A VECTOR AUTOREGRESSIVE APPROACH TO ESTIMATE CASSAVA SUPPLY RESPONSE

UN ENFOQUE VECTORIAL AUTORREGRESIVO PARA ESTIMAR LA RESPUESTA DE OFERTA DE YUCA

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Abstract

Cassava production is an important part of Colombia´s economy as it is a source of income and food supply for small-scale farmers and their families. Therefore, the aim of the present study was to estimate the cassava output supply response to own-price and production using time series data from 1996-2016. A quantitative, correlational and non-experimental research design was selected and the vector autoregressive framework was employed. The impulse-response function and the decomposition variance were also used to verify the impact of price transmission and the interaction between variables. The empirical results showed that the signs and the magnitude of the coefficients were statistically significant and that own-price elasticity was above the unit (1.88). In addition, the impulse response and the variance decomposition analysis suggests that price plays an important role in the variability of cassava supply response. Therefore, the proposed model contributes to the understanding of the dynamics in cassava output supply.

Keywords: Vector autoregressive model; impulse response; variance decomposition; cassava output supply

Resumen

La producción de yuca en Colombia es una importante fuente de ingresos para los pequeños agricultores y sus familias. Por consiguiente, el propósito del estudio fue cuantificar la reacción de la oferta de yuca ante cambios en su propio precio y producción utilizando datos de series de tiempo de 1996-2016. Se seleccionó un diseño de investigación cuantitativo, correlacional y no experimental y se empleó como metodología el modelo de vectores autorregresivos. Igualmente, se utilizó la función impulso-respuesta y la varianza de descomposición para verificar el impacto de la transmisión de precios y la interacción entre variables. Los resultados empíricos mostraron que los signos y la magnitud de los coeficientes fueron estadísticamente significativos y que la elasticidad precio de la oferta fue mayor a la unidad (1.88). Además, el análisis de descomposición de la varianza y de impulso-respuesta sugirieron que el precio posee un papel importante en la variabilidad de la respuesta de la oferta de yuca.

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Palabras clave: Modelo vector autorregresivo; descomposición de la varianza; impulso-respuesta; respuesta oferta yuca

Introduction

Cassava (*Manihot esculenta crantz*) is native to South America and was introduced by Portuguese traders in western Africa in the mid sixteenth century and in Asia by European explorers in the nineteenth century (Onwueme, 2002; Legg, Somado and Barker et al, 2014; Pérez, Mora and López-Carrascal, 2019). It is a starchy tropical root crop grown in over 100 countries by small-scale farmers and the third largest source of carbohydrates contributing to the diet of over a billion people worldwide (Patiño and Best, 2002; Guira et al., 2016; Ikuemonisan et al, 2020). It is cultivated for food, animal feed and industrial purposes and its major advantages is that is it compatible with other crops and flexible as to time of harvest (Henry and Hershey, 2002; Montagnac, Davis and Tanumihardjo, 2009).

Africa and Asia together are the world´s largest cassava producers (85.7%) with Latin America currently representing approximately one-fifth of global output. Nigeria alone accounts for 59.4 million (M) tons (T) followed by Thailand (31.6 MT), Democratic Republic of Congo (29.9 MT) and Brazil (17.6 MT) (FAO-STAT, 2018).

In Colombia, cassava is grown at altitudes of up to 2.000 meters above sea level and production in 2019 was reported at 2.8MT, with a cultivated area of 259.931 hectares (ha) and an 11.34-ha/ton average yield. The highest proportion of the cassava production comes from the Atlantic Coast region (43%) mainly the departments of Bolivar (17%), Cordoba (11%), Sucre (8%) and Magdalena (7%) (Agronet, 2018).

Cassava is the country´s fifth most important food crop and is used in its fresh form for human consumption (sweet cassava) and industrial purposes (bitter cassava). Moreover, it is an important part of the country´s total economy as it generates over 130.000 direct and indirect jobs as well as a source of income and food supply for small-scale farmers and their families (Colombian Ministry of Agriculture and Rural Development, 2017; Aristizábal, García and Ospina, 2018). It´s production is mainly traded in intraregional markets and is influenced by production cycles, market prices, input applications and acreage allocation, consequently small-scale farmers faces many challenges. Thus, supply response analysis is an important and useful tool to evaluate small-scale farmer's planting and out-put decisions. Whilst there are various studies on the agricultural and the biological aspects of cassava production, supply response analysis in Colombia receives very little attention.

In this manner, the aim of the present study was to estimate the cassava output supply response to own-price and production using the vector autoregressive model (VAR). The VAR model not only overcomes the problems of spurious regression, but also allows the use of the impulse-response function and the decomposition variance to verify the impact of price transmission and the interaction between variables.

The remainder of the paper is organized as follows: Section 2 provides the theoretical framework of which the study is based on followed by section 3 with a brief literature review on supply response studies. The data and proposed econometric methodology are described in Section 4. Section 5 explains the model´s empirical results, and the final section offers a summary and the conclusion.

Theoretical Framework

According to Ozkan, Rahmive and Kizilay (2011) there are three methodologies used in the literature to estimate supply response such as the dual approach derived from the profit and cost functions, the direct reduced form, known as the Nerlovian partial adjustment/ adaptive expectation model, and the vector autoregressive framework (VAR).

The dual approach is built on the assumption of a competitive market, of which the goods are homogeneous; sellers are price takers, profit-maximizing agents and technically efficient (Varian, 2016; Mankiw, 2018). It involves the joint estimation of the supply and demand equations derived from the Hotelling´s Lemma (Mythili, 2008). This approach has been widely used in microeconomics analysis to understand how price change influences farmer´s production behavior, however, one of its drawback is that it is static, thus, it does not distinguish between the short and long run responses (Khan et al, 2019).

The Nerlove model, on the other hand, describes the supply response dynamics using price expectations and/or adjustment costs. It assumes that producers adjust their crop output supply on their expectations of future prices thus; the framework consists of the following functional forms (Askaria and Cummings, 1977, p. 257):

$$Q_t^* = a_0 + a_1 P_t^* + a_2 X_t + \varepsilon_t \quad (1)$$
$$P_t^* = P_{t-1}^* + (\lambda P_{t-1} - Pt_{t-1}^*) \quad (2)$$
$$Q_t = Q_{t-1} + \gamma (Q_t^* - Q_{t-1}) \quad (3)$$

where P_t^* and Q_t^* denote expected price and desired output at time t; P_{t-1} and Q_{t-1} are the actual and observed price and output at time t-1, respectively; X_t represents non-price exogenous variables that affect supply; λ and γ are the expected and adjusted coefficients.

The Nerlovian approach is considered a simple procedure as it employs the ordinary least square technique to estimate supply response. However, its major criticism is that the processed data are stationary which can lead to spurious regression and invalid results (Rainier, 2000; Mose, Burger and Kuvyenhoven 2007; Tripathi and Prasad, 2009; Obayelu and Ebute, 2016), consequently one way to overcome this problem is to use the maximum-likelihood estimating techniques (Kohli, 1996).

As a result, the use of the vector autoregressive (VAR) method introduced by Sims (1980) is an alternative to supply response studies. It is an extension of the univariate autoregressive model and is widely used due to its relative flexibility as well as for forecasting time series and evaluating the consequences of policy action (Shah and Ghonasgi, 2016). The VAR framework is based on a multi-equation system where all variables are endogenous (dependent) and modeled as a function of their past values, that is, the predictors are the lagged values of the time series(Asmah, 2013). It is important to note that proper lag length selection is an essential aspect when using the VAR model, as the longer the lag length, the faster the degrees of freedom are eroded. In addition, stationary and co-integration must be taken into consideration in order to select the correct model specification (Zhao and Qian, 2014).

An equally significant feature of the VAR model is that it requires a minimal number of restrictions and provides two efficient tools in the assessment of economic policies such as the impulse response functions (IRF) and the variance decompositions (VD) (Asmah, 2013). In this manner, the IRF´s main purpose is to describe the dynamic effects of a model´s variable in reaction to a shock in each of the variables whereas the VD quantifies how important each of the shocks is as a component of the overall variance of each of the variables in the system (Lanne and Hyberg, 2016).

Literature Review

Since the works of Nerlove (1958) on the estimation of supply response to price and non-price incentives, a number of studies have been undertaken for different agricultural commodities. However, despite its importance, there are very few empirical research related to cassava using the vector autoregressive framework. Nevertheless, Abu (2017) investigated the relationship among producer prices, harvested area and cassava yield in Nigeria for the period 1991 to 2014 using a VAR approach. The study identified that the time series were integrated of order one and there was no long-run relationship among the variables. In addition, the results showed that producer prices had a significant influence on cassava harvested area and yield in the short run.

Likewise, Obayelu and Ebute (2016) examined cassava farmers' responsiveness to price from the period 1966 to 2010 under a vector error correction (VEC) model. The study concluded that the short run adjustment of the time series towards equilibrium was in line with theory and that both cultivated area and own-price in the short and long run were inelastic and had a positive influence on cassava supply.

Concerning research related to other staple crops, Khan et al. (2019) employed a VAR model to examine the supply response of rice in Khyber Pakhtunkhwa and estimate the short and long run rice supply elasticities for the period 1976 to 2010. The empirical results showed that the lagged production and price coefficients had a positive and significant effect on production, and that the competitive crop price (maize) had a negative but significant response on rice output supply.

On the other hand, Mose, Burger and Kuvyenhoven (2007) used a VEC model in order to investigate the influence of market liberalization on maize production in Trans-Nzoia District for the period 1980 to 2003. The study identified that farmers' respond strongly to price incentives as evidenced by the short and long run elasticities of fertilizer (1.05 and -1.26) and maize price (0.53 and 0.76). In the same manner, Ozkan, Rahmive and Kizilay (2011) applied the Johansen´s co-integration technique to understand the effects of real price changes on supply of wheat in Turkey between the years 1960 to 2009. The estimated coefficients implied that wheat supply was significantly affected by the previous year's supply conditions and lagged prices were inelastic both in the short and long run.

Methodology

To address the purpose of the study a quantitative, correlational and non-experimental research design was selected. In addition, desk review was conducted to collect data from different secondary sources, which included the Food and Agriculture Organization of the United Nations, the Colombia´s Ministry of Agricultural and Rural Development database, reports and surveys published by the Colombian government and economic and agricultural literature.

Data and Variables

Taking into account the availability of the time series, annual data covering the period from 1996 to 2016 were used and the study´s variables consisted of cassava production (ton) and domestic price (COP). Cassava prices were deflated by the Colombian producer´s price index (2016 = 100) and natural logarithms were used throughout. The estimated model was analyzed using E-views®9 package.

Model Specification

A VAR (p) is a system regression model that considers all the variables as endogenous, of which the dependent variable is a function of its lagged values and lagged values of the other variables in the model. Formally, a VAR (p) can be defined as follows (4) (Lutkepohl, 2005):

$$Y_t = \alpha + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} \ldots . \Pi_p Y_{t-p} + \mathcal{E}_t \quad (4)$$

Where: Y_t denotes an (n x 1) vector of the time series; α represents the intercept (n x 1) vector; Π_t are (n x n) coefficients matrices and $\mathcal{E}_t$ is a white noise disturbance term.

It is important to note that too many variables and lags could lead to over-fitting and inefficient estimators (Hamilton, 1994; Lutkepohl, 2005), thus, the VAR equation of cassava supply response function was specified as in (5):

$$LnQ_t = \alpha_0 + \alpha_1 LnQ_{t-1} + \alpha_2 LnP_{t-1} + \mathcal{E}_{t-1} \quad (5)$$

Where: LnQ_t is cassava quantity supply; LnQ_{t-1}, LnP_{t-1} are the lagged logarithm of cassava production and price; $\alpha_{1,}$ $\alpha_{,2}$ are short run coefficients and $\mathcal{E}_{t-1}$ refers to the error correction term.

Unit Root Tests

In order to provide valid statistical inference and avoid problems of spurious regression unit root tests were performed. There are different tests available, however, the study used the two most common ones such as the Augmented Dickey Fuller (1979) (ADF) and Phillips Perron (1988) (see Gujarati, 2003 and Maddala and Kim, 1998 for an introduction; Hamilton, 1994 for an advanced level overview).).

Johansen´s Co-integration Test

Following the VAR (p) framework and to identify the correct econometric model specification that best fits the time series the Johansen (1988) and the Johansen and Juselius´ (1990) co-integration procedure was employed. The method uses a maximum likelihood approach based on two different statistics such as the Trace and the Maximum Eigenvalue tests. The Trace statistics tests the null hypothesis of no co-integration (H_O: r = 0) against the alternative hypothesis of co integration (H_1: r > 0) whilst the Maximum Eigenvalue tests the null hypothesis of r = 0 against the alternative of r+1 co-integrating vectors (Lajdová, Kapusta, & Bielik, 2015).

Lag-length Selection Criteria and Validity Tests

As the outcomes of the findings can be highly affected by the number of lags the lag-length selection for the proposed VAR (p) model was performed using the Schwarz (SC) information criteria. In addition, model validation was carried out in order to verify that the residuals meet the assumptions of normality, constant error variance and unrelated error terms.

Impulse Response Function and Variance Decomposition Analysis

In order to interpret the linear multivariate times series model, two important tools such as the impulse response function and the variance decomposition were employed. In this manner, according to Asmah (2013) the impulse response function describes the reaction of each variable to a shock in each equation of the VAR (p) system, whilst the variance decomposition provides complementary information in order to understand the relationship between the variables.

Results

As a preliminary step for the estimation of the VAR (p) model, the times series under consideration were tested for the presence of unit root. Therefore, to ensure accuracy both the ADF and the Phillips-Perron tests were conducted, with constant and with constant plus trend, both at level and at first difference for each series with a maximum of one lag using the Schwarz (SC) information criteria.

As presented in Table 1, following the ADF and the Phillips-Perron tests in the level form, both series are non-stationary at a 5% significance level (p-value > 0.05). That is, the critical values are greater than the absolute values; therefore, the null hypothesis of the presence of a unit root cannot be rejected. However, in the first difference, all variables are found to be stationary at 1% significance level, meaning that they do not present a unit root and, therefore, are integrated of order one; I(1).

Table 1 Unit root test results

At level	Constant				Constant and trend			
	Test Statistic		p-value*		Test Statistic		p-value*	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
LnQ	-1.870	-1.853	0.338	0.345	-3.566	-3.565	0.059	0.059
LnP	-2.486	-2.420	0.133	0.141	-5.020	-8.192	0.063	0.060
At first difference								
	Test Statistic		p-value*		Test Statistic		p-value*	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
LnQ	-5.043	-3.831	0.000	0.000	-4.830	-9.682	0.006	0.000
LnP	-6.490	-14.556	0.000	0.000	-6.204	-14.301	0.000	0.000

Note: *MacKinnon (1996) one-sided p-value
Source: Own elaboration

Johansen´s Co-integration Test

Since the times series are stationary in the first difference the Johansen co-integration procedure was employed. The results shown in Table 2 indicate that the trace and maximum eigenvalue statistics are lower than their critical value with a probability above the 5% significance level, which suggests that there is no evidence to support the existence of a co-integration equation; therefore, a VAR modelling was carried out.

Table 2. Johansen´s co-integration test

Null hypothesis	Eigenvalue	Trace statistic	Critical value (0.05)	p-value*	Maxeigen statistic	Critical value (0.05)	p-value*
None	0.3795	9.4453	15.4947	0.325	9.0703	14.2646	0.280
At most 1	0.0195	0.3749	3.8414	0.540	0.3749	3.8414	0.540

Trace test indicates no co-integration at the 0.05 level
*MacKinnon (1996) p-values
Source: Own elaboration

VAR Estimation

Having confirmed the existence of no co-integration an equally significant aspect of the estimation of the VAR system was the choice of the lag order, as all inferences depend on the selection of a correct model specification. Therefore, subject to a maximum of four lags, the Schwarz information criterion suggested an optimal lag length of one.

The VAR estimate, as can be seen in Table 3, captures the short run relationship among the variables and the results showed that the expected signs and the magnitude of the estimated supply response coefficients were within reasonable range and statistically significant at the 1% level. In addition, the goodness of fit of the estimated equation as measured by the R^2 was reasonably good, meaning that the independent variables jointly explained 63.6% of the variations in the cassava production.

Furthermore, cassava production was significantly explained by its own past (LnQ_{-1}) and lagged price by one period (LnP_{-1}) with short-run elasticities of 0.46 and 1.8, respectively. In other words, lagged cassava production was inelastic suggesting a less than proportionate percentage increase, whilst the lagged own- price was elastic implying that an increase in 1% in price will rise output in 1.88%, *ceteris paribus*. Therefore, as own-price elasticity is above the unit there is a strong indication that it is an important variable in cassava cultivation, thus price policies might be effective in increasing production levels. These findings corroborate those of Obayelu and Ebute (2016) on his study on the supply response of cassava in Nigeria who also found a positive relationship between cassava output and lagged production, price and yield, however, estimated own-price in the short run was inelastic.

Table 3. Vector autoregressive estimates

Variable	Coefficient	t-statistic	p-value
LnQ_{-1}	0.4668	2.9050	0.009
LnP_{-1}	1.8877	3.1171	0.006
Constant	2.8907	1.2966	0.212
R-squared	0.6367		
F-statistic	14.9004		
Prob (F-Statistic)	0.000		
$LnQ = 2.89 + 0.46LnQ_{-1} + 1.88\ LnP_{-1}$			

Source: Own elaboration

Validity Tests

From the results outlined in Table 4 it is clear that the estimated VAR model does not present specification errors as the assumptions of no serial correlation, homoscedasticity and normality were not violated.

Table 4. VAR residual diagnostic tests

Test	Statistical	p-value
Serial correlation LM (two lags)	$X^2 = 3.57$	0.467
Heteroskedasticity No cross terms (Joint)	$X^2 = 14.58$	0.264
Cholesky Normality test (Joint)	JB = 2.38	0.665

Source: Own elaboration

Impulse Response Function

In order to understand the effect of the models response to shocks the impulse response function was simulated over 5 years as reported in Figure 1, of which the solid lines represent the variable percent change of the endogenous variables (LnQ and LnP) in response to a standard deviation of one whereas the dotted lines depicts the 95% error bands. The graph shows (Figure 1a) that the initial effects of a one standard deviation in production to its own shocks are strong for the first two periods before it eventually levels towards the end of the period implying that the effects die down and the variables return to their initial equilibrium. This is consistent with the economic theory, that following an increase in production the market would face a situation of excess supply.

Furthermore, the response of production to shock in prices (Figure 1b) presents a sharp rise during the first two periods and remains strong for the entire time horizon, which is also in line with economic logic, as farmers will tend to expand their output supply if prices increase. Moreover, Figure 1c reveals that the initial response of farm price to production shocks presents a small decrease at the initial period and gradually declines towards zero. In addition, a close examination of the effect of a price shock on itself indicates (Figure 1d) that it is always positive and greater than zero however; the effect presents a significant drop in the first two periods.

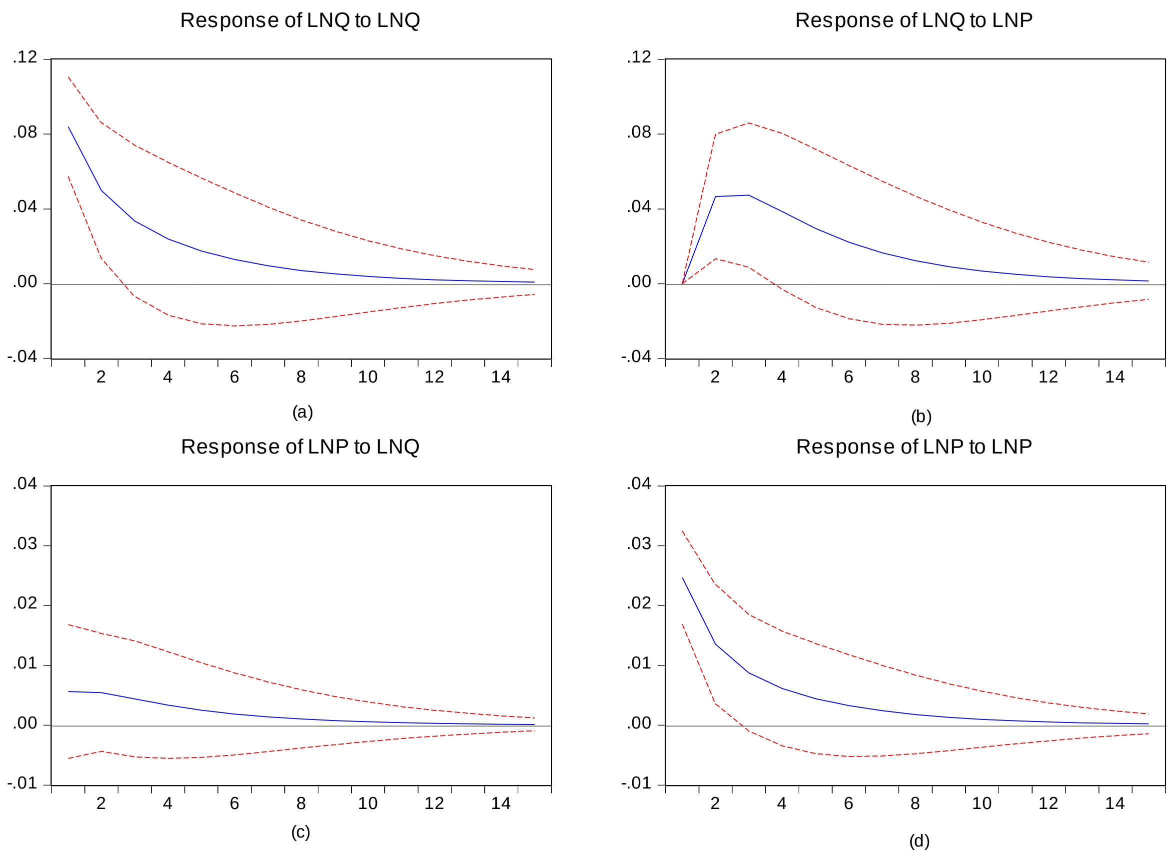

Figure 1. Response to Cholesky one standard deviation innovations (± 2 standard error)
Source: Own elaboration

Variance Decomposition

Variance decomposition offers an alternative for examining the VAR system dynamics and its purpose is to understand the fluctuation in a series explained by its own shocks and from shocks of other variables, thus the results of the 5 years forecast are presented in Table 5. As can be seen at first, for both LnQ and LnP, the variables themselves explain the variance of their forecasting errors. However, the LnQ predicted variance in relation to its own contribution to changes declines after the first period and reaches 63% in the fifth period, whereas the LnP contribution rates, as expected, gradually rises to 36%. Moreover, the predicted variance of LnP explained by its own shock over the course of the years remains high with about 90.4%, without significant influence of LnQ, which suggests that prices play an important role in the variability of cassava supply.

Table 5. Variance decomposition

	Variance Decomposition of LnQ			Variance Decomposition of LnP		
Period (years)	S.E.	LnQ	LnP	S.E.	LnQ	LnP
1	0.083976	100.0000	0.000000	0.025312	4.957794	95.04221
2	0.108198	81.46270	18.53730	0.029220	7.197116	92.80288
3	0.122766	70.74758	29.25242	0.030813	8.500308	91.49969
4	0.130897	65.57908	34.42092	0.031593	9.209389	90.79061
5	0.135333	63.02338	36.97662	0.032002	9.590341	90.40966
Cholesky Ordering: LnQ						

Source: Own elaboration

Conclusion

The aim of the study was to examine the relationship between cassava supply to price changes by employing the vector autoregressive framework. The findings confirmed that cassava past price (LnP_{-1}) and lagged production (LnQ_{-1}) had a positive effect on supply response and that the magnitude of the coefficients were statistically significant and in line with economic theory. Furthermore, lagged own-price was elastic which suggests that price policies may be effective in increasing production levels. Moreover, the analysis of the impulse response functions and the variance decomposition reinforced that price shocks contributed to the variability of cassava production.

Overall, it can be seen from the above analysis that the use of the VAR model can contribute to better understand the short-term dynamics in cassava output response and, therefore help to evaluate the effectiveness of price policies in farmer´s resource allocation and output decision. Nonetheless, it is recommended that follow-up research should be undertaken which should include additional variables in the existing model or a larger dataset.

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