

Trends in Agricultural Economics

ISSN 1994-7933





Trends in Agricultural Economics 8 (1): 13-20, 2015 ISSN 1994-7933 / DOI: 10.3923/tae.2015.13.20 © 2015 Asian Network for Scientific Information



Supply Response of Maize in Ethiopia: Cointegeration and Vector Error Correction Approach

Birhanu Ayalew Ethiopian Institute of Agricultural Research, P.O. Box 2003, Addis Ababa, Ethopia

ABSTRACT

This study aimed at estimating the supply response of maize and suggest measures for improving production using secondary data from FAOSTAT pertaining from the year 1966-2010. Augmented Dick Fuller was used for unit root test while both maximum eigen value and trace statistics used for cointegeration test. Vector error correction (VECM) approach was used to estimate long run and short run relationships between maize supply and its estimators. The result of the study indicated that one of the series are non stationary at level but not for the first difference while, some of the series were stationary and the Johanson's method indicated the cointegration of the series. Price factors were more important in the long run than in the short run and maize supply was price inelastic in the long run and technology in elastic in the low lands of the country could be due to predominance of small and marginal land holdings, weak R&D and extension. Non-price factors were comparatively more important for higher supply growth of maize so that policy interventions should focus on improving rural infrastructure specially in the lowlands. More investment on R&D would bring about shift on the maize supply by assuring technological breakthrough on maize yield that many countries have achieved and made the subsector attractive.

Key words: Cointegration, maize, supply response, vector error correction, Ethiopia

INTRODUCTION

Maize is a strategic crop grown in 13 agro-ecological zones covering 90% of Ethiopia. In any one year, small holder farmers produce over 95% of the total maize. Ethiopia in one of the largest maize producing countries in Africa (FAO., 2013). Within the country, maize is the largest cereal commodity in terms of total production and yield and the second in terms of acreage next to teff. It is also the most important crop where 9.2 million small holder farmers engaged in its cultivation (CSA., 2012).

Maize is instrumental for the food security of Ethiopian households and is the lowest cost caloric source among all major cereals, which is significant given that cereals dominate household diets in Ethiopia. The unit cost of calories per US dollar for maize is one-and-a-half and two times lower than wheat and teff respectively. Maize is also a low-cost source of protein in comparison to other cereals: maize provides 0.2 kg of protein per USD, compared to 0.1 kg of protein per USD from teff and 0.2 kg of protein from wheat and sorghum. An average Ethiopian consumes a total of 1,858 kcal daily of which four major cereals (maize, teff, wheat and sorghum) account for more than 60%, with maize and wheat representing 20% each (Rashid *et al.*, 2010).

Despite the importance of maize in the farming calculus of the Ethiopian farmers, their responsiveness to economic stimuli largely determines agriculture's contribution to the national economy. Response studies are therefore important for policy decision regarding agricultural

growth. The concept of supply response is dynamic and different from supply function which is the static concept. The supply function describes a price quantity relation, where all other factors are held constant. The response relation shows the change in quantity with changes in prices as well as supply shifters and therefore, approximates to the long run, dynamic concept of supply theory. In this context, this study aimed at estimating the supply response of maize and suggest measures for improving its production in the country.

MATERIALS AND METHODS

Data and variables: The data required for the study has been met from different data sources. The data for the period 1966 - 2010 was obtained from Food and Agriculture Organization's (FAO) statistical database. The price data from FAO were indexed at the 2004-06 prices and all variables except weather index and dummy converted to natural logarithm.

Agricultural supply is determined by both price and non-price factors. The supply response of maize in this study is estimated using the function:

$$Y_t = f(P_t, WI, D, T)$$

Where:

- Y_t : Is the dependent variable representing area planted at time t. Area planted is preferred to output as the latter fails to reflect planned production decisions of farmers.
- P_t : Is the relative price of maize with its competing crop. It was calculated by dividing the real farm harvest price of maize with its competing crops sorghum and wheat. Sorghum and wheat were taken as competing crops for maize to represent low land (moisture stressed) and mid-altitude maize producing areas of the country respectively.
- WI: Is weather index for maize. The impact of weather on yield variability is measured with a Stalling index (Stalling, 1960). Yield is regressed on time to obtain expected yield. The actual to the predicted yield ratio is defined as the weather variable. The weather effects such as rainfall, temperature etc. may be captured by this index in supply response model.
- D : Is dummy variable for structural break in maize area which is identified based on Quandt-Andrews unknown structural break point test.
- T : Stands for time trend. It is included in the long run equation to capture the collective effect of historical data of infrastructural developments, expenditure on agricultural research and extension, applications of modern techniques like fertilizers and improved seed varieties on supply. It may refer response of maize to technology.

Analytical framework: In applied econometric work of supply response studies standard classical methods of estimation are based on the assumption that the means and variances of the variables are well-defined constants and independent of time. Non-stationary or unit root variables are those variables whose means and variances change over time. Using classical estimation methods, such as the Ordinary Least Squares (OLS), to estimate relationships with unit root variables results in spurious regression which gives misleading inferences. Cointegration is the appropriate technique to estimate the equilibrium or long-run parameters in a relationship with unit root variables (Rao, 2007).

The test of co-integration involves estimating Vector Error Correction Models (VECM) of the form:

$$\begin{split} \Delta \boldsymbol{Y}_t = \boldsymbol{\Sigma} \boldsymbol{\alpha}_j \; \Delta \boldsymbol{Y}_{t\text{-}i} \; + \boldsymbol{\Sigma} \boldsymbol{\gamma}_j \boldsymbol{X}_{jt\text{-}i} + \boldsymbol{\delta}_i \boldsymbol{D}_{it} + \boldsymbol{\lambda} \boldsymbol{\epsilon}_{t\text{-}1} + \boldsymbol{\nu}_t \\ \boldsymbol{\epsilon}_{t\text{-}1} = \boldsymbol{Y}_{t\text{-}1} - \boldsymbol{\Sigma} \boldsymbol{\beta}_j \boldsymbol{X}_{jt\text{-}i} \end{split}$$

Where:

- Y_t : Dependent variable
- X_t : Non-stationary endogenous explanatory variable
- γ_i : Parameter of endogenous variables
- D_t : Vector of stationary exogenous variables
- δ_i : Vector of parameters of exogenous variables
- ϵ_{t-1} : Error correction term
- $\lambda \quad : \quad Coefficient \ of \ error \ correction \ term$
- v_t : Random error term

Co-integration and vector error-correction techniques are applied in this study. These techniques are believed to overcome the problem of spurious regressions and to give consistent and distinct estimates of long-run and short-run elasticities that satisfy the properties of the classical regression procedure. This is because all variables in an Error Correction Model (ECM) are integrated of order zero, I (0). Spurious regression and inconsistent and indistinct short-run and long-run elasticity estimates are major problems exhibited by traditional Adaptive Expectation and Partial Adjustment models (Hallam and Zanoli, 1993; McKay *et al.*, 1999).

Empirical model: The empirical model to estimate supply response of maize in this study is given as:

 $AREA_{t} = f (AREA_{t-1}, RP_{t-1}, WI, DUM, TREND)$

In logarithmic form, the model is represented as:

 $\Delta LNAREA = \lambda \left(LNAREA_{t-1} + \alpha_0 LNRP_{t-1} - \gamma TREND - \delta_0 \right) + \rho \Delta LNAREA_{t-1} + \alpha_1 \Delta LNRP_{t-1} + \delta_1 + \eta WI + \mu DUM$

Where:		
LNAREA	:	Natural logarithm of area under maize
LNRP	:	Natural logarithm of real relative price of maize
TREND	:	Time trend
WI	:	Weather index of maize
DUM	:	Structural break dummy of maize
λ	:	Error Correction Term (ECT)
α ₀ , β ₀ , γ	:	Coefficients of the concerned variables in the long run relationship
α ₁ , β, ρ, η, μ	l :	Coefficients of the concerned variables for the short run relationship
δ_0, δ_1	:	Constants in the long run and short run equations respectively

RESULTS AND DISCUSSION

Order of integration (Unit root test): The test for the order of integration is the first step in any co-integration analysis. If a series is integrated, it accumulates past effects. This means that perturbation to the series does not return to any particular mean value. Therefore, an integrated

series is non-stationary. Order of integration of such a series is determined by the number of times that it must be differenced before it is actually made stationary. It follows that if two or more series are integrated of the same order then a linear relationship can be estimated. Examining the order of integration of this linear relationship is similar to testing for the null hypothesis that there is no co-integration against its alternative that there is co-integration (Alemu *et al.*, 2003). In this section, an attempt is made to determine the order of integration of the variables followed by the test for co-integration.

Table 1 shows that area under maize is integrated of order 1 or I (1) both in the non-trended and trended models but not real relative price of maize competing with sorghum, real relative price of maize competing with wheat and weather index of maize. These mixed results were dealt by differencing the series as it is in line with literature that differencing, even though the true data generating process is stationary, has little consequence on the consistency of parameter estimates compared to working with levels while the true data-generating process is difference stationary (Maddala, 1992). What differencing does to data, which is already a stationary process, is to create a moving average error and hence, inefficient estimates, which can be corrected by estimating the differenced equation using an OLS technique. But, if data in levels are wrongly considered stationary and are modelled without being differenced, its likelihood of violating the assumptions of classical regression procedure is very high. This results from an overtime increase in the variance of errors. Therefore, it is a widely accepted view that it is best, with most economic time series, to work with differenced data rather than data in levels (Plosser and Schwert, 1978). The consequence of differencing is loss of information on the long-run relationships among variables, which can be handled by estimating an VECM. With this in mind, all the I (1) and the other with inconclusive test result were differenced. According to the results obtained on ADF tests for the differenced series, all are stationary processes or I (0).

Co-integration: The Johansen method provides two likelihood ratio tests, namely the Trace and the Maximum Eigen Value statistic tests, which are used to determine the number of co-integrating equations given by the co-integration rank r. A co-integration equation is the long-run equation of co-integrated series. The two approaches are used in this study only to support evidence on the long-run equilibrium relationships among variables.

Table 1: Unit root tes	st			
	Level			
	Without trend		With trend	
Variables	t-statistic	p-value	t-statistic	p-value
LNMAREA	-0.9895	0.7489	-3.1158	0.1154
LNRPMS	-4.4542	0.0009	-4.4457	0.0050
LNRPMW	-3.7478	0.0065	-5.637115	0.0002
WIM	-4.7383	0.0004	-4.7081	0.0025
	First difference			
	Without trend		With trend	
	t-statistic	p-value	t-statistic	p-value
LNMAREA	-6.3150	0.0000	-6.3281	0.0000
LNRPMS	-10.2327	0.0000	-10.1417	0.0000
LNRPMW	-8.96467	0.0000	-8.855475	0.0000
WIM	-6.8445	0.0000	-6.7619	0.0000

Lag length selection was automatic based on Eviews' Schwarz Information Criteria, LNMAREA: Natural logarithm of maize area real relative area with Sorghum, LNRPMS: Natural logarithm of relative price of maize with sorghum, LNRPMW: Natural logarithm of relative price of maize with wheat, WIM: Weather index of maize

Hypothesized No. of CE(s)	Eigen value	Trace statistic	0.05 critical value	Prob.**
None *	0.669359	75.67529	63.87610	0.0037
At most 1	0.277480	28.08630	42.91525	0.6169
At most 2	0.186501	14.11085	25.87211	0.6485
At most 3	0.114630	5.235216	12.51798	0.5630

Table 2: Co-integration test for maize using trace statistics test

*Rejection of the hypothesis at the 0.05 level, **p-values

Co-integration			

Hypothesized No. of CE(s)	Eigen value	Max-Eigen statistic	0.05 critical value	Prob.**
None *	0.669359	47.58899	32.11832	0.0003
At most 1	0.277480	13.97545	25.82321	0.7246
At most 2	0.186501	8.875634	19.38704	0.7372
At most 3	0.114630	5.235216	12.51798	0.5630

*Rejection of the hypothesis at the 0.05 level, **p-values

Table 4: Co-integration test for maize using trace statistics test

Hypothesized No. of CE(s)	Eigen value	Trace statistic	0.05 critical value	Prob.**
None *	0.621919	79.51113	63.87610	0.0014
At most 1	0.397246	37.68732	42.91525	0.1512
At most 2	0.238448	15.91873	25.87211	0.4991
At most 3	0.093175	4.205641	12.51798	0.7122

*Denotes rejection of the hypothesis at the 0.05 level, **p-values

Table 5: Co-integration test for maize using maximum eigen value test

Hypothesized No. of CE(s)	Eigen value Max-Eigen statistic		0.05 critical value	Prob.**	
None *	0.621919	41.82381	32.11832	0.0024	
At most 1	0.397246	21.76859	25.82321	0.1570	
At most 2	0.238448	11.71309	19.38704	0.4423	
At most 3	0.093175	4.205641	12.51798	0.7122	

*Rejection of the hypothesis at the 0.05 level, **p-values

Cointegration test for area under maize with competing crop sorghum resulted in the rejection of the null hypothesis that there is no cointegration vector in the series. Both procedures indicate the existence of cointegration relationships between planned supply and the variables that are predicting it (Table 2 and 3).

Similarly, cointegeration test for area under maize with competing crop wheat also resulted in the rejection of the null hypothesis that there is no cointegration vector in the series indicating the existence of cointegrating relationships between planned supply and its predictors (Table 4 and 5).

Estimation of vector error correction model: Vector Error Correction Model (VECM) is formulated establishing a long run relationship between area and influencing variables for the maize. According to Hallam and Zanoli (1993), a high R^2 in the long-run regression equation is necessary to minimize the effect of small sample bias on the parameter estimates of the cointegrating regression, which may otherwise be carried over to the estimates of the errorcorrection model. Moreover, according to Granger (1980) and Engle and Granger (1987), as long as two or more variables are cointegrated, a causality has to exist in at least one direction. That is, in the error correction model, the Granger causality implies causality from the independent variables in levels to the dependent variable area under study crops. Testing for Granger causality requires only testing whether the Error Correction Coefficient (ECT) is significantly different from zero. Even, if the coefficients of the lagged changes in the independent variables are not statistically significant, Granger causality still can exist as long as ECT is significantly different from zero (Choudhry, 1995). As a result for the models specified below the significance of the ECT may also refer presence of Granger causality from the independent variables to the dependent variables.

Variables			Long run
LNMZA(-1)			1.000
LNRPMS(-1)			0.463 (0.180)*
TREND			0.009 (0.004)*
Constant			13.808
	Short run		
	ΔLNMZA		
Error correction	Coefficient	S.E	p-value
CointEq (ECT)	-0.606	0.115	0.000
ΔLNMZA(-1)	0.036	0.128	0.779
$\Delta LNRPMS(-1)$	-0.139	0.080	0.092
Constant	0.086	0.100	0.394
DUM	0.314	0.062	0.000
WIM	-0.190	0.095	0.053
R-squared	0.484		
Adj. R-squared	0.414		
F-statistic	6.939		
AIC	-1.471		
SIC	-1.225		
DW stat	2.186		

Table 6: Long run and short run vector error correction estimates taking sorghum as competing crop for maize

*Significance at 5 % level, figures in parenthesis denotes standard error, S.E.: Standard error, DUM: Structural break dummy of maize, WIM: Weather index of maize, AIC: Akaike information criterion SIC: Schwarz information criterion, DW stat: Durbin: Watson stat, TREND: Time trend, ECT: Error correction coefficient, SE: Standard error, LNRPMS: Natural logarithm of relative price of maize with sorghum, LNMZA: Natural logarithm of maize area

Table 7: Long run and short run vector error correction estimates taking wheat as competing crop for maize

Variables			Long run
LNMZA(-1)			1.000
LNRPMW(-1)			1.178(0.38185)*
TREND			-0.019 (0.00504)*
Constant			-13.092
	Short run		
	Δ LNMZA		
Error correction	Coefficient	S.E	p-value
CointEq (ECT)	-0.416	0.110	0.001
Δ LNMZA(-1)	-0.025	0.141	0.858
Δ LNRPMW(-1)	0.247	0.156	0.121
Constant	0.077	0.114	0.505
DUM	0.185	0.053	0.001
WIM	-0.130	0.107	0.234
R-squared	0.349		
Adj. R-squared	0.261		
F-statistic	3.964		
AIC	-1.239		
SIC	-0.993		
DW stat	2.112		

*Significance at 5% level, figures in parenthesis denotes standard error, S.E.: Standard error, DUM: Structural break dummy of maize, WIM: Weather index of maize, AIC: Agriculture inputs corporations, SIC: Standard industrial classification, DW stat: Durbin: Watson stat, TREND: Time trend, ECT: Error correction coefficient, SE: Standard error, LNRPMS: Natural logarithm of relative price of maize with sorghum, LNMZA: Natural logarithm of maize area

The estimates of VECM for maize with competing crop sorghum showed R² of 48% significant at 1% level. The long-run supply response model showed relative price of maize has a positive and significant effect (0.463) on maize supply. A positive and highly significant effect was also noticed with regards to 'trend' variable. The trend variable may explain the positive response of maize supply to technology. The short run relationship showed the error correction term with the expected

sign and highly significant indicating about 61% rate of adjustments towards the long-run equilibrium of maize supply and its explanatory variables in this model in the next period. It has also been found that planned supply is significantly affected by the dummy variable for structural break in 1995 might be due to the lagged effect of the introduction of free-market economic system in the country in 1992 (Table 6).

Similarly, supply response model for maize was estimated using wheat as competing crop. The VECM estimates showed R^2 of 48.4% which is significant at 10% level. The long run relationship indicated a negative response of maize in the country while showing positive and significant response for relative price (1.178). Maize supply was observed to be price elastic in the long run but price inelastic in the short run. The short run relationship also showed highly significant ECT with the expected stating about 42% rate of adjustments towards the long-run equilibrium within one year period. The structural dummy also observed to very important (Table 7).

CONCLUSION

The study made clear the fact that price factors are more important in the long run than in the short run might be due to poor infrastructure that has hindered the price mechanism to work in the short run. Furthermore, maize supply was price inelastic in the long run and technology inelastic in the low lands of the country could be due to predominance of small and marginal land holdings, weak R&D and extension.

From the estimated results, it was inferred that non-price factors are comparatively more important for higher supply growth of maize so that policy interventions should focus on improving rural infrastructure specially in the lowlands. More investment on R&D would bring about shift on the maize supply by assuring technological breakthrough on maize yield that many countries has achieved and make the sector attractive.

REFERENCES

- Alemu, Z.G., K. Oosthuizen and H.D. van Schalkwyk, 2003. Grain-supply response in Ethiopia: An error-correction approach. Agrekon, 42: 389-404.
- CSA., 2012. Agriculture sample survey 2010-2011. Central Statistical Agency (CSA), Ethiopia, Addis.
- Choudhry, T., 1995. Long-run money demand function in Argentina during 1935-1962: Evidence from cointegration and error correction models. Applied Econ., 27: 661-667.
- Engle, R.F. and C.W.J. Granger, 1987. Co-integration and error correction: Representation, estimation and testing. Econometrica, 55: 251-276.
- FAO., 2013. FAOSTAT. Food and Agriculture Organization of the United Nation, Rome, Italy.
- Granger, C.W.J., 1980. Long Memory relationships and the aggregation of dynamic models. J. Econ., 14: 227-238.
- Hallam, D. and R. Zanoli, 1993. Error correction models and agricultural supply response. Eur. Rev. Agric. Econ., 20: 151-166.
- Maddala, G.S., 1992. Introduction to Econometrics. 2nd Edn., Macmillan Publishing Com., New York.
- McKay, A., O. Morrisey and C. Vaillant, 1999. Aggregate supply response in Tanzanian agriculture. J. Int. Trade Econ. Dev., 8: 107-123.
- Plosser, C.I. and G.W. Schwert, 1978. Money, income and sunspots: Measuring economic relationships and the effects of differencing. J. Monetary Econ., 4: 637-660.

- Rao, B.B., 2007. Cointegration for the Applied Economics. 2nd Edn., Palgrave Macmillan, New York, USA., pp: 3-11.
- Rashid, S., K. Getnet and S. Lemma, 2010. Maize value chain potential in Ethiopia: Constraints and opportunities for enhancing the system. IFPRI Working Paper, International Food Policy Research Institute, Washington, DC., USA., July 2010.
- Stalling, J.L., 1960. Weather indexes. J. Farm Econ., 42: 180-186.