Weather Derivatives as Risk Management Tool in Ecuador:

A Case Study of Rice Production

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Introduction

Rice is one of the largest cereal crops in Ecuador. It is cultivated on the coast and employs 11% of labor force in agriculture. The provinces of Guayas and Los Rios produce 47% and 40%, respectively of the Ecuador total production of rice. Together these two provinces account for 83% of hectares planted with rice.

According to the 2000 Census, 45% of the production units (UPA[1]) that are dedicated to rice production have at most 5 hectares, and 75% of the UPA's are small producers with less than 20 hectares.

Ecuador exports rice mainly to Colombia, Peru and Venezuela. The volume of the rice trade does not exhibit a sustained trend over time. Rather, it depends on domestic supply, domestic producer price paid relative to exports, the supply situation in neighboring countries, and formal and informal current regulations at the northern and southern borders regarding the trade of rice.

The existing price support policy contributes to distortions in Ecuadorian rice market. In 2009, the government of Ecuador signed the ministerial agreement No.0071 with the rice producers, which established a price support for rice at USD 28 per a 200-pound bag. The policy is used to guarantee a minimum price in case of overproduction, with the government buying excess rice in order to keep the price at the established level. A government agency — Unidad Nacional de Almacenamiento[2] (UNA) — was created to provide a nationwide network of grain storage that would meet the domestic requirements and also serve as a resource in times of surplus production in order to supply international markets.

However, small farmers do not always benefit from this policy. When the government purchases rice due to overproduction, the producers must bring their production to UNA in order to receive the support price. Small farmers usually do not have access to the infrastructure to bring their rice to the storage units. Thus, they lose the opportunity to receive the price at the support level. On the other hand, the farmers borrow money to cover their planting cost. Intermediaries who lend them money then buy small farmers' production at a lower price than the price support.

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[1] UPA stands for Unidad Productiva Agropecuaria (Agricultural Production Unit).

[2] National Storage Unit

There are other threats to small farmers' well-being. The extreme weather often affects rice yields in Ecuador. During the winter season (February and March) excessive rains could affect the growth of the plant. When El Niño occurs rains become more intensive. On the other hand, low temperatures are primary concerns during the summer season (August and September), especially with La Niña.

Agronomists have observed evidence of relationship between low rice yield and El Niño events. Figure 1[3] shows that both cereal GDP and Agricultural GDP[4] fell as a result of El Niño in 1998. In the years preceding the 1998 El Niño, cereals represented 13.1% of the total agricultural GDP, while after the El Niño, they only contributed 9.56%. This is just one example of how extreme weather event could push rural and smallholder farm households into a cycle of poverty (Skees, 2008), especially when they have poor access to infrastructure.

Since Ecuador lacks both the traditional crop insurance and general insurance markets, weather derivatives, if appropriately designed, could be used as risk management tools for rice production.

Literature Review

In the last two decades the literature about weather index contracts has grown significantly (Skees, et al., 2001; World-Bank, 2005; Barnett,Barrett and Skees, 2008). However, the idea is not new. In 1943 the Congress of The United States decided to liquidate the federal crop insurance system. According to Sanderson, 1943), the high-risk on wheat production and the considerable underwriting losses were the main reasons. At that time, Sanderson argued that the failure of the crop insurance program was not due to unfavorable weather. It was caused by a mixture of mismanagement and perverse incentives created by the program. Thus, he suggested that the success of any weather contract would depend on: "(1) on the correlation existing between the weather factors included in the estimating equation and the state average yield, and (2) on the degree of similarity in the response of individual-farm yields to fluctuations in these weather factors"[5].

More recent, studies have divided their attention between two aspects — the design and pricing of weather contracts, and the risk-reducing effectiveness of these.

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[3] Figures 3 and 4 display the evolution of rice production for winter and summer respectively.

[4] Central Bank of Ecuador reports that rice and corn together represents around 80% of cereal GDP. For that reason, any bad event on rice production makes cereal GDP moves down.

[5] Sanderson (1943).

In 1980s, the Federal Crop Insurance Program consistently reported poor actuarial performance and a low participation rate. Miranda, 1991) argued that the problems were caused because the Federal Crop Program tried to tailor coverage to individual farmer yield losses. He proposed that the individual producer yield risk can be divided into a systemic risk and a nonsystemic risk[6]. Because the nonsystemic part is extremely expensive to measure, Miranda suggests that a Federal Program (what he calls area-yield crop insurance) should cover only the systemic part. To illustrate his ideas, he used farmer level yield data for 102 soybean producers in the state of Kentucky. Using empirical yield distributions he concluded that the area-yield program tends to reduce farmers' risk exposure. However, he warns that this program could not be widely accepted.

Skees,Black and Barnett, 1997) discuss the procedures used in the Group Risk Plan to design and rate the area yield crop insurance contract. They point out that area yield program (AYP) can be improved in many ways. They pay attention in the county boundaries as a way to reduce basis risk. Also, they argued that a better contract design could improve the AYP performances, and AYP will work in areas where yield risks are largely systemic.

Earlier studies have also analyzed how effective weather derivatives are in reducing risk exposure, especially if some effort is made to minimize the basis risk (Turvey, 2001). Martin,Barnett and Coble, 2001) propose an insurance instrument for cotton in Mississippi, which gives more flexibility to the purchasers because they are allowed to choose the parameters of the contract according to their risk management needs. Their results encourage the use of weather derivatives within the US agriculture. Turvey (2001) examines the pricing of weather derivatives in Ontario. He finds that specific-event weather conditions affect crop yield risk. His results show that pricing a weather derivative on large area would be inadequate. He also points out to the need to minimize basis risk.

Vedenov and Barnett, 2004) evaluate the efficiency of weather derivatives for three crops in The United States. The relationship between yield and weather variables is estimated using alternatives specifications. Using the data for six crop reporting districts, they construct "elementary" contracts for each district. They find the weather insurance contracts to differ across regions and crops, but the designed contracts do provide risk protection against yield shortfalls.

[6] Miranda (1991) defines systemic risk as "…explained by factor affecting all producers in his area …"

Deng,Barnett and Vedenov, 2007) analyze the risk reduction performance of an index contract and a farm-level contract[7] for cotton and soybean production for heterogeneous regions in Georgia and South Carolina. They argue that actuarially fair premium rates commonly used to compare both programs tends to bias results in favor of MPCI and therefore they use three different premiums rating schemes. Their results indicate that GRP performs better than MPCI not only within homogenous production region, but also with heterogeneous ones. They find that the GRP works well when MPCI premium rates are large and GRP basis risk is moderate.

In developing countries, informal insurance and credit markets have been characterized by high interest and premiums rates. Nonmarket institutions[8] (such as family, local, or community lending institutions) have been utilized as informal risk transfer mechanisms in rural areas of developing countries. Informal loans, diversification of income sources, and crop diversification have been mechanisms used by rural household to smooth consumption (Morduch, 1995; Fafchamps and Lund, 2003). In some cases, these systems have been better able to address the asymmetric information and transaction costs problems than formal insurance markets (Stiglitz, 1990; Barnett,Barrett and Skees, 2008).

However, when an extreme weather event makes farmers' losses correlated, these nonmarket institutions fail as risk management tool and as mechanism to avoid poverty traps (Zimmerman and Carter, 2003; Hess, et al., 2005; Santos and Barrett, 2006). In general, both governments and rural household of developing countries have not been effective managing risk transfer neither ex-ante nor ex-post of a shock (Carter and Barrett, 2006; Carter, et al., 2007; Barnett,Barrett and Skees, 2008).

In recent years, weather derivative products have also been used in developing countries as a way to reduce the negative impacts of natural disasters. For example, Skees, et al., 2001) develop a rainfall-based index insurance in Morocco. Focusing on the three main cereal crops, they find a basic cumulative rainfall contract could reduce basis risk for cereal, and at the same time provide income protection to farmers. They argue that this type of contracts is feasible in the more favorable agro climatic zones, where data reveal strong correlation between rainfall and cereal revenues. They conclude that a new program based on this type of insurance would make farmers better off.

Data

[7] GRP (Group Risk Program) and MPCI (multiple peril crop insurance), respectively.
[8] Besley, 1995) uses this term as *a catchall for many different arrangements*.

The province of Guayas and Los Rios produces around 87% of the total rice production. In this study we focus on the information reported for two counties: Daule and Babahoyo, which are located in Guayas and Los Rios respectively. The county-level rice data per season are obtained from MAGAP in the period 1990-2008. MAGAP reports the total rice production for each county.

The county-level weather data used for analysis are observations of average monthly total rainfall and temperature for the two winter months (February and March) and two summer months (August and September). Data for each weather station are collected from databases of the Instituto Nacional de Meteorología e Hidrología[9] (INAMHI) which gather this information from the weather stations located in both provinces.

Data Exploration

According to MAGAP, since 2000 these two counties have represented more than 35% of rice production in Ecuador. Descriptive statistics of the collected data are presented in Table 1. The table provides basic information about these counties. Figures 1-2 present historical rice yields in each county. Two unit root tests — Augmented Dickey-Fuller and Phillip-Perron — were performed on the data (Table 2). The test results suggest that there is no evidence of unit root in all counties in both seasons.

Detrending Data

The historical yield graphs in Figure 1-2 9 also suggest that the rice production is affected by a trend. To account for this effect, yields and weather data are detrended using a log-linear trend model:

$$log(Y_t^{tr}) = \beta_0 + \beta_1(t - 1990)$$

The detrended yields were calculated as:

$$Y_t^{det} = Y_t \, \frac{Y_t^{tr}}{Y_{1990}^{tr}}$$

Yield-Weather Relationship

[9] National Institute of Meteorology and Hydrology.

The weather models used to define the weather index are constructed based on the relationship between rice yield and weather variables. As mentioned above, winter production is affected mainly by rainfall, while low temperatures are the primary concern during the summer. Tables 2 and 3 list weather models estimated as a part of the preliminary analysis. Of the models analyzed, the best one has a goodness of fit of only $R^2 = 0.33$ (for Babahoyo in winter season).

Design and Pricing of Weather Derivatives

Following Vedenov and Barnett (2004), a weather derivative is modeled as an "elementary contract" with the payoff according to the schedule:

$$(1) \qquad I(\varepsilon|x,\varepsilon^*,\mu) = x \times \begin{cases} 0 & if\ \varepsilon > \varepsilon^* \\ \frac{\varepsilon^*-\varepsilon}{\varepsilon^*-\mu\varepsilon^*} & if\ \ \mu\varepsilon^* < \varepsilon \le \varepsilon^* \\ 1 & if\ \varepsilon \le \mu\varepsilon^* \end{cases}$$

where ε is a realization of the index. The contract starts to pay when the index ε falls below the specified "strike" ε^*. Once the index falls below the limit $\mu\varepsilon^*$, the insured receives the maximum indemnity x. When the index falls between the strike and the limit, the contract pays a proportion of the maximum indemnity. The parameter μ varies between 0 and 1, with the limiting case of 0 corresponding to the conventional proportional payoff with deductible, and 1 corresponding to a "lump-sum" payment once the contract is triggered regardless of the severity of the shortfall. The contract is completely designed once the values of strike, limit and maximum indemnity are specified (See Figure 3).

In order to price the designed contract for a given set of parameter values, the probability distribution $h_\varepsilon(\varepsilon)$ of the index should also be specified. Using historical weather observations from each selected location, the weather-yield models are used to calculate the "historical realizations" of the index for each location. In this study it is assumed that the index can be modeled with a normal probability function.

The actuarially-fair premium is set equal to the expected payoff of the contract, i.e.

$$(2) \qquad P(x,\varepsilon^*,\mu) = \int I(\varepsilon|x,\varepsilon^*,\mu)\, h_\varepsilon(\varepsilon) d\varepsilon$$

The parameters in equation (1) are selected for each location/index analyzed so as to provide the maximum risk reduction for the buyers who are exposed to the risk area-wide yield loss. In particular, the parameters are selected so as to maximize the expected utility

(3) $$max_{\mu,x,\varepsilon*}\ Eu\big(y + I(\varepsilon|x, \varepsilon^*, \mu) - P(x, \varepsilon^*, \mu)\big)$$

The strikes, limits, and maximum liabilities for optimal contracts are reported in table 5. A CRRA[10] power function was used to get the parameters on the contracts

(4) $$u(R; \gamma) = \frac{R^{1-\gamma}}{1-\gamma}$$

The weather models estimated (table 4) suggest that each season/county combination has its own index and the models fail to capture the relationship between weather and yields. The result shown in table 5 suggests that weather derivatives vary across county and season (e.g. Daule during the winter vs Daule during the summer). Thus, location, season, edaphology, and agricultural practices imply the need for different weather derivatives.

Efficiency Analysis

The risk-reducing effectiveness of weather derivatives as a risk management tool was evaluated using the certainty-equivalent revenue. It is assumed that an economic agent (a representative farmer or a “risk aggregator”) who is exposed to rice yield risk in a given seasons buys the weather derivative for the season. The agent is considered a price taker and therefore only affected by the yield risk.

For each location/season combination, the revenues without and with the contract were calculated as

(5) $$R_{without} = qy$$

(6) $$R_{with} = qy + I(\varepsilon|x, \varepsilon^*, \mu) - P(x, \varepsilon^*, \mu)$$

where q is the (fixed) rice price. The expected revenues were then obtained as

(7) $$ER_{without} = \int qy\, h_y(y)\, dy$$

[10] CRRA stands for Constant Relative Risk Aversion.

(8) $ER_{with} = \iint [qy + I(\varepsilon|x, \varepsilon^*, \mu) - P(x, \varepsilon^*, \mu)]\, h(y, \varepsilon)\, dy\, d\varepsilon$

Where $h_y(y)$ and $h(y, \varepsilon)$ are the univariate and joint density function, respectively. The univariate density functions for each location/season combination were estimated using a normal distribution. The joint distributions of indices and yields were estimated using a Gaussian Copula (Wand and Jones, 1995; Cherubini,Luciano and Vecchiato, 2004; Vedenov and Power, 2008)

The expected utilities of revenues without and with the weather derivatives were calculated as

(9) $EU(R_{without}) = \int u(qy)\, h_y(y)\, dy$

(10) $EU(R_{with}) = \iint u[qy + I(\varepsilon|x, \varepsilon^*, \mu) - P(x, \varepsilon^*, \mu)]\ h(y, \varepsilon)\, dy\, d\varepsilon$

For a given level of risk premium θ and each revenue/location/season distribution, the parameter γ was calibrated to be equal to 1, 2, and 3, so as to reflect producers' willingness to forgo a certain amount of "risk-premium" in exchange for elimination of uncertainty in the baseline case (without the insurance).

The certainty-equivalent revenues without and with the weather contract were calculated from the conditions,

(11) $EU(CER_{without}) = E_R U(R_{without})$

(12) $EU(CER_{with}) = E_R U(R_{with})$

Finally, the risk reduction due to the weather derivative was computed as $\Delta CER = CER_{with} - CER_{without}$.Table 6 shows the results of this procedure.

Results

Risk-reducing efficiency of weather derivatives as primary insurance instruments varies across county and season. In all cases the risk reduction is less than 1% except for Daule during the summer when the parameter γ is equal to 2 and 3.

The risk reduction is small, apparently the poor performance of the weather models to capture the relationship between yields and weather is one of the reasons. Producers would not gain much if they buy the contract. The higher of value for γ, the more risk reduction producers get

Conclusion

The efficiency of weather derivatives was analyzed for rice production in two counties during two seasons. For each county/season combination, the relationship between yield and selected weather variables was estimate for alternative functional forms, and a weather derivatives was constructed based on the function which best fit the data. This analysis was conducted using yields measured at county level. The constructed weather derivatives provided a little risk protection, apparently due to the high basis risk.

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Figure 1: Dynamics of Rice Production in Babahoyo, 1990-2008

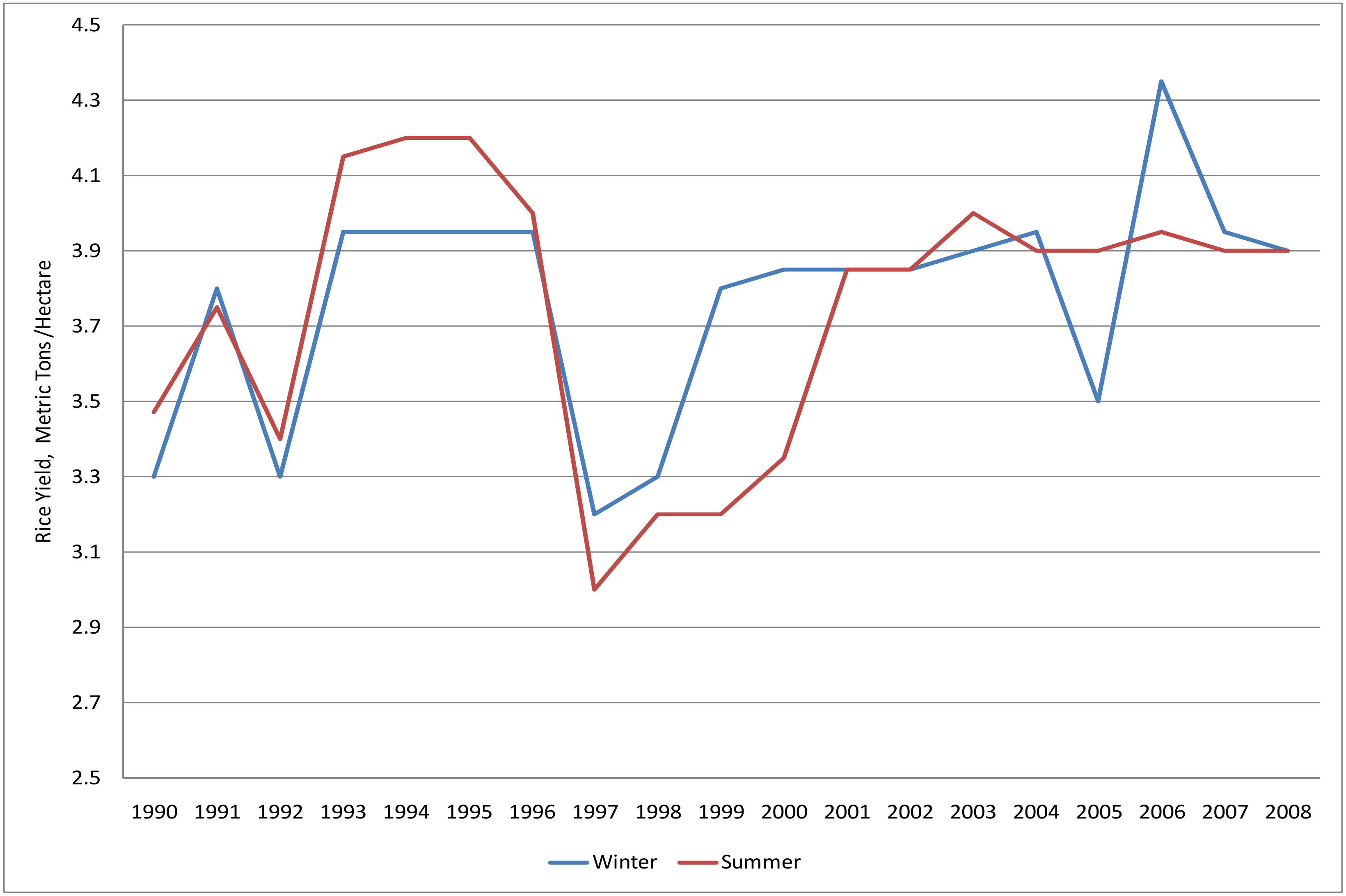

Figure 2: Dynamics of Rice Production in Daule, 1990-2008

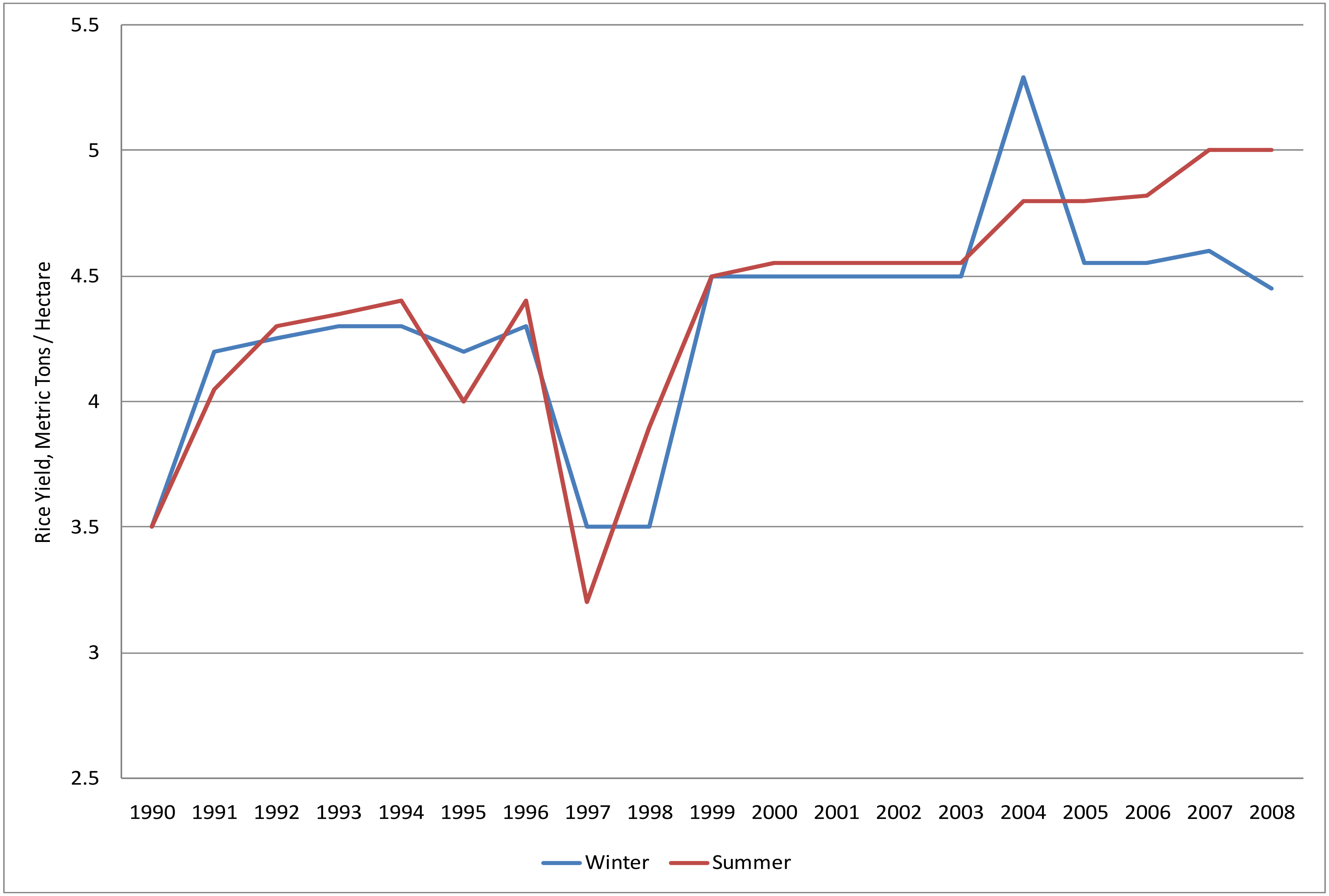

Figure 3: Payoff Schedule for a Weather Derivatives Contract

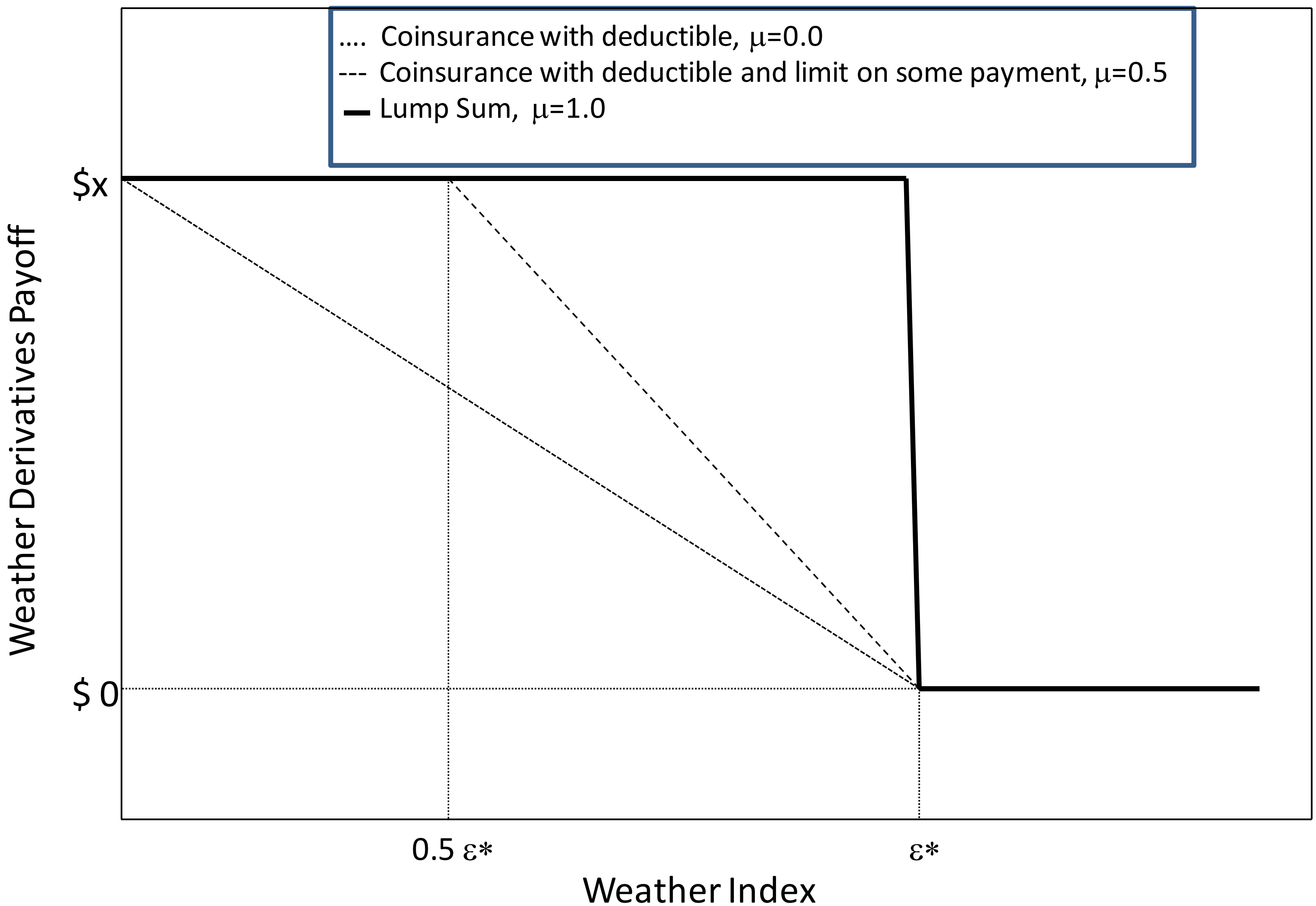

Table 1: Descriptive Statistics of Rice Yields for Main Producing Counties

	Winter		Summer	
	Babahoyo	Daule	Babahoyo	Daule
Sample Statistics				
Mean	3.768	4.315	3.746	4.380
Median	3.850	4.450	3.900	4.500
Maximum	4.350	5.290	4.200	5.000
Minimum	3.200	3.500	3.000	3.200
Std. Dev.	0.302	0.432	0.363	0.477
Skewness	-0.562	-0.440	-0.661	-0.941
Kurtosis	2.634	3.792	2.222	3.411
Jarque-Bera	1.107	1.108	1.862	2.939
Probability	0.575	0.575	0.394	0.230
Observations	19	19	19	19
Correlation Matrix				
Babahoyo	1.000		1.000	0.512
Daule	0.689	1.000	0.512	1.000

Table 2: Unit Root Tests of Yield Data Series

	Winter		Summer	
	Babahoyo	Daule	Babahoyo	Daule
ADF				
c	-3.98	-3.045	-2.26	-2.6
	(-3.04)	(-3.04)	(-3.04)	(-3.04)
ct	-4.19	-3.15	-2.2	-3.41
	(-3.69)	(-3.69)	(-3.69)	(-3.69)
PP				
c	-3.98	-3.06	-2.3	-2.57
	(-3.04)	(-3.04)	(-3.04)	(-3.04)
ct	-4.2	-3.21	-2.25	-3.42
	(-3.69)	(-3.69)	(-3.69)	(-3.69)
Lags	3	3	3	3

Note: The variables are expressed in logarithms. Lags is the number that minimize the Schwartz criterio. ADF= Augmmented Dickey-Fuller Test; PP= Phillips-Perron Test.

Table 3: Weather Models for Winter Season Based on 1990-2008 Data

	Winter	
	Babahoyo	Daule
Rainfall February	0.00704	0.0110
	(0.0313)	(0.0426)
Rainfall March	0.225	0.0390
	(0.154)	(0.104)
Rainfall February square	-0.00183	-0.00209
	(0.00267)	(0.00446)
Rainfall March square	-0.0155	-0.00400
	(0.0121)	(0.00793)
Constant	0.570	1.388***
	(0.471)	(0.284)
Observations	19	19
R-squared	0.334	0.199

Standard errors in parentheses

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

Table 4: Weather Models for Summer Season Based on 1990-2008 Data

	Summer	
	Babahoyo	Daule
Temperature August	4.816	-6.222
	(9.313)	(16.19)
Temperature September	-11.71	8.533
	(13.55)	(20.47)
Temperature August square	-0.0302	0.0417
	(0.0596)	(0.109)
Temperature September square	0.0742	-0.0572
	(0.0865)	(0.137)
Constant	271.8	-85.13
	(322.9)	(317.6)
Observations	19	19
R-squared	0.186	0.029

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

Table 5: Parameters of Optimal Weather Instruments

Season/County	Strike (qq/hec)	Limit: Absolute Value (qq.hec)	Limit: % of Strike	Maximum Liability (qq/hec)	Premium (qq/hec)	Premium Rate
			γ=1			
Winter/Daule	3.8	2.014	0.53	1	1.43	143.0%
Winter/Babahoyo	3.5	2.66	0.76	1	1.54	146.3%
Summer/Daule	3.9	3.12	0.8	1	3.34	317.3%
Summer/Babahoyo	3	1.95	0.65	0.75	0.26	22.1%
			γ=2			
Winter/Daule	3.5	1.925	0.55	1	0.87	87.0%
Winter/Babahoyo	3.1	2.17	0.7	1.5	0.38	25.3%
Summer/Daule	4.2	3.318	0.79	1.25	4.14	331.2%
Summer/Babahoyo	2.5	1.625	0.65	2	0.01	0.5%
			γ=3			
Winter/Daule	3.6	1.8	0.5	1.25	0.96	76.8%
Winter/Babahoyo	3	1.95	0.65	1.75	0.22	12.6%
Summer/Daule	4	2.8	0.7	1.25	2.82	225.6%
Summer/Babahoyo	3.2	1.888	0.59	0.75	0.44	58.7%

Table 6: Efficiency of Weather Derivatives as Measured by Certainty Equivalent

Season/County	With Contract (qq/hec)	Without Contract (qq/hec)	Percent Change	With Contract (qq/hec)	Without Contract (qq/hec)	Percent Change	With Contract (qq/hec)	Without Contract (qq/hec)	Percent Change
		γ=1			γ=2			γ=3	
Winter/Daule	1.943	1.95	-0.4%	1.988	1.996	-0.4%	2.032	2.045	-0.6%
Winter/Babahoyo	1.929	1.93	-0.1%	1.959	1.969	-1.0%	1.996	2.007	-1.1%
Summer/Daule	1.922	1.931	-0.5%	1.956	1.969	-1.3%	1.979	2.007	-2.8%
Summer/Babahoyo	1.946	1.946	0.0%	1.988	1.988	0.0%	2.026	2.03	-0.4%