International Journal of Social Science and Economic Research

ISSN: 2455-8834

Volume:06, Issue:09 "September 2021"

IMPACT OF FERTILIZERS AND PESTICIDES ON INDIA'S AGRICULTURAL PRODUCTIVITY: A STUDY USING OLS MODEL

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DOI: 10.46609/IJSSER.2021.v06i09.018 URL: https://doi.org/10.46609/IJSSER.2021.v06i09.018

ABSTRACT

The significance of the secondary and tertiary sectors in India's GDP is increasing, yet the primary sector or agriculture, in particular, has always been vital for India's growth. The agriculture sector depends on critical inputs such as pesticides and fertilizer. This paper seeks to quantify and analyze the impact of fertilizers and pesticides on India's agricultural yield from 1980 to 2014. A multiple linear regression model using the Ordinary Least Squares (OLS) method is derived to obtain the required results. The paper also presents additional tests performed to check for OLS violations and validate the results derived from the model. The paper's findings suggest that an increase in 1% of the fertilizer consumption by Indian farmers increases India's mean predicted total agriculture yield by 0.186406%, keeping consumption of pesticides constant. Likewise, an increase of 1% of the consumption of pesticides by Indian farmers increases India's mean predicted total agriculture yield by 0.0746664%, keeping fertilizers constant.

Keywords: Agriculture yield, Farmers, Fertilizer, India, Pesticide, Ordinary Least Squares

1. Introduction

1.1 Why is a study on India's agriculture sector critical?

The role of the agriculture sector in boosting the Indian Economy can be considered significant because it was the only sector that clocked positive growth of 3.4% at constant prices in 2020-21. The agriculture sector continues to be the largest employer of the unskilled and partially skilled labour force since Independence, employing more than 50% of India's population. Although India is the fourth-largest producer of agricultural goods, its agriculture sector, like any other economy, is highly dependent on fertilizers and pesticides to increase agricultural productivity. Fertilizers have proven to revolutionize the agriculture sector of many countries experiencing non-agriculture friendly environments like Qatar and Bahrein and, therefore, can be considered a

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critical input to increase crop yield of various food grains commercial crops. The role of pesticides must also not be underrated. They have been a fundamental part of the agriculture process by mitigating the losses from weeds, diseases and insect pests that can significantly impact the volume of harvestable produce. Warren (1998) scrutinized the unforeseen growth in crop production by using pesticides in the US in the twentieth century. Webster *et al.* (1999) claimed that farmers might incur economic losses without the use of pesticides and measured the remarkable enrichment in crop yield and economic margin that resulted from the use of pesticides. Since both fertilizers and pesticides are primary inputs in the agriculture process, carrying an intensive study of how consumption of fertilizers and pesticides by Indian farmers has affected the total agriculture yield of India becomes a matter of great concern.

Hence, this paper estimates the impact of these two inputs on India's total crop yield from 1980 to 2014 by implementing an OLS (Ordinary Least Squares) regression model. OLS is widely used to estimate the parameter of a linear regression model.

2. Material and Method

2.1 Reference to a research paper

This paper derives its base from the research paper written by John W. McArthur and Gordon C. McCord, which focuses on the role of agriculture inputs, primarily fertilizers including other inputs, in the growth of the agriculture output of the world. The estimation tool adopted by them concentrates upon a cross-country panel data set built for developing countries over the period 1961–2001. Their model employs a novel instrumental variable to study the ultimate connection between alternations in cereal yields and aggregate economic outcomes.

2.2 Reference to an article

Another insightful article written by Md. Wasim Aktar, Dwaipayan Sengupta, and Ashim Chowdhury provides essential information on the role of pesticides in the agriculture process by explaining the benefits and shortcomings of its use and comparing its pattern of use in India with global standards. The article is unique because it highlights various examples where the overuse of pesticides has negatively impacted agriculture yield.

2.3 About the statistical tool employed

The paper administers multiple linear regression as the primary statistical tool to estimate the influence of pesticides and fertilizers on India's agriculture yield. The regression is carried out using GRETL's OLS method. OLS is widely used to estimate the unknown parameter of a linear

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regression model as they are considered the best linear unbiased estimators. The objective of the OLS method is the minimization of the difference between given values and predicted values. However, the OLS method makes certain assumptions that need comprehension before performing regression:

1) The regression model is linear in parameter; it may or may not be linear in the variables. 2) The explanatory variable is stochastic and uncorrelated with the error term.

3) Given the value of an explanatory variable, the mean value of the error term is zero. 4) The variance of each error term is constant or homoscedastic.

5) There is no autocorrelation, or two error terms are not correlated.

6) The regression model is correctly specified.

7) Error terms should be normally distributed.

8) There is no multi-collinearity (or perfect collinearity).

9) Number of observations should be more than the number of explanatory variables.

3. Data

3.1 Description of data used

Total agriculture yield (in tonnes per hectare) measures the total yield of major commercial crops and food grains produced (in tonnes per hectare) by farmers in India annually. The data for total agriculture yield (dependent variable) is extracted from the official website of the Reserve Bank of India.

2) Consumption of fertilizers (in tonnes per hectare) measures the total quantity of fertilizers (Nitrogen + Phosphorous + Potassium) used by Indian farmers annually (in tonnes per hectare) to increase their agriculture output. The data for consumption of fertilizers (independent variable) has also been obtained from the Food and Agriculture Organization of the United Nations.

3) Consumption of pesticides (in tonnes per hectare) measures the total quantity of pesticides (Technical Grade Materials) used by Indian farmers annually (in tonnes per hectare) in the agriculture process. The data for the consumption of pesticides (independent variable) has been obtained from the Food and Agriculture Organization of the United Nations.

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3.2 Transforming the original variables

To obtain better results, all three variables have been scaled and transformed into their respective natural logarithmic forms. Hence, in the OLS model, the variables are interpreted as follows:

LogF = Log_e[Consumption of fertilizers(in tonnes per hectare)]

LogP= Log_e[Consumption of pesticides(in tonnes per hectare)]

LogAY= Log_e[Total agriculture yield(in tonnes per hectare)

4. Graphs and OLS Model

4.1 Graphs

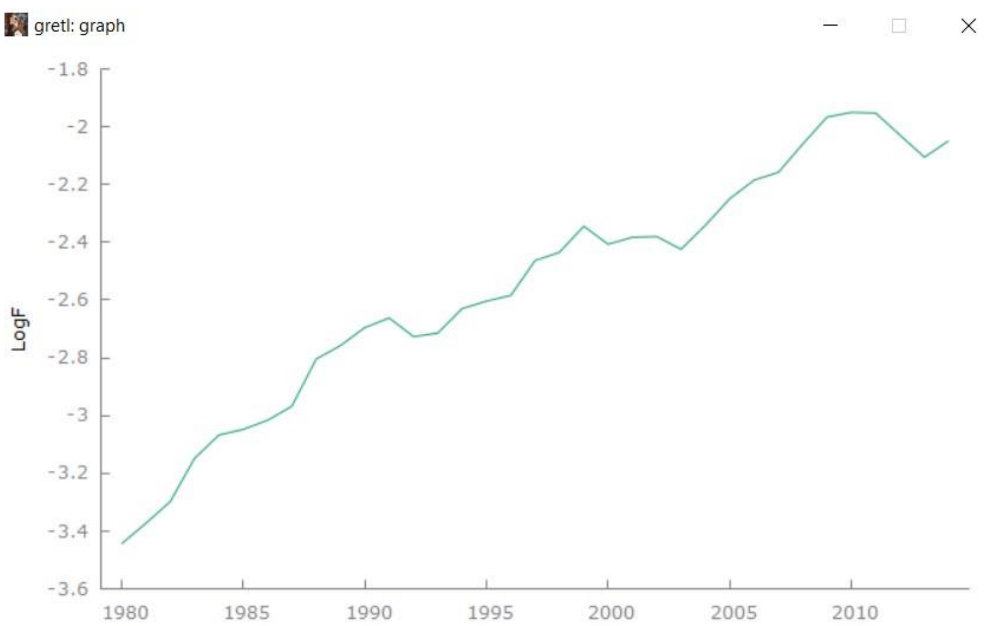

Figure 1: Graph showing the values of LogF from 1980 to 2014
Source: Computed from GRETL

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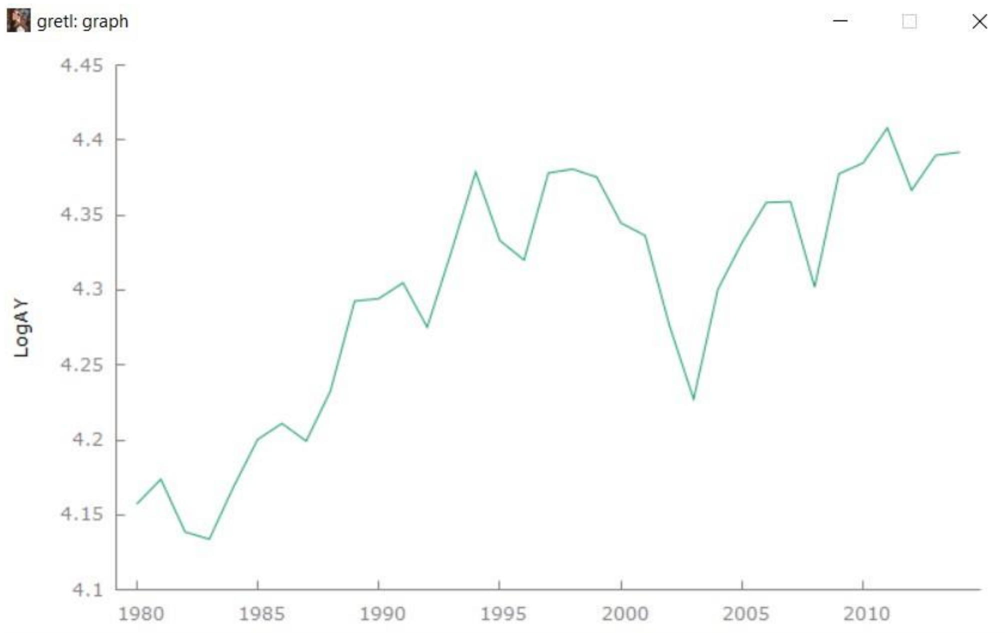

Figure 2: Graph showing the values of LogAY from 1980 to 2014
Source: Computed from GRETL

Figure 3: Graph showing the values of LogP from 1980 to 2014
Source: Computed from GRETL

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Figures 1, 2 and 3 portray the logarithm graphs of the variables used in OLS model 1. They represent relative change rather than an absolute one. The first difference of log for all figures illustrates the corresponding percentage change in their Y-axis variable.

4.2 OLS Model

The OLS Model 1 quantifies the impact of explanatory variables (LogF and LogP) on LogAY (dependent variable).

gretl: model 1

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```
Model 1: OLS, using observations 1980-2014 (T = 35)
Dependent variable: LogAY

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       5.38181      0.273200      19.70     1.87e-019 ***
  LogF        0.186406     0.0172184     10.83     3.14e-012 ***
  LogP        0.0746664    0.0309012      2.416    0.0216    **

Mean dependent var   4.297887   S.D. dependent var   0.082223
Sum squared resid    0.047441   S.E. of regression   0.038504
R-squared            0.793609   Adjusted R-squared   0.780710
F(2, 32)             61.52279   P-value(F)           1.08e-11
Log-likelihood       65.90051   Akaike criterion    -125.8010
Schwarz criterion   -121.1350   Hannan-Quinn        -124.1903
rho                  0.549309   Durbin-Watson        0.877736
```

Figure 4: OLS Model 1 showing the impact of LogF and LogP on LogAY

Note: 0.05 or 5% is assumed as the level of significance while building all models and conducting all tests

Source: Computed from GRETL

From figure 4, we can derive the regression equation as follows:

$LogY_t = 5.38181 + 0.186406LogX_{1t} + 0.0746664LogX_{2t} + \mu_t$

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Where,

Y_t= Total agriculture yield (in tonnes per hectare) in time period t
X_{1t} = Consumption of fertilizers (in tonnes per hectare) in time period t
X_{2t}= Consumption of pesticides (in tonnes per hectare) in time period t
β_1= intercept term= 5.38181
β_2= slope coefficient of LogX_{1t}= 0.186406
β_3= slope coefficient of LogX_{2t}= 0.0746664
μ_t= error term

5. OLS Violations

5.1 Multicollinearity

Multicollinearity is the situation of high intercorrelations between independent variables in a multiple regression model. The high correlation poses a problem because explanatory variables should not influence each other, leading to skewed results. For verifying whether the OLS Model 1 suffers from multicollinearity, we use two methods in particular.

1) Correlation matrix:

(Null hypothesis) H_0: No multicollinearity

(Alternate hypothesis) H_A: Multicollinearity is present

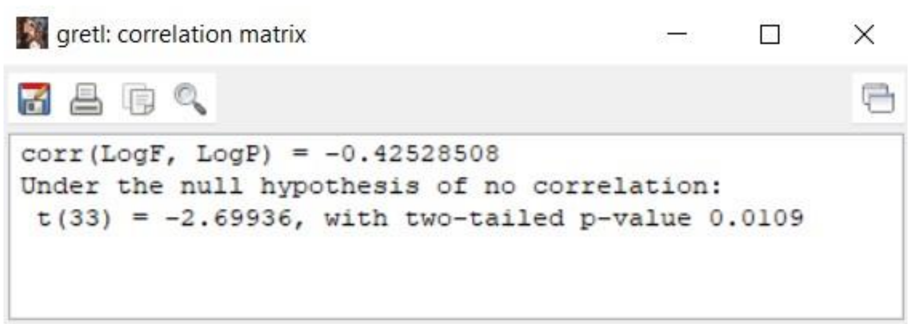

Figure 5: Matrix portraying the correlation between LogF and LogP

Source: Computed from GRETL

Figure 5 shows that the explanatory variables are not highly correlated as the correlation between them is only -0.42 approximately. Therefore, the problem of multicollinearity must not persist in

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the model. However, we also check for multicollinearity through the method of variance inflation factors.

2) Variance inflation factors(VIF):

```
gretl: collinearity

Variance Inflation Factors
Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem

        LogF    1.221
        LogP    1.221

VIF(j) = 1/(1 - R(j)^2), where R(j) is the multiple correlation coefficient
between variable j and the other independent variables

Belsley-Kuh-Welsch collinearity diagnostics:

  variance proportions

  lambda    cond    const    LogF    LogP
   2.981   1.000    0.000   0.002   0.000
   0.019  12.528    0.004   0.747   0.007
   0.000  98.431    0.996   0.251   0.993

  lambda = eigenvalues of inverse covariance matrix (smallest is 0.000307648)
  cond   = condition index
  note: variance proportions columns sum to 1.0
```

Figure 6: Testing for multicollinearity in OLS Model 1 using VIF
Source: Computed from GRETL

Figure 6 shows that the VIF values of the variables in question are less than 10. Both the explanatory variables have a VIF value of 1.221. Hence, we can rightfully claim that the model does not have a collinearity problem.

5.2 Heteroscedasticity

OLS assumes that the variance of the error term is constant (Homoscedasticity).The model suffers from heteroscedasticity if the error terms do not have constant variance. The existence of heteroscedasticity is a major concern in applying regression analysis, including the analysis of variance, as it can invalidate statistical tests of significance.

White's test:

H_0: Heteroscedasticity is not present (Homoscedasticity)

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H_a: Heteroscedasticity is present

gretl: LM test (heteroskedasticity)

```
White's test for heteroskedasticity
OLS, using observations 1980-2014 (T = 35)
Dependent variable: uhat^2

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const      -0.967807     0.686585     -1.410    0.1693
  LogF       -0.0767335    0.0715435    -1.073    0.2923
  LogP       -0.212829     0.151018     -1.409    0.1694
  sq_LogF    -0.00394841   0.00194905   -2.026    0.0521  *
  X2_X3      -0.00674873   0.00853766   -0.7905   0.4357
  sq_LogP    -0.0119549    0.00832852   -1.435    0.1619

  Unadjusted R-squared = 0.158264

Test statistic: TR^2 = 5.539238,
with p-value = P(Chi-square(5) > 5.539238) = 0.353663
```

Figure 7: Testing for heteroscedasticity in OLS Model 1 using White's test

Source: Computed from GRETL

Since the p-value in figure 7 is greater than the level of significance (0.353663 > 0.05) therefore we have insufficient evidence to reject the null hypothesis (H_0). That means heteroscedasticity is not present in the model.

5.3 Autocorrelation

Autocorrelation in the model exists when the error terms are correlated with each other, which leads to skewed and misleading results. Breusch-Godfrey test and Durbin Watson test are executed to check for autocorrelation in the model.

1) Breusch-Godfrey test:

H_0: Autocorrelation is not present

H_a: Autocorrelation is present

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gretl: autocorrelation

```
Breusch-Godfrey test for first-order autocorrelation
OLS, using observations 1980-2014 (T = 35)
Dependent variable: uhat

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const      0.0206966     0.231968     0.08922   0.9295
  LogF       0.00159168    0.0146219    0.1089    0.9140
  LogP       0.00203950    0.0262356    0.07774   0.9385
  uhat_1     0.549846      0.150132     3.662     0.0009  ***

  Unadjusted R-squared = 0.302010

Test statistic: LMF = 13.413254,
with p-value = P(F(1,31) > 13.4133) = 0.000924

Alternative statistic: TR^2 = 10.570355,
with p-value = P(Chi-square(1) > 10.5704) = 0.00115

Ljung-Box Q' = 11.4909,
with p-value = P(Chi-square(1) > 11.4909) = 0.000699
```

Figure 8: Testing for autocorrelation in OLS Model 1 using Breusch-Godfrey test
Source: Computed from GRETL

Since the p-value in figure 8 (0.000924) is smaller than the level of significance (0.05), so there is sufficient evidence to reject the null hypothesis (H_0). Hence, autocorrelation exists in our model.

2) Durbin Watson test:

H_0: No positive autocorrelation

H_a: No negative autocorrelation

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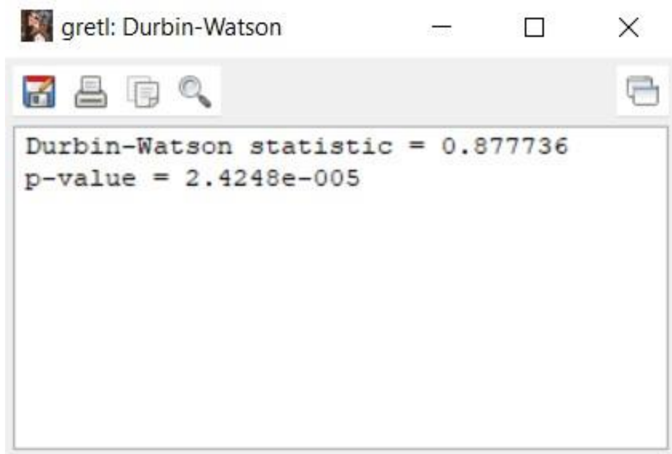

Figure 9: Testing for autocorrelation in OLS Model 1 using Durbin Watson test

Source: Computed from GRETL

k'=2 (Calculated)

d_L=1.303 (Calculated)

d_U=1.584 (Calculated)

Since the Durbin Watson statistic (0.877736) in figure 9 is smaller than d_L, we reject the null hypothesis (H_0). Hence, there is no positive autocorrelation in the model, but negative autocorrelation exists.

5.4 Remedial measure of autocorrelation

In order to remove autocorrelation from OLS Model 1, PraisWinsten's approach is used as a remedy.

We regress,

$LogAY_t^* = \beta_1^* + \beta_2^*(LogF_t^*) + \beta_3^*(LogP_t^*) + \hat{u}_t$

Where,

$LogAY_t^* = LogAY_t - \hat{\rho}LogAY_{t-1}$

$LogF_t^* = LogF_t - \hat{\rho}LogF_{t-1}$

$LogP_t^* = LogP_t - \hat{\rho}LogP_{t-1}$

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and,

$LogAY_1^* = LogAY_1(1-\hat{p}^2)^{0.5}$

$LogF_1^* = LogF_1(1-\hat{p}^2)^{0.5}$

$LogP_1^* = LogP_1(1-\hat{p}^2)^{0.5}$

$\hat{p}$= 0.549309(obtained from OLS Model 1), $\hat{p}^2$= 0.3017403

Now, running a regression model on the starred variables using OLS on GRETL and checking for autocorrelation, the following results are obtained:

```
gretl: autocorrelation

Breusch-Godfrey test for first-order autocorrelation
OLS, using observations 1980-2014 (T = 35)
Dependent variable: uhat

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       0.00293527   0.0868073     0.03381   0.9732
  LogP_aaa    0.00428067   0.0338448     0.1265    0.9002
  LogF_aaa   -0.0115474    0.0557865    -0.2070    0.8374
  uhat_1      0.334082     0.171175      1.952     0.0601  *

  Unadjusted R-squared = 0.109429

Test statistic: LMF = 3.809110,
with p-value = P(F(1,31) > 3.80911) = 0.0601

Alternative statistic: TR^2 = 3.829998,
with p-value = P(Chi-square(1) > 3.83) = 0.0503

Ljung-Box Q' = 4.08646,
with p-value = P(Chi-square(1) > 4.08646) = 0.0432
```

Figure 10: Testing for autocorrelation after executing Prais Winston's remedy

Source: Computed from GRETL

Since the test statistic p-value (0.0601) in figure 10 is greater than the level of significance (0.05) so there is insufficient evidence to reject the null hypothesis (H_0). Hence, the model does not have autocorrelation anymore. Moreover, the Durbin Watson statistic of the new model is 1.311, which is greater than d_L,so there is no autocorrelation in the model now.

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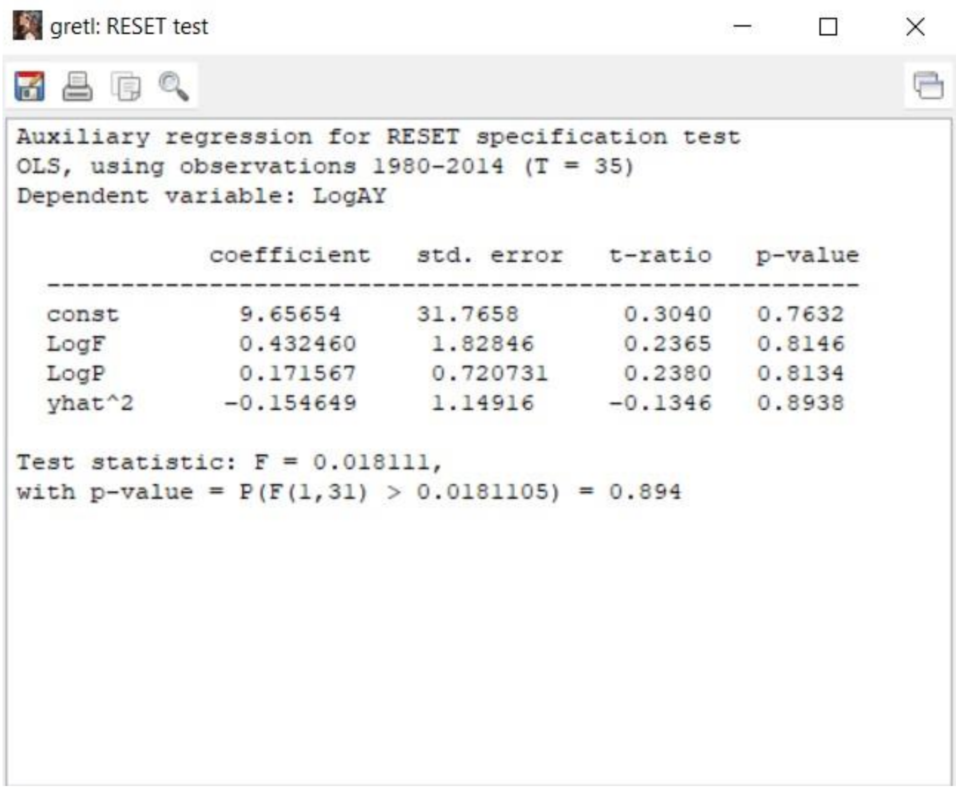
5.5 Specification biasedness

Ramsey's RESET test (squares only):

H_0: Specification is adequate

H_a: Specification is inadequate



```
gretl: RESET test

Auxiliary regression for RESET specification test
OLS, using observations 1980-2014 (T = 35)
Dependent variable: LogAY

              coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const         9.65654     31.7658       0.3040   0.7632
  LogF          0.432460     1.82846      0.2365   0.8146
  LogP          0.171567     0.720731     0.2380   0.8134
  yhat^2       -0.154649     1.14916     -0.1346   0.8938

Test statistic: F = 0.018111,
with p-value = P(F(1,31) > 0.0181105) = 0.894
```

Figure 11: Testing for specification biasedness in OLS Model 1 using RESET test
Source: Computed from GRETL

Since the p-value (0.894) in figure 11 is greater than the level of significance (0.05), so there is insufficient evidence to reject the null hypothesis (H_0). Hence, the specification is adequate.

6. Additional Tests

6.1 Joint Significance test

H_0: $\beta_2 = \beta_3 = 0$

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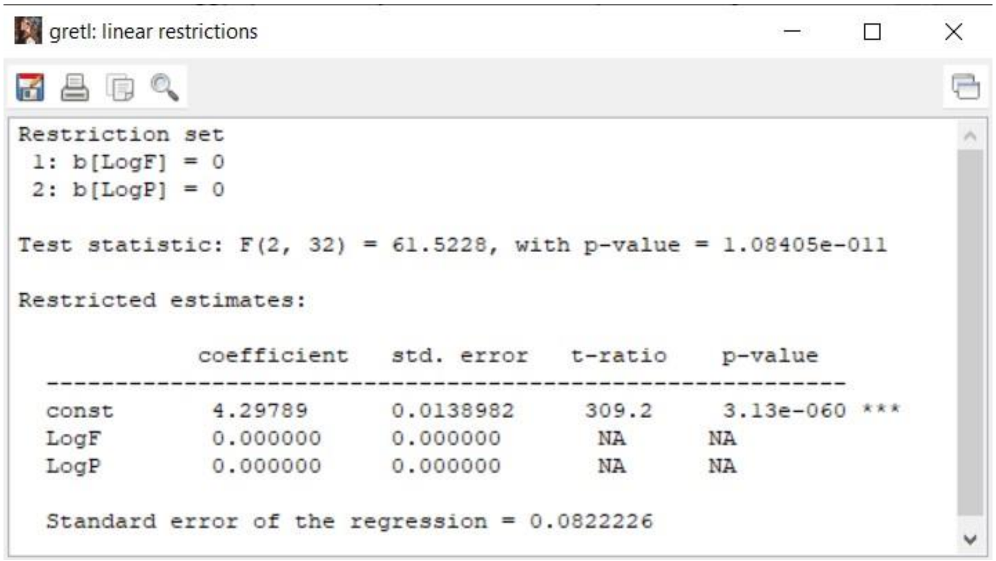
H_a: $\beta_2 \neq \beta_3 \neq 0$



gretl: linear restrictions

```
Restriction set
 1: b[LogF] = 0
 2: b[LogP] = 0

Test statistic: F(2, 32) = 61.5228, with p-value = 1.08405e-011

Restricted estimates:

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const        4.29789     0.0138982     309.2     3.13e-060 ***
  LogF         0.000000    0.000000       NA       NA
  LogP         0.000000    0.000000       NA       NA

  Standard error of the regression = 0.0822226
```

Figure 12: Testing for overall significance of OLS Model 1

Source: Computed from GRETL

Since the p-value (1.08405e-011) in figure 12 is smaller than the level of significance (0.05), so there is sufficient evidence to reject the null hypothesis (H_0). Hence, the model is overall significant. In other words, LogF and LogP together strongly influence LogAY.

6.2 Mackinnon White Dan Davidson test (MWD test)

The MWD tests aids in choosing whether linear or log-linear/double-log model should be used to conduct estimation.

H_0: Linear model: Y is a linear function of regressors, the X's

H_a: Log-linear model: lnY is a linear function of X's, or the log of X's Here,

Y = Total crop yield (in tonnes per hectare)

Regressors = Consumption of pesticides (in tonnes per hectare) and consumption of fertilizers (in tonnes per hectare)


```
gretl: model 2
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Model 2: OLS, using observations 1980-2014 (T = 35)
Dependent variable: AgricultureYieldtonnesper

                       coefficient   std. error   t-ratio   p-value
  -------------------------------------------------------------
  const                  60.4473      3.73146     16.20     1.11e-016 ***
  ConsumptionofFer~     141.178      17.1600       8.227    2.72e-09  ***
  ConsumptionofPes~    5296.99     9308.39         0.5691   0.5734
  Z1                   -131.194      31.4541      -4.171    0.0002    ***

Mean dependent var   73.74909   S.D. dependent var   5.912142
Sum squared resid    226.4792   S.E. of regression   2.702921
R-squared            0.809428   Adjusted R-squared   0.790985
F(3, 31)             43.88932   P-value(F)           2.86e-11
Log-likelihood      -82.34069   Akaike criterion     172.6814
Schwarz criterion    178.9028   Hannan-Quinn         174.8290
rho                  0.482826   Durbin-Watson        0.982327

Excluding the constant, p-value was highest for variable 4 (ConsumptionofF
```

Figure 13: Part 1 of MWD test

Source: Computed from GRETL

```
gretl: model 3
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Model 3: OLS, using observations 1980-2014 (T = 35)
Dependent variable: LogAY

              coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       5.05828       0.315081     16.05     1.43e-016 ***
  LogF        0.167633      0.0193950     8.643    9.24e-010 ***
  LogP        0.0407803     0.0348618     1.170    0.2510
  Z2          0.0132593     0.00710078    1.867    0.0713    *

Mean dependent var    4.297887   S.D. dependent var    0.082223
Sum squared resid     0.042644   S.E. of regression    0.037089
R-squared             0.814476   Adjusted R-squared    0.796523
F(3, 31)              45.36489   P-value(F)            1.89e-11
Log-likelihood        67.76583   Akaike criterion     -127.5317
Schwarz criterion    -121.3103   Hannan-Quinn         -125.3840
rho                   0.486813   Durbin-Watson         0.967487

Excluding the constant, p-value was highest for variable 7 (LogP)
```

Figure 14: Part 2 of MWD test

Source: Computed from GRETL

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Since the p-value of Z_1 in figure 13, that is, 0.0002 is lower than the significance level (0.05), we have sufficient evident to reject the null hypothesis (H_0). Moreover the p-value of Z_2 in figure 14, that is, 0.0713 is greater than the significance level (0.05). Hence,we have insufficient evidence to reject H_a. Hence, we can say that Z_2 is not statistically significant. It implies that the log-linear model or double-log model fits correct.

6.3 Chow test

The Chow test assists in detecting structural change in the data used for conduction estimation. Here, Chow test is implemented to verify whether structural change persists in 1991.

H_0: No structural change in 1991

H_a: Structural change in 1991

gretl: Chow test output

```
Augmented regression for Chow test
OLS, using observations 1980-2014 (T = 35)
Dependent variable: LogAY

              coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const        4.82920      0.645868      7.477     3.06e-08 ***
  LogF         0.184681     0.0966315     1.911     0.0659   *
  LogP         0.00807336   0.111183      0.07261   0.9426
  splitdum     0.629134     0.774825      0.8120    0.4234
  sd_LogF     -0.0418084    0.104320     -0.4008    0.6915
  sd_LogP      0.0874816    0.119645      0.7312    0.4705

Mean dependent var   4.297887   S.D. dependent var   0.082223
Sum squared resid    0.037261   S.E. of regression   0.035845
R-squared            0.837896   Adjusted R-squared   0.809947
F(5, 29)             29.97953   P-value(F)           1.28e-10
Log-likelihood       70.12737   Akaike criterion    -128.2547
Schwarz criterion   -118.9226   Hannan-Quinn        -125.0333
rho                  0.391638   Durbin-Watson        1.191368

Chow test for structural break at observation 1991
  F(3, 29) = 2.64095 with p-value 0.0681
```

Figure 15: Testing for structural change in data using Chow test
Source: Computed from GRETL

Since the p-value in figure 15 is greater than the significance level (0.0681 > 0.05), so there

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is insufficient evidence to reject the null hypothesis (H_0). It implies that there is no structural change in 1991.

6.4 Normality of residual

If the error terms are not normally distributed,then the forecasts, confidence intervals yielded by a regression model may not be BLUE (BEST LINEAR UNBIASED ESTIMATOR).

H_0: Errors are normally distributed

H_a: Errors are not normally distributed

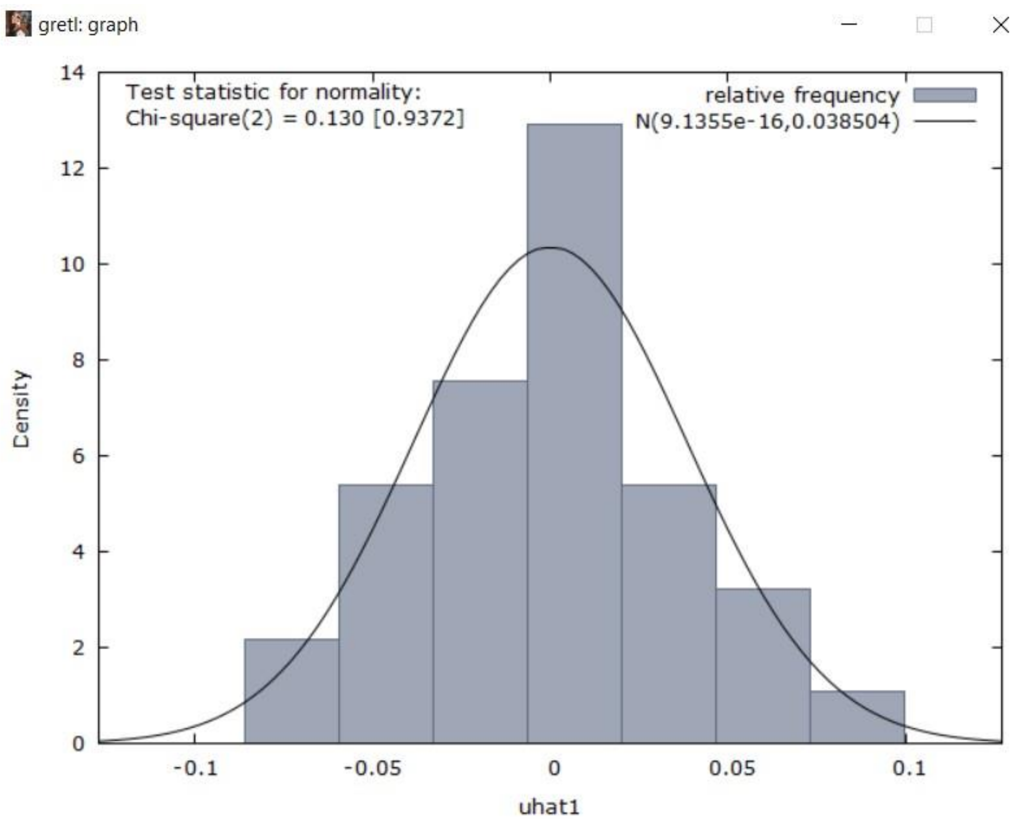

Figure 16: Testing for normal distribution of errors in OLS Model 1
Source: Computed from GRETL

Test statistic: Chi-square (2) = 0.130

With p-value = 0.9372

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Since the p-value (0.9372) in figure 16 is more than the significance level (0.05) therefore there is insufficient evidence to reject the null hypothesis (H_0). It implies that errors are normally distributed.

7. Results

7.1 Interpretation of OLS Model 1

The OLS Model 1 indicates that an increase in 1% of the consumption of fertilizer by Indian farmers increases India's mean predicted total agriculture yield by 0.186406%, keeping consumption of pesticides constant. In other words, β_2 measures the partial elasticity of Y_t with respect to X_{1t}, holding the influence of X_{2t} constant. Hence, total agriculture yield is partially inelastic with respect to the consumption of fertilizers. An increase of 1% of the consumption of pesticides by Indian farmers increases India's mean predicted total agriculture yield by 0.0746664%, keeping consumption of fertilizers constant. In other words, β_3 measures the partial elasticity of Y_t with respect to X_{2t}, holding the influence of X_{1t} constant. Hence, total agriculture yield is partially inelastic with respect to the consumption of pesticides. The mean predicted LogAY is 5.5818 when LogF and LogP are fixed at zero. The t ratios for all the explanatory variables are significant. Moreover, the signs of coefficients satisfy economic theory. R-squared of 0.793609 signifies that LogF and LogP explain 79.3609% of the variation in LogAY.

7.2 Summarising the results of all tests

As far as the validity of the results derived from the model is concerned, the model is overall significant. OLS violations such as specification biasedness, heteroscedasticity and collinearity are not present in the model. The residuals are normally distributed in the model, implying that the classical linear regression model assumptions hold. Although autocorrelation persists, the problem is resolved by applying Prais Winston's approach. Finally, the chow test confirms that there is no structural change in 1991.

8. Discussion

As stated before, the objective of the study was to determine the impact of consumption of fertilizers (in tonnes per hectare) and consumption of pesticides (in tonnes per hectare) on total crop yield (in tonnes per hectare). The OLS model results agree with the empirical evidence, which suggests that fertilizers and pesticides are crucial for enhancing agriculture yield. However, it is essential to realize that factors outside the scope of this study, such as labour, capital employed, rainfall and other climatic factors, also contribute towards raising the agriculture yield, as economic theory suggests. Therefore, drawing keen attention to the adequate

ISSN: 2455-8834

Volume:06, Issue:09 "September 2021"

supply of these inputs is also critical for meeting production goals.

9. Acknowledgement

I would like to express my deep and sincere gratitude to my professors at the Economics Faculty of Aryabhatta College for granting me the opportunity to research on the chosen topic and providing invaluable guidance throughout this research. I acknowledge them for their valuable support, cooperation, and patience, which helped me successfully complete this paper.

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