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Adriel Ong[1][2]

Abstract

Developing countries rely on sectors like agriculture for production and sustenance. Climate change threatens their economic activity by impacting crop yields and affecting seasonal planting and harvests. Using advances in econometric modeling, however, one may analyze the effects of variable climate on crop yields. We study the case of the Philippines, which remains vulnerable to climate change. Using a MIDAS regression model comparing both daily and monthly climate data to monthly farmgate rice prices, we analyze how sensitive rice supply is to climate factors.

Keywords: Climate, Historical Climate, Agriculture, Philippines, Rice, MIDAS

JEL Classification: Q10, Q110, Q50, Q54

Introduction

Climate change remains a pressing issue affecting the world. Its existence stands to hurt economic activity and growth, especially in developing countries. The Philippines, a Southeast Asian country, would see bad effects on its agricultural sector. Its seasonal flooding and rainfall would have farmers see decreased crop yields (Bernstein et al, 2008). The East Asian monsoon would also worsen in intensity, compounding the coming problem. Indeed, the Philippines had been listed as one of the most vulnerable countries to climate change (Index of Global Peace, 2019). Especially pertinent to the Philippines is its reliance on rice as a grain. Since prehistoric times, people in the Philippines have eaten rice as a staple (Snow et al., 1986). Changes in the supply of rice would prove disruptive to daily life.

While farmers before relied on wits and grit to deal with inclement weather, advances in Econometric modeling allows us to analyze sensitivity to climate changes. Data collected by weather agencies becomes useful in determining weather effects on crop yields (Jones, Hansen, Royce, and Messina, 2000). The Mixed Data Sampling method (MIDAS) by Ghysels, Santa-Clara , and Valkanov (2007) allows regressions between high and low frequency data. This proves useful with data such as

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prices and weather, where agencies respectively collect monthly and daily data. Variables like solar irradiance are most tangible daily, while relative humidity, rainfall, and temperature can be averaged over months (Angryk et al., 2020).

Methodology

Data

We use data collected by various government agencies in the Philippines. Our monthly data on rice prices come from the Philippine Statistics Authority, gathered from 1990 to 2020. We use farmgate prices for they better reflect locally produced supply of rice (Martinez, Shively, and Masters, 1998). Data on monthly rainfall, temperature, and humidity comes from the Philippine Atmospheric Geophysical and Astronomical Services Administration. Our solar irradiance data comes from the Solar Radiation and Climate Experiment, a University of Colorado venture sponsored by the American National Aeronautics and Space Administration. We note that because of the nature of days and months, we randomly sampled 163 observations out of 11323 from the humidity and solar irradiance data for removal, in order to properly perform the MIDAS regression.

Model

We use a MIDAS regression to estimate our model:

$$y_t = \alpha + \beta_1 B\left(L^{\frac{1}{m}};\ \theta\right) x^{(m)} + \beta_2 z + \varepsilon^{(m)}$$

where y_t is monthly rice prices, $B\left(L^{\frac{1}{m}};\ \theta\right)$ is a lag distribution which filters our vector of daily data $x^{(m)}$, z is a vector of monthly data, $m = 30$ represents an equivalence of days to months, and ε^{m} is an error term.

Abundant high frequency data also allowed us to regress on the filtered variable's lags. To find which lag in the filtered term best suits our model, we follow Borup and Jakobsen (2019). Their method was to perform repeated regressions with different lags until their marginal gain in model likelihood had vanished. In our case, we found that a lag of 19 days provided an optimal value for our model.

Results and Discussion

One may find our regression results in in the Appendix below. We used the natural logarithm of farmgate prices, rainfaill, temperature, and relative humidity to calculate elasticity values. We left our filtered daily data on solar irradiance untouched to provide a log-linear coefficient. As said before, we used 19 lags for solar irradiance to maximize our model's F-score. Using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, we found that our solar irradiance data needed first differencing. Our data on farmgate prices simply needed detrending for use. Lastly, our regression residuals allowed us to find that our data approximated a normal distribution rather well, such that performing Ordinary Least Squares was valid.

Our first variable, solar irradiance, gave differing values for each lag. Cumulatively, its unit effect was -0.03153653, or a 3.15 percent decrease on rice prices. Taking only significant lags, the unit effect became -0.0218 , or a 2.18 percent decrease. As supply and price are inversely proportional, we find that increased solar irradiance benefits rice production. This first result concurs with agricultural research by Yoshida (1981) and Vergara (1992) which points to more sunlight causing higher rice yields.

Rainfall, our next variable, produces an inelastic effect on rice prices. This implies that the rice supply responds negatively to rainfall, although inelastically. Previous literature on rice damage from weather (Blanc and Strobl, 2016) conform to this result, with typhoons being a prime danger to rice production locally. One may note, however, that an inelastic response shows that rice production may easily recover from inclement events. On the other hand, our last two variables, Mean Temperature and Relative Humidity, both showed insignificant results. These variables have not been shown to affect rice yields in Vergara's work, and consequently pose no impact on prices.

On a last note, our Multiple R^2 is 0.1097, such that our model explains only 10.97 percent of variance in the data. Yoshida notes that socioeconomic factors and terrain pose greater impact on rice yield, with climate factors held equal. As such, climate historically has less importance on rice supply. However, the threat of climate change remains, and this relationship may change in the future.

Conclusion and Recommendation

We find that solar irradiance and rainfall are the most significant climate factors which have historically affected farmgate prices of rice in the Philippines. Solar irradiance increases in watts per square meter (W/m^2) were associated with percent decreases in rice farmgate prices. As increases in supply decrease prices, we interpret this result to mean that solar irradiance benefits rice production. On the other hand, rainfall in milimeters per second produced a positive inelastic effect on rice farmgate prices. In accordance with the law of supply, greater rainfall hurts rice production. The inelastic result may mean that rice production recovers easily from inclement weather.

Our study deal with elasticities, and did not explore long term effects. For example, rainfall may pose benefits in the short run but long run effects, like flooding, hurt rice yields. Our study also used only one daily dataset, while our other variables may also be recorded daily and filtered through a MIDAS regression. Lastly, we used national averages and did not account for heterogeneity in locales. Future research may deal with these problems and use new model specifications like panel regressions to solve our study's limitations. Additionally, non-climate factors like terrain and socioeconomics may enter new models to better simulate how rice prices respond to nuances in conditions.

Policymakers, however, can still note our results and act appropriately. Local governments may encourage rice production in locales with better sunlight and moderate rain. Other places may adapt and develop new farming culture based on other crops. Organizations like the International Rice Research Institute may also develop new rice varieties more resistant to inclement weather and more receptive in poor-sunlight areas. Lastly, policymakers can encourage areas with already existing rice production to note our results and act accordingly.

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Appendix

Regression Results and Diagnostics

Regression Residuals				
Min	1Q	Median	3Q	Max
-0.25624	-0.05308	0.00352	0.05301	0.53057

Variable	Estimate	Standard Error	t-value	p-value
(Intercept)	1.851	1.809	1.023	0.30701
Irradiance in Watts/sqm (Lag 1)	-0.005962	0.01696	-0.352	0.72543
Irradiance (Lag 2)	0.00425	0.02506	0.17	0.86543
Irradiance (Lag 3)	-0.04335	0.03162	-1.371	0.17127
Irradiance (Lag 4)	0.0004137	0.009424	0.044	0.96501
Irradiance (Lag 5)	0.01318	0.0073	1.805	0.07196*
Irradiance (Lag 6)	0.01167	0.005128	2.275	0.02353**
Irradiance (Lag 7)	-0.002691	0.008221	-0.327	0.74365
Irradiance (Lag 8)	0.002104	0.004625	0.455	0.64944
Irradiance (Lag 9)	-0.003936	0.01452	-0.271	0.78656
Irradiance (Lag 10)	0.005769	0.01463	0.394	0.69358
Irradiance (Lag 11)	-0.000774	0.01536	-0.05	0.95983

Irradiance (Lag 12)	0.01181	0.01376	0.858	0.39127
Irradiance (Lag 12)	0.008797	0.01998	0.44	0.66
Irradiance (Lag 13)	-0.00007983	0.02094	-0.004	0.99696
Irradiance (Lag 14)	-0.0005034	0.01019	-0.049	0.96063
Irradiance (Lag 15)	-0.001544	0.00463	-0.333	0.73899
Irradiance (Lag 16)	0.01596	0.01636	0.976	0.33
Irradiance (Lag 17)	-0.01636	0.006206	-2.637	0.00875***
Irradiance (Lag 18)	-0.05048	0.02014	-2.507	0.01264**
Irradiance (Lag 19)	0.02019	0.01043	1.936	0.05367*
Ln(Rainfall in mm)	0.03127	0.01662	1.881	0.06081*
Ln(Mean Temperature in Celsius)	-0.118	0.158	-0.747	0.45588
Ln(Relative Humidity in percent)	-0.3693	0.3788	-0.975	0.33039
Significance:	0.001-0.01 ***	0.01-0.05 **	0.05-0.10 *	0.10 < N/A
Multiple R-squared:	0.1097		Residual standard error:	0.09486 on 336 degrees of freedom
F-statistic:	1.801 on 23 and 336 DF		p-value:	0.01439

KPSS Test

KPSS Test Results	
Variable (Stationary type)	p-value
Solar Irradiance (Level)	< 0.01
Rice Farmgate Price (Trend)	< 0.01
First-Differenced Solar Irradiance (Level)	0.1 <
Detrended Rice Farmgate Price (Trend)	0.1 <

Rainfall	0.1 <
Mean Temperature	0.1 <
Humidity	0.1 <