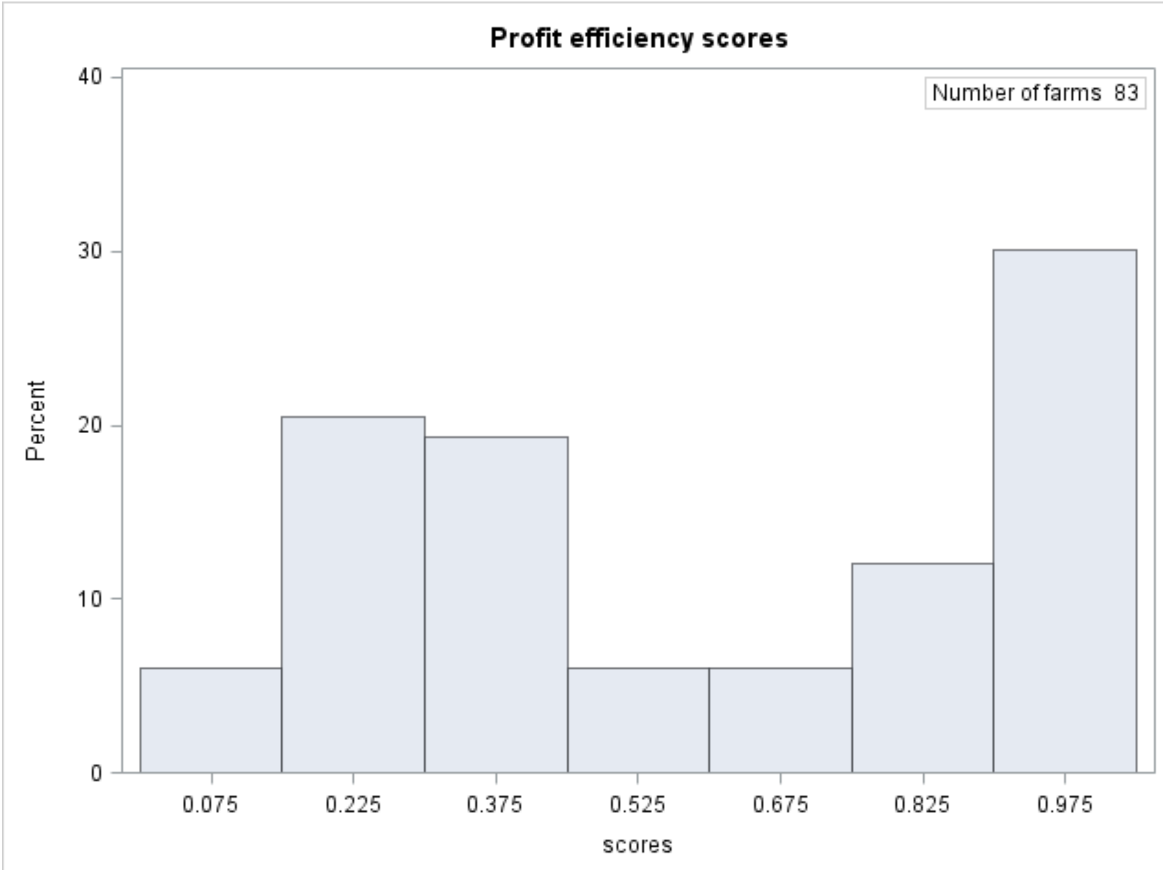

Figure 2.1. Profit Efficiency Scores of Rice Farmers

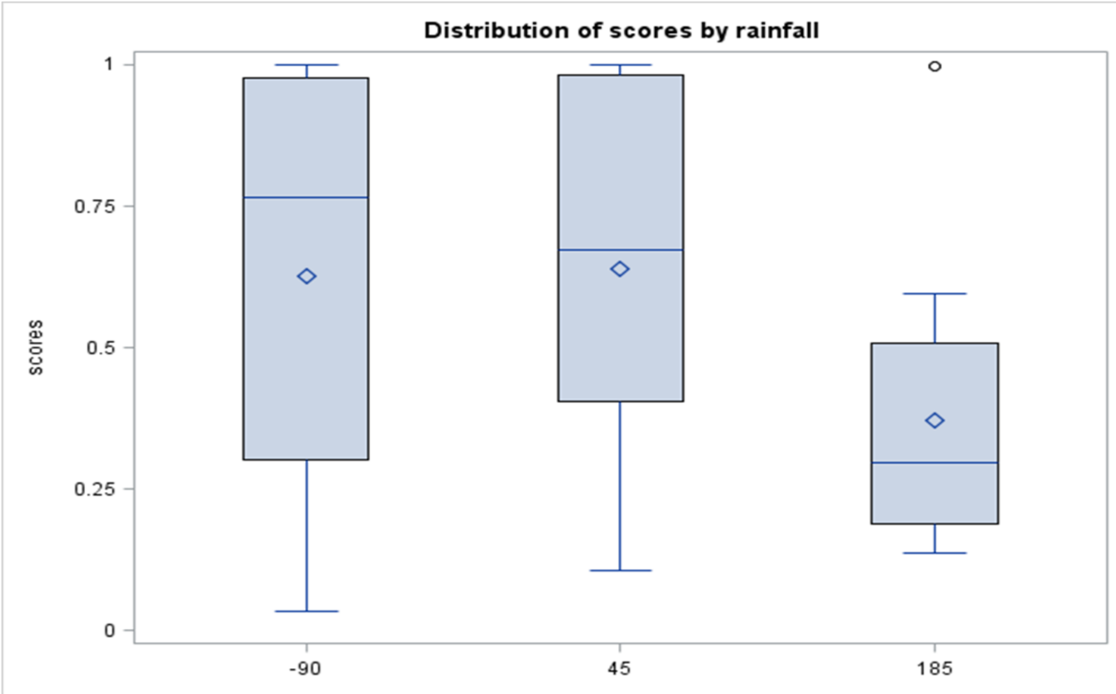

Figure 2.2. Quantile Plots of Profit Efficiency Scores by Rainfall Anomaly

Chapter 3

Impacts Of Climate Change on The U.S. Peanut and Peanut Butter Market

3.1. Introduction

Peanuts are deemed one of the healthiest foods in the world due to their richness in protein, biotin as well as other minerals and vitamins (copper, manganese, niacin, molybdenum, folate, vitamin E, phosphorus, vitamin B1)[19]. U.S. peanuts are planted in 13 states: Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, New Mexico, Oklahoma, South Carolina, Texas and Virginia since they have warm climate and sandy, well-drained chalky soils that altogether nourish the development of peanuts (National Peanut Board). Georgia is the top peanut producer with over 49% of the total production in 2016, followed by Alabama (11%) and Florida (10%) (Southern Region News Release Annual Crop Production, USDA, 2017)[20]. According to the U.S. Department of Agriculture (USDA), the United States was the world 4th largest producer and 3rd largest exporter of peanuts in 2016. Peanut production plays an important role in the agricultural economy of several states located in Southeastern and Southwestern United States (Schnepf, 2016). Peanut is the most consumed nut by Americans. In comparison with other nuts, peanut consumption per capita is extremely high. For example, in 2016 per capita consumption of peanut was 7.21 pounds, while that number of almonds, pecans, walnuts, and pistachios were 2.16, 0.42, 0.56, and 0.41 pounds, respectively (USDA) (figure 3.1).

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[19] http://www.whfoods.com/genpage.php?tname=foodspice&dbid=101

[20] https://www.nass.usda.gov/Statistics_by_State/Regional_Office/Southern/includes/Publications/Crop_Releases/Annual_Summary/2017/Annual_Crop_Prod16.pdf

As with other crops, peanut production is vulnerable to changing climate. As reported by USDA, peanut and corn producers are most impacted by climate change and weather variability[21]. Wheeler et al. (1997) and Prasad (2000) found that the short or long-term exposure to high temperatures during reproductive development causes a significant loss in peanut yield[22]. It was observed by Prasad et al. (2003) that at ambient carbon dioxide of 350 ppm, peanut seed yield decreased progressively by 14%, 59% and 90% as temperature increased from 32/22 (daytime maximum/nighttime minimum) to 36/26, 40/30 and 44/34^{0}C, respectively. A doubling of carbon dioxide (from 350 to 700 ppm) would increase pod yield of peanut by 30% on average across all temperatures. Hence, the yield increase from doubling CO_2 can merely negate the yield loss caused by a rise of 4^{0}C beyond 32/22^{0}C in temperature. The study emphasized that under the impact of global warming, peanut yield loss would occur in regions where current temperatures were close to or above the optimum. A 10% yield loss in peanut at the middle of 21th century and more than 20% at the end of the century were found in Ruane et al. (2014) when taking carbon-temperature-water change under climate change into consideration.

Moreover, it is well known that water deficit during plant development reduces peanut yield (Kambiranda et al., 2011; Balota, 2012; and Arruda et al., 2015). Drought, a deficit of rainfall over time window in a certain area, was accused of annual losses of $520 million in world peanut production (Kambiranda et al., 2011). The Oil Crops Outlook (Ash, 2017) released in January 2017 reported that although peanut acreage sown in 2016-2017 increased by nearly 3% from last year, U.S. peanut production is estimated to fall by 5% due to an extended period of dryness and high temperature in

[21] https://www.usda.gov/oce/climate_change/hubs/SoutheastFactSheet.pdf

[22] Short term is defined as a period of 1-6 days of exposure to daytime temperature between 28 and 48^{0}C.

Georgia. Global Climate Change Impacts in the U.S. 2014 report projected that the Southeast and Southwest (where peanuts are primarily grown) would suffer water shortage and heat-related stresses due to increasing air and water temperatures (Carter et al., 2014 and Garfin et al., 2014). According to the report, average annual temperature in the Southeast has increased by 2^0F and is projected to increase by 4.5^0F to 9^0F by the end of the century.

The most recent drought in 2011 resulted in a serious shortage of U.S. peanut supply, bringing a concern that peanut butter shortage may possibly come back in 2030 due to severe and widespread droughts suffered by peanut-growing states. According to USDA, peanut supply in 2012 was down by 580,000 pounds from 2011, causing a sharp increase in peanut butter price (Planter brand peanut increased by 40%, Per Pan brand increased more than 20%)[23]. A small change in supply can result in a relatively large movement in peanut and peanut product prices since demand for them are fairly inelastic (Schnepf, 2016). Peanut butter, snacks, and candy are popular types of U.S. peanut consumption as a food source. As can be seen from figure 3.2, per capita consumption of peanut butter has been the largest share and accounts for about half of total peanut consumption since 1980.

The question is what is the potential impact of changes in climate on peanut and peanut butter prices? In this study, we hope to provide some answers to the question using a two-step modelling approach. We first developed an Equilibrium Displacement Model for U.S peanut butter industry through which climate change-induced market responses may be evaluated. Changes in climate indirectly impact on peanut butter market through their direct impacts on peanut supply. To the best of my knowledge, that such impact has not been estimated. Therefore, in the second step, a translog

[23] http://money.cnn.com/2011/10/31/markets/peanut_butter_prices

restricted profit function was employed to estimate the impacts of climate variations (temperature and rainfall) on peanut supply. The translog restricted profit specification is a function of input and output prices and fixed factors which are exogenously determined. Thus, the estimation is free of possible endogeneity known in production function estimation.

The paper is organized as follows. The next section is the description of the methodology, study area, and summary statistics. Section 3 presents the results, including estimation of translog profit function and the impact of climate change on peanut supply, peanut price and peanut butter price. The final section draws a conclusion.

3.2. Methodology

The impact of climate change on peanut butter market

Following Muth (1964), the structural models for U.S. peanut butter industry with the assumption of homogeneous product, are described as:

(1)	$x = D(P_x)$	Demand function for peanut butter
(2)	$x = f(X, L)$	Production of peanut butter
(3)	$X = g(P_X, W)$	Supply function of peanut
(4)	$P_X = h(P_x) * f_X$	Demand function for peanut
(5)	$P_L = P_x * f_L$	Demand function for the bundle of marketing inputs
(6)	$L = k(P_L)$	Supply function for the bundle of marketing inputs

x is demand for peanut butter, responds to its price (P_x). As an output, x depends on main input peanut (X) and a bundle of marketing inputs (L). The production function of peanut butter is assumed to be homogeneous of degree 1: if the inputs are multiplied by t then the output (x) is multiplied by t. Equation (3) describes the supply of input factor (X) that depends on its price (P_X) and climate variable (W). The climate fluctuation indirectly affects peanut butter market through its impact on peanut supply. P_x, P_X, and P_L are peanut butter price, peanut price and price of the bundle of marketing inputs respectively. Equation (4) and (5) indicates that the input factors are paid at their marginal products. Equation 6 expresses supply of marketing inputs needed to produce peanut butter.

In the model, all exogenous variables that affect endogenous variables except climate change are suppressed. The model contains 6 endogenous variables (x, X, P_x, P_X, P_L, and L) one exogenous variable (W).

To address impacts of changes in climate on peanut supply and peanut butter industry, a set of equations in equilibrium displacement form is constructed as follows:

$$(1') \qquad x^* = \eta P_x^*$$

$$(2') \qquad x^* = S_X X^* + S_L L^*$$

$$(3') \qquad X^* = \varepsilon_X P_X^* + \varepsilon_W W^*$$

$$(4') \qquad P_X^* = \theta P_x^* - \frac{S_L}{\sigma} X^* + \frac{S_L}{\sigma} L^*$$

$$(5') \qquad P_L^* = P_x^* + \frac{S_X}{\sigma} X^* - \frac{S_X}{\sigma} L^*$$

$$(6') \qquad L^* = \varepsilon_L P_L^*$$

where the asterisked variables indicate the relative change $(x^* = dx/x)$; η is the own price elasticity of demand for peanut butter; S_X (=$XP_X/xh(P_x)$) is the peanut farmer's share of the retail dollar; S_L (=LP_L/xP_x) is the marketing inputs' share of the retail dollar; under assumption of perfect competition $S_X + S_L = 1$; ε_X and ε_L are the own-price elasticity of supply for peanut and marketing inputs, respectively; ε_W is the elasticity of climate variable with respect to peanut supply; and θ is the price transmission elasticity that links the peanut price to the peanut butter price. σ (assumed to be >0) is the elasticity of substitution between peanut and the bundle of marketing inputs.

Solving equations (1′) - (6′) to obtain the effect of climate variable on peanut butter price in reduced form

$$(7) \qquad P_x^* = \frac{S_X \varepsilon_L \varepsilon_W}{-(D)} W^*$$

where $D = \varepsilon_L \varepsilon_X(\theta S_X + S_L) + (S_L \varepsilon_L - \eta)\sigma - \eta S_X \varepsilon_L - \eta \varepsilon_X S_L$. D is positive since $\theta, S_X, S_L, \sigma, \varepsilon_L,$ and $\varepsilon_X > 0$ and $\eta < 0$. Peanut butter price will change $\frac{S_X \varepsilon_L \varepsilon_W}{-(D)}$ % in response to a 1% change in climate variable. It is obvious that the denominator in equation (7) is negative. Thus, if $\varepsilon_W > 0$ (climate change has positive effect on peanut supply), the numerator is positive since $S_X, \varepsilon_L > 0$ and therefore, the effect of climate variable on the peanut butter price is negative. Inversely, if $\varepsilon_W < 0$ (climate change has negative effect on peanut supply), the sign of the effect is positive. The underlying economic reason is that if an increase in climate variable shifts peanut supply outward, peanut butter supply will increase since production function of peanut butter has a positive slope. A rise in supply of peanut butter will result in a decrease in its price.

The impact of climate change on peanut supply

Translog restricted profit function is utilized to facilitate the examination of climate change impact on peanut supply. The profit function is empirically expressed as follows:

(8)

$$\ln \pi = \alpha_0 + \sum_{i}^{4} \alpha_i \ln P_i$$

$$+ \frac{1}{2}\sum_{i}^{4}\sum_{j}^{4} \alpha_{ij} \ln P_i \ln P_j + \sum_{i}^{4}\sum_{k}^{4} \beta_{ik} \ln P_i \ln Z_k$$

$$+ \frac{1}{2}\sum_{k}^{4}\sum_{h}^{4} \gamma_{kh} \ln Z_k \ln Z_h + \sum_{k}^{4} \gamma_k \ln Z_k + \ g * D + \ l * T + m * IRRI$$

$$+ \varepsilon$$

where π is the restricted peanut profit (here defined as total revenue less total variable cost), P_i is the output and input prices for which i = 1: output price, 2: seed price, 3: fertilizer price, 4: chemical price; Z_k is the fixed input factor for which k = 1: average maximum temperature during the peanut development, 2: average maximum temperature during the harvesting period, 3: rainfall during the planting period, 4: rainfall during the harvesting period; D is the variable for states; T is time trend which controls for technological change; $IRRI$ is the dummy variable for irrigation; all other expressions are parameters to be estimated. Restrictions are imposed on the parameters that ensure homogeneity and symmetry with respect to both fixed factors and prices:

(9a) $\alpha_{ij} = \alpha_{ji}$ and $\gamma_{kh} = \gamma_{hk}$ $\quad \forall\, i,j \quad i \neq j$ and $\forall\, k,h \quad k \neq h$

(9b) $\sum_j \alpha_{ij} = \sum_k \beta_{ik} = 0$

(9c) $\sum_i \alpha_i = \sum_k \gamma_k = 1$ and $\sum_i \alpha_{ij} = \sum_i \beta_{ik} = \sum_k \gamma_{kh} = 0$

Hotelling's lemma permits the share equations to be expressed as follows:

(10) $$S_i = \frac{P_i q_i}{\pi} = \frac{P_i}{\pi}\frac{\partial \pi\ (p,z)}{\partial P_i} = \frac{\partial ln\pi}{\partial lnP_i}$$

The equation for output share (S_1) is given by:

(10a) $$S_1 = \alpha_1 + \sum_{j=1}^{4} \alpha_{1j}\, lnP_j + \sum_{k=1}^{4} \beta_{1k}\, lnZ_k$$

and the equations for input shares (S_2, S_3, S_4) are:

(10b) $$-S_i = \alpha_i + \sum_{j=1}^{4} \alpha_{ij}\, lnP_j + \sum_{k=1}^{4} \beta_{ik}\, lnZ_k \qquad (i = 2,3)$$

Since $S_1 - S_2 - S_3 - S_4 = 1$, one of the share equations, the output share S_1, is dropped during estimation to avoid singularity in the variance-covariance matrix. The coefficients of the output share equation are recovered using restrictions mentioned above. The restricted profit function and two share equations are jointly estimated using seemingly unrelated regression (SUR). Input demand and supply elasticities with respect to climate factors are expressed in equations (11)-(14):

Elasticities of demand for seed with respect to average maximum temperature during peanut development (η_{21}), average maximum harvesting temperature (η_{22}), planting rainfall (η_{23}), and harvesting rainfall (η_{24}):

(11) $$\eta_{2k} = \sum_{i=1}^{4} \beta_{ik}\, lnP_i + \sum_{h=1}^{4} \gamma_{kh}\, ln\, Z_h + \gamma_k - \frac{\beta_{2k}}{S_k} \qquad (k = 1,2,3,4)$$

Elasticities of demand for fertilizer with respect to average maximum temperature during peanut development (η_{31}), average maximum harvesting temperature (η_{32}), planting rainfall (η_{33}), and harvesting rainfall (η_{34}).

(12) $$\eta_{3k} = \sum_{i=1}^{4} \beta_{ik}\, lnP_i + \sum_{h=1}^{4} \gamma_{kh}\, ln\, Z_h + \gamma_k - \frac{\beta_{3k}}{S_k} \qquad (k = 1,2,3,4)$$

Elasticities of demand for chemicals with respect to average maximum temperature during peanut development (η_{41}), average maximum harvesting temperature (η_{42}), planting rainfall (η_{43}), and harvesting rainfall (η_{44}).

$$\eta_{4k} = \sum_{i=1}^{4} \beta_{ik}\, lnP_i + \sum_{h=1}^{4} \gamma_{kh}\, ln\, Z_h + \gamma_k - \frac{\beta_{4k}}{S_k} \qquad (k = 1,2,3,4) \tag{13}$$

Supply elasticities with respect to average maximum temperature during peanut development (ε_{11}), average maximum harvesting temperature (ε_{12}), planting rainfall (ε_{13}), and harvesting rainfall (ε_{14}).

$$\varepsilon_{1k} = \sum_{i=1}^{4} \beta_{ik}\, lnP_i + \sum_{h=1}^{4} \gamma_{kh}\, ln\, Z_h + \gamma_k - \frac{\beta_{2k} + \beta_{3k} + \beta_{4k}}{1 + S_2 + S_3 + S_4} \qquad (k = 1,2,3,4) \tag{14}$$

Study areas

According to the National Peanut Board, six states including Alabama, Florida, Georgia, North Carolina, Texas, and Virginia grow nearly all of the U.S. peanut. They all together produced 89%, 92%, and 88% of total peanut production in the United States in 2014, 2015 and 2016 respectively. In terms of area planted, they account for 88%, 89%, and 88% of total peanut area planted in 2014, 2015 and 2016 respectively. Georgia is the leading peanut producer with 47%, 56%, and 49% of the total production in 2014, 2015, and 2016 respectively, followed by Alabama and Florida (USDA). Then, six states above were chosen in the study. They are located in the Southern part of the United States.

Summary statistic

Table 3.1 presents the summary statistics of the variables used in the profit function model. State-level data (1980 – 2016) on peanut price, seed price, fertilizer price, and chemical price are obtained from the United States Department of

Agriculture[24]. Among these major inputs, expenditure for chemicals ($105.08/ ha) accounts for the largest share of total input cost, followed by seed ($85.83/ ha) and fertilizer ($59.36/ ha). Temperature and rainfall data by states are collected from National Oceanic and Atmospheric Administration[25]. The state-level planting and harvesting dates for peanut particularly and other crops in general are calculated based on 20 years of historical crop progress estimates (USDA). Therefore, two planting and harvesting calendars for peanuts are used in this study (1982-1996 and 1997-2016) to compute the average maximum temperature during plant development, average maximum temperature during the harvesting period, rainfall during the planting period, and rainfall during the harvesting period. Peanut in the study area is primarily grown in May and harvested in October. As shown in table 3.1, average maximum temperature during the development of peanut is about 7^0F higher than that during the harvesting period and rainfall during the planting period is higher than that during the harvesting period.

3.3. Results

Translog profit function estimation

Table 3.2 displays estimates of translog restricted profit function jointly estimated with three variable input (seed, fertilizer, and chemical) share equations. 48 parameters were estimated, 24 of them are statistically significant at 10% level at least in the profit function. The statistical significance of coefficients for interaction terms demonstrates the fitness of the translog function.

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[24] https://www.ers.usda.gov/data-products/commodity-costs-and-returns/commodity-costs-and-returns/#Recent%20Costs%20and%20Returns:%20Peanuts

[25] https://www.ncdc.noaa.gov/cag/statewide/time-series/5/tavg/p12/1/1975-2016?base_prd=true&firstbaseyear=1901&lastbaseyear=2000

Impacts of temperature and rainfall on peanuts supply and input demands

Table 3.3 details elasticities of input demand (seed, fertilizer, and chemical) and output supply (peanut). Forty elasticities were computed based on the parameters estimated from the profit function. More than 50% of them (21/40) are significantly different from 0 at 10% level at least. As expected, all own-price elasticities for demand of three input variables were negative. Two of them were statistically significant.

Three out of four climate variables, average maximum temperature during the plant development, average maximum temperature during the harvesting period and rainfall during the harvesting period had a significant effect on peanut supply. The response of peanut supply to changes in average maximum temperature during the peanut development is highest.

Average maximum temperature during the plant development and rainfall during the harvesting period negatively impacted on peanut supply. Whereas, the effect of average maximum temperature during the harvesting period on peanut supply was positive. Peanut supply will decrease by 9.91% in response to a rise of 1% in average maximum temperature during the plant development. This negative effect was also found in Wheeler et al. (1997), Prasad (2000), Prasad et al. (2013), and Ruane et al. (2014). On the other hand, an increase of 1% in average maximum temperature during the harvesting period will raise the peanut supply by 4.99%. The reason is that average maximum temperature during the development of peanut is 83 ^{0}F and about 7^{0}F higher than that during the harvesting period (table 3.1). Highest maximum temperature during peanut development was 90.21^{0}F while the optimum temperature for peanut development is 86^{0}F[26]. Further, Wheeler et al. (1997) and Prasad (2000) emphasized

[26] http://agropedia.iitk.ac.in/content/climatic-requirements-groundnut-cultivation

that 1-6 days of exposure to daytime temperature between 82.4^{0}F and 118.4^{0}F during reproductive development of peanut causes a significant loss in peanut yield.

Like other crops, rainfall plays an important role in peanut development. However, according to NOAA, rain should taper off by harvesting season, or peanut pods can't be easily pulled out of the ground. In this study, the result shows that an increase of 1% of rainfall during the harvesting period may reduce peanut supply by 0.32%.

Impacts of temperature and rainfall on peanut price and peanut butter price

As reported in the estimation above, the climate variables affecting peanut supply are W_1- average maximum temperature during the plant development, W_2- average maximum temperature during the harvesting period, and W_4- rainfall during the harvesting period. Thus, the equation $(3')$ becomes

$$(3'') \qquad X^* = \varepsilon_X P_X^* + \varepsilon_{11} W_1^* + \varepsilon_{12} W_2^* + \varepsilon_{14} W_4^*$$

where ε_{11}, ε_{12}, and ε_{14} are the elasticities of average maximum temperature during the plant development, average maximum temperature during the harvesting period, and rainfall during the harvesting period with respect to peanut supply respectively.

In order to determine the impacts of climate change on peanut price and peanut butter price, equations $(1')$, $(2')$, $(3'')$, $(4')$, $(5')$ and $(6')$ were simulated. The values of ε_{11}, ε_{12}, and ε_{14} were taken from the estimations above. As estimated in Zhang et. al (1995), the price transmission elasticity, defined as the percentage change in the peanut butter price in response to a 1% change in the price of peanut, is 0.16 in the long run or $\frac{P_x^*}{P_X^*} = \frac{1}{\theta} = 0.16 \rightarrow \theta = \frac{1}{0.16} = 6.25$. The value of the peanut framer's share of the retail dollar, $S_X = 0.67$, is 2010-2016 mean value computed based on the data obtained from USDA. The own price elasticity of demand for peanut butter (η) is -0.2 taken from Beghin and

Matthey (2003). And the value of the long-run price elasticity of peanut supply (ε_X) is 2 obtained from Schmitz and Schmitz (2010). Like wheat in the example of Gardner (1975), peanut is a specific factor to the peanut butter production while other inputs are not and peanut is land-intensive, it seems likely that $\varepsilon_X < \varepsilon_L$. Thus, ε_L is assigned to be 3 in this paper.

Gardner (1975) mentioned that the opportunity of substitution between farm-based input and marketing inputs is limited, implying a small value of σ. In food industry, Wohlgenant (1989) found that the elasticity of substitution between farm output and marketing inputs in beef and veal, pork, eggs, dairy, and fresh vegetables are 0.72, 0.35, 0.25, 0.96, and 0.54, respectively. Hence, in this paper, σ is assigned to be equal 0.01. All parameter used for simulation are presented in table 3.4.

The results from the simulation are presented in table 3.5. An increase of 1% in average maximum temperature during the plant development may raise the peanut price by 4.88% and peanut butter price by 0.72%, and therefore, equilibrium quantity of peanut butter may drop about 0.14%. The adverse effect of rainfall during the harvesting period on peanut supply also causes a modest increase in peanut butter price. In detail, peanut price and peanut butter price will increase 0.16% and 0.02% respectively in response to an increase of 1% in rainfall during the harvesting period. Thus, equilibrium quantity of peanut butter will fall by 0.005%. On the other hand, 1% increase in average maximum temperature during the harvesting period may reduce peanut price by 2.46% and peanut butter price by 0.36%. As a result, equilibrium quantity of peanut butter will increase by 0.07%.

The impact of climate change on peanut and peanut butter market could be worse since there is a change in precipitation pattern reported by U.S. Global Change

Research program[27]. According to the report, total precipitation has been increasing by a small amount, but significantly changing in pattern. Rainfall increases substantially in Autumn (when peanut is harvested and it is indicated in the results that rainfall during the harvesting period has a negative effect on peanut supply) and falls sharply for the rest of the year in the Southeast. These changes cause the possibility of flood as well as drought in Spring and Summer when peanut is at its developing period.

3.4. Conclusion

This is the first paper evaluating impact of climate change on peanut and peanut butter market. An Equilibrium Displacement Model for U.S. peanut butter industry was developed to address how changes in climate variables affect peanut butter price as well as demand for peanut butter. Peanut is the fundamental ingredient to produce peanut butter. Then, in the next step, a translog profit function was employed to evaluate the impacts of climate changes on peanut supply.

The results suggested that average maximum temperature during peanut development and rainfall during the harvesting period are tied to peanut supply reduction. Such that reduction causes peanut price and peanut butter price to increase. An increase of 1% in average maximum temperature may raise peanut price and peanut butter price by 4.88% and 0.72% respectively, resulting in a fall of 0.14% in demand for peanut butter. Rainfall during the harvesting period has a modest effect on peanut and peanut butter market. Peanut price and peanut butter price may increase by 0.16% and 0.02% respectively in response to 1% increase in rainfall during the harvesting period. On the other hand, average maximum temperature during the harvesting period has a positive effect on peanut supply. This effect brings a fall in peanut price and

[27] https://nca2009.globalchange.gov/southeast/index.html

peanut butter price. 1% increase in average maximum temperature during the harvesting period may reduce peanut price and peanut butter price by 2.46% and 0.36% respectively, causing demand for peanut butter to increase 0.07%.

Table 3.1. Description, Measure and Summary Statistics of the Variables.

Variables	Description	Measurement	Mean	Std Dev	Min	Max
$\boldsymbol{\pi}$	Restricted profit	Dollars	1.1E+08	1.1E+08	1.6E+06	7.0E+08
$\boldsymbol{P_1}$	Peanut price	Dollars/lb	0.26	0.05	0.16	0.43
$\boldsymbol{P_2}$	Seed price	Dollars/ha	85.83	21.53	42.57	140.33
$\boldsymbol{P_3}$	Fertilizer price	Dollars/ha	59.36	34.13	16.07	167.02
$\boldsymbol{P_4}$	Chemicals price	Dollars/ha	105.08	35.08	33.92	164.34
$\boldsymbol{Z_1}$	Average max temperature during plant development	Fahrenheit	83.65	3.10	76.10	90.21
$\boldsymbol{Z_2}$	Average max temperature during the harvesting period	Fahrenheit	76.37	6.69	62.70	88.45
$\boldsymbol{Z_3}$	Rainfall during the planting period	Inches	3.67	1.64	0.40	9.57
$\boldsymbol{Z_4}$	Rainfall during the harvesting period	Inches	3.29	1.64	0.08	9.30
$\boldsymbol{T}$	Time trend	Number	18.00	10.33	1.00	35.00
$\boldsymbol{D}$	States	Indexed (1 = Alabama; 2 = Florida; 3 = Georgia; 4 = North Carolina; 5 = Texas; 6 = Virginia)	3.57	1.72	1.00	6.00
$\boldsymbol{IRRI}$	Irrigation	Indexed (1 = irrigated; 0 = dryland)	0.17	0.38	0.00	1.00

Table 3.2. Parameter Estimates of the Restricted Profit Function and Share Equations.

Variables	Parameters	Coefficients	t ratios
Profit function			
Constant	α_0	-2257.8600	-2.89***
$ln\,P_P$	α_1	107.4420	3.32***
$ln\,P_S$	α_2	3.8651	3.39***
$ln\,P_F$	α_3	2.4034	1.12
$ln\,P_C$	α_4	5.1072	3.58***
$\frac{1}{2}(ln\,P_P \times ln\,P_P)$	α_{11}	1.7598	0.81
$ln\,P_P \times ln\,P_S$	α_{12}	0.3164	6.41***
$ln\,P_P \times ln\,P_F$	α_{13}	0.2311	2.84***
$ln\,P_P \times ln\,P_C$	α_{14}	0.4364	7.02***
$\frac{1}{2}(ln\,P_S \times ln\,P_S)$	α_{22}	-0.2192	-8.23***
$ln\,P_S \times ln\,P_F$	α_{23}	0.0142	1.11
$ln\,P_S \times ln\,P_C$	α_{24}	-0.0250	-1.57
$\frac{1}{2}(ln\,P_F \times ln\,P_F)$	α_{33}	-0.1553	-8.77***
$ln\,P_F \times ln\,P_C$	α_{34}	-0.0066	-0.50
$\frac{1}{2}(ln\,P_C \times ln\,P_C)$	α_{44}	-0.2222	-9.26***
$ln\,P_P \times ln\,Z_{Tav}$	β_{11}	-22.2882	-2.87***
$ln\,P_P \times ln\,Z_{Tha}$	β_{12}	-1.7950	-0.58
$ln\,P_P \times ln\,Z_{Rpl}$	β_{13}	-0.3497	-0.72
$ln\,P_P \times ln\,Z_{Rha}$	β_{14}	-0.5901	-2.00**
$ln\,P_S \times ln\,Z_{Tav}$	β_{21}	-0.8876	-3.01***
$ln\,P_S \times ln\,Z_{Tha}$	β_{22}	0.3070	2.39**
$ln\,P_S \times ln\,Z_{Rpl}$	β_{23}	0.0007	0.04
$ln\,P_S \times ln\,Z_{Rha}$	β_{24}	-0.0195	-1.62
$ln\,P_F \times ln\,Z_{Tav}$	β_{31}	-0.6054	-1.22
$ln\,P_F \times ln\,Z_{Tha}$	β_{32}	0.2395	1.20
$ln\,P_F \times ln\,Z_{Rpl}$	β_{33}	0.0012	0.04
$ln\,P_F \times ln\,Z_{Rha}$	β_{34}	-0.0175	-1.05
$ln\,P_C \times ln\,Z_{Tav}$	β_{41}	-1.2942	-3.64***
$ln\,P_C \times ln\,Z_{Tha}$	β_{42}	0.4881	3.64***
$ln\,P_C \times ln\,Z_{Rpl}$	β_{43}	0.0088	0.35
$ln\,P_C \times ln\,Z_{Rha}$	β_{44}	-0.0231	-1.60
$ln\,Z_{Tav}$	γ_1	737.7969	1.98**
$ln\,Z_{Tha}$	γ_2	324.1788	2.11**
$ln\,Z_{Rpl}$	γ_3	1.9224	0.15
$ln\,Z_{Rha}$	γ_4	6.6476	1.19
$\frac{1}{2}(ln\,Z_{Tav} \times ln\,Z_{Tav})$	γ_{11}	-42.3488	-0.41
$ln\,Z_{Tav} \times ln\,Z_{Tha}$	γ_{12}	-133.9070	-3.45***

Table 3.2. Parameter Estimates of the Restricted Profit Function and Share Equations. *(Continued)*

Variables	Parameters	Coefficients	t ratios
$ln\, Z_{Tav} \times ln\, Z_{Rpl}$	γ_{13}	-0.3106	-0.08
$ln\, Z_{Tav} \times ln\, Z_{Rha}$	γ_{14}	0.8547	0.45
$\frac{1}{2}(ln\, Z_{Tha} \times ln\, Z_{Tha})$	γ_{22}	62.3862	2.62***
$ln\, Z_{Tha} \times ln\, Z_{Rpl}$	γ_{23}	-0.2114	-0.12
$ln\, Z_{Tha} \times ln\, Z_{Rha}$	γ_{24}	-2.5844	-2.33**
$\frac{1}{2}(ln\, Z_{Rpl} \times ln\, Z_{Rpl})$	γ_{33}	-0.2479	-1.02
$ln\, Z_{Rpl} \times ln\, Z_{Rha}$	γ_{34}	0.0719	0.43
$\frac{1}{2}(ln\, Z_{Rha} \times ln\, Z_{Rha})$	γ_{44}	-0.1786	-2.47**
D	g	-0.1787	-1.85*
T	l	0.0052	1.03
$IRRI$	m	0.6611	1.69*
Seed share equation			
Constant	α_2	3.8651	3.39***
$ln\, P_P$	α_{12}	0.3163	6.41***
$ln\, P_S$	α_{22}	-0.2192	-8.23***
$ln\, P_F$	α_{23}	0.0142	1.11
$ln\, P_C$	α_{24}	-0.0250	-1.57
$ln\, Z_{Tav}$	β_{21}	-0.8877	-3.01***
$ln\, Z_{Tha}$	β_{22}	0.3070	2.39**
$ln\, Z_{Rpl}$	β_{23}	0.0007	0.04
$ln\, Z_{Rha}$	β_{24}	-0.0195	-1.62
Fertilizer share equation			
Constant	α_3	2.4034	1.12
$ln\, P_P$	α_{13}	0.2311	2.84***
$ln\, P_S$	α_{23}	0.0142	1.11
$ln\, P_F$	α_{33}	-0.1553	-8.77***
$ln\, P_C$	α_{34}	-0.0066	-0.50
$ln\, Z_{Tav}$	β_{31}	-0.6054	-1.22
$ln\, Z_{Tha}$	β_{32}	0.2395	1.20
$ln\, Z_{Rpl}$	β_{33}	0.0012	0.04
$ln\, Z_{Rha}$	β_{34}	-0.0175	-1.05
Chemicals share equation			
Constant	α_4	5.1072	3.58***
$ln\, P_P$	α_{14}	0.4364	7.02***
$ln\, P_S$	α_{24}	-0.0250	-1.57
$ln\, P_F$	α_{34}	-0.0066	-0.50
$ln\, P_C$	α_{44}	-0.2222	-9.26***
$ln\, Z_{Tav}$	β_{41}	-1.2942	-3.64***
$ln\, Z_{Tha}$	β_{42}	0.4881	3.64***

Table 3.2. Parameter estimates of the restricted profit function and share equations. *(Continued)*

Variables	Parameters	Coefficients	t ratios
$ln\, Z_{Rpl}$	β_{43}	0.0088	0.35
$ln\, Z_{Rha}$	β_{44}	-0.0231	-1.60
Observations		201	

Note: P_i= output and input prices, and Z_k = fixed inputs; subscripts P peanut price, S = seed price, F = fertilizer price, C = chemicals price, Tav = average temperature during the peanut development, Tha= average temperature during the harvesting period, Rpl = rainfall during the planting period, and Rha = rainfall during the harvesting period

* Significant at 10% level ($p < .10$).

** Significant at 5% level ($p < .05$).

*** Significant at 1% level ($p < .01$).

Table 3.3. Estimated Elasticities of Translog Profit Function

	Peanut price	Seed price	Fertilizer price	Chemicals price	Average max temperature during the plant development	Average max temperature during the harvesting period	Rainfall during the planting period	Rainfall during the harvesting period
Peanut supply	0.0	-0.08	-0.06	-0.12	-9.91	4.99	-0.09	-0.32
	(0.5)	(-4.03)***	(-3.21)***	(-5.47)***	(-3.36)**	(4.43)***	(-0.71)	(-3.46)***
Seed demand	0.2	-0.21	-0.22	-0.16	-7.53	4.21	-0.08	-0.26
	(0.87)	(-1.74)*	(-3.73)***	(-2.22)**	(-1.67)*	(3.14)***	(-0.55)	(-2.34)**
Fertilizer demand	0.15	-0.31	-0.15	-0.23	-7.67	4.07	-0.09	-0.24
	(0.28)	(-3.73)***	(-1.26)	(-2.75)***	(-1.38)	(2.76)***	(-0.39)	(-1.73)*
Chemicals demand	0.07	-0.13	-0.13	-0.48	-6.93	3.86	-0.11	-0.27
	(0.33)	(-2.22)**	(-2.75)***	(-5.48)***	(-1.54)	(2.94)***	(-0.73)	(-2.44)**

Note: Elasticity estimates computed at mean values. Figures in parentheses are *t* ratios.

* Significant at 10% level ($p < .10$).

** Significant at 5% level ($p < .05$).

*** Significant at 1% level ($p < .01$).

Table 3.4. Definitions and Baseline Values of Parameters for Simulation.

Parameters	Definitions	Values	Sources
$\boldsymbol{\eta}$	Own price elasticity of demand for peanut butter	-0.2	Beghin and Matthey (2003)
$\boldsymbol{\varepsilon_X}$	Price elasticity of peanut supply	2	Schmitz and Schmitz (2010)
$\boldsymbol{\varepsilon_L}$	Price elasticity of marketing input supply	3	
$\boldsymbol{\varepsilon_{11}}$	Elasticity of average maximum temperature during peanut development w.r.t. peanut supply	-9.91	Estimated in the study
$\boldsymbol{\varepsilon_{12}}$	Elasticity of average maximum temperature during harvesting period w.r.t. peanut supply	4.99	Estimated in the study
$\boldsymbol{\varepsilon_{14}}$	Elasticity of rainfall during harvesting period w.r.t. peanut supply	-0.32	Estimated in the study
$\boldsymbol{S_X}$	Peanut framer's share of the retail dollar	0.67	Computed based on the data from USDA
$\boldsymbol{S_L}$	Marketing inputs' share of the retail dollar	0.33	
$\boldsymbol{\theta}$	Price transmission elasticity that links the peanut price to the peanut butter price	6.25	Computed based on Zhang et. al (1995)
$\boldsymbol{\sigma}$	Elasticity of substitution between farm_based input and marketing inputs	0.01	

Table 3.5. The Impact of Climate Change on Peanut and Peanut Butter Market

	Average max temperature during the peanut development	Average max temperature during the harvesting period	Rainfall during the harvesting period
Peanut butter demand	-0.144	0.073	-0.005
Peanut supply	-0.147	0.074	-0.005
Peanut butter price	0.721	-0.363	0.023
Peanut price	4.881	-2.458	0.158

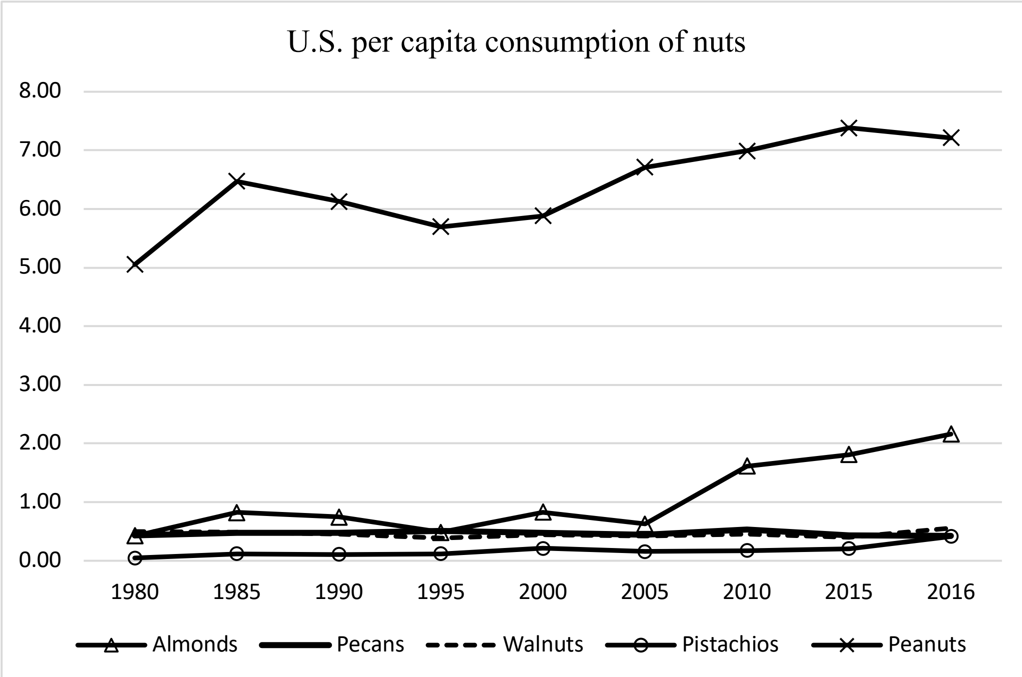

Figure 3.1. U.S. Per Capita Consumption of Nuts

Source: USDA

https://www.ers.usda.gov/data-products/food-availability-per-capita-data-system/

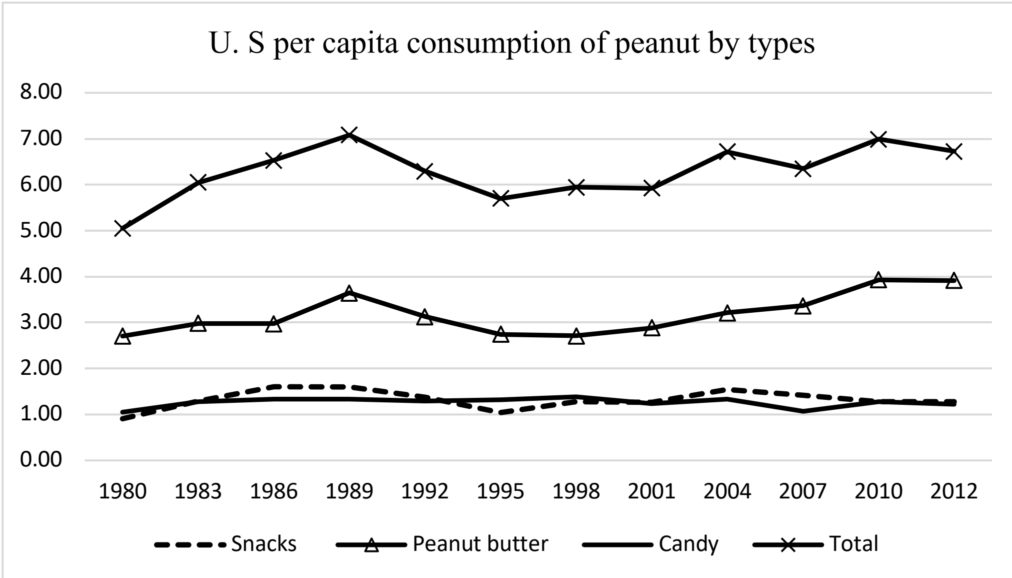

Figure 3.2. U.S. Per Capita Consumption of Peanut by Types

Source: USDA

https://www.ers.usda.gov/data-products/food-availability-per-capita-data-system/

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Appendix

Mathematical derivations for equation (1′) – (6′)

(1) $x = D(P_x)$

$$dx = \frac{\partial x}{\partial P_x} dP_x$$

$$\frac{dx}{x} = \frac{\partial x}{\partial P_x}\frac{dP_x}{x} = \frac{\partial x}{\partial P_x}\frac{P_x}{x}\frac{dP_x}{P_x} = \frac{\frac{\partial x}{x}}{\frac{\partial P_x}{P_x}}\frac{dP_x}{P_x}$$

(1′) $x^* = \eta P_x^*$

(2) $x = f(X, L)$

$dx = f_X dX + f_L dL$ from (4) we have $P_X = h(P_x) * f_X$ or $f_X = \frac{P_X}{h(P_x)}$

from (5) we have $P_L = P_x * f_L$ or $f_L = \frac{P_L}{P_x}$

$$\frac{dx}{x} = \frac{P_X}{h(P_x)}\frac{dX}{x} + \frac{P_L}{P_x}\frac{dL}{x} = \frac{P_X}{h(P_x)}\frac{X}{x}\frac{dX}{X} + \frac{P_L}{P_x}\frac{L}{x}\frac{dL}{L}$$

(2′) $x^* = S_X X^* + S_L L^*$ where $S_X = \frac{P_X}{h(P_x)}\frac{X}{x}$ and $S_L = \frac{P_L}{P_x}\frac{L}{x}$

(3) $X = g(P_X, W_1, W_2, W_3)$

$$dX = \frac{\partial X}{\partial P_X} dP_X + \frac{\partial X}{\partial W_1} dW_1 + \frac{\partial X}{\partial W_2} dW_2 + \frac{\partial X}{\partial W_3} dW_3$$

$$\frac{dX}{X} = \frac{\partial X}{\partial P_X}\frac{P_X}{X}\frac{dP_X}{P_X} + \frac{\partial X}{\partial W_1}\frac{W_1}{X}\frac{dW_1}{W_1} + \frac{\partial X}{\partial W_2}\frac{W_2}{X}\frac{dW_2}{W_2} + \frac{\partial X}{\partial W_3}\frac{W_3}{X}\frac{dW_3}{W_3}$$

(3′) $X^* = \varepsilon_X P_X^* + \varepsilon_1 W_1^* + \varepsilon_2 W_2^* + \varepsilon_3 W_3^*$

(4) $P_X = h(P_x) * f_X$

$$dP_X = f_X * dh(P_x) + h(P_x) * df_X$$

$$\frac{dP_X}{P_X} = f_X * \frac{dh(P_x)}{h(P_x)}\frac{h(P_x)}{P_X} + \frac{h(P_x)}{P_X}\frac{df_X}{f_X} * f_X$$

$$\frac{dP_X}{P_X} = \frac{P_X}{h(P_x)}\frac{dh(P_x)}{h(P_x)}\frac{h(P_x)}{P_X} + \frac{h(P_x)}{P_X} * \frac{df_X}{f_X} * \frac{P_X}{h(P_x)} \text{ since } P_X = h(P_x) * f_X \rightarrow f_X = \frac{P_X}{h(P_x)}$$

$$P_X^* = h(P_x)^* + f_X{}^*$$

$$h(P_x)^* = \frac{dh(P_x)}{h(P_x)} = \frac{\partial h}{\partial P_x}\frac{dP_x}{h} = \frac{\partial h}{\partial P_x}\frac{P_x}{h}\frac{dP_x}{P_x} = \theta P_x^*$$

$$f_X{}^* = \frac{df_X}{f_X} = \frac{f_{XX}*dX + f_{XL}*dL}{f_X} = \frac{f_{XX}}{f_X} * dX + \frac{f_{XL}}{f_X} * dL$$

$$f_X{}^* = \frac{Xf_{XX}}{f_X} * \frac{dX}{X} + \frac{Lf_{XL}}{f_X} * \frac{dL}{L} = \frac{Xf_{XX}}{f_X}X^* + \frac{Lf_{XL}}{f_X}L^*$$

since $f(X)$ is homogeneous of degree 1, f_X is homogeneous of degree 0. By Euler's theorem $\frac{Xf_{XX}}{f_X} + \frac{Lf_{XL}}{f_X} = 0 \rightarrow \frac{Xf_{XX}}{f_X} = -\frac{Lf_{XL}}{f_X}$

then

$$P_X^* = \theta P_x^* + \frac{Lf_{XL}}{f_X}(L^* - X^*)$$

Noting that, elasticity of substitution between 2 inputs, $\sigma = \frac{f_X f_L}{xf_{XL}}$

$$\rightarrow f_{XL} = \frac{f_X f_L}{x\,\sigma}$$

$$P_X^* = \theta P_x^* + \frac{Lf_X f_L}{x\,\sigma f_X}(L^* - X^*) = \theta P_x^* + \frac{Lf_L}{x\,\sigma}(L^* - X^*) = \theta P_x^* + \frac{LP_L}{x\,\sigma P_x}(L^* - X^*) \qquad (4') \qquad P_X^* = \theta P_x^* + \frac{S_L}{\sigma}(L^* - X^*)$$

(5) $\quad P_L = P_x * f_L$

$$dP_L = f_L * dP_x + P_x * df_L$$

$$\frac{dP_L}{P_L} = f_L * \frac{dP_x}{P_x}\frac{P_x}{P_L} + \frac{P_x}{P_L}\frac{df_L}{f_L} * f_L$$

$$\frac{dP_L}{P_L} = \frac{P_L}{P_x} * \frac{dP_x}{P_x}\frac{P_x}{P_L} + \frac{P_x}{P_L}\frac{df_L}{f_L} * \frac{P_L}{P_x} \text{ since } P_L = P_x * f_L \rightarrow f_L = \frac{P_L}{P_x}$$

$$P_L^* = P_x{}^* + f_L{}^*$$

$$f_L{}^* = \frac{df_L}{f_L} = \frac{dLf_{LL} + dXf_{LX}}{f_L} = \frac{dLf_{LL}}{Lf_L}L + \frac{dXf_{LX}}{Xf_L}X = \frac{Lf_{LL}}{f_L}L^* + \frac{Xf_{LX}}{f_L}X^*$$

Following steps described in equation 4, we get

$$(5') \qquad P_L^* = P_x^* + \frac{S_X}{\sigma}(X^* - L^*)$$

$$(6) \qquad L = k(P_L)$$

$$dL = \frac{\partial L}{\partial P_L} dP_L$$

$$\frac{dL}{L} = \frac{\partial L}{\partial P_L}\frac{dP_L}{L} = \frac{\partial L}{\partial P_L}\frac{P_L}{L}\frac{dP_L}{P_L} = \frac{\frac{\partial L}{L}}{\frac{\partial P_L}{P_L}}\frac{dP_L}{P_L}$$

$$(6') \qquad L^* = \varepsilon_L P_L^*$$