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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

Agriculture is a critical source of food and income, making it a key component of poverty reduction and ensuring food security across the globe. The sector generates 88.8 percent of the trade profit and contributes 36.7 percent of GDP. 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). The central statistical agency (CSA) provided the data for this study, which covered the entire country from 1990 to 2012 Ethiopian Calendar (E.C). In the long run, the study found that a one percent increase in fertilizer use resulted in a 2.686 percent increase in productivity of grain crops in Ethiopia, while a corresponding increase in improved seed per hectare and land size resulted in a 48.31 percent and 10.58 percent increase in productivity of grain crops per crop type, respectively. As the value of improved seed increased by one percent with a period lag among commercial farmers, the short-term production of cereal crops increased by 30.29 percent. Grain crop productivity improved by 40.6 percent when area increased by one percent at the first difference. The results of this study show that fertilizer use, improved seed use, and cropland size made homogeneous significant contributions to improved grain crop productivity in the long run across all cross-sectional units. However, in the short run, agricultural inputs such as pesticide use and improved seed use made heterogeneous significant contributions to the first lagged value.

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].

Ethiopia's primary source of income and employment is agriculture. 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 due to the employment of antiquated farming methods and tools, as well as the limited use of more contemporary farm inputs, which led to the sector's subpar 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 contends that net export, inflation, interest rate, nominal exchange rate, government expenditure, and money supply all influence agricultural productivity [15]. 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:

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

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. Co-integrated variables' reactivity to any departure from long-run equilibrium is one of their key characteristics.. 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:

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

Where:
GCP_{it} = Grain crop productivity of i^{th} cross-sectional unit at time t.
F_{it} = consumption of fertilizer by cross-sectional unit i^{th} at time t.
L_{it} = the land area of the 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 ith cross-sectional unit at a time t that is lagged by one period. 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 and Pooled mean group (PMG) estimators developed by and DFE estimator [28,29]. 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:
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]. Contrarily, the Pool Mean Group was used to identify both long- and short-term relationships between agricultural inputs and agricultural production as well as to examine potential homogenous and heterogeneous dynamic issues among grain crop categories. The appropriate technique to be used for the analysis of dynamic panels is the 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:

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

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 ith cross-sectional unit at jth time lag. ECMit is represent the error correction term lagged by one period of the ith 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 [31,32]. IPS is less restrictive and more appropriate compared to unit root tests developed by which don't permit heterogeneity within the autoregressive coefficient [33]. IPS gives arrangement to Levin and Lin's serial relationship issue by expecting heterogeneity between units in an energetic board system [34]. For each cross-section, IPS specifies an Augmented Dickey-Fuller (ADF) regression with a unique intercept and a temporal trend as follows:

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

Where Yit is the selected variable in crop type i and t, αi 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 can be expressed as follows and is based on averaging individual Augmented Dickey-Fuller (ADF) statistics to create a standardised test:

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

where $t_i T$ 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

After determining the co-integration order, we carry out a panel co-integration test. In this study, we use the panel co-integration test advocated by the Kao residual co-integration 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 co-integrated. By determining if the error correction term in a conditional error correction model equals zero, the null hypothesis is put to the test. If the null hypothesis of no error correction is rejected, so is the null hypothesis of no co-integration [36].

The Kao-test begins with the following model for homogeneous and heterogeneous cross-sectional parameters across the group:

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

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:

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

The hypothesis is stated as:
H0: no co-integrating equation ($\rho_i = 1$)
H1: H0 is false i.e $\rho_i < 1$

The series is co-integrated if test statistics are higher than tabulated values, in which case the estimated residuals for each cross-sectional unit have I(0) and vice versa. The model is analyzed using PMG when the panel data series variables exhibit co-integration relationships and the order of stationarity is I (1) or a combination of I(0) and I(1) [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. In a given year, commercial farms use an average of 122.5 tonnes of fertilizer for cereal crops, 119.7 kg of fertilizer per hectare for pulse crops, and 108.4 kg of fertilizer per hectare for oil crop productivity. Furthermore, commercial farms with 83, 17.3, and 31.1 acres of land produced 136.6, 135, and 132.7 tonnes 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
Yield	Cereal	69	136.7	32.7	186	107
	Pulse		135	30.5	171	103
	Oil		132.7	29.0	196	97.4
Pesticide	Cereal	69	54.61	18.29	96	28
	Pulse		55.61	18.25	98	30
	Oil		54.10	17.98	93.5	26
Area	Cereal	69	83	16.7	123	59
	Pulse		17.3	10.9	30	8
	Oil		31.1	5.0	56	19
Improve seed	Cereal	69	47.26	41.4	75	19
	Pulse		47.18	32.4	88	14
	Oil		45.10	35.4	84.5	13
fertilizer	Cereal	69	122.5	58.44	237.6	87
	Pulse		119.7	39.97	227.8	98
	Oil		108.4	68.40	226.8	94

On average, commercial farms brought 134.805 tonnes of grain crop productive increment value from 1990 to 2012 E.C, according to the 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					

Ethiopia's Productivity of Grain Crops from 1990 to 2012

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

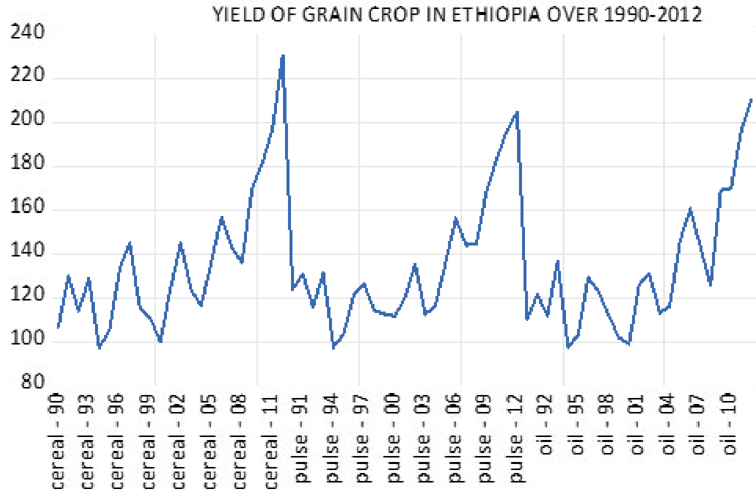

Figure 1: Trend in Ethiopia's grain crop productivity from 1990 to 2012

Panel Unit Root

Table 3 displays the statistics from the panel unit root test. The variables are identified by the letters F, P, IMP, and A, where F stands for fertilizer consumption, P for pesticide use, IMP, and A, for improved seed usage. All variables except fertilizer seem to be non-stationary at this level, according to the test statistic. All panel unit root tests reject the non-stationarity null hypothesis at the 1% level of significance, showing that all variables are stationary at the first difference level. As a result, we can infer that order one integration applies to panel variables (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 = fertilizers, IMP = improved seed, P = pesticide usage, and 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-term relationship, the series are related and can be combined in a linear fashion. Even if there are shocks in the short run that 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

S.N	Diseases	Frequency (%)
Model	**AIC**	**Specification**
1	7.614	ARDL (1,1,1,1)
2	7.225	ARDL (1,2,2,2,2)
3	7.658	ARDL (2,1,1,1)
4	7.630	ARDL (2,2,2,2,2)

To select the best-fit model, we use Akaike information criteria (AIC) and the values are shown in Table 5 and 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.

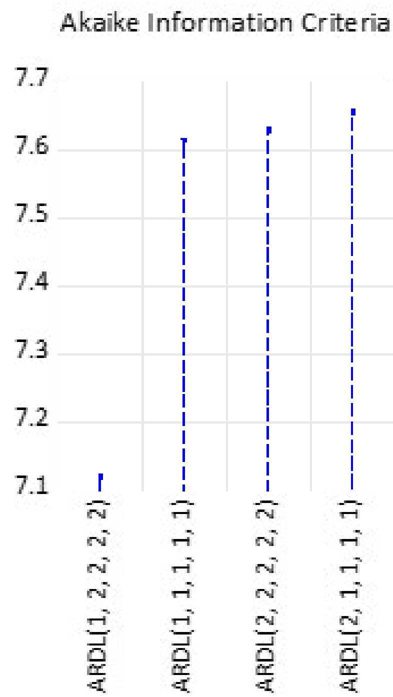

Figure 2: Grain crop productivity model order selection by AIC method

Pooled Mean Group Estimation (PMGE)

Table 6 displays the regression findings from the PMGE technique. For comparison, the outcomes of the mean group estimator (MGE) and the DFE are also provided. Shared long-run coefficients are a restriction that causes MGE and DFE to have bigger standard errors and adjustment speeds than PMGE. This outcome is anticipated given that the MGE and DFE methods are less constrained and potentially ineffective.

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)
Δ*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)
Δ*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)
Δ*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

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

The coefficients of the independent variables can be understood as elasticity with regard to crop yield per crop type because we have stated our productive model in a log-linear form. Fertilizer has a coefficient of 0.027. This suggests that, over the long term, assuming other factors remained the same, an increase in fertilizer usage per hectare of one percent led to an increase in grain crop productivity in Ethiopia of 2.686 percent. 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 long-run coefficients of the productive equation are accepted, the short-run coefficients of the ECM model are 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 calculated equilibrium error correction coefficient, which is -0.853, is highly significant, has the right sign, and suggests a very quick return to equilibrium following a shock to the input parameters affecting cereal crop output. In the current year, about 85.29 percent of the disequilibrium caused by the shock of the previous year converges back to long-run equilibrium. Another indication that the input variables affecting cereal crop yield have a stable, long-term relationship is the presence of such a highly significant error correction term.

The estimated short-run model shows that the expansion of the land area, and improved seed utilization (one period delayed value) have significantly boosted cereal crop productivity. Short-term cereal crop yield improves by 40.60 percent for every 1% increase in land area. 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

Based on the findings in Table 9, the estimated equilibrium error correction coefficient of -1.712 is extremely significant, has the right sign, and suggests that the input components for pulse crop productivity will adapt to equilibrium fairly quickly following a shock. The shock disequilibrium from the previous year converges to the long-run equilibrium in the current year by about 1.712 percent.

The estimated short-run model shows that the amount of treated chemicals used does not have a significant short-run impact on the productivity of the pulse crop type, but the amount of land area used (one period delayed value), fertiliser consumption, and amount of improved seed used do. 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 Eun 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

Discussion

Agricultural input (fertilizer consumption) had a significant long-run effect on grain crop productivity over each cross sectional unit. The positive influence of fertilizer consumption on agricultural crop productivity was consistent with other similar studies [16-17]. and in Ethiopia but inconsistent with other study [3,22].

Amount of improved seed used had significant long-run contribution on grain crop productivity in Ethiopia (p-value <0.001). The positive influence of improved seed use on productivity is consistent with other similar studies such as [15].

Use of pesticide had positively and significant long-run effect on agricultural productivity since p-value<0.011. The significant long-run influence of use of pesticide on productivity was consistent with other studies but inconsistent with the study [16,22].

However, land use of holder has no significant long-run effect on grain crop productivity across all cross-sectional units in the study. This insignificant effect of the land size used on grain crop productivity was opposed with other studies in Ethiopia [15-17].

fertilizer consumption had positive and significant effect on grain crop productivity in the short-run. The positive short-run influence of fertilizer consumption on the productivity of agricultural productivity was supported by other studies in Ethiopia [16,19].

However, agricultural inputs like land size use and the use of improved seed had no significant short-run effect on grain crop productivity in Ethiopia. The short-run insignificant effect of land size on the agricultural productivity is opposed with other study in Ethiopia [22].

Conclusion

Agriculture is a vital source of food and economic activity and thus a fundamental component of programs to reduce poverty and achieve food security in the land mass. The main objective of the study was to determine the homogeneous and heterogeneous effects of agricultural inputs on the productivity of three-grain crops in Ethiopia. Four explanatory variables, namely fertilizer use, improved seed use, pesticide use, and land size, were included with the expectation that they would affect agricultural productivity. A stationary test was conducted using the Im-Pesaran-Shin test (IPS). With the exception of fertilizer use, the null hypotheses of a unit root at the level were not rejected. Consequently, the first differenced series was used for further analysis because 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 study used the P-ARDL model of the PMG estimator approach to co-integration and the error correction model (ECM) using a panel data set for the period from 1990 to 2012 (E.C.) from the CSA farm survey database. Both the Kao co-integration test and the error correction model confirmed the presence of co-integration (long-term relationship) among the variables included in the model. Based on the Hausman test, the PMGE method was found to be the most appropriate. The appropriate lagged order of the selected model was chosen 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 The appropriate PMGE model assumes that both ECM coefficients and short-term coefficients are heterogeneous across cross-sectional units (Grain crops). However, across cross-sectional units, the ECM coefficient was statistically significant and negative, indicating a strongly adjusted shock in the long run. In contrast to the long-term relationships, pesticide use has a significant impact on crop productivity in the short term The results of this study show that fertilizer use, improved seed use, and cropland size were homogeneous in the long run, while in the short run, agricultural inputs such as pesticide use and improved seed use made a heterogeneous significant contribution to improving grain crop productivity at the first lagged value 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

References

1. Gollin, D. (2010). Agricultural productivity and economic growth. Handbook of agricultural economics, 4, 3825-3866.
2. King, A., & Ramlogan-Dobson, C. (2015). Is Africa actually developing? World Development, 66, 598-613.
3. Shita, A., Kumar, N., & Singh, S. (2018). Agricultural technology adoption and its determinants in Ethiopia: A reviewed paper. Asia Pacific Journal of Research, 1(55), 99-104.
4. Tadesse, M., Turoop, L., & Ojiewo, C. O. (2017). Survey of Chickpea (Cicer arietinum L) Ascochyta Blight (Ascochyta rabiei Pass.) disease status in production regions of Ethiopia. Plant, 5(1), 22-30.
5. Satapathy, S., Mishra, D., Realyvásquez Vargas, A., Satapathy, S., Mishra, D., & Realyvásquez Vargas, A. (2022). Literature on the Global Agri-Sectors: An Overview. Innovation in Agriculture with IoT and AI, 13-28.
6. Ethiopia, M. (2012). Ethiopia's Progress towards Eradicating Poverty: An Interim Report on Poverty Analysis Study (2010/2011). Photocopy, Addis Ababa.
7. Giuliano, G. (2004). Land use impacts of transportation investments. The geography of urban transportation, 3, 237-273.
8. Belay, K., & Abebaw, D. (2004). Challenges facing agricultural extension agents: A Case Study from South-western Ethiopia. African development review, 16(1), 139-168.
9. Ehrensaft, P. (1971). Semi-industrial capitalism in the Third World: Implications for social research in Africa. Africa Today, 18(1), 40-67.
10. Chand, R., Prasanna, P. L., & Singh, A. (2011). Farm size and productivity: Understanding the strengths of smallholders and improving their livelihoods. Economic and Political Weekly, 5-11.
11. Gizaw, W., & Assegid, D. (2021). Trend of cereal crops production area and productivity, in Ethiopia. Journal of Cereals and Oilseeds, 12(1), 9-17.
12. Bachewe, F. N., Berhane, G., Minten, B., & Taffesse, A. S. (2018). Agricultural transformation in Africa? Assessing the evidence in Ethiopia. World Development, 105, 286-298.
13. Parayil, G. (2003). Mapping technological trajectories of the Green Revolution and the Gene Revolution from modernization to globalization. Research policy, 32(6), 971-990.
14. Pingali, P. L., & Heisey, P. W. (2001). Cereal-crop productivity in developing countries: past trends and future prospects. Agricultural science policy: Changing global agendas, 99(3), 56-82.
15. Rehman, A., Chandio, A. A., Hussain, I., & Jingdong, L. (2019). Fertilizer consumption, water availability and credit distribution: Major factors affecting agricultural productivity in Pakistan. Journal of the Saudi Society of Agricultural Sciences, 18(3), 269-274.
16. Kadir, S. U. S. A., & Tunggal, N. Z. (2015). The impact of macroeconomic variables toward agricultural productivity in Malaysia. South East Asia Journal of Contemporary Business, Economics and Law, 8(3), 21-27.
17. Ketema, A. M. (2020). Determinants of agricultural output in Ethiopia: ARDL approach to co-integration. International Journal of Business and Social Research, 10(03), 01-10.
18. Kumar, A., Sharma, P., & Joshi, S. (2015). Effects of climatic factors on agricultural productivity in India: A state-wise panel data analysis. International Journal of Basic and Life Sciences, 3(1), 48-67.
19. Shita, A., Kumar, N., & Singh, S. (2018). Determinants of agricultural productivity in Ethiopia: ARDL approach. The Indian Economic Journal, 66(3-4), 365-374.
20. Gadissa, B., Biftu, A., & Sida, A. (2020). Pre-extension Demonstration of Improved Fenugreek Varieties in Bale zone, Southeastern Oromia, Ethiopia. Scientific Journal of Crop Science, 9(3).
21. Lanamana, W., & Supardi, P. N. (2020). A Comparison of economic efficiency of monoculture and multiple cropping patterns: The case of cassava farming in Ende, Indonesia. Caraka Tani J. Sustain. Agric, 36, 69.
22. Gebeyehu, M. G. (2016). The impact of technology adoption on agricultural productivity and production risk in Ethiopia: Evidence from rural Amhara household survey. Open Access Library Journal, 3(2), 1-14.
23. Musah, M., Owusu-Akomeah, M., Boateng, F., Iddris, F., Mensah, I. A., Antwi, S. K., & Agyemang, J. K. (2022). Long-run equilibrium relationship between energy consumption and CO2 emissions: a dynamic heterogeneous analysis on North Africa. Environmental Science and Pollution Research, 29(7), 10416-10433.
24. Jilito, M. F., & Wedajo, D. Y. (2020). Trends and challenges in improved agricultural inputs use by smallholder farmers in Ethiopia: A review. Turkish Journal of Agriculture-Food Science and Technology, 8(11), 2286-2292.

25. Pesaran, M. H. (2004). General diagonist tests for cross section dependence in panels. June 2004. Mimeo, University of Cambridge.
26. Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data MIT press. Cambridge, ma, 108(2), 245-254.
27. Glasure, Y. U., & Lee, A. R. (1998). Cointegration, error-correction, and the relationship between GDP and energy: The case of South Korea and Singapore. Resource and Energy Economics, 20(1), 17-25.
28. Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289-326.
29. Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American statistical Association, 94(446), 621-634.
30. Baltagi, B. H., Griffin, J. M., & Xiong, W. (2000). To pool or not to pool: Homogeneous versus heterogeneous estimators applied to cigarette demand. Review of Economics and Statistics, 82(1), 117-126.
31. Omay, T., Hasanov, M., & Shin, Y. (2018). Testing for unit roots in dynamic panels with smooth breaks and cross-sectionally dependent errors. Computational Economics, 52, 167-193.
32. Breitung, J., & Das, S. (2005). Panel unit root tests under cross-sectional dependence. Statistica Neerlandica, 59(4), 414-433.
33. Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. Journal of econometrics, 108(1), 1-24.
34. Apergis, N., & Danuletiu, D. C. (2014). Renewable energy and economic growth: Evidence from the sign of panel long-run causality. International Journal of Energy Economics and Policy, 4(4), 578-587.
35. Westerlund, J. (2007). Testing for error correction in panel data. Oxford Bulletin of Economics and statistics, 69(6), 709-748.
36. Elliott, G., & Pesavento, E. (2009). Testing the null of no cointegration when covariates are known to have a unit root. Econometric Theory, 25(6), 1829-1850.
37. Ghouali, S., Feham, M., & Ghouali, Y. Z. (2014, January). Causal relationships between cardiorespiratory hemodynamics signals: test analysis using panel Co-integration. In 2014 World Congress on Computer Applications and Information Systems (WCCAIS) (pp. 1-8). IEEE.