CLIMATE CHANGE IMPACT ON RICE YIELD AND PRODUCTION RISK

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Abstract
The relationship among rice yield and weather variables in Korea is explored using a stochastic production function. The results reveal that average rice yield is positively related to temperature and negatively associated with precipitation. Both temperature and precipitation, which are risk-increasing inputs, are positively related to rice yield variability. The widened yield variability can be transferred to the fluctuation of rice production and rice price instability. Larger market risk is expected in the future since both temperature and precipitation are anticipated to increase. An evaluation of climate change impact on rice yield variability reveals that it may increase by up to 10%~20%. Reducing yield variability and managing market risk would be the primary goals of the government's farm policy and research.

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I. Introduction

Crop yield depends on many factors including soil qualities, technology, planting practices and certainly weather conditions. Hazell (1984) suggested that high-yielding varieties, common field operation and uniform planting practices make many crops more sensitive to weather conditions. The year-to-year crop yield *variability* owing to weather conditions is an important source of production risk. Crop yield variability can result in the fluctuation of crop production, instability of crop price, and in turn a larger market risk. Government farm policies and risk managements are closely related to unstable crop price and market risk.

Regarding weather conditions, future climate change has been taken into consideration because the global climate has been changing enough to alter weather conditions to be favorable or unfavorable to crop yield and production. According to the Intergovernmental Panel on Climate Change (IPCC), global warming is indisputable and global average temperature is anticipated to increase by 2℃ to 4℃ by the end of this century (Meehl *et al.*, 2007). Using a climate simulation model, Min *et al.* (2005) insisted that temperature in Korea will increase faster than the global average, by 4.5℃ to 6.5℃ by the end of this century. In addition to temperature, precipitation is expected to increase by 6% to 10%. Boo *et al.* (2004) also pointed out that temperature may rise by 6℃ and precipitation by 25% by the end of the 21st century.

These changes in climate conditions will affect crop yield and yield variability. Thus, it is natural to investigate how sensitive crop yield and yield variability are to weather conditions and future climate change. It is important to learn how much crop yield and yield variability change over climate change because it is the basis of formulating government farm policies and farm research programs.

Kwon and Kim (2008) is the first attempt to examine the relationship between rice yield and climate change in Korea. The results from nonparametric and semiparametric models illustrate that rice yield is positively associated with temperature and negatively related to precipitation. Also, they showed that there exists a non-linear relationship between rice yield and weather variables. Kwon and Kim (2008), however, focused on average yield changes over weather conditions and didn't discuss rice yield variability responding to weather conditions.

Chen, McCarl and Schimmelpfennig (2004), Chen and Chang (2005), and Isik and Devadoss (2006) considered that crop yield variability is also a function of weather conditions. Weather variables affect not only average crop yield but also the variability of crop yield. The results of average crop yield and yield variability are mixed (some are positive and some are negative). The responsiveness relies on the characteristics of crops and physical growing locations. Generally, the average crop yield in hotter and drier weather conditions is lower and the variability in hotter and drier conditions tends to be larger.

The above studies brought in the stochastic production function to investigate the average crop yield and crop yield variability changes over weather variables. The stochastic production function was introduced by Just and Pope (1978 and 1979). The basic concept of the stochastic production function is that a production function can be specified as the sum of two components: one associated with the output level and the other related to the variability of output. A considerable number of studies have been made on differentiating the impact of inputs on the output level and the variability of output using this approach.

The purpose of this paper is to explore the impacts of weather variables on rice yield level and variability in Korea. We adopt a stochastic production function and historical data. We attempt to quantify the relationship between rice yield and variability, and weather variables. The estimated stochastic production function reveals whether weather variables increase or decrease the variability of rice yield. The estimates in the stochastic production function will be utilized to analyze the impact of climate change on rice yield and variability. The paper consists of three parts. Section II introduces the methods including the stochastic production function, functional specification and estimation. Section III discusses the estimation results and section IV concludes the paper.

II. Methods

1. Stochastic production function

The stochastic production function is introduced, which is elaborated in Just and Pope (1978 and 1979), to estimate the effects of weather variables on the prob-

ability distribution of rice yield in Korea. The stochastic production function has been attractive among applied economists and is still used in recent literatures (Kumbhakar and Tveterås, 2003). As mentioned in the preceding section, the basic idea is to denote the production function as the sum of yield level and the variability of the yield. A stochastic production function is given by

$$y = f(\mathbf{x} \mid \boldsymbol{\beta}) + h(\mathbf{x} \mid \boldsymbol{\alpha})\varepsilon, \quad \mathrm{E}(\varepsilon) = 0, \mathrm{var}(\varepsilon) = 1 \tag{1}$$

where y is the rice yield over time and regions $\mathbf{x}$ is the vector of independent variables such as precipitation, temperature and possibly other factors. The vectors α and β are unknown parameters to be estimated. $f(\mathbf{x}|\beta)$ is an average yield function and $h(\mathbf{x}|\alpha)$ is a yield variance function or a *risk* function. ε is an error term with mean zero and unit variance. Equation (1) allows weather variables to affect both the average and the variance of rice yield as shown in equation (2)

$$\mathrm{E}(y) = f(\mathbf{x} \mid \boldsymbol{\beta}) \quad \text{and} \quad \mathrm{var}(y) = h^2(\mathbf{x} \mid \boldsymbol{\alpha}) \tag{2}$$

Because the production function in equation (1) does not presume any *priori* restriction, $\partial \mathrm{var}(y)/\partial x_k$ can be positive or negative. If the sign is positive, it indicates that weather variables are risk-increasing inputs. If the sign is negative, it shows that weather variables are risk-decreasing inputs. Equation (2) also implies that the effects on the average and the variability of yield are independent.

2. Econometric Model Specification

We choose the Cobb-Douglas (CD) functional form and the linear quadratic (LQ) form for the average yield function, $f(x)$. These two functional types are consistent with the postulates in Just and Pope (1979) which is an additive interaction between the average and variability functions. In addition, these two functional forms are flexible enough to approximate the average yield equation. The translog specification may be more appealing but it has the multiplicative interaction which violates Just and Pope's assumptions (Tveterås, 2000). The average yield function is written as

$$y = \beta_0 + \beta_t T + \prod_j x_j^{\beta_j} \qquad \text{Cobb-Douglass,} \qquad (3)$$

$$y = \beta_0 + \beta_t T + \sum_j \beta_{1j} x_j + \sum_j \beta_{2j} x_j^2 + \sum_j \sum_{k(k \neq j)} \beta_{jk} x_j x_k \quad \text{Linear-Quadratic}$$

where x_j and x_k are inputs including weather variables, T is a time trend variable and β are the coefficients to be estimated. The time trend variable is added to represent the effect of the technological progress during the sample period. The technological progress might be attributed to increasing fertilizer application, introduction of new rice varieties, and improved crop planting practices.

For the variability function, we only consider CD form because it would be highly non-linear (square of the risk function, equation (2)) and it complicates the analysis. Also CD form is consistent with Just and Pope (1978 and 1979) and Kumbhakar and Tveterås (2003). The variability function is given by

$$h(\mathbf{x} \mid \mathbf{\alpha}) = \alpha_0 + \alpha_t T + \prod_j x_j^{\alpha_j}, \qquad (4)$$

where T is the time trend, x_j are inputs including weather variables, and α are coefficients to be estimated.

3. Estimation

All the parameters in equations (3) and (4) can be estimated using the feasible generalized least squares (FGLS) suggested by Just and Pope (1979) or the maximum likelihood estimation (MLE) proposed by Saha, Havenner and Talpaz (1997). The MLE provides consistent and more efficient estimates than the FGLS, especially under a small sample (Saha, Havenner and Talpaz, 1997). The log-likelihood function is given by

$$\ln L = -\frac{1}{2} \left[n \ln(2\pi) + \sum_{i=1}^{n} \ln h^2(\mathbf{x} \mid \mathbf{\alpha}) + \sum_{i=1}^{n} \frac{(y_i - f(\mathbf{x} \mid \mathbf{\beta}))^2}{h^2(\mathbf{x} \mid \mathbf{\alpha})} \right]. \qquad (5)$$

The parameters α and β can be estimated in a maximization of equation (5), under the assumptions that $y \sim N(f(\mathbf{x} \mid \mathbf{\beta}), h^2(\mathbf{x} \mid \mathbf{\alpha}))$.

4. Data

We are interested in the impacts of weather variables on rice yield in Korea. Pooled time-series cross-sectional data are collected among 8 regions from 1977 to 2008. We obtained rice yields data from the crop production statistics of the Ministry for Food, Agriculture, Forestry and Fisheries (MIFAFF). The rice yield data includes time series average rice yields at the jurisdictional district-level "Do" except Jeju[1]. The data on precipitation and temperature are acquired from the statistical database at the Korea Meteorological Administration (KMA). Precipitation data are time series of total rainfall within a year. This reflects the direct water usage for rice cultivation and the inter-seasonal water accumulation within the year. Temperature data contain average observations for the growing season from April to October. The summary statistics of data are reported in Table 1.

TABLE 1. Descriptive Statistics of Data

	Unit	N	Mean	St.Dev	Max	Min
Rice Yield	Tons/ha	256	4.638	0.425	5.517	2.970
Trend		256	16.500	9.251	1.000	32.000
Temperature	℃	256	19.729	0.801	22.150	17.519
Precipitation	mm	256	1296.37	295.57	2136.30	1279.58
Regional Dummies		256	0.125	0.331	1	0

Pooled panel data have more advantages than single time-series or cross-sectional data because pooled data give more informative data, provide more degrees of freedom and control individual heterogeneity. However, if the individual time series data is nonstationary, it may cause a spurious regression. In this case, the standard asymptotic properties of the regression model might be useless. We perform the unit root test to check nonstationarity of pooled data using the test statistics suggested by Im, Pesaran and Shin (2003). They pro-

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[1] Due to abnormal weather, for example cold-weather damage or disease outbreak, the existence of outliers might be suspected. Outliers can be detected using the Grubbs' test (Grubbs, 1969). One outlier is detected using the test at 5% significance level and will be ignored in the analysis because it doesn't affect estimates.

posed unit root tests for panel data based on the mean of individual unit root statistics. The test results are shown in Table 2. The first column of Table 2 shows the unit root test result with serially uncorrelated errors in data which means that each data series is independently and normally distributed. The second column of Table 2 reports the test statistics with serially correlated errors of which patterns are different across groups. All the null hypotheses of the unit root are rejected at the 1% significance level. The critical value at 1% significance level is given by -2.43 (Im, Pesaran and Shin, 2003, Table 2). All the variables in the model are stationary.

TABLE 2.　Panel Unit Root Test Results

	Serially Uncorrelated Errors	Serially Correlated Errors and Heterogeneous Group
Rice Yield	$-15.23*$	$-13.99*$
Temperature	$-30.09*$	$-31.79*$
Precipitation	$-7.05*$	$-5.70*$

* indicates that the test statistics are significant at the 1% level. The critical value is given by -2.29 when N=7 and T=40; See Table 2 in Im, Pesaran and Shin (2003), pp.61-62.

III. EMPIRICAL ANALYSIS

As we discussed, CD-CD and LQ-CD models are estimated using MLE. The optimization procedure in GAUSS program is employed to obtain estimates. The estimated equations show the effects of weather variables on the average and the variability of rice yield. Regional dummies are added to the model to capture regional differences in the average yield function. In contrast, regional dummies are not included in the risk equation because we assume that the yield variability among regions is not quite different. In other words, rice yield distribution has a different mean across regions but it has similar variances across regions. This is reasonable since Korea is small and it doesn't have much difference in weather conditions across regions[2]. The time trend variable is included to describe the technological progress as discussed in the above section.

The estimation results for alternative functional forms are presented in Table 3. We also report in Table 3 Akaike Information Criterion (AIC) and Schwarz Criterion (SC) used to select proper functional forms. In this sense, the CD-CD functional form behaves better. The elasticities (at the mean) for weather variables are also calculated for comparison purpose.

TABLE 3.   Estimation Results

	Cobb-Douglass Cobb-Douglass	Linear-Quadratic Cobb-Douglass
Mean yield		
Trend	0.0021 (0.0005)*	0.0090 (0.0024)*
Temperature	0.8201 (0.1513)*	1.2975 (1.1915)
Precipitation	−0.0474 (0.0236)**	0.0030 (0.0249)
Temp2		−0.0282 (0.0282)
Precip2		−0.00004 (0.00003)
TempPrecip		−0.00014 (0.0011)
Kyeonggi	0.0129 (0.0211)	0.0575 (0.0967)
Gangwon	−0.0164 (0.0208)	−0.0379 (0.0980)
Chungnuk	0.0176 (0.0171)	0.0774 (0.0760)
Chungnam	0.0887 (0.0193)*	0.4170 (0.0835)*
Jeonbuk	0.0703 (0.0176)*	0.3316 (0.0790)*
Gyeongbuk	−0.0385 (0.0155)**	−0.1524 (0.0731)**
Gyeongnam	−0.0416 (0.0155)*	−0.1665 (0.0731)**
Constant	−0.7315 (0.5240)	−10.4460 (12.69)
Yield variability		
Trend	0.0007 (0.0003)*	0.0031 (0.0015)**
Temperature	0.2462 (0.0692)**	0.9159 (0.4052)**
Precipitation	0.0184 (0.0162)	0.0834 (0.0819)
Constant	−0.9035 (0.2533)*	−3.4975 (1.4331)**
Model statistics		
Log lik. value	315.04	−68.747
AIC	−2.3440	0.6777
SC	−2.1363	0.9270

Numbers in parenthesis are standard errors.
*, **, and *** indicate that the parameter is significant at the 1%, 5% and 10% levels

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2 All of regional dummies in the risk equation are not statistically significant in both models. This is another reason to remove regional dummies from the risk equation

This is a good way to interpret the estimated coefficients because the co-efficients in the LQ-CD model and risk equations are not easily readable due to nonlinearity and interaction between temperature and precipitation. Table 4 reports the elasticities for weather variables.

Temperature is positively related to the average rice yield in both models. Elasticity for temperature is computed as 0.82~0.89 and thus 1% rise in temperature increases the average rice yield by 0.8~0.9%. Precipitation has negative effect on the average rice yield in both models. LQ-CD models show that the average rice yield is more sensitive to precipitation but it is not statistically significant. The elasticity for precipitation is estimated as $-0.14 \sim -0.05$, which are relatively small. The time trend has positive impact on the average rice yield in both models as expected. The Results from the model are consistent with Kwon and Kim (2008).

It is noteworthy that both temperature and precipitation enlarge the yield variability. The coefficient for temperature is statistically significant in both risk equations but that of precipitation is not significant (Tables 3 and 4). The 1% rise in temperature will induce the rice yield variability to increase by 0.5% ~ 1.8% while 1% increase in precipitation will cause the rice yield variability to increase by 0.04% ~0.2%. All together, it is expected that the rice yield variability may increase by about 0.5% ~ 2% when both temperature and precipitation increase by 1%. The increased rice yield variability can result in a wide fluctuation of rice production, make rice price unstable, and in turn increase the market risk. We conclude that both weather variables are risk-increasing inputs[3] in this sense.

Note that elasticities for the average and the variability of rice yield are confined to the neighborhood of minimum and maximum of observed temperature and precipitation. Beyond these points, elasticities may be different. They could be larger or smaller than estimates. As shown in Kwon and Kim (2008), rice yield (average) increases as temperature rises when the temperature is under 18℃, but rice yield decreases as temperature rises when it is over 20℃. Thus, the interpretation of elasticities should be made with care and discretion.

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[3] Precipitation may not be necessarily a risk-increasing input because it is not statistically significant. The 90% confidence interval of elasticity for precipitation includes negative numbers, which are $-0.02 \sim +0.09$ in CD-CD model and $-0.10 \sim +0.44$ in LQ-CD model. However, as we concluded here, precipitation is a risk-increasing input on average.

TABLE 4. Elasticities of Temperature and Precipitation at Means

	CD-CD	LQ-CD
Mean yield		
Temperature	0.819	0.890
Precipitation	-0.047	-0.141
Yield variability		
Temperature	0.491	1.839
Precipitation	0.037	0.166

As we discussed in the previous section, the future temperature and precipitation in Korea are expected to increase as shown in Min *et al*. (2005) and Boo *et al*. (2005). This change would be favorable to the average rice yield but it would enlarge the rice yield variability. Table 5 contains the simulation results over climate change scenarios. The scenario 8 is based on the projection from Min *et al*. (2005) in the end of this century. In this sense the scenario 3 or 4 can be a plausible future in years 2040~2050. If temperature increases by 2C and precipitation increases by 60 mm, rice yield variability can be increased by up to 20%, while rice average yield increases by 8%. Note that the average yield and variability may not increase monotonically over climate changes as we computed here. It is more reasonable that the average yield and variability increase at decreasing rates[4]. Thus, the magnitude of changes might not be too magnificent as our expectation. Even so, however, the future climate change in Korea would adversely affect the rice yield variability. The widened rice yield variability can be transferred to a larger production fluctuation, and in turn unstable rice prices. Ultimately, these effects are transported to a bigger market risk. Such results indicate that the direction of government farm policies and public or private research programs should be focused on how to reduce rice yield variability and thus how to manage market risk. It is also important to devise tools to mitigate market risk in the rice sector.

Note, again, that the interpretation of simulation results should be made with caution and discretion because the elasticities from the model are confined

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[4] Kwon and Kim (2008) confirmed this for the average rice yield. Kwon and Kim (2008) showed that the average rice yield increases along with temperature at diminishing rates. The authors presume that this logic would work for the rice yield variability.

to the neighborhood of minimum and maximum observed weather data as pointed out above. Beyond these points, especially scenarios 5, 6, 7 and 8 in Table 5, the average of rice yield would not increase as much as computed. In addition, unfortunately, the possibility to be negative cannot be excluded.

TABLE 5.   Climate Change Scenarios and Rice Yield Change

Scenarios	Changes in Climate Condition		Changes in Rice Yield (%)	
	Temp	Precip	Mean	Variability
1	1℃	0 mm	+4.15 ~ +4.51	+2.49 ~ +9.32
2	0℃	60 mm	−0.22 ~−0.65	+0.17 ~ +0.77
3	**2℃**	**60 mm**	**+8.09 ~ +8.37**	**+5.15 ~ +19.42**
4	**2℃**	**120 mm**	**+7.87 ~ +7.72**	**+5.32 ~ +20.18**
5	4℃	60 mm	+16.39 ~ +17.39	+10.13 ~ +38.06
6	4℃	120 mm	+16.17 ~ +16.74	+10.30 ~ +38.83
7	6℃	60 mm	+24.70 ~ +26.40	+15.11 ~ +56.71
8	6℃	120 mm	+24.48 ~ +25.75	+15.28 ~ +57.48

IV. CONCLUDING COMMENTS

This study has developed a quantitative estimation of the impacts of weather conditions on the rice yield and yield variability in Korea. The Just-Pope stochastic production function and pooled panel data are used to answer our research questions. The results show that the average rice yield is positively related to temperature and negatively associated with precipitation. The responsiveness is estimated as +0.8 ~ +0.9 for temperature and −0.14 ~−0.05 for precipitation. Both weather variables are risk increasing inputs which indicate that both weather variables enlarge the rice yield variability. The elasticity of yield variability is estimated as +0.5 ~ +1.80 for temperature and +0.04 ~ +0.2 for precipitation, respectively. An evaluation of the climate change impact on the rice yield variability reveals that the rice yield variability can increase by up to 10% ~20%. This change may be challenging to rice producers, consumers and the Korean government because the increase in yield variability can be transferred to the fluctuation of rice production, rice price instability,

and market risk. As suggested in the preceding section, government farm poli-
cies and research programs should be directed to reduce the yield variability
and mitigate market risk.

Lastly two caveats should be mentioned in relation to the conclusion.
First, as discussed, the interpretation of estimates should be made with caution.
This is because the computed elasticities are confined to neighborhood of the
range of observed data set. Beyond these points the mean rice yield would not
increase as much as simulated. Second, estimates may have some limitations in
detecting the climate change impact on rice yield because weather data used
here don't show a noticeable change over time.

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