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Estimating the Impact of Oil Price Volatility on the Ecuadorian Economy: A MIDAS Approach

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ABSTRACT

This paper provides empirical evidence about the impact of oil price volatility on government spending, tax revenues, and economic growth for Ecuador. The effects are estimated via a MIDAS regression using quarterly and monthly data for the period 2004 to 2019. The results show that oil price volatility has a positive impact on government spending and tax revenues which is an indicative of a non-prudence behavior in fiscal policy. The impact of GDP is non-significant, contrary to economic intuition and previous studies. These findings have several policy implications that are consistent with the literature of fiscal policy in oil-exporting countries.

Keywords: MIDAS, Ecuador, volatility, oil price, fiscal policy.
JEL Classifications: H50, C32, E62.

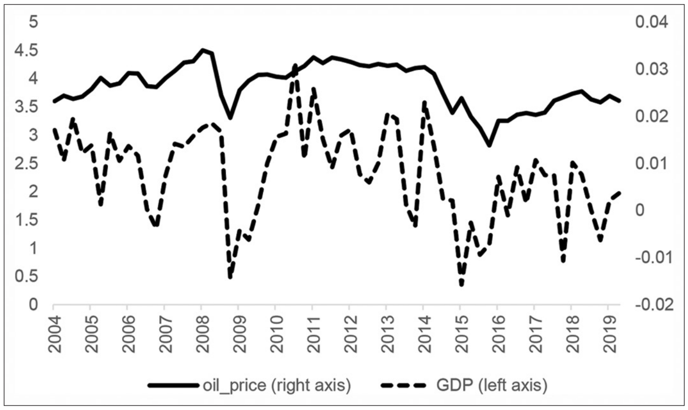
1. INTRODUCTION

Ecuador is a small oil-exporting country whose economy is severely exposed to oil price fluctuations. Oil revenues are one of the main sources of financing for the government of Ecuador. According to official figures, oil exports represented 35.5% of total exports in 2022 while oil revenues rounded 32% of the total fiscal revenues in the same year. The interaction of oil revenues and fiscal policy has caused oil price to play a fundamental role for the Ecuadorian economy. In fact, since 2000 when Ecuador dollarized its economy, fiscal policy began to occupy a leading role in public policy given that the country lost the ability to implement conventional monetary policy. This situation was evident when the country focused on government spending since 2007.

According to García-Albán et al. (2021) government spending increased from an average 22% of gross domestic product (GDP) during the 2000–07 period to 38% during the 2008–18 period. This increase was achieved mainly due to the oil price boom. Figure 1 shows the GDP quarterly growth and oil price as a function of time. The comovement is clear.

Although the impact of oil price on the Ecuadorian economy has been documented through various investigations (see, García-Albán et al. 2021), the effect of oil volatility has not been studied in depth. Price volatility is a common characteristic in energy financial markets. From a statistical point of view, a market with volatile prices is one in which price variation or changes in the price variations are not constant over time. Oil price volatility has different effects on the economy and fiscal policy in comparison to oil price *perse*. Moreover, there is empirical evidence that in some countries the effects of oil prices vary according to the level of volatility (see, Lee and Ratti, 1995). From 2001 to 2019, energy prices in international exchange platforms have been rising strongly and record high prices for oil have been accompanied by important volatility and sudden decrease (Bouazizi et al. 2022).

Figure 1: Ecuador's GDP (first log difference) and oil price (logs)



Source: Central Bank of Ecuador, U.S. Energy Information Administration and authors' computations

Theoretically, volatility could affect fiscal policy and economy in a negative way introducing uncertainty and lowering the predictability of inflows, both at the level of public finance as well as the private sector budgets. The evidenced exposure of the Ecuadorian economy to oil price fluctuations, mixed with the unsustainability path of its public finances highlight the importance of empirically assess the impact of oil price volatility. In this paper, we show evidence about the effects of oil price volatility on three variables that characterize Ecuadorian economy and fiscal policy: GDP, government spending and tax revenues. Employing a MIDAS regression framework, we use quarterly and monthly data to model the link between oil price volatility and economy. We derive a volatility measure using several models of the GARCH family. The results show that oil price volatility has a positive impact on government spending and tax revenues which is an indicative of a non-prudence behavior in fiscal policy, while the impact on economic growth is non-significant. The rest of this paper is structured as follows: section 2 reviews the relevant literature, section 3 and 4 describes the econometric methodology and the data, section 5 presents the results and section 6 discuss alternative model specification. Finally, in section 7 we present the conclusions and policy implications.

2. LITERATURE REVIEW

The study of oil price volatility and its impact on the economy is not new. Lee and Ratti (1995) showed that the price of oil has a greater effect on economic activity in the United States in periods in which oil prices are stable, than in an environment where oil price movements have been frequent and erratic.

Using a threshold regression model, Tehranchian and Seyyedkolaee (2017) test for the relationship between oil price volatility and economic growth in Iran. The authors find a positive impact of oil price volatility on GDP growth. Although the magnitude of the effect decreases once volatility crosses the threshold value, the positive sign is difficult to reconciliate with theory, especially for an oil exporting country.

Akinlo and Apanisile (2015) test for the impact of oil price volatility on economic growth using a pool of oil and non-oil exporting countries. Oil price volatility is proxied by the fitted values of an EGARCH model, and then used as input in a panel regression model. The research concludes that oil price volatility has a positive and significant effect only for the oil exporting countries. Ebrahimi (2011) also examine the effect of oil price and exchange rate volatility on GDP fluctuations in oil exporting countries. Similarly, the author uses a GARCH model to estimate volatility and then use the predicted conditional variances as input for a VAR model. Estimated relationship between oil price volatility and GDP growth is positive for all countries in the sample. Like the study of Tehranchian and Seyyedkolaee (2017), these results are difficult to interpret.

Recently, Ogunjumo et al. (2024) investigates the impact of volatile oil revenue on economic growth in Nigeria from 1986 to 2020, using the ARDL methodology. In the short-run, oil revenue volatility depressed economic growth, while in the long-run, oil volatility improves economic growth in Nigeria.

On the other hand, studies that combine the effect of oil price volatility on economic and fiscal policy are more limited. Anshasy and Bradley (2012) derive and estimate a fiscal policy equation that links government spending not only to oil price shocks, but also to oil price volatility and the skewness of oil price changes for a panel of oil-exporting countries. They find a negative impact of oil price volatility on government spending suggesting a prudence behavior in fiscal policy.

Oriakhi and Osaze (2013) employ a VAR model to estimate the impact of oil price volatility on several macroeconomic variables for the Nigerian economy, including government expenditure. Although it is not clear if the estimated effect of oil price volatility on government spending is positive or negative, the authors indicate that there exists a significant effect. Moreover, they don't find a significant direct effect from oil to GDP, suggesting that volatility is transmitted only through the government fiscal policy. Pan et al. (2017) estimates a regime switching GARCH-MIDAS model to study the impact of macroeconomic fundamentals on oil price volatility. This is the opposite to what we are looking for in the present research.

Studies that look for the relationship among oil volatility and other economic variables different from GDP and fiscal indicators are more widely available. For example, Bouazizi et al. (2022) estimate the effects of conditional oil volatility on exchange rate and stock markets returns. The authors model conditional volatility of oil price using a battery of ARMA and ARCH models and then combine this estimation into a VAR model with stock and exchange rate returns for United States, Germany and Japan. They conclude that oil price volatility has a positive effect on stock market return for United States and Germany, and a negative impact on Japan market.

When focusing on Ecuador, the literature about the relationship between oil price volatility and fiscal policy is even more restricted. García-Albán et al. (2021) is the more recent study that examine and test a rich set of hypotheses about the relationship among oil revenues, economic growth, and fiscal policy in Ecuador. They propose a procedure to clarify the mechanism of propagation of oil price shocks in a price taker oil-exporting country using Ecuador as example. However, in that model, volatility does not play any role.

3. METHODOLOGY

3.1. The MIDAS Regression

We use a Mixed Data Sampling (MIDAS) regression model proposed by Ghysels et al. (2004) in order to capture the relationship between oil price volatility, fiscal policy and economic growth. What motivates the use of MIDAS regression is the fact that oil price is observed at a lower frequency than fiscal variables and GDP. Oil price typically is reported at a monthly and daily frequency. Moreover, fiscal policy decisions are made based on that basis. GDP is published at a quarterly frequency and with lags. Fiscal measures, on the other hand, are reported monthly but are subject to a lot of noise derived from policy or political decisions. Fiscal variables are usually examined at quarterly frequency. This makes the identification of parameters easier by exploiting some features of the institutional process of the fiscal policy implementation (see Blanchard and Perotti, 2002; García-Albán et al., 2021).

A MIDAS regression adopts the following structure:

$$y_t = X_t^{'}\beta + f(\{X_{\frac{t}{C}}^{H}\},\theta,\lambda) + \varepsilon_t \tag{1}$$

where:

y_t is the dependent variable at a lower frequency. In this research we run three regressions using three different dependent variables: government spending (GOVSPEN), tax revenues (TAXREV), and GDP. X_t is a vector of random variables at a lower frequency. X_t is composed by the lags of government spending, tax revenues, and GDP. The lags of the three variables are included in each regression. is a vector of high frequency variables with C records for each low frequency value. In our exercise contains the oil price volatility, f is a function that describes the effect of the higher frequency data on the lower frequency regression. β, λ y θ are vector of parameters to be estimated.

It is necessary to choose a function f to map the weights in a MIDAS regression. We have chosen the Almon function or PDL. For a more detailed description of the MIDAS regression methodology see Ghysels et al. (2004) and Ghysels et al. (2006).

3.2. The Oil Price Volatility Regression

To run our MIDAS regression model, it is necessary to choose the oil price volatility variable. There are several approaches to approximate volatility. Figure 2 displays the simpler volatility measure, commonly used as benchmark in the literature: the squarer $t-1$variation of oil price at a monthly frequency.

A first look at the plot confirms the time dependent nature of the conditional variance of the series. This has been previously documented by several research like Herrera et al. (2018) and Mohammadi and Su (2010). In this research, we try several models that belong to the GARCH family to capture volatility dynamics. GARCH models proposed by Engle (1982) and Bollerslev (1986) are the most standard models used in the estimation of conditional variance. A GARCH(1,1) model can be described by the following dynamics:

$$r_t = \mu_t + \epsilon_t = \mu_t + h_t^{1/2}\eta_t$$

$$h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

$$\eta_t \sim iid(0,1)$$

Where μ_t is the conditional mean and h_t is the conditional variance with sufficient conditions $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ as long as $h_t > 0$. Glosten et al. (1993) propose a variation of the GARCH model, which accounts for asymmetric effects: the GJR model. A GJR(1,1) model is given by:

$$h_t = \omega + (\alpha + \gamma I\left(\epsilon_{t-1} < 0\right))\epsilon_{t-1}^2 + \beta h_{t-1} \tag{3}$$

Where I(.)is an indicator function. $I(.) = 1$ when condition (.) holds, and 0 otherwise. The asymmetric effect is captured by $\gamma \geq 0$.

We also consider the exponential GARCH model or EGARCH proposed by Nelson (1991). An EGARCH(1,1) model can be expressed as:

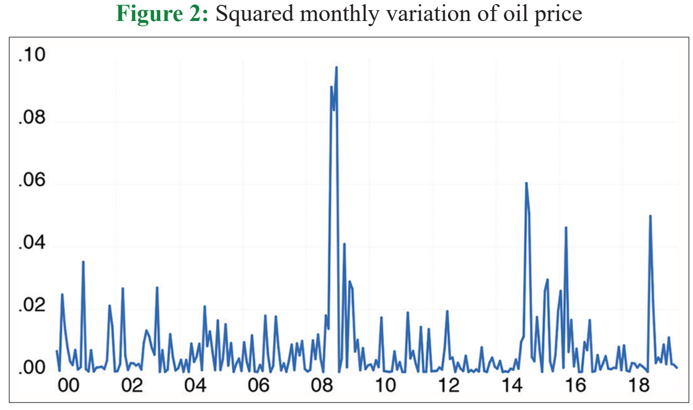
$$\ln h_t = \omega + \alpha\left(\left|\eta_{t-1}\right| - E\left|\eta_{t-1}\right|\right) + \gamma\eta_{t-1} + \beta h_{t-1} \tag{4}$$

We run all these volatility models and select one based on the information criteria AIC (see Akaike, 1973), BIC (see Schwarz, 1978) and HQ (see Hannan and Quinn, 1979). The models are fitted on the oil price return which is defined as the log difference of the monthly oil price DLWTI. Also, all the models consider a constant and the lagged oil price return in the conditional mean equation.

4. DATA

Data about GDP, government spending and tax revenues are obtained from the Central Bank of Ecuador. We construct fiscal variables as in García-Albán et al. (2021). An exception is

Figure 2: Squared monthly variation of oil price



Source: U.S. Energy Information Administration and authors' computations government spending. We define government spending as the sum of government investment and government consumption calculated in García-Albán et al. (2021). Also, we use variables in real terms instead of real per capita units. See García-Albán et al. (2021) appendix for a detailed description of the dataset.

We use spot West Texas Intermediate oil price recorded by the U.S. Energy Information Administration to recover oil price volatility. In our model, GDP and fiscal variables are used at quarterly frequency while oil price volatility is in monthly basis. The data run from 2004q1 to 2019q3 because is the longest period for which official data is comparable.

5. EMPIRICAL RESULTS AND DISCUSSION

Table 1 reports the information criteria calculated for each volatility model. The GJR(1,1) model shows the best performance based on the minimization of the information criteria. Also, the GJR model have been shown to have good out-of-sample performances when forecasting the oil price volatility one step ahead (see, Hou and Suardi, 2012; Mohammadi and Su, 2010).

Figure 3 shows the estimated conditional variances for each volatility model. The pattern among all models is similar. However, the EGARCH model produces a less smoother series. We use the GJR model as benchmark and test for robustness using the GARCH model which is the most used in this kind of exercise (see, Hansen and Lunde, 2005; Xu and Ouenniche, 2012). Table 2 displays the estimated coefficient of the GJR (1,1) model. Although the ARCH coefficient is not significant at any standard confidence level, the coefficient that capture the asymmetric behavior is. The constant in the conditional mean equation is also non-significant.

The MIDAS regressions are run using two lags of each of the variables: GDP, government spending and tax revenues. Also, each regression includes a constant and a linear time trend. The choice of this functional form is based on the setting and results of García-Albán et al. (2021).[1] The MIDAS regression with Almon weights also requires setting the order of the polynomial, which we fix at two. The number of lags of the high frequency component is chosen based on information criteria using a maximum lag length of six. Table 3 display the results of the three MIDAS regressions, while Figures 4-6 show the lag coefficients and their lag distribution for the high frequency share of the model.

In the regression of government spending, three lags were selected by information criteria.[2] Lags of government spending and GDP are significant using conventional confidence levels. The tax revenues variables, as well as the constant and trend, are nonsignificant.

1 García-Albán et al. (2021) use the series in levels, and do not allow the possibility of stochastic trends. Also, Sims et al. (1990) argue that it is possible to estimate a VAR model without cointegration restriction, even when there is evidence of unit roots. Since the MIDAS regression is based on each equation of the VAR model, we rely on the estimation in levels.

2 The models were run in Eviews. The MIDAS regression includes the contemporaneous value as one of the lags. Strictly speaking, when three lags are selected, the model contains the contemporaneous value of the high frequency variable and two lags.

Table 1: Information criteria of volatility models

	AIC	BIC	HQ
GARCH (1,1)	−2.16	−2.09	−2.13
GJR (1,1)	−2.19	−2.10	−2.15
EGARCH (1,1)	−2.18	−2.09	−2.15

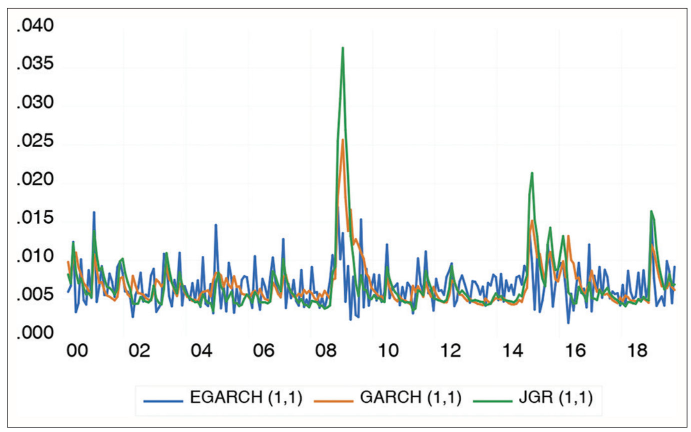
Source: Authors' computations

Table 2: Results of GJR (1,1) model

Dependent Variable: DLWTI				
Mean equation				
Variable	Coefficient	Std. Error	z-Stat	Prob
DLWTI(-1)	0.196**	0.076	2.567	0.01
c	0.002	0.005	0.32	0.75
Variance equation				
c	0.001**	0.001	2.292	0.022
ARCH(-1)	−0.056	0.072	-0.769	0.442
ARCH(-1)*I(ϵ_(-1) <0)	0.282**	0.114	2.478	0.013
GARCH(-1)	0.683***	0.131	5.195	0
Adj R^2	0.065			
standard error of regression	0.084			
Log likelihood	263.3691			

*, ** and *** denote 10%, 5% and 1% significance levels respectively.
Source: Authors' computations

Figure 3: Predicted conditional variance by volatility models



Source: Authors' computations

The estimated coefficients associated to the polynomial weights are significant at 10%. The lag pattern is decreasing as is shown in the lag coefficient graph: the zero high frequency lag of oil volatility has a large impact on government spending, but the effect dies very quickly in a linear way becoming the effect to negative. A positive effect of oil price volatility on government spending means that government does not maintain a prudence behavior in fiscal policy. Moreover, there is an economic intuition behind the decreasing effect in the lags: initially the government overspends until it realizes that there is a volatility episode in the market and turn his policy to a more prudent behavior (negative effect at lag two). These results are compatible with Anshasy and Bradley (2012) although the authors find uniquely a positive linear effect.

The tax revenues equation tells a similar story regarding to the impact of oil price volatility. Four lags were selected. Estimated coefficients associated with the polynomial weights are significant

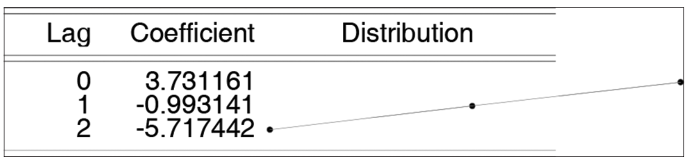
Table 3: Results the MIDAS regression models

Dependent variable	GOVSPEN		TAXREV		GDP	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
GOVSPEN(−1)	0.606***	0.143	0.17	0.184	0.032**	0.013
GOVSPEN(−2)	0.279*	0.142	0.133	0.188	0.004	0.014
TAXREV(−1)	0.044	0.096	0.08	0.123	−0.01	0.008
TAXREV(−2)	0.012	0.098	0.265**	0.125	−0.012	0.009
GDP(−1)	2.711**	1.158	−2.571*	1.496	1.028***	0.113
GDP(−2)	−2.23*	1.167	3.491	1.499	−0.13	0.113
C	−3.989	3.947	−6.14	5.077	0.86**	0.37
Trend	−0.004	0.003	−0.005	0.004	0	0
POLYNOMIAL COEFFICIENTS						
PDL01	8.455*	4.917	11.516**	4.364	0.001	0.232
PDL02	−4.724*	2.357	−4.859***	1.686	−0.097	0.076
Selected lags	3		4		5	
Adj R^2	0.96		0.907		0.997	
standard error of regression	0.074		0.096		0.007	
Log likelihood	77.113		62.013		221.78	

*, ** and *** denote 10%, 5% and 1% significance levels respectively

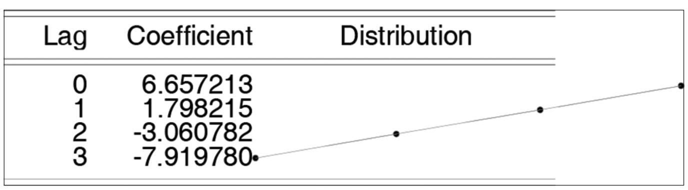
Source: Authors' computations

Figure 4: Lag coefficients and distribution for the government spending dependent variable



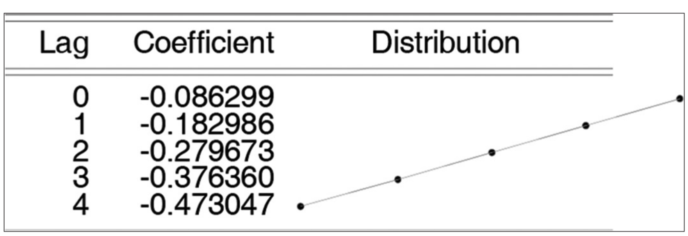
Source: Authors' computations

Figure 5: Lag coefficients and distribution for the tax revenues dependent variable



Source: Authors' computations

Figure 6: Lag coefficients and distribution for the GDP dependent variable



Source: Authors' computations

al 5%, while the overall effect of volatility is decreasing in the lags from positive to negative. An important feature of these model in comparison to traditional fiscal VARs is that there is no possible to distinguish changes in the policy from the automatic response to economic cycle. In this sense, it is difficult to think that the tax policy changes in response to oil price volatility. The initial positive effect could be attributed to the fact that government spending reacts positively to oil price volatility, increasing GDP and henceforth tax revenues. This implies the existence of a government spending multiplier that have been documented previously in García-Albán et al. (2021). On the other hand, the quarterly coefficients are not significant, except for the two lags of GDP and the second lag of tax revenues.

The GDP equation, on the other hand, does not show a significant effect of oil price volatility. Although the effect of oil price volatility is negative and decreasing across all the lags, the polynomial weights are non-significant, meaning that the effect is not statistically different from zero. Five lags of the oil price volatility were selected in this equation.

6. ALTERNATIVE SPECIFICATIONS AND MODEL DISCUSSION

There are at least two interesting features of the model that we can change to check for the robustness.[3] First, we try another measure of volatility. Instead of using the GJR model, we incorporate the GARCH volatility measure. This volatility model is used in Ogunjumo et al. (2024), and usually is considered a benchmark within the volatility models family. The results are quite similar. The contemporaneous effect of oil price volatility on government spending is positive and decreasing in the number of lags. A similar behavior happens with tax revenues. In the case of GDP, it reacts negatively to changes in oil price volatility, but the estimates are non-significant as in the benchmark specification.

Finally, we check whether the conclusions change once the effect of oil price is accounted by the model. The inclusion of the oil price in levels, or differences, could be debatable. For instance, it is difficult to think that the dynamic of oil price volatility does not depend on oil price movements. Moreover, by construction volatility was estimated from the conditional mean and variance equations from oil price. The literature is not clear about this choice. For example, Ogunjumo et al. (2024) only model the volatility variable, while Anshasy and Bradley (2012) include both, volatility

3 Both results are available upon request.

and the original variables, and even a measure of kurtosis. Strictly speaking, a complete modeling approach should include the entire dynamic of oil price including its conditional covariance matrix and identifying the appropriated shocks. This could be addressed, for example, using a VAR model with stochastic volatility (see, Nakajima, 2011). Such models go beyond the scope of this paper. In the present robust exercise, we simplify the assumptions and include log differences of oil price in the high frequency piece of the model. The configuration of the tunning parameters is the same as the oil price volatility. Some results remain. For example, oil price volatility impact negatively on contemporaneous government spending. Other results do not match previous literature: oil price has a contemporaneous negative effect on GDP, in opposite to the results of García-Albán et al. (2021). However, in all cases the inclusion of oil price seems to remove the effect of oil price volatility. This could be the result of not properly modeling the link between oil price and its volatility, as explained before.

7. CONCLUSIONS AND POLICY IMPLICATIONS

In the present research we have estimated the impact of oil price volatility on government spending, tax revenues and economic growth in an oil exporting country, Ecuador. Oil price volatility was estimated by a battery of GARCH models, and then it was included as regressor in several MIDAS regressions, one for each dependent variable. The main results suggest that oil price volatility has a significant and positive effect on government spending suggesting that the Ecuadorian government behave with no prudence when formulating spending policy. The effect becomes negative as time passes. Tax revenues response is similar, which is attributed to the existence of a government spending multiplier. The GDP response is non-significant.

In the light of these results, government should adopt a more prudent behavior regarding spending policies. Although there is not a visible impact on economy, the response of government spending could have a significant impact in the sustainability and foreseeability of public finances. The oil dependence of Ecuadorian economy plays a deeper role in the transmission of oil price volatility shocks. The oil dependence of the country can be softened through the implementation of fiscal rules designed for that purpose as explained by Pieschacón (2012).

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