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Case Report

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Homogeneous and Heterogeneous Effect of Agricultural Inputs on Crop Productivity of the Three-Grain Crop Types in Ethiopia

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Abstract

Background: Agriculture is a critical source of food and income, making it a key component of initiatives aimed at reducing poverty and ensuring food security across the globe. It is the backbone of Ethiopia's economy, contributing significantly to the country's financial development. The sector earns 88.8 percent of trade profit and contributes 36.7 percent of GDP. The purpose of this paper was to identify the homogeneous and heterogeneous effects of agricultural inputs on crop productivity of the three-grain crop types in Ethiopia.

Method: The central statistical agency (CSA) provided the data for this study, which covered the entire country from 1990 to 2012 Ethiopian Calendar (E.C). Crop productivity, which is assessed in kilograms per hectare for cereal, pulse, and oil crops, was utilized as the response variable. For three-grain crop types from 1990 to 2012 E.C, the study used the pooled mean group estimate method, which allows for long-run homogeneity effects across cross-sections as well as short-run heterogeneity.

Results: In the long run, the study found that a one percent increase in fertilizer consumption resulted in a 2.686 percent increase in grain crop productivity in Ethiopia, while a one percent increase in improved seed per hectare and land size, resulted in a 48.31 percent and 10.58 percent increase in grain crop productivity per crop category respectively. Short-run productivity for grain crops increased by 30.29 percent as the amount of improved seed value at one period lag value of commercial farm holders is increased by one percent. In the same way, when the arable land at the first difference is increased by one percent then the productivity of grain crops increased by 40.61 percent.

Conclusion: The findings of this research showed that in the long run, fertilizer consumption, amount of improved seed use, and arable land area size had homogeneous significant contributions, while in the short run, agricultural inputs like the use of pesticides and improved seed use at first lagged value had heterogeneous significant contributions to grain crop productivity improvement across all cross-sectional units.

Keywords: Heterogeneous effect, Homogeneous effect, Grain crop productivity, Panel co-integration, Pooled mean group estimator, Ethiopia

Background

Agriculture remains the central impression of numerous African countries since it is considered the region's biggest financial sector [1]. Agriculture is a vital source of food and business, making it a basic component of programs that look to decrease poverty and achieve nutrition security within the landmass. Several African economies have experienced consistent net residential item (GDP) growth for a long time up on agriculture [2].

Ethiopia is a nation arranged in the eastern portion of Africa with a population of more than 100 million. Agriculture is the backbone of the Ethiopian economy, playing a crucial part in the country's financial advancement. The sector accounts for 36.7% of the GDP and generates 88.8% of trade profit. Ethiopian agriculture, on the other hand, could be a rain feed because its development is dependent on a favorable climate, among other things [3]. For example, the rural division displayed a lower development rate of 2.3% in 2015/16, generally on account of source impact [4].

In Ethiopia, agriculture is the major source of income and employment. This suggests that development in agricultural efficiency directly influences the welfare of the bulk of the rural poor [5]. The government of Ethiopia has made critical efforts in terms of open investments to speed up the development of agriculture, which implies accelerating financial change [6]. In any case, open investments did not meet the expected targets, and rapid population growth may be stifling any rural investments [7].

Ethiopian agriculture has suffered for years from the utilization of ancient farm implements and agriculture systems, as well as restricted use of recent farm inputs that resulted in the sector's poor performance (i.e., low productivity of the sector) [8]. In any case, surplus production at the productivity facet will increase as listed for the last six consecutive months, indicating that the agricultural framework as a whole, and thus the crop production subsector, in particular, is changing in terms of productivity, the degree and utilization of recent farm inputs, and advanced farming system practices [9].

Out of the overall crops produced within the country, grain crops took the lion's share, both in terms of the whole zone of arrival scope and yield generation [3]. Of the overall area, 89.5% of it was covered by grain crops (cereals, pulses, and oilseeds), which did not constitute the major food crops for the larger part of the country's population but, moreover, served as a source of salary at the family level and supported the country's financial profit [10]. Cereals secured 79.88% of the available hectares in the full-grain edit zone [11].

Agricultural Change in many developing nations that have resulted in a significant increase in rural efficiency resulted from programs of rural research, expansion, and infrastructural advancement that occurred in the late 1960s, and this revolution was known as the Green Revolution [12]. Transformation refers to a quick increment in wheat and rice efficiency brought about by the appropriation of improved seed assortments, fertilizers, and pesticides [13]. Technological alteration in farming comprises the presentation of a high-yielding assortment of seeds, fertilizers, plant assurance measures, and water systems. These changes in the rural segment improve the efficiency per unit of arrival and bring approximately a quick increment in a generation [14].

A literature review distinguished different factors that influence agricultural efficiency. Cropped area, fertilizer utilization, improved seed, credit conveyance, and water accessibility have been identified as the major components influencing rural generation in Pakistan [14].

A comparative study in Malesia [15] contends that net export, inflation, interest rate, nominal exchange rate, government expenditure, and money supply all influence agricultural productivity. On the other hand, rainfall, fertilizer input imports, trade openness, inflation rate, and dry season were found to be the essential macroeconomic variables impacting agricultural productivity [17-19].

The study focused on agricultural inputs like fertilizer, pesticide use, amount of improved seed, and land size per hectare as a determinant of grain crop efficiency. The panel information set included three cross-sectional units, which are cereals, pulses, and oil crop types. The study assessed the sources of grain crop productivity in Ethiopia for the period 1990–2012 E.C [20].

Although there have been research on agricultural productivity using univariate ARDL, panel regression models, and multiple regression models [17,19,21,22] but this study used the Panel-ARDL model of the PMG estimator because this model has a few preferences that incorporate the expanded productivity of the evaluated results due to the use of more diverse information and also the comprehensiveness of the analysis result for cross-sectional data along with time-series data [23]. The purpose of this paper is to identify the homogeneous and heterogeneous effects of agricultural inputs on crop productivity of three-grain crop types in Ethiopia using an appropriate PMG estimator, as well as to evaluate the effect of agricultural input heterogeneity and homogeneity across individual cross-sectional units (crops).

Methodology

Data source

The data for this study used a panel data set from CSA on the annual average yield of chosen grain crops during the study period of 1990–2012 Ethiopian Calendar (E.C), and the survey would cover all regions of the country.

Response variable of the study

Grain crop productivity (yield) of cereals, pulses, and oil crops in kilograms (kg) per unit area used in hectares (ha) in Ethiopia is the response variable. It is the i^{th} grain crop type yield, i = 1,2,3, which is measured by the combined cereal yield, pulse yield, and oil yield in kg/ha.

Independent variable

The basic explanatory variables included in this research were: - the amount of fertilizer consumption(F), arable land (L) use, amount of improved seed use (IMP), time-lagged value of the independent variable, amount of pesticide (P) use, and time-lagged value of the dependent variables.

P-ARDL Model

To determine the relationship between agricultural productivity and agricultural input for grain crops in the categories in Ethiopia, the P-ARDL model approach was used [24]. This model was used because the series was not stationary in the same order, i.e., to investigate factors regardless of whether they were stationary I(0), I(1), or both I(0) and I(1), and differenced to become stationary, and the model was used because it takes into account any co-integration relationships among variables [25]. This study is employed based on four basic variables, which include fertilizer consumption, number of improved seeds used, use of pesticides, and area of arable land [26]. The P-ARDL technique is selected to investigate the long-term and short-term co-integration correlations between the determinants and extract the ECM (error correction model) of the panel characteristics to identify the short-term dynamic [27]. It can be used with the study factors regardless of whether they are I(0), I(1), or both I(0) and I(1) [28]. Assume an autoregressive distributive lag (ARDL) ($p, q_1, q_2, \ldots q_k$) dynamic panel specification of the form: The general P-ARDL GCP model is given by:

$$GCP_{it} = \alpha_i + \sum_{j=1}^{p_i} \beta_{ij} GCP_{it-j} + \sum_{j=0}^{q_{1i}} \lambda_{ij} F_{it-j} + \sum_{j=0}^{q_{2i}} \gamma_{ij} L_{it-j} + \sum_{j=0}^{q_{3i}} \delta_{ij} IMP_{it-j} + \sum_{j=0}^{q_{4i}} \rho_{ij} P_{it-j} + \varepsilon_{it} \ldots\ldots.(1)$$

If the variables in equation (1) have I(1) and, are co-integrated, then the error term is an I(0) process for all i. A principal feature of co-integrated variables is their responsiveness to any deviation from long-run equilibrium. This feature implies an error correction model in which the short-run dynamics of the variables in the system are influenced by the deviation from equilibrium and the above P-ARDL model can be reformulated as given below:

$$\Delta GCP_{it} = \alpha_i + \beta_{1i} F_{it} + \beta_{2i} L_{it} + \beta_{3i} IMP_{it} + \beta_{4i} P_{it} +$$
$$\sum_{j=1}^{q_{1i}} \alpha_{ij} \Delta F_{it-1} + \sum_{j=1}^{q_{2i}} \gamma_{ij} \Delta L_{it-1} + \sum_{j=1}^{q_{3i}} \delta_{ij} \Delta IMP_{it-1} + \sum_{j=1}^{q_{4i}} \rho_{ij} \Delta P_{it-1} + \eta_i ECM_{it} + \upsilon_{it} \ldots\ldots\ldots\ldots\ldots(2)$$

Where:

GCP_{it} = Grain crop productivity of i^{th} cross-sectional unit at time t.

F_{it} = Fertilizer consumption of i^{th} cross-sectional unit at time t.

L_{it} = Land size of i^{th} cross-sectional unit at time t.

IMP_{it} = Amount of improved seed use of i^{th} cross-sectional unit at time t.

P_{it} = Use of pesticide for i^{th} cross-sectional unit at time t.

α_i= Is the group-specific effect and v_{it} is the error term assumed to be independently distributed across i and over time t.

ECM_{it} = Error correction term lagged by one period of i^{th} cross-sectional unit at a time t.

β_{1i}, β_{2i}, β_{3i} β_{4i} and α_{ij}, σ_{ij}, γ_{ij}, ρ_{ij} are representing long run and short run coefficients respectively at i^{th} cross-sectional unit at j^{th} time lag. The appropriate technique used for the analysis of dynamic panels is the Autoregressive distributed lag ARDL (p,q) model and then estimate the model based on the mean group (MG) presented by [28] and Pooled mean group (PMG) estimators developed by [29] and DFE estimator. Based on the aim this study used a PMG estimator, sine PMG estimator is more appropriate than others to show homogeneous and heterogeneous effects [30].

Pooled Mean Group Estimation

To estimate the effects of agricultural inputs on commercial farm crop productivity, this study applies the method of pooled mean group estimation (PMGE) of dynamic heterogeneous panels [29]. The Pool Mean Group, on the other hand, was applied to detect the long and short-run association between agricultural inputs and agricultural productivity, and also investigate the possibly homogeneous and heterogeneous dynamic issue across grain crop categories, the appropriate technique to be used to the analysis of dynamic panels is Autoregressive distributed lag ARDL (p,q) model in the error correction form and then estimate the model based on the Pooled mean group (PMG) estimators developed by [28]. The ARDL of the PMG estimator specification of the GCP model is formulated as follows:

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$$\Delta GCP_{it} = \alpha_i + \beta_1 GCP_{it-1} + \beta_2 F_{it-1} + \beta_3 L_{it-1} + \beta_4 IMP_{it-1} + \beta_5 P_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta GCP_{it-j} + \sum_{j=0}^{q_{1i}} \lambda_{ij} \Delta F_{it-j} + \sum_{j=0}^{q_{2i}} \gamma_{ij} \Delta L_{it-j} + \sum_{j=0}^{q_{3i}} \delta_{ij} \Delta IMP_{it-j} + \sum_{j=0}^{q_{4i}} \rho_{ij} \Delta P_{it-j} + \theta_i ECM_{it} \quad \text{......................................(3)}$$

Where: β_1, β_2, β_3, β_4, and β_5 are long-run coefficients and assume homogeneous across cross-sectional units and β_{ij}, λ_{ij}, σ_{ij}, γ_{ij}, and ρ_{ij} short-run coefficients and heterogeneous of the i^{th} cross-sectional unit at j^{th} time lag. ECM_{it} is represent the error correction term lagged by one period of the i^{th} cross-sectional unit at a time t.

Panel Unit Root Test

This study applies panel unit root tests rather than traditional unit root tests to extend testing control from extra data given by the pooled cross-section time series. Earlier in the PMGE examination, panel root tests were required to decide the arrangement of integration of the factors. In this study, we use IPS, which stands for a widely used unit root test proposed by [31] and [32]. IPS is less restrictive and more appropriate compared to unit root tests developed by [33], which don't permit heterogeneity within the autoregressive coefficient. IPS gives arrangement to Levin and Lin's serial relationship issue by expecting heterogeneity between units in an energetic board system [34]. IPS specifies an Augmented Dickey-Fuller (ADF) regression with an individual intercept and a time trend for each cross-section as follows:

$$\Delta Y_{it} = \alpha_i + \rho Y_{it-1} + \sum_{j=0}^{q_i} \lambda_{ij} \Delta Y_{it-j} + \varepsilon_{it};\ i = 1, 2, ..., N, t = 1, 2, ..., T \ldots\ldots\ldots\ldots\ldots (4)$$

Where Y_{it} is the selected variable in crop type i and t, α_i is the individual fixed effect, and ρ is selected to make the residuals uncorrelated over time. The null hypothesis is that $\rho_i < 0$ for some $i=1,2,\ldots\ldots, N_1$ and $\rho_i = 0$ for $i=N_1+1,\ldots\ldots.., N$. The IPS statistics is based on averaging individual Augmented Dickey-Fuller (ADF) statistics to produce a standardized test, and can be written as follows:

$$t_{cal} = \frac{\sum_{i=1}^{N} t_i T}{N}$$

where $\mathbf{t}_{iT}$ is the ADF t-statistic for crop type i based on the country-specific ADF regression, as in Equation (1). The t statistic is assumed to be normally distributed under H_0 and the critical values for given values of N and T are provided in [31].

Panel Cointegration Test

Next, we conduct a panel cointegration test after identifying the order of cointegration. In this study, we use the panel cointegration test advocated by the Kao residual cointegration test to ascertain the existence of a long-run relationship amongst the variables in the model, which enables us to avoid the common factor restriction problem [35]. The null hypothesis that would be applied to the model hypothesis is that the variables are not cointegrated. The null hypothesis is tested by inferring whether the error correction term in a conditional error correction model is equal to zero. If the null hypothesis of no error correction hypothesis is rejected, then the null hypothesis of no cointegration is also rejected [36]. The starting point of the Kao-test considers the following model for homogeneous and heterogeneous cross-sectional parameters across the group.

$$GCP_{it} = \alpha_i + \beta_1 F_{it} + \beta_2 L_{it} + \beta_3 IMP_{it} + \beta_4 P_{it} + e_{it},\ i = 1, 2, 3,\ t = 1, 2, \ldots, 23$$
$$\leftrightarrow \hat{e}_{ij} = G\hat{C}P_{ij} - (\hat{\alpha}_i + \beta_1 \hat{F}_{it} + \beta_2 \hat{L}_{it} + \beta_3 I\hat{M}P_{it} + \beta_4 \hat{P}_{it}) \ldots\ldots\ldots\ldots(5)$$

Where α_i is the fixed effects varying across the cross-section observations, β_1, β_2, β_3, and β_4 are the slope parameter. From equation (5) reformulated the $\hat{e}_{it}$ as below:

$$\hat{e}_{it} = \rho_i \hat{e}_{it} + \sum_{j=1}^{p} \theta_j \Delta\hat{e}_{it-1} + v_{itp} \ldots\ldots\ldots\ldots\ldots(6)$$

The hypothesis is stated as:

H_0: no co-integrating equation ($\rho_i = 1$)

H_1: H_0 is not true i.e $\rho_i < 1$

If test statistics are greater than tabulated values, then the series is co-integrated, i.e., the estimated residuals for each cross-sectional unit have I(0) and vice versa. When the panel data series variables have co-integration relationships and the order of stationarity is I (1) or a mix of I(0) and I(1), the model is analyzed using PMG [37].

Results

Cereal, pulse, and oil crop types had 136.7, 135, and 132.7 average productivity increment values for the 1990–2013 E.C, respectively, as shown in Table 1. This suggests that during the period 1990–2013 E.C, commercial farms' harvested cereal crop types were more productive than others in Ethiopia. Commercial farms use an average of 122.5 tons of fertilizer for cereal crops, 119.7 kg of fertilizer per hectare for pulse crops, and an average of 108.4 kg of fertilizer per hectare, for oil crop productivity per the given year. Furthermore, commercial farms with 83, 17.3, and 31.1 acres of land produced 136.6, 135, and 132.7 tons of cereal, pulse, and oil crop production, respectively, during the given year.

Table 1: Summary Statistics for each cross-sectional unit

Variable/statistics	crop type	obsn	mean	Std.dv	max	min
	Cereal		136.7	32.7	186	107
Yield	Pulse	69	135	30.5	171	103
	Oil		132.7	29.0	196	97.4
	Cereal		54.61	18.29	96	28
Pesticide	Pulse	69	55.61	18.25	98	30
	Oil		54.10	17.98	93.5	26
	Cereal		83	16.7	123	59
Area	Pulse	69	17.3	10.9	30	8
	Oil		31.1	5.0	56	19
	Cereal		47.26	41.4	75	19
Improve seed	Pulse	69	47.18	32.4	88	14
	Oil		45.10	35.4	84.5	13
	Cereal		122.5	58.44	237.6	87
fertilizer	Pulse	69	119.7	39.97	227.8	98
	Oil		108.4	68.40	226.8	94

On average, commercial farms brought 134.805 grain crop productive increment value from 1990 to 2012 E.C, according to summary statistics in Table 2. Between 1990 and 2012, the average increase in treated chemicals and improved seed use on commercial farms was 54.772 and 46.516, respectively.

Table 2: overall Summary Statistics

Variable	**Obsn**	**Mean**	**Std. Dev.**	**Min**	**Max**
F(**kg/ha**)	69	116.867	55.6033	87	237.6
IMP(**kg/ha**)	69	46.516	36.043	13	88
Y(**kg/ha**)	69	134.805	30.733	97	196
A(ha/person)	69	43.783	30.785	8	123
P (**kg/ha**)	69	54.772	17.915	26	98
ΔP	66	2.583	12.263	-14	41
ΔA	66	0.818	10.220	-39	41

ΔIMP	66	5.168	23.887	-63	67
ΔY	66	4.624	18.378	-39.44	3.3

Where Y = Yield, F = fertilizer consumption, P = use of pesticide A = arable land, IMP = improved seed, Δ = first difference

Grain Crop Productivity in Ethiopia from 1990 to 2012

We can see from Figure 1 that agricultural productivity grows with time for all crop types. Cereal crop increments, on the other hand, are higher than pulse and oil crop increments. Furthermore, yield growth was poor in all cross-sectional unit crop productivity between 1990 and 1998. However, improvements in productivity growth in cereal, pulse, or oil crop types do not fluctuate continually.

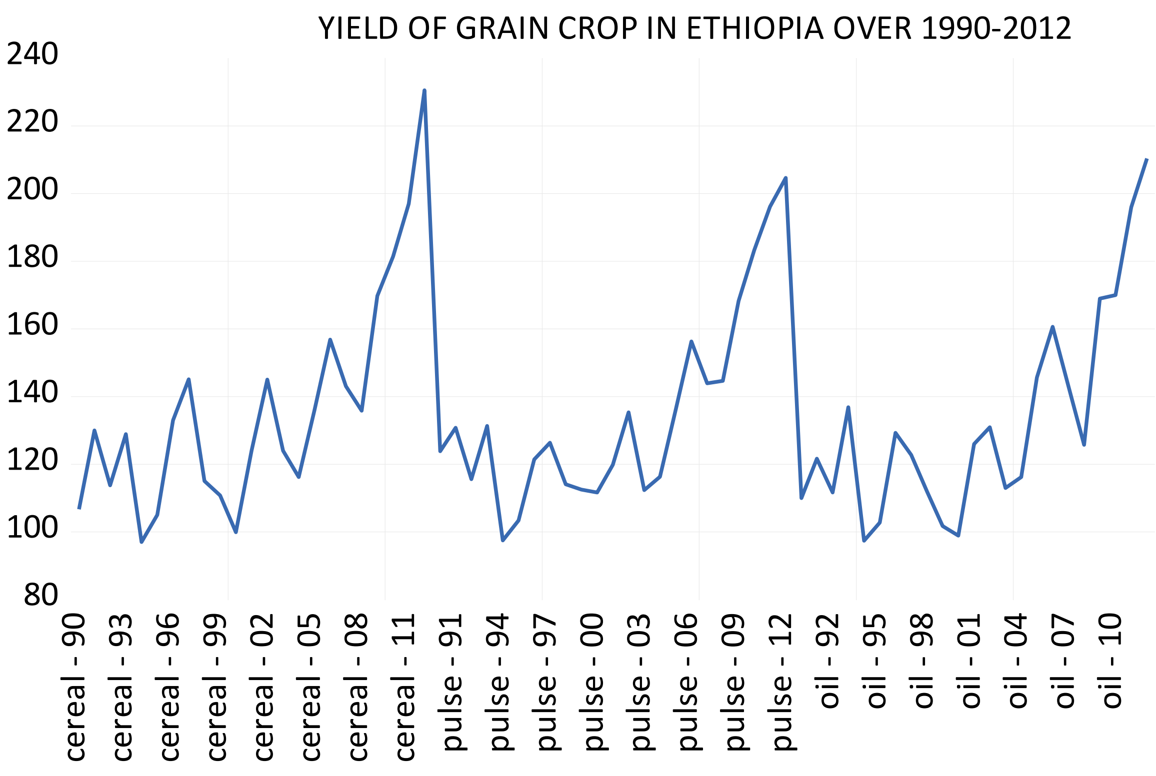

Figure.1 Trend of grain crop productivity in Ethiopia over 1990-2012

Panel Unit Root

The statistics from the panel unit root test as shown in Table 3, the variables are labeled F for fertilizer consumption, P for pesticide use, IMP for improved seed usage, and A for land area. According to the test statistic, all variables except fertilizer appear to be non-stationary at the level. At the one-percent level of significance, all panel unit root tests reject the null hypothesis of non-stationarity, indicating that all variables are stationary at first-difference. As a result, we can deduce that panel variables are integrated with order one (1).

Table 3: Panel unit root test results

	IPS	
Variable	**LEVEL**	**first difference**
Y	0.208(0.999)	-4.711(0.000)
F	-0.769(0.020)	-4.652(0.000)
IMP	4.667(1.000)	-12.288(0.000)
P	1.094(0.863)	-6.819(0.000)
A	-1.637(0.051)	-6.651(0.000)

where Y = yield, F = fertilizer, IMP = improved seed, P = use of pesticide, A = arable land

Panel Co-integration Test

According to the Kao Residual Co-integration Test (1999), the hypothesis of zero non-co-integration is rejected and the existence of a long-term relationship between research variables is confirmed, since the p-value (0.000) is less than the 5% level of significance (Table 4).

Table 4: Kao- residual co-integration test

	Kao-residual co-integration test	
	Test statistics	**Probability-value**
Co-integration	-6.394	<0.001

If a series is co-integrated, that is, if they exhibit a long-run relationship, the series are related and can be combined in a linear fashion. Even if there are shocks in the short run which may affect movement in the individual series, they will converge with time in the long run. Hence, we can estimate both long-term and short-term models.

Optimal lag selection

The procedure is to select the model with the lowest AIC value as this is the best model. We, therefore, select the lowest AIC value as the optimal lag for our analysis, and our findings specify the most appropriate model with ARDL (1,2, 2, 2, 2, 2), as depicted in Table 5 below.

Table 5: Results of optimal lag selection for P-ARDL Model

Model selection criteria		
Model	**AIC**	**Specification**
2	7.225	ARDL (1,2,2,2,2)
1	7.614	ARDL (1,1,1,1)
4	7.630	ARDL (2,2,2,2,2)
3	7.658	ARDL (2,1,1,1)

To select the best fit model, we use Akaike Information Criteria (AIC) and the values are shown in Table 5, also supported graphically in Figure 2. The decision is also the same. From the figure below, the smallest AIC value among optional specifications is the batter model. So, the specification of order ARDL (1,2,2,2,2) was better.

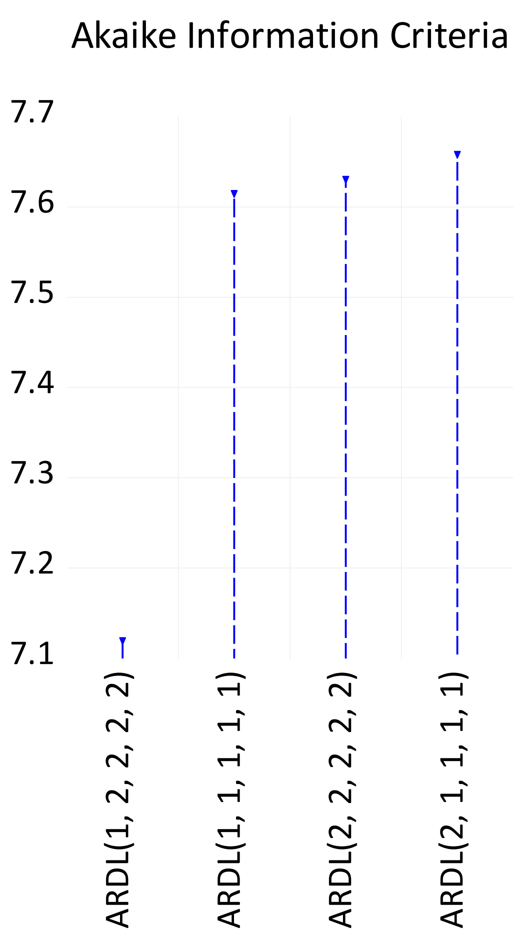

Figure 2: Grain crop productivity model order selection by AIC method

Pooled Mean Group Estimation (PMGE)

The regression results obtained using the PMGE approach are shown in Table 6. The results of the mean group estimator (MGE) and the DFE are also presented for comparison. Due to the constraint of shared long-run coefficients, MGE and DFE have larger standard errors and adjustment speeds than PMGE. Because the MGE and DFE procedures are less restrictive and thus possibly inefficient, this result is expected.

Table 6: Short term and long-term coefficients P-ARDL (1,2,2,2,2)

Estimation for Ethiopian grain crop type productivity 1990–2012			
Variable	**MG**	**PMG**	**DFE**
	Long run coefficient		
A	-0.143 (0.835)	-0.406 (<0.001)	0.087 (0.586)
F	0.029 (<0.001)	0.027 (<0.001)	0.036 (0.000)
IMP	0.316 (<0.001)	0.483 (<0.001)	0.154 (0.209)
P	0.062 (0.617)	-0.005 (0.935)	0.253 (0.075)
ECT	-1.306(<0.001)	-1.146 (<0.001)	-1.095 (<0.001)
Short run coefficient			
ΔA	0.727 (0.041)	0.879(0.14)	0.051 (0.773)
ΔA(-1)	-0.230(0.015)	-0.069 (0.783)	-0.167 (0.258)
ΔF	-0.015 (0.113)	-0.008 (0.273)	-0.013(0.050)
$\Delta\boldsymbol{F}$(-)	-0.005 (0.252)	-0.004 (0.462)	-0.006 (0.094)
ΔIMP	0.006(0.977)	-0.029(0.835)	0.134(0.260)
$\Delta\boldsymbol{IMP}$(-1)	0.245 (0.016)	0.231(0.019)	0.239 (0.002)
ΔP	0.310 (0.079)	0.346 (0.035)	0.042(0.767)
$\Delta\boldsymbol{P}$(-)	0.212 (0.447)	0.241(0.430)	0.154(0.266)
Constant	111.297 (0.002)	107.529(0.000)	74.096(0.000)
Hausman (PMG/MG)	1.79(0.774)		
Hausman (MG/DFE)	1.08(0.896)		
Hausman (PMG/DFE	1.51(0.824)		
No. unit	3	3	3

No. obsn	69	69	69

Note: Probability values are in parenthesis. Model selection method: Alkaike Info Criterion (AIC), Where No. Unit = number of cross-sectional units, No. Obsn = number of observations

Test the null hypothesis of PMGE preferred, PMGE is more preferred than MGE (0.774 >0.05) and PMGE is more preferred than DFE (0.824>0.05) in this model, according to the results from Table 6. One of PMGE's fundamental assumptions is that the long-run coefficient should be the same for all cross-sectional units, whereas the short-run coefficient should vary.

Homogeneous effect of factors across units on productivity

As shown in Table 7, the estimated coefficients of fertilizer consumption, the amount of improved seed used, and land area per holder across grain crop categories (for cereal, pulse type, and oil crop type) are statistically significant, while the amount of treated chemical (pesticide) used per hectare is not statistically significant in the long run.

Since we have specified our productive model in a log-linear form, the coefficient of the independent variables can be interpreted as elasticity with respect to crop yield per crop type. The coefficient of fertilizer is 0.027. This indicates that, in the long run, holding other things constant, a one percent increase in fertilizer consumption per hectare brought a 2.686 percent increase in grain crop productivity in Ethiopia. A one percent increase in the amount of improved seed use per hectare has resulted in 48.31 percent change in Ethiopia's grain crop productivity. Furthermore, a 1% increase in land size has resulted in 10.58% increase in grain crop productivity.

Table 7: Results of estimating long term coefficients by PMGE -ARDL (1,2,2,2,2)

Dependent variable is yield of grain crop

Regressor	**Coef.**	**Std. Err.**	**P>|z|**	**[95% Conf. Interval]**	
Area	0.106	0.108	<0.001	0.618	-0.194
fertilizer	0.027	0.003	<0.001	0.023	0.032
Improved seed	0.483	0.053	<0.001	0.378	0.588
pesticide	-0.006	0.067	0.935	-0.138	0.127

Heterogeneous effect of factor across unit on productivity

Short Run Error Correction Estimates

After the acceptance of the long-run coefficients of the productive equation, the short-run ECM model is estimated. PMGE also assumes that the short run coefficient differs across each cross-sectional unit. This research included three cross-sectional units, i.e., cereal crop types, pulse crop types, and oil crop types, and an estimated short run or error correction model, discussed separately below.

Short run ECM model interpretation for grain crop productivity (cereal crop type)

According to table 8, the equilibrium error correction coefficient, estimated at -0.853, is highly significant, and has the correct sign, and implies a very high speed of adjustment to equilibrium after a shock to cereal crop productivity input factors. Approximately 85.29 percent of the disequilibrium from the previous year's shock converges back to the long-run equilibrium in the current year. Such a highly significant error correction term is another proof of the existence of a stable long-term relationship among cereal crop productivity input variables.

The estimated short-run model reveals that land area size and improved seed use (one period lagged value) have greatly contributed to productivity for cereal crop types. When land area increases by one percent, short-run cereal crop yield increases by 40.60 percent. Next to land area, the amount of improved value at one period lag value changes the cereal crop type yield by 0.303, while others remain constant. However, agricultural inputs like fertilizer consumption and the use of pesticides have no significant short-run effect on cereal crop productivity in Ethiopia.

Table 8: Error correction representation for the selected ARDL (1,2,2,2,2)

Dependent variable is yield

regressor	coef	Std.err	95%conf. interval	
	Cereal Crop Type Estimated Value			
ECM	-0.853(<0.001)	0.179	-1.204	-0.502
ΔA	0.406(0.015)	0.167	0.078	0.733
ΔA(-1)	0.079(0.556)	0.135	-0.185	0.344
ΔF	-0.001(0.848)	0.006	-0.013	0.011
ΔF(-1)	0.001(0.855)	0.004	-0.007	0.009
ΔIMP	0.043(0.740)	0.129	-0.209	0.295
ΔIMP(-1)	0.303(<0.001)	0.092	0.122	0.484
ΔP	0.247(0.128)	0.162	-0.071	0.565
ΔP(-1)	0.093(0.650)	0.205	-0.308	0.493

cons	96.409(<0.001)	20.540	56.152	136.667

Short run ECM model interpretation for grain crop productivity (pulse crop type)

Based on the results in table 9, the equilibrium error correction coefficient, estimated at -1.712, is highly significant, also has the correct sign, and implies a very high speed of adjustment to equilibrium after a shock for pulse crop productivity input factors. Approximately 1.712 percent of the disequilibrium from the previous year's shock converges back to the long-run equilibrium in the current year.

The estimated short-run model reveals that land area used (one period lagged value), fertilizer consumption, and amount of improved seed used have a negative short run significant effect on pulse crop productivity change, while the amount of treated chemical use has no significant short run effect on productivity of pulse crop type. In Ethiopia, when land size (one period lagged value), fertilizer consumption, and use of improved seed increased by one percent, the yield of pulse crop type decreased by 55.64 percent, 22.22 percent, and 29.6 percent, respectively.

Table 9: Error correction representation for the selected ARDL (1,2,2,2,2)

Dependent variable is yield for Pulse Crop Type				
regressor	coef	Std.err	95%conf. interval	
ECM	-1.712(<0.001)	0.322	-1.204	-0.502
ΔA	0.170(0.530)	0.271	0.079	0.733
ΔA(-1)	-0.557(0.001)	0.169	-0.185	0.344
ΔF	-0.022(0.021)	0.009	-0.013	0.011
ΔF(-1)	0.002(0.512)	0.003	-0.007	0.009
ΔIMP	-0.296(0.019)	0.126	-0.209	0.295
ΔIMP(-1)	0.035(0.494)	0.052	0.122	0.484
ΔP	0.123(0.285)	0.115	-0.071	0.565
ΔP(-1)	-0.199(0.103)	0.122	-0.308	0.493
con	149.435(<0.001)	29.019	56.152	136.667

Short run ECM model interpretation for grain crop productivity (Oil crop type)

Based on the results in table 10, the equilibrium error correction coefficient, estimated as -0.874, is highly significant, it has also the correct sign, and implies a very high speed of adjustment to equilibrium after a shock to the oil crop type productivity input factors. Approximately 87.39 percent, of the disequilibrium from the previous year's shock converges back to the long-run equilibrium in the current year.

The estimated short-run model revealed that use of pesticide and its one period lagged value are the main contributors to oil crop productivity change, followed by land area size, fertilizer consumption (one period lagged value) and the amount of improved seed used (one period lagged value). When improved seed use at one period lagged value, land size, pesticide use, and pesticide (one period lagged value) increase by one percent, oil crop yield increases by 35.433, 2.062, 66.63, and 83.06 percent, respectively. Oil crop type yields increase by 1.37 percent when fertilizer consumption (one period lag value) is reduced by one percent.

Table 10: Error correction representation for the selected ARDL (1,2,2,2,2)

Dependent variable is yield (Oil Crop Type)				
regressor	coef	Std.err	95% conf.interval	
ECM	-0.874(<0.001)	0.130	-1.129	-0.619
ΔA	2.062(<0.001)	0.288	1.497	2.627
ΔA(-1)	0.270(0.361)	0.296	-0.310	0.851
ΔF	-0.002(0.967))	0.005	-0.009	0.009
ΔF(-1)	-0.014(<0.001)	0.003	-0.020	-0.007
ΔIMP	0.167(0.070)	0.092	-0.014	0.348
ΔIMP(-1)	0.354(<0.001)	0.068	0.222	0.487
ΔP	0.666(<0.001)	0.150	0.372	0.961
ΔP(-1)	0.831(<0.001)	0.152	0.533	1.128
cons	168.435(<0.001)	27.015	55.132	176.576

Conclusion

Agriculture is a vital source of food and business, making it a basic component of programs that look to decrease poverty and achieve nutrition security within the landmass. The main objective of the study was to identify the homogeneous and heterogeneous effects of agricultural inputs on crop productivity of the 3-grain crop types in Ethiopia. It included four explanatory variables, namely fertilizer consumption, amount of improved seed use, use of pesticides, and land size, with the expectation of their influence on agricultural productivity. A stationary test was carried out using Im–Pesaran–Shin (IPS) tests. Except for fertilizer consumption, the null hypotheses of a unit root at the level were not rejected. Consequently, the first differenced series was considered for further analysis, as the corresponding unit root tests indicated the absence of unit-roots.

The study employed the P-ARDL model of the PMG estimator approach to co-integration and the error correction model (ECM) model by using a panel data set for the period from 1990 to 2012 E.C retrieved from the CSA commercial farm survey database. Both the Kao co-integration test and the error correction model confirmed the existence of co-integration (long-run relationship) between the variables included in the model. Based on the Hausman test, the PMGE method was found to be the most appropriate method. The appropriate lagged order of the selected model was selected with one for crop productivity and two for other agricultural input factors, and the selected model was P-ARDL (1,2,2,2,2) selected by AIC.

In the short run, the appropriate PMGE model assumes that ECM coefficients, as well as short-run coefficients, are heterogeneous across cross-sectional units (grain crop categories). However, across cross-sectional units, the ECM coefficient was statistically significant and negative, indicating a highly adjusted shock in the long run. Unlike in long-term relationships, pesticide use has a significant effect on agricultural crop productivity in the short run.

The findings of this research show that in the long run, fertilizer consumption, amount of improved seed use, and arable land area size were homogeneous, while in the short run, agricultural inputs like the use of pesticides and improved seed use at first lagged value had heterogeneous significant contributions to grain crop productivity improvement across all cross-sectional units.

Abbreviations

CSA	Central Statistics Agency
DFE	Dynamic Fixed Effect
ECM	Error Correction Model
GCP	Grain Crop Productivity

IPS Im-Pesaran-Shin

LLC Levin-Lin-Chu Test

MGE Mean Group Estimator

P-ARDL Panel Autoregressive Distributed Lag Model

PCD Pesaran Cross Section Dependence Test

PMGE Pooling Mean Group Estimator

Declarations

Ethical approval and consent of participant: Not applicable

Consent for publication: Not applicable

Availability of data and materials: The datasets generated and/or analyzed during the current study are not publicly available due to the data is using for another analysis but are available from the corresponding author at the reasonable request of Lantesle Amsalu via lant75br@gmail.com.

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Authors' contributions: L.A.A contributed to the conceptualization of the research problem, study design, analysis of the data and interpretation of the final result, and formulation of the manuscript;

H. K. Y. contributed in guidance, consultation, and continued to follow up and encouragement from the beginning to the end of the study, revision of the paper and the manuscript;

A. A. G participated in the revision of the research, guidance, supervision, data analysis, and editing of the paper.

Each author of the paper carefully read, edited, and finally approved the final manuscript.

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