ELASTICITIES OF DIESEL IN BRAZIL

Leonardo Chaves B. Cardoso, Federal University of Viçosa (UFV), +5571992212849, leonardocardoso@ufv.br.
Cleiton Silva de Jesus, State University of Feira de Santana (UEFS), +5571991899161, cleiton.uefs@gmail.com.

Overview

Reducing pollution and fossil fuels dependence, favoring other transport modes and increasing government revenues can be policy goals (Li et al., 2014, Levin et al., 2017). Regarding pollution, how to reduce in 10% greenhouse gases (GHG) related to diesel consumption, for example? To address this question its possible to use price increasing by taxes, addition of biofuels by mandate or even a combination of policies. And, the knowledge of price and income elasticities has a central role on this issue.

Despite the importance of diesel elasticities, surveys as Graham and Glaister (2002) and Dahl (2012) show a higher relative interest in gasoline elasticities than in diesel markets in the world. In Dahl (2012), for example, there are thousand of studies related to gasoline market, while only 120 studies for diesel elasticities. This higher interest in light fuels remains in Brazil, where there a lot of studies related to ethanol and gasoline demand, while only Iootty et al. (2009) studied diesel elasticities. The authors used an annual database in a time series approach with 33 observations (1970-2005) and found that the price elasticity was -0.63, while income elasticity was around one.

Therefore, this article aims to estimate the price and income elasticities for diesel demand in Brazil using monthly data from 2003m1 to 2018m3. For this goal, two econometric methodologies are used: i) a Partial Adjustment Model (PAM) with Instrumental Variables (IV), including fixed size rolling regressions; ii) an Autoregressive Model with Distributed Lags (ARDL).

Methods

Partial Adjustment Model with Instrumental Variables (PAM-IV)

The first method used is a PAM-IV approach where the lagged of quantities are included as explanatory variable and the own-price is considered endogenous. So, the own-price is estimated in the first stage (Eq. 1) and its fitted values are included in the second stage (Eq. 2).

$$First \quad Stage: \quad Ln(\hat{P}_t) = \sigma_0 + \sigma_1 Ln(Y_t) + \sigma_2 Ln(Oil_t) + \sigma_3 Ln(Exchange_t) + \sigma_4 Ln(P_{t-1}) + z_t \tag{1}$$

$$Second \quad Stage: \quad Ln(Q_t) = \theta_0 + \theta_1 Ln(\hat{P}_t) + Ln(Y_t) + \lambda Ln(Q_{t-1}) + U_t \tag{2}$$

In Equations 1 and 2, P_t is the diesel pump price and Q_t is the sold quantity of diesel, both variables are found in ANP (2018). Oil_t is the Brent price from WB (2018). $Exchange_t$ and Y_t are, respectively, real exchange rate and a proxy for real income (IBC-BR index), both from Central Bank of Brazil. U_t and z_t are the error terms. σ_i are the parameters of the first stage, θ_1 is the short-run elasticity, and $\frac{\theta_1}{1-\lambda}$ is the long-run price elasticity.

Autoregressive Distributed Lag (ARDL)

The long-run relationship between variables are often studied with cointegration approach from Engle and Granger (1987) and Johansen (1991). Recently, ARDL models proposed by Pesaran and Shin (1998) and Pesaran et al. (2001) have increased their participation on the cointegration analyzes.

Considering that Equation 3 describe the long-run relationship between the variables, Equation 4 tests the stability of this relationship using a F-test ($H0: \lambda_1 = \lambda_2 = \lambda_3 = 0$)[1].

$$Ln(Q_t^*) = Ln(\alpha_0) + \alpha_1 Ln(P_t) + \alpha_2 Ln(Y_t) + u_t \tag{3}$$

$$\begin{aligned} \Delta Ln(Q_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \Delta Ln(Q_{t-i}) + \sum_{i=1}^{p} \alpha_2 \Delta Ln(P_{t-i}) + \sum_{i=1}^{y} \alpha_3 \Delta Ln(Y_{t-i}) + \\ \lambda_1 Ln(Q_{t-1}) + \lambda_2 Ln(P_{t-1}) + \lambda_3 Ln(Y_{t-1}) + \varepsilon_t \end{aligned} \tag{4}$$

[1] *Bound Test* proposed by Pesaran et al. (2001).

However, previously to test if there is a long-run relationship among variables, the number of lags used need (q, p and y) to be chosen using BIC criteria. If actually there is a long-run relationship, the Equation 5 is estimated by Ordinary Least Squares:

$$\begin{split}\Delta Ln(Q_t) = \theta_0 + \sum_{i=1}^{q} \theta_1 \Delta Ln(Q_{t-i}) + \sum_{i=1}^{p} \theta_2 \Delta Ln(P_{t-i}) + \sum_{i=1}^{y} \theta_3 \Delta Ln(Y_{t-i}) + \\ \kappa_1 Ln(Q_{t-1}) + \kappa_2 Ln(P_{t-1}) + \kappa_3 Ln(Y_{t-1}) + \gamma ECM_{t-1} + \mu_t\end{split} \quad (5)$$

ECM is the residual of Equation 3. The short-run elasticities are found directly by the first-difference parameters (when i=1). The long-run elasticities are found dividing the sum of price parameters by the ECM parameter ($\frac{\sum_{i=1}^{p} \theta_2 \Delta Ln(P_{t-i})}{\gamma}$).

Results

The results of PAM-IV showed short-run price elasticity of -0.16 and the income elasticity of 0.40. In the long-run, price elasticity was -0.46, while income elasticity was 1.18. In ARDL models, a richer dynamic between short and long-run is allowed, and the results indicated that income has no effect in the short-run for diesel demand, while the long-run elasticity was around one. On the other hand, price has an effect in both, short-run (-0.40) and in the long run (-0.80).

Conclusions

Our study contributes to the literature calculating diesel elasticities to both long and short-run in Brazil on monthly basis, showing that diesel demand is price-inelastic. In both models, income elasticity are higher than price elasticity, so, environmental policies based on consumption reduction need to increase affordability of diesel. In other words, price should increase faster than income to reduce consumption.

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