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Oil Price and Real GDP Growth of Ecuador: A Vector Autoregressive Approach

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Abstract. Ecuador is an oil exporter country but it is also an importer of oil derivatives products, in this research the relationship between the world average price of oil and the GDP per capital of Ecuador is studied, taking annual data of both from 1980 to 2015 and using the methodology of Vector Autoregressive (VAR), it is concluded according to the Impulse Response Function that a positive shock on the price of oil affects positively the GDP growth of Ecuador for 2 unit times and then returns to its natural state later. This must be explained because Ecuador is a net exporter of oil, the VAR model showed itself stable, in addition it was demonstrated that there is a causal relationship of GDP to the Price according to methodology of Toda-Yamamoto.
Keywords. Average Oil price, GDP, VAR, Ecuador.
JEL. C32, 040, F20.

1. Introduction

The VAR model is used to explain the dynamics of relationships between variables, considered within the model as endogenous, and expressed under their own delays and delays of the other variables. The dependence of GDP on oil prices is analyzed; Very important issue, since economic policies should be focused on this point. Oil is and will be one of the most used resources on the planet.

The price of the same has had an upward trend since the 80's, with the exception of the last period which has been severely affected due to global over-supply. Likewise the consumption of the same has increased for its use of industries. It is important to study the variations in GDP in relation to the price of oil, since Ecuador is an exporter of this resource, but in turn also imports petroleum products that are subject to the price of oil. This research tries to analyze the relation between the global price of oil and the GDP of Ecuador. For this, an autoregressive vector model (VARM) was used.

2. Literature Review

There are studies of the 1990s, where they have determined a correlation between the impact of oil prices and recessions on the US economy (Hamilton, 1996). In this subsequent investigation the author increased evidence and concluded that if data were included after 1995, that negative correlation did occur, otherwise the causality of Granger was lost (Mork, 1989).

By using a VARM. They determined that OECD member countries have a direct relationship between changes in oil prices and GDP growth. In general, oil-importing member countries showed that, in the face of declining oil prices, each

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country's GDP increased except for Japan. While an increase in the price of oil in the short term decreased the GDP of those countries except Japan (Rodriguez & Sanchez, 2004).

They studied the short- and long-term relationship of oil prices and several macroeconomic variables such as GDP, demonstrating that there is no causality of prices to GDP for oil-exporting countries. And long-term GDP is affected by the price of oil (Lescaroux & Mignon, 2008). They conducted a study on the ratio of GDP to oil prices in China, resulting in a dependence on GDP in relation to prices. These results showed that China's GDP is correlated with prices. An increase in oil prices resulted in an increase in GDP. Giving opposite results to previous studies (Du, Yanan, & Wei, 2010).

The relation of oil prices and the GDP of Spain indicate a statistically significant dependence (Gómez-Loscos, Montañés, & Gadea, 2011). In relation to the study of the same variables in Turkey resulted in a negative effect on GDP in terms of variations in the price of oil, ie an increase in the price showed a decrease Of GDP in general (Aydın & Acar, 2011).

Concluded that oil prices do not affect the countries of this medium as Bahrain, Djibouti, Egypt, Israel, Jordan, Morocco, and Tunisia, but if there is a significant positive impact in countries like Algeria, Iran, Iraq, Kuwait, Libya, Oman, Qatar, Syria, and the United Arab Emirates. Positive impacts on the Oil Price affect the economies of the importing countries of Oil other than the oil exporting countries. The price of Oil could be considered as bad for oil importing countries but good for oil exporting countries. The opposite could be expected for oil price declines (Berument, Ceylan, & Dogan, 2010).

They studied the relationship between oil prices and macroeconomic variables in Turkey and GDP among others, determined that high oil prices are not statistically significant in relation to macroeconomic variables (Aktaş, Özenç, & Arica, 2010). Calculated the elasticity of growth of the economy in relation to the price and consumption of oil. They showed that a decrease or an increase in the price of oil would cause a decrease in the growth of the economy in the same year (Leesombatpiboon, 2009).

3. Methodology

In this research to study the dynamics between world average oil price and Ecuador's GDP growth, annual data from 1980 to 2015 are taken from the World Bank's online database (World Bank Group, 2006).

GDP per capita was taken in real constant values, and the average price for equal weights of oil according to Brent, Dubai and WTI prices in nominal values. Both variables were transformed to their natural logarithm

In order to analyze the relationship of dependence between the GDP per capita of Ecuador and the world average price of oil, the following procedure was followed:

1. Determine the stationarity of the series.
2. Verify causality between variables by the Toda-Yamamoto procedure.
3. Develop the VAR model, and
4. Carry out several tests to determine stability of the model.

4. Findings

4.1. Unitary Root Test

There are important differences between stationary and non-stationary time series. Changes in stationary series are necessarily temporary, over time, the effects of shocks will dissipate and the series will return to their mean level in the long run. While a non-stationary series necessarily has permanent components. The mean and variance of a non-stationary series are time dependent (Enders, 2015).

Have computed the critical values of the t-statistic based on Monte Carlo simulations. This t-statistic is known as the Dickey-Fuller (DF) test (Dickey & Fuller, 1981), which does not follow the usual t-distribution. DF test is estimated using three different equations: With intercept, prone and Intercept and *random walk* (random walk). In each case, the null hypothesis is that there is unit root. The DF tests assume that the errors are independent and have a constant variance (Agung, 2009; Enders, 2015).

The tests are valid only if u_t is white noise, ie it is assumed that is uncorrelated. If this is the case, the test would be overstating the value P. The solution is to "increase" the test using P delays (lags) of the dependent variable. Now the lags of Δ and_t reduce any dynamic structure on the dependent variable, to ensure that u_t is not autocorrelated. The test is known as the enhanced Dickey-Fuller test (ADF). Phillips and Perron have developed a more complete theory of the non-stationary unit root. The tests are similar to the ADF tests, but they incorporate an automatic correction of the DF procedure to allow autocorrelated residuals (Brooks, 2008).

They were subjected to a unit root test to Ecuador's oil price series and GDP. Both the Dickey-Fuller Augmented Test (ADF) and the Phillips-Perron (PP) test (Phillips & Perron, 1988) showed that both series have unit root in levels, but at first difference they do not have either intercept or with tendency and intercept, showing significant values at 1%, both series being I (1).

Table 1. *Unit Root Tests*

Variables	P values in levels		P values in differences	
	ADF	PP	ADF	PP
Log (oil)	0.55	0.50	0.00	0.00
Log (gdper)	0.94	0.94	0.00	0.00

4.2. Toda-Yamamoto Causation Procedure (TY)

Granger causality using the chi ^{2} test used this is conditional on many items if the variables are stationary, so the statistical is invalid if the series are not stationary.

If any of the variables are not stationary, and whether or not cointegrated, the test statistic of Wald not have a chi^2 asymptotic distribution. One procedure to handle this is through (Toda & Yamamoto, 1995).

A solution to this is proposed by (Toda & Yamamoto, 1995) cited by (Ghosh & Kanjilal, 2013) which use a modified Wald test to be applied to a restriction VAR model parameters with k delays. Where k is modified after being maximized integration value (d_{max}), then the VAR model (k + d_{max}) is estimated coefficients of the latter vector delay (d_{max}) being ignored. The Wald statistic converges to a variable distribution Chi ^{2} degrees of freedom equal to the number of delayed variables excluded, regardless if the process is stationary, with linear trend or are cointegrated.

According to the results using the procedure (TY), a P - value of 0.002 Chi ^{2} is observed. Therefore, the null hypothesis of non-causality is rejected and we can say that the log of oil Granger Cause GDP per capital.

Table 2. *Test Toda-Yamamoto*

Dependent variable: Log(GDP)			
Excluded	Chi-square	gl	P value
Log(oil)	14.47061	3	0.0023

4.3. Vector Autoregressive Model (VARM)

Autoregressive Vector models (VARs) were popularized in econometrics by Sims (1980) as a natural generalization of univariate autoregressive models. A VAR is a model of regression systems (there is more than one dependent variable) that can be considered as a hybrid class between univariate time series models and models of simultaneous equations (Brooks, 2008).

It was chosen 3 as the lag length according to model selection criteria given by Lütkepohl (1991). Table 3 shows the VAR model, it is observed that the changes in the GDP per capita of Ecuador, is influenced by the Price of the Oil of a previous time unit (-1).

Table 3. *VAR results*

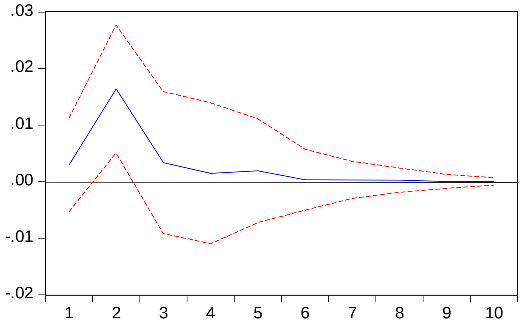
	d(logoil)	d(logpibper)
d(logoil(-1))	0.027662	0.055338
	(0.22476)	(0.01805)
	[0.12308]	[3.06625]
d(logoil(-2))	-0.000542	0.007350
	(0.25386)	(0.02038)
	[-0.00213]	[0.36055]
d(logoil(-3))	0.001274	0.007654
	(0.25214)	(0.02025)
	[0.00505]	[0.37802]
d(logpibper(-1))	-2.233337	0.061853
	(2.44717)	(0.19650)
	[-0.91262]	[0.31477]
d(logpibper(-2))	2.501706	0.037167
	(2.43653)	(0.19565)
	[1.02675]	[0.18997]
d(logpibper(-3))	-0.241371	0.007269
	(2.13505)	(0.17144)
	[-0.11305]	[0.04240]
c	0.019316	0.008725
	(0.06221)	(0.00500)
	[0.31049]	[1.74662]

4.4. Impulse-Response Function (FIR)

Since the individual coefficients in the estimated VAR models are often difficult to interpret, practitioners often estimate the FIR (Gujarati, 2010). They propose a type of Impulse - Generalized Response that consists in constructing a set of orthogonal innovations (shocks), such that they do not depend on the ordering in the VAR (Pesaran & Shin, 1998).

The FIR traces the response of the dependent variables in a VAR to shocks of each of the variables. Then, for each variable of each equation separately, a shock unit is applied to the error, and the effect on the VAR system over time is noted. The way to achieve in practice is to express the VAR model as a VMA - which is an autoregressive vector model as a moving average vector (Brooks, 2008).

According to results we have that one standard deviation innovation through the Choleski decomposition to the GDP per capita of Ecuador, has an effect positive but it declines after 2 unit times, corroborating the practice, since Ecuador is a net oil exporting country, in agreement with similar investigations of Gómez-Loscos, Montañés, & Gadea (2011), Lescaroux & Mignon, (2008) and Berument, Ceylan, & Dogan, (2010). Besides the shock gradually die away, asserting the model is stable (Brooks, 2008), and the confidence bands show significant values for the response of d(logpibper) to a d(logoil) shock.



Graph 1. *Response-Impulse Function. Response of d(logpibper) to d(logoil)*

4.5. Analysis of Decomposition of Variance

The prediction of error variance decompositions are also popular tools for interpreting VAR models (Lütkepohl & Krätzig, 2004).

The variance decomposition offers a slightly different method for examining the dynamics of a VAR system. They give the proportion of the movements in the dependent variables that are due to their own shocks, to shocks of other variables. A shock to the variable i_{th} will directly affect that variable, but will be transmitted to all other variables in the system through the dynamic structure of the VAR (Brooks, 2008).

When analyzing the Table 5 it is observed that the variability of the GDP per capital growth can be explain until 33% approximately by the oil price.

Table 4. *Variance Decomposition*

d(logoil):			d(logpibper):		
Period	d(logoil)	d(logpibper)	Period	d(logoil)	d(logpibper)
1	100	0	1	1.586267	98.41373
2	96.93219	3.067812	2	33.67561	66.32439
3	93.93017	6.069826	3	34.41854	65.58146
4	93.98375	6.016252	4	34.29111	65.70889
5	93.85844	6.141561	5	34.57179	65.42821
6	93.81918	6.180822	6	34.57974	65.42026
7	93.81986	6.180136	7	34.58188	65.41812
8	93.8189	6.181097	8	34.58688	65.41312
9	93.81828	6.181716	9	34.58697	65.41303
10	93.8183	6.181703	10	34.58704	65.41296

4.6. Diagnostic Tests

As the VAR technique is relatively flexible and dominated by the endogeneity of the variables, it is not customary to analyze the estimated regression coefficients and their statistical significance; Nor is the goodness of the fit (R2, it is usual to verify that the absence of serial correlation of the residuals of the individual equations of the model and the normal multivariate distribution of the variables is observed. Sometimes the variables are expected to reflect behaviors consistent with the expected Some researchers perform additional tests, such as the stability of the model, the joint significance of the variables considered, their direction of causality, the cointegration of the residuals of the individual regressions and the Decomposition of Variance Of the forecast error (DV) (Arias & Torres, 2004).

4.6.1. Normal

It is necessary the normality of the underlying data of the generated processes, for example to establish forecast intervals (the forecast errors used in the construction of forecast intervals are weighted sums of the U*t*). Non-normal residuals may indicate that the model is not a good representation of the processes of the generated data. For this reason, testing this distribution assumption is desirable (Lütkepohl, 2005).

The normality test by means of the Cholesky orthogonalization method results in a P value of 0.2639 for the Jarque-Bera (JB) statistic showing in Table 6, giving the not rejection of the null hypothesis that residuals are multivariate normal, so it can be concluded that the residuals have a normal distribution. But taking into account that the sample is small, and the JB statistic follows an asymptotic distribution.

TABLE 5: *Normality*

Component	Jarque-Bera	df	Prob.
1	3.253337	2	0.1966
2	1.982681	2	0.3711
Joint	5.236018	4	0.2639

4.6.2. Autocorrelation

The LM test of autocorrelation of residues of a VAR, results in non-rejection of the null hypothesis of non-autocorrelation until the 4th lag. Determining the absence of correlation between residuals at Table 7.

TABLE 6: *Autocorrelation*

Lags	LM-Stat	Prob. *
1	0.583504	0.9649
2	0.356194	0.9859
3	4.668666	0.323
4	3.345586	0.5017

* Probs from chi-square with 4 df.

4.6.3. Heteroskedasticity

The proof of White without cross-terms, in which the null hypothesis is absence of heteroskedasticity in the VECM, is not rejected in this model, having a P-value of Chi-square, of 0.9529. Although this assumption is not ruled out since the White test is for asymptotic distributions.

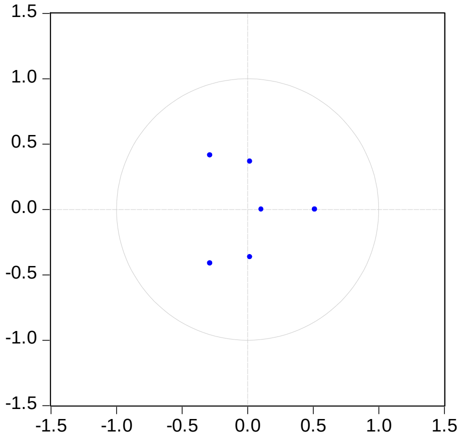
Table 7. *Heteroskedasticity*

Chi-sq	df	Prob.
23.08632	36	0.9529

4.6.4. Stability Model

The estimated VAR is stable (stationary) if all roots have modules less than one and lie within the unit circle. If the VAR is not stable, certain results (such as standard impulse response errors) are not valid.

According to the graph of unit roots, we conclude that the model is dynamically stable.



Graph 2. *Stability Model*

5. Conclusions

The dynamic relationship between Ecuador's GDP per capita and the Oil Price is very important in the development of economic policies. This research was carried out according to annual data transformed to its natural logarithm of two variables, the GDP per capita of Ecuador (GDP growth) and the average price of oil. Using two tools of the self-regressive Vector Model, such as the FIR and the Decomposition of Variance, it was concluded a high relationship between this two variables.

Since the stability tests of the VAR were significant, the results of the forecast by the FIR are significant, impacts on the Oil Price affects the GDP growth positively. The VAR demonstrates the dynamic relationship that exists between the variables studied, resulting also according to the methodology of Toda-Yamamoto in a causal relationship of the GDP growth of Ecuador to variations in the Price of Oil.

Findings were similar to previous studies from Gómez-Loscos, Montañés, & Gadea, (2011), Lescaroux & Mignon, (2008) and Berument, Ceylan, & Dogan, (2010). Although this model could be improved by adding a dummy variable showing some possible breakpoint in the oil price serie.

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