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Modeling and Forecasting Gasoline Consumption in Cameroon using Linear Regression Models

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ABSTRACT

In this study we model and forecast gasoline consumption in Cameroon till 2020. We start by estimating price and income elasticities of gasoline consumption using historical data for the period 1994-2010. Our estimates of price elasticity range between −1.433 and −0.151, while income elasticity range between 0.179 and 1.801. These results are similar with findings in other developing countries. We then establish a dynamic regression model for forecasting gasoline consumption. Usual statistical performance measures are used to validate the model. Results suggest that price, gross domestic product and income are significant drivers of gasoline consumption in Cameroon. Projected results show that gasoline consumption will increase by over 7% yearly, reaching 1078 504 m^3 by 2020. Following these findings, we recommend energy policies in Cameroon to prioritize the discovery of new oil fields, expand and modernize refining capacities to increase production, and improve storage capacities of petroleum products by at least 2020.

Keywords: Gasoline Consumption, Forecasting, Cameroon
JEL Classifications: Q4, Q47

1. INTRODUCTION

Energy issues in general and petroleum products in particular are directly related to the development of a nation and the living standards of its people. In fact, energy demand is an important criterion in measuring the economic performance of any nation for it is a key factor of production in virtually all sectors of the economy. With the oncome of industrialization and globalization, the consumption of fossil fuels has increased by manifolds (Aydin, 2015). The growing worldwide economic crisis has proven that developing countries are severely affected (Aydin, 2014). Countries like Cameroon with weak economies are less capable of adjusting to the price shocks associated with oil price increases since the 1970s and lately in February 2008(GESP, 2009). It is therefore undeniable that energy management in an optimal manner is crucial for the future economic prosperity and environmental security (Aydin, 2015). Hence, a sound forecasting technique is essential for accurate investment planning of energy consumption in Cameroon.

Primary and secondary sectors in Cameroon rely on the transport sector. This sector has contributed on average 4.1% of the gross domestic product (GDP) for the last 10 years (GESP, 2009). The transport sector greatly influences the cost of living in Cameroon. For instance, food crops price are greatly related to transport costs, especially when food crops are supplied from rural to urban areas (GESP, 2009). This has led to an inflation rate of 5.3% in 2008, a record that has ever been registered by the country (GESP, 2009), leading to social instabilities**.** Measuring the factors influencing gasoline consumption generally has two purposes: For apprehending the variations of gasoline consumption in the transport sector; and to regulate the impacts of economic and environmental policies.

There is a vast literature surrounding different approaches to forecast gasoline consumption. Eltony and Al-Mutairi (1995), Birol and Guerer (1993), Ramanathan (1999) modeled gasoline consumption in terms of real income and gasoline price. In order to capture the effect of rising fuel efficiency in Denmark, Bentzen (1994) specified gasoline consumption in terms of a time trend, price and per capita vehicle stock. Eltony (1993) in his works used a lagged endogenous model to specify gasoline consumption as a function of real price and per capita stock of automobiles. Wasserfallen and Güntensperger (1988) adopted a partial equilibrium model that explains the consumption for gasoline and the total vehicle stock in Switzerland. They concluded that gasoline consumption became more price sensitive after the oil shock that occured 1973, while Polemis (2006) modeled gasoline consumption as a function of a time trend, per capita income, real prices of gasoline and diesel and per capita vehicle stock for the Greece economy. In Akinboade et al. (2008), an autoregressive distributed lag model was applied to analyze gasoline consumption for South Africa for 1978-2005. Their study confirms that gasoline consumption in South Africa is price and income inelastic. Recently, Hughes et al. (2008) and Wadud et al. (2010) have estimated gasoline consumption elasticities with more current consumption data and innovative techniques. In the works of Hughes et al. (2008), macroeconomic factors such as inflation are controlled for, supply disruptions in an instrumental variables model are used to control for the endogeneity of prices and quantities. Meanwhile Wadud et al. (2010) controlled for household characteristics such as urban/rural residence and found a median price elasticity of −0.47. More recently, Sene (2012) estimated gasoline consumption in Senegal for the period from 1970 to 2008. He points out that variation of oil price only play a major role in the short-run. Coyle et al. (2012) estimated gasoline supply and consumption functions for the U.S. market using data from excise tax returns for the years 1990-2009. They found that gasoline elasticities using IRS and EIA data are similar. Pock (2010) modeled gasoline consumption using a dynamic model for 14 European countries over the period 1990-2004.

In all, we can note that modeling issues on gasoline consumption are greatly dominated by studies on gasoline elasticities using different models. For example, Sterner and Dahl (1992) and Goodwin et al. (2004) surveyed a hundred and sixty past studies of which a great majority focused on gasoline elasticities in different countries. The models used in these studies mainly included static and dynamic partial adjustment models (PAMs), and lagged endogenous models. All studies have used real income and real price of gasoline as the independent variables. Studies on gasoline consumption forecast are scarce. Among the numerous works that exist in the literature, no study has been undertaken in Cameroon to estimate gasoline elasticities and future gasoline consumption. Thus, the present study represents the first move to specifically model and forecast gasoline consumption in Cameroon.

2. SCOPE OF STUDY

The objective is to estimate gasoline elasticities for Cameroon using data set over the years 1994-2013. For this, we propose different models based on co-integrated or stationary data in order to analyze the connections between gasoline consumption, gasoline price and disposable income. Another target is to forecast gasoline consumption till 2020 using a dynamic multiple linear regression (MLR) model. The validity of the proposed MLR model is confirmed by separating the data into training (1994-2010) and test data (2011-2013), and by conducting usual statistical inferences.

The year 1994 is chosen as the starting year because it corresponds to the restart of economic growth in Cameroon. Cameroon witnessed an economic crisis in the 1980s that led to the devaluation of FCFA in 1994. Immediately after the crisis, the Government launched major reforms in key sectors of infrastructure by increasingly entrusting major responsibilities to the private sector, by investing heavily to ensure the maintenance, rehabilitation, and development of communication and production infrastructure, thereby fixing goals to be achieved by 2020 in the growth and employment strategy paper (GESP, 2009). The Government of Cameroon intends to invest massively in the energy sector during the implementation period of the strategy. For this reason, our forecasting horizon is 2020 to be in line with the strategy that has already been undertaken by the Government of Cameroon.

3. DATA SETS

Deciding on which variables to use as independent variables is a regularly occurring difficulty in developing reliable forecasting models. If input data is insufficient, the outcome will be poor; similarly, if input data is useless or redundant, modeling will be difficult. Even though complex forecasting techniques provide accurate predictions, they are very difficult to manage and are data consumption. For this, less accurate forecasting techniques are appreciated not only because of their simplicity but also because the forecasting module is just part of a more complex forecasting tool.

Annual gasoline consumption, prices, vehicle fleet, GDP, and GDP per capita were collected for the period 1994-2013. Data on gasoline consumption, price and vehicle fleet were collected from the hydrocarbon price stabilization fund (HPSF, 2016). GDP and GDP per capita were obtained from the World Development Indicators Database of the World Bank (2015). Historical data on gasoline consumption as well as price, vehicle fleet, GDP and GDP per capita are presented in Figure 1. The profiles in Figure 1 all show an increasing trend of the parameters. If these parameters are the main determinants of gasoline consumption in Cameroon, then it follows that gasoline consumption could grow and reach record levels over the coming decades. This partly explains why the government is reluctant to cancel gasoline grants as the price at the pump strongly influences transportation costs, which in turn is directly related to the cost of living.

4. METHODOLOGICAL FRAMEWORK

4.1. Estimating Gasoline Consumption Elasticities

4.1.1. PAM

In order to estimate gasoline elasticities, we express annual gasoline consumption in terms of real GDP per capita and real price of gasoline. Throughout this paper, we use variables in their logarithmic form. With this logarithmic transformation, the coefficients are straightforward interpreted as percentage changes. The model takes the following form:

$$D_t = \delta_0+\delta_1 CAP_t+\delta_2 PR_t+\delta_3 PR_{t-1}+\delta_4 D_{t-1}+v_t \quad (1)$$

Where D_t is gasoline consumption, CAP_t is the real GDP per capita (which is considered as a proxy for income throughout),PR_t is real gasoline price at the pump, δ_i;$_i$=0,1,2,3,4 are the estimators, and v_t is the error term.

The model in Eq. (1) is known as a PAM. Such a model accounts for possible frictions in the market that cause adaptation to fluctuations in gasoline price or income at time t+1 not to take place in situ (at time t). Whenever the series are integrated of order 1, I(1), the coefficients δ_1 and δ_2 represent the short-run income and price elasticities of gasoline consumption respectively (Hughes et al., 2008). Sene (2012) showed that dividing short-run elasticities by $(1-\delta_4)$, we obtain long-run estimates of elasticities:

$$y_1 = \delta_1/(1-\delta_4) \quad (2)$$

$$y_1 = \delta_2/(1-\delta_4) \quad (3)$$

Where y_1 and y_2 are the long-run income and price elasticities of gasoline consumption respectively.

4.1.2. Model with interactions

Sometimes, it is interesting to study the interaction between price elasticity and income. For this, we define a regression model that includes a price-income interaction term in as follows:

$$D_t = \pi_0+\pi_1 CAP_t+\pi_2 PR_t+\pi_3 CAP_t PR_t+u_t \quad (4)$$

Where π_i;I = 0,1,2,3 are parameters to be estimated, and u_t is the error term.

The partial effect (or semi-elasticity) of gasoline consumption WWholding price fixed (i.e., the price elasticity of consumption) is:

$$\frac{\partial D_t}{\partial PR_t}=\pi_2+\pi_3 CAP_t \quad (5)$$

The coefficient π_3 indicates the degree of sensibility of consumers to price fluctuations (increases or decreases) as income changes. If π_3 is positive, it means that price elasticity of gasoline consumption and income have an opposite relationship.

In summarizing the effect of PR_t on gasoline consumption, we must evaluate Eq. (5) at particular values of CAP_t, such as the mean value, or the lower and upper quartiles in the sample. Often, it is useful to reparameterize the model so that the coefficients on the original variables have an interesting meaning (Wooldridge, 2012). The model is reparameterize as:

$$D_t = \theta_0+\theta_1 CAP_t+\theta_2 PR_t+\pi_3(CAP_t-\overline{CAP_t})(PR_t-\overline{PR_t})+u_t \quad (6)$$

Where θ_i;i = 0,1,2 are the new coefficients, $\overline{CAP_t}$ is the sample mean of CAP_t and $\overline{PR_t}$ is the sample mean of PR_t. By comparing Eq. (4) and Eq. (6), we easily obtain the price elasticity of gasoline consumption at mean income:

$$\theta_2 = \pi_2+\pi_3\overline{CAP_t} \quad (7)$$

4.1.2. Error correction model (ECM)

In several studies to analyze gasoline consumption, real income and price were used as the main determinants of gasoline consumption. A functional form for such a model as described in (Eltony and Al-Mutairi, 1995; Ramanathan, 1999; Akinboade et al., 2008; Kim and Yoo, 2016) is as follows:

$$D_t = a_0+a_1 CAP_t+a_2 PR_t+e_t \quad (8)$$

Eq. (8) is at the basis of an ECM. When defining an ECM, it is wise to start by examining the stationarity of series. If each series is I(1), then in general, a linear combination of these series is also I(1) (Engle and Granger, 1987). However we can sometimes find particular coefficients such that these series become I(0). When this is possible, we say the series are cointegrated. Such series have a long-run relationship. When this is the case, a_1 and a_2 in Eq. (8) are interpreted as long-run elasticities of income and price respectively (Johansen and Juselius, 1990). The existence of a cointegrating equation allows constructing an ECM. We take first differences of variables and include all lags as follows:

$$\Delta D_t = \beta_0+\sum_{i=1}^{L}\beta_{1i}\Delta CAP_{t-i}+\sum_{j=1}^{M}\beta_{2j}\Delta PR_{t-j}+\sum_{k=1}^{N}\beta_{3k}\Delta D_{t-k}+\beta_4\mu_{t-1}+e_t \quad (9)$$

Δ is the percentage difference operator. L, M, and N are the numbers of lags. e_t is the serially uncorrelated error term,ε_{t-1} is the error correction term (ECT), which works to restore equilibrium at the speed β_4, while β_{11} and β_{21} are the short-run elasticities of income and price respectively.

4.3. Gasoline Consumption Forecast for Cameroon :2014-2020

In order to investigate annual gasoline consumption till 2020, we use a MLR model. We specify gasoline consumption (D_t) as a function of real gasoline price PR_t, vehicle fleet (V_t), real gross domestic product (GDP_t), real GDP per capita (CAP_t), and u_t, an error term. On one hand, we include vehicle fleet as a variable because the transport sector in Cameroon accounts for more than 65% of the total consumption of both local refined gasoline and imported gasoline principally from Nigeria. The dynamic multiple linear gasoline consumption function is written as:

$$D_t = \beta_0+\beta_1 PR_t+\beta_2 V_t+\beta_3 GDP_t+\beta_4 CAP_t+\beta_5 D_{t-2}+\beta_6 PR_{t-3}+u_t \quad (10)$$

;(=0, 1, 2, 3, 4, 5, 6)are the regression coefficients. One expects β_1 and β_6 to be negative while β_2, β_3, β_4 and β_5 are expected to be positive for usual economic reasons. Lagged values of PR_t and D_t help to capture fluctuations in gasoline consumption that do not take place immediately.

If the variables in Eq. (10) are non-stationary, it becomes impossible to conduct conventional inference on the coefficients. We remedy this by taking the first differences of variables. The new model becomes:

$$\Delta D_t = \beta_0+\beta_1\Delta PR_t+\beta_2\Delta V_t+\beta_3\Delta GDP_t+\beta_4\Delta CAP_t+\beta_5\Delta D_{t-2} +\beta_6\Delta PR_{t-3}+u_t \quad (11)$$

Δ is the percentage difference operator and the variables are still defined as in Eq. (10). Data for the period 1994-2010 is used to estimate the coefficients of the model.

To generate future (i.e., t+1) values of gasoline consumption, we need values of PR_{t+1},V_{t+1}, GDP_{t+1} and CAP_{t+1}; plug them in Eq. (11) and generate D_t for t>2013. Unfortunately, we do not know the value of the explanatory variables in future time periods. One way out the dilemma is to forecast all independent variables by a simple regression over time or specify a model that depends only on lagged values of endogenous variables. This saves us the extra step of having to forecast a right-hand side variable before forecasting D_t. The kind of model we have in mind is as follows:

$$\Delta D_t = \beta_0'+\beta_1'\Delta PR_{t-1}+\beta_2'\Delta V_{t-1}+\beta_3'\Delta GDP_{t-1}+\beta_4'\Delta CAP_{t-1}+\beta_5'\Delta D_{t-2} +\beta_6'\Delta PR_{t-3}+u_{t-1} \quad (12)$$

4.4. Model Evaluation: Residual Diagnostics, Accuracy and Validation

It is important to always verify that serial correlation and heteroscedast icity do not invalidate a regression model. The presence of serial correlation and heteroscedasticity in a regression model invalidates t and F-statistics, as well as any inferent hypothesis made on regression coefficients (Wooldridge, 2012).

Serial correlation in the residuals and heteroscedasticity are tested with the Breusch-Godfrey Serial Correlation LM and the Breusch-Pagan-Godfrey tests respectively. In addition to these tests, a regression results are reinforced when the residuals exhibit a Gaussian (normal) distribution. One way to check the distribution of the residuals is to evaluate its Jarque-Bera and the corresponding P-value alongside its kurtosis and skewness. Table 1 shows the residuals are free from heteroscedasticity and are also normally distributed.

An accuracy measure is the gap between actual and for casted data. There are a wide number of performance measures in the literature, each with its advantages and limitations (Makridakis, 1983). The most common include: Root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE):

$$RMSE=\sqrt{\frac{1}{N}\sum_{t=1}^{N}(D_t-\widehat{D}_t)^2} \quad (13)$$

$$MAE=\frac{1}{N}\sum_{t=1}^{N}\left|D_t-\hat{D}_t\right|^2 \quad (14)$$

$$MAPE=\frac{1}{N}\sum_{t=1}^{N}\left|\frac{D_t-\hat{D}_t}{D_t}\right|.100 \quad (15)$$

Where D_t is actual consumption, $\underline{\hat{D}_t}$ is forecasted consumption given by the model, and N is the number of observations.

In order to evaluate the model's performance, errors analysis based on RMSE, MAE and MAPE are provided. The model in Eq. (11) has an average RMSE, MAE and MAPE of 1.12%, 0.99% and 7.65% respectively. A graphical representation of the adjustment between actual consumption profile and the sample regression function is shown in Figure 2. By splitting dataset into training (1994-2010) and test data (2011-2013) we can easily assess how well the proposed model excels in forecasting (Askari et al., 2015; Zhu et al., 2015; Panklib et al., 2015). Actual and predicted consumptions are reported in Table 2. The model seems to forecast gasoline consumption with a good accuracy and with acceptable deviation compared to actual data. Finally, as claimed by Aydin (2014; 2015), and Panklib et al. (2015), a regression model is appropriate when the residual plots are haphazardly distributed about the horizontal axis. Figure 3 thus confirms the accuracy of the model. The residuals do not display any trending behavior and they all fit in the ±3% range. Hence from performed validation tests, we conclude that the model in Eq. (11) is a valid model to estimate future gasoline consumption in Cameroon.

When using an ECM model, it is essential to verify that there are no structural breaks or instabilities provoked by omitted

Table 1: Residual test

Test type	Observation*R²	P	Jarque-Bera
Serial correlation test	4.33	Chi-square (2) 8.21%	
Heteroscedasticity test	13.03	Chi-square (6) 22.27%	
Normality test		66.16%	0.83

variable biased, or either over specification or under specification (Sene, 2012; Chang, 2016). This is done with the cumulative sum of squares (CUSUMSQ) test (Sene, 2012; Kim and Yoo, 2016). Figure 4 shows that we fail to reject the null hypothesis of absence of a structural break meaning that the ECM model is stable.

5. RESULTS

5.1. Results of Unit Roots

Pantula et al. (1994) reported in their works that PP test is more robust as a tool for detecting unit roots than other tests. Hence, we apply Phillips-Perron (PP) test to both level and differenced series. From PP statistics (Table 3), the null hypothesis of a unit root cannot be rejected at the 5% level of significance for all the series. PP statistics reveal that first difference of series are integrated of order 1, I(1), in nature. Hence we interpret δ_1, δ_2, γ_1 and γ_1 as indicated in section 4.

Table 2: Validation of the regression model with data ranging from 1994 to 2010

Year	Gasoline demand (m^3)				
	Actual	Predicted	Year	Actual	Predicted
1994	325,856.0	-	2010	470 562.0	471 714.4
1995	312,247.0	-	R^2		98.60%
1996	342,920.0	-	Adjusted R^2		97.40%
1997	314,269.0	329 252.5	RMSE		1.11%
1998	349,057.0	358 430.1	MAE		0.92%
1999	361,230.0	366 571.8	MAPE		7.17%
2000	328,675.0	333 531.0	Testing		
2001	336,429.0	348 585.3	2011	519 322.0	521 908.2
2002	341,272.0	347 146.2	2012	571 381.0	570 916.8
2003	358,747.0	371 370.4	2013	616 601.0	617 624.0
2004	370,999.0	378 326.0	R^2		99.73%
2005	372,760.0	376 767.1	Adjusted R^2		99.49%
2006	367,263.0	361 596.2	RMSE		1.40%
2007	379,071.0	383 094.1	MAE		1.28%
2008	388,629.0	393 355.6	MAPE		9.72%
2009	428,272.0	443 663.7			

Table 3: Phillips-Perron (PP) unit root test on the logarithm of all variables to be used in this study

Variables	PP test statistics (%)	Test equation
Level		
D_t	−0.082 (99.09)	Constant, trend
PR_t	2.510 (99.50)	No constant, no trend
V_t	−0.177 (61.10)	No constant, no trend
GDP_t	3.257 (99.91)	No constant, no trend
CAP_t	1.859 (98.06)	No constant, no trend
Residuals for Eq. (1)	−3.741 (1.33)	No constant, no trend
First difference		
D_t	−5.556 (0.16)	Constant, trend
PR_t	−2.667 (1.11)	No constant, no trend
V_t	−3.354 (0.22)	No constant, no trend
GDP_t	−2.412 (1.87)	No constant, no trend
CAP_t	−3.181 (0.33)	No constant, no trend

( ) Represents the P values of the t-statistics. GDP: Gross domestic product

5.2. Price and Income Elasticities

5.2.1. Partial adjustment model

Table 4 shows the short and long-run elsticities that are calculated from the PAM model. The short-run elasticity is not significantly different from zero. This shows consumers are highly inelastic in the short-run. As is often the case, long-run elasticities are larger in magnitude and are even greater than unity (Akinboade et al., 2008; Sene, 2012; Kim and Yoo, 2016). This shows that consumers are more elastic in the long-run as they have enough time to respond to higher prices. We note that none of the estimated elasticities from the PAM model is significant because of the presence of the lag terms.

5.2.2. Model with interactions

The regression results for the price-income interaction model represented by Eq. (7) are reported in Table 5. When evaluated at mean income, price elasticity is estimated to be −0.163. The significant positive estimate of the price-income interaction term indicates that decreasing income results in an increase in the consumer adjustment to gasoline price changes.

In Cameroon, the increasing budget share of gasoline consumption has made consumers more responsive to higher prices. This was verified in 2008 when gasoline price was increased by 17 FCFA driving up along the prices of food crops and basic commodities, leading quasi-instantaneously to riots (SIE-Cameroon, 2015).

5.2.3. ECM

Johansen cointegration test for the series (D_t,CAP_t,PR_t) are reported in Table 6. On one hand, we reject null hypothesis of absence of cointegrating relation at the 5% level of significance

Table 4: Summary of statistics, coefficients and estimation of elasticities over the period 1994-2013 for Eq. (1)

Variable	Coefficient	t-statistics
Constant	−0.301	−1.274
CAP_t	0.189	2.919
PR_t	−0.151	−3.745
PR_{t-1}	0.122	3.305
D_{t-1}	0.895	9.342
R^2	96.36%	
Adjusted R^2	95.32%	
F-statistics	92.75	
Elasticities	Short run	Long run
Income elasticity	0.190	1.801
Price elasticity	−0.151	−1.433

Table 5: Model of gasoline demand with price-income interaction

Variable	Coefficient	t-statistics
Constant	42.013	1.108
CAP_t	−4.331	−1.645
PR_t	−5.342	−2.247*
$CAP_t \times PR_t$	0.768	2.264*
R^2	73.71%	
Adjusted R^2	68.78%	
Gasoline price elasticity	−0.163	−0.380

*Denotes significance at 1%

Table 6: Results of the Johansen co-integration tests

Null hypothesis	Max-Eigen statistics	P	Trace statistics	P
None* (R = 0)	23.34	2.41%	34.89	1.19%
At most 1 (R ≤ 1)	11.09	14.96%	11.56	17.94%

Cointegrating equation: $D_t = 0.121 + 1.689CAP_t - 1.205PR_t$. The optimal lag length is chosen as two by using SIC. R is the number of cointegrating equation. *Denotes the rejection of the null hypothesis at the 5% level

Table 7: Estimated gasoline demand elasticities for the ECM model

Elasticity	Short-run	Long-run
Income elasticity	0.179*	1.689**
Price elasticity	−0.207*	−1.205**

* and **Denote statistical significance at the 5% and 10% levels, respectively.
ECM: Error correction model

Table 8: Results of coefficients estimation using data for the period 1994-2010

Variable	Coefficient	t-statistics
Constant	10.23	7.33*
ΔPR_t	−1.19	−14.85*
ΔVt	0.01	4.57*
ΔGDPt	2.75	8.61*
ΔCAPt	−2.66	−7.77*
ΔDt−2	0.22	2.03***
ΔPRt−3	−0.26	−2.51**
R^2	99.63%	
Adjusted R^2	99.41%	
F-statistics	452.75*	

*, ** and ***Denote statistical significance at the 1%, 5% and 10% levels, respectively.
GDP: Gross domestic product

Table 9: Forecast of gasoline demand for the period 2014-2020

Year	Demand (m^3)	Annual % change[α]	Index (2013=100)
2014	682 328.8	10.67	110.67
2015	811 128.3	20.89	131.55
2016	865 629.2	8.84	140.39
2017	942 009.2	12.39	152.77
2018	988 099.6	7.47	160.25
2019	1 039 778.7	8.38	168.63
2020	1 078 504.1	6.28	174.91

[a]Average annual change is 10.70%

based on Max-Eigen and Trace statistics. On the other hand, we fail to reject the null hypothesis of existence of at most one cointegrating relation. Therefore there is only one cointegrating equation at the 5% level of significance, which is found to be $D_t = 0.121+1.689CAP_t-1.205PR_t$.

Thus, the long-run income and price elasticities for gasoline consumption is 1.689 and −1.205 respectively. Elasticity signs are aligned with the economic theory. Moreover, gasoline consumption is inelastic with respect to both price and income. The short-run price elasticity for gasoline consumption is estimated to be −0.207 while the short-run income elasticity is 0.179 (Table 7).

Both are statistically significant at the 5% level. Elasticity signs are consistent with economic theory, and gasoline consumption is elastic with respect to price and income. Finally, we note from the ECM model that the ECT is significant and has a value of 0.314, suggesting that the gasoline consumption adjusts toward its long-run equilibrium, with almost 31.4% of the total adjustment taking place in the 1st year.

5.3. Gasoline Consumption Forecasting

Ordinary least squares estimates for Eq. (11) are presented in Table 8. Figure 5 illustrates the prediction curve while Table 9 shows future values of gasoline consumption till 2020. Gasoline consumption will increase by 10.70% on average yearly reaching 1 078 504 cubic meters by 2020. This represents an increase of 74.91% with respect to the year 2013.

6. DISCUSSION OF RESULTS

6.1. Price and Income Elasticities

The three models specified to measure price and income elasticities of gasoline consumption between 1994 and 2013 lead to consistent estimates. The price-income interaction model and the ECM model produce significant estimates of price elasticity ranging between −1.205 and −0.793. These two models equally yield robust and significant estimates of income elasticities, ranging between 0.179 and 1.801. We put less weight on the PAM model because lag terms appears to crowd out the effects of price and income on gasoline consumption at time t. These terms are highly correlated with gasoline price due to the tendency to stay the same despite changes in the economy. Consequently, most of the variation of gasoline consumption at time t is explained by these correlations.

In the short-run, elasticities are less than unity. Consumers are highly inelastic in the short-run. It makes sense because in the short-run consumers have less time to adjust by changing their driving behavior such as mileage or affording new or alternative fuel driven vehicles, which are believed to be long-run responses. The best they can do in the short-run is to use public transportation. These findings were also obtained by Moosa (1988) for a number of developing countries. In Cameroon, like in many developing countries, as stated in Moosa (1988) "*gasoline consumption in the long-run is principally determined by the pace of economic activity, proxies by a measure of aggregate output or income and population growth.*" This result is similar to that found by Akinboade et al. (2008) in South Africa and by Belhaj (2002) in Morocco.

In the long-run, elasticities are larger in magnitude than the short-run estimates. Consumers are more elastic in the long-run because they have time to respond to higher prices by modifying their driving behavior or affording more fuel efficient cars. As there are no previous studies on gasoline consumption elasticities for Cameroon, we compare our results with that of other developing countries, especially those obtained in African countries (Table 10). Compared with Senegal for instance, which is believed to share similarities

Table 10: Summary of gasoline demand elasticity estimates for African (developing) countries

Country	Author	Study period	Price elasticity		Income elasticity		Model
			Short-run	Long-run	Short-run	Long-run	
Senegal	Sene (2012)	1970-2008	−0.121	−0.301	0.458	1.136	MLR
South Africa	Akinboade et al. (2008)	1978-2005		−0.470		0.360	ARDL
Morocco	Belhaj (2002)	1970-1996	−0.130	−0.300		0.500	MLR

MLR: Multiple linear regression, ARDL: Autoregressive distributed lag

with Cameroon in its economic development and demographics, our estimates are very close to that obtained by Sene (2012).

6.2. Gasoline Consumption Forecasting

The R^2 value indicates that 99.63% variations in gasoline consumption are explained by the independent variables. Only 0.37% variation in gasoline consumptions are explained by all other variables not found in Eq. (11). Such omitted explanatory variables could be population and transport cost. However, population and transport cost are highly correlated with income and price respectively. Hence, they are not included in the model to avoid the problem associated with multicolinearity.

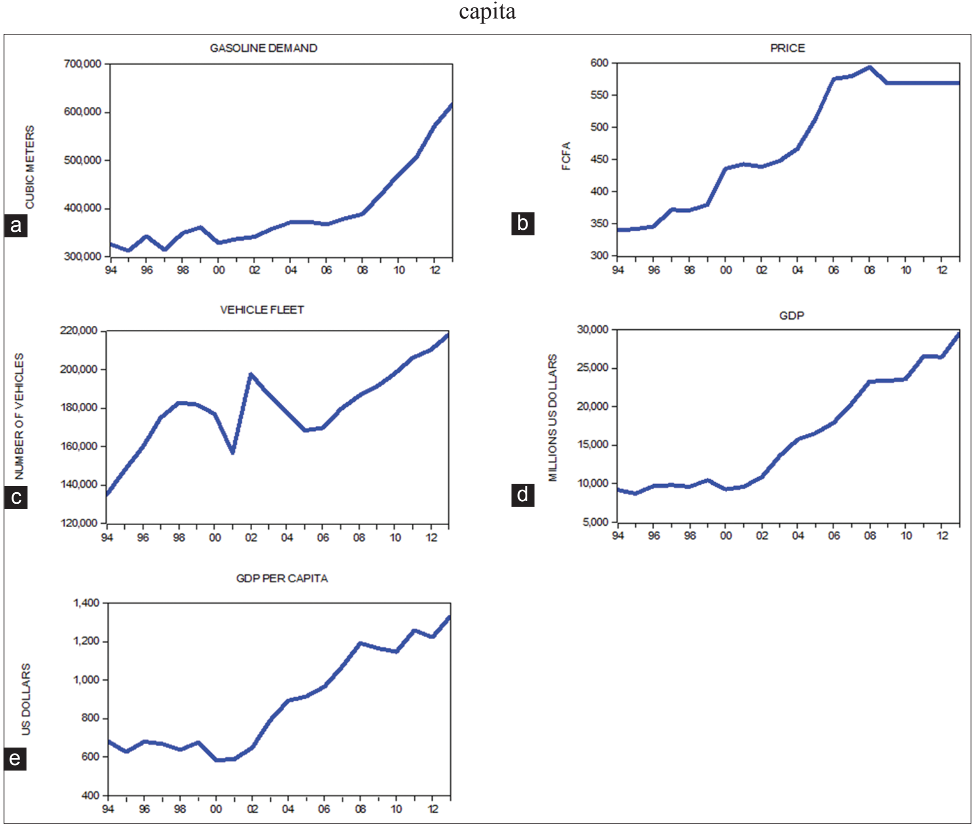
Price, vehicle fleet, GDP and lagged consumption all have the expected signs except income. Unlike our expectations, the model reveals that increasing income will instead decrease gasoline consumption. This is not very surprising because higher wealth in Cameroon instead makes consumers to turn towards diesel fuel which is not only an alternative to gasoline but is less costly. Also, electrical vehicles are more and more afforded thereby forgoing fossil fuel driven vehicles.

The estimation of coefficients in Table 8 shows that price, GDP and income are highly significant in explaining gasoline consumption. Gasoline consumption will decrease by 1.19% given a unit change in its price holding every other factor constant. This shows that consumers a highly sensitive to price changes. We note that fluctuation of price is the main determinant of gasoline consumption in Cameroon. The immediate consequence is that increase in gasoline price holding every other factor constant will result in a tendency of consumers' preferences to shift from driving personal vehicles to using public transportation. The result is similar to that found by Sene (2012) in Senegal.

We note a considerable large effect of GDP and income on gasoline consumption in Cameroon. If GDP increases by 1% then gasoline consumption increases by 2.75% meanwhile gasoline consumption will fall by 2.66% if income increases by 1%, holding every other factor constant. The fact that increasing income decrease gasoline consumption can only be explained in the long-run as consumers buy clean energy driven vehicles, more efficient vehicles, or diesel driven vehicles which is not only a direct substitute of gasoline but is cheaper than the later.

Also, we note that gasoline consumption will rise by 0.01% if the vehicle fleet increases by 1%. This estimated increase is not especially large. It is explained by the fact that a considerable

Figure 1: Historical data: (a) Gasoline demand, (b) real gasoline price, (c) vehicle fleet, (d) real gross domestic product (GDP), (e) real GDP per capita



portion of the fleet runs on gasoline supplied by the black market. The later is cheaper but of poor quality. Moreover, many vehicles are not recorded. In 2009 for instance, the Ministry of transports recorded 35 853 new registered gasoline driven vehicles (SIE-Cameroon, 2015); this number would be higher if one takes into account vehicles that circulate illegally.

Future consumption will increase by 10.7% on average reaching 1078 504 cubic meters by 2020. This represents an increase of 74.91% with respect to the year 2013. Although this growth rate reflects a sign of development that Cameroon may achieve in the energy sector, the great responsibility placed on the state to meet this growing consumption is central to future planning.

7. CONCLUSION AND POLICY IMPLICATIONS

The objectives of this paper were to estimate gasoline consumption equations for Cameroon using historical data for the period 1994-2013, and to forecast gasoline consumption till 2020 using a dynamic MLR model.

We have used three models to estimate the price and income elasticities of gasoline consumption in Cameroon. Our models produce significant estimates of price elasticity ranging between −1.433 and −0.151, and significant estimates of income elasticity ranging between 0.179 and 1.801. Other estimations of gasoline elasticities for Cameroon are not available in the literature; therefore a comparison is not possible. Nevertheless, after a comparative analysis with earlier studies for developing countries in general and African countries in particular, we believe our estimation results are consistent and robust.

Figure 2: Adjustment between actual and projected gasoline demand

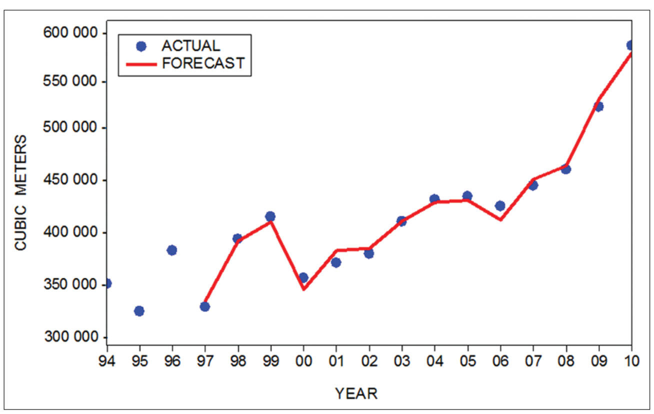
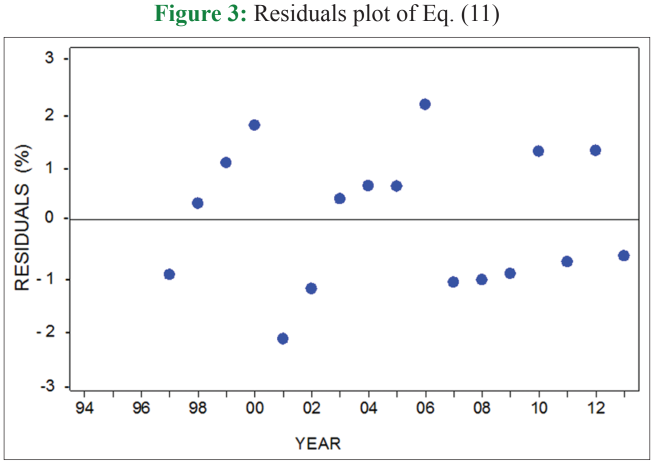


Figure 3: Residuals plot of Eq. (11)



The long-run elasticities are higher than the short-run elasticities, indicating that the gasoline consumption response is higher in the long-run than in the short-run. This result is confirmed in three other African countries; in Senegal by Sene (2012), in South Africa by Akinboade et al. (2008) and in Morocco by Belhaj (2002). These estimates have led to one measure policy implication: As the Government of Cameroon is interested in the stabilization of gasoline consumption by limiting price change, a policy to replace gasoline is to increase its price gradually through taxes, because consumers are too sensitive to price changes. Cameroon's transport sector is unreliable and poor. This encourages the use of personal vehicles. Our findings thus show that price increases alone is insufficient to reduce gasoline consumption.

Forecasted consumption indicates that gasoline consumption can be modeled and predicted using a dynamic MLR model. The predicted values are highly trustable as they deviate by only 1.12%, 0.99% and 7.65% from actual values based on RMSE, MAE and MAPE respectively. The current energy situation in Cameroon presents a

Figure 4: Cumulative sum of recursive residuals

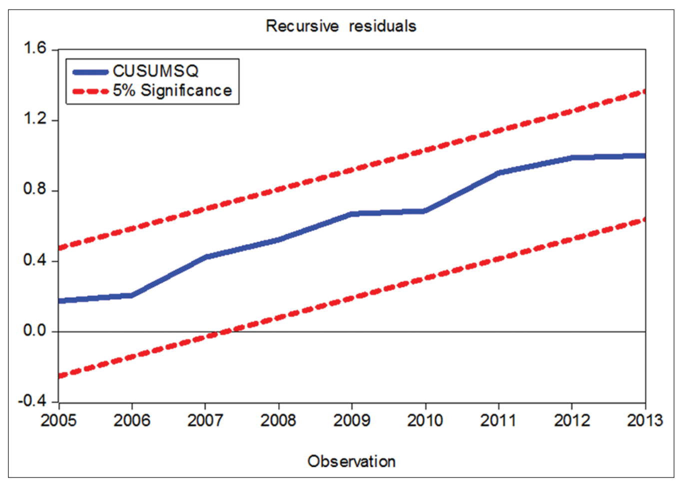
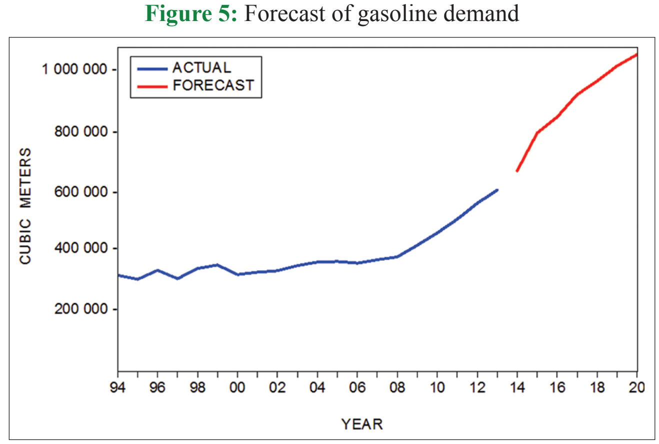


Figure 5: Forecast of gasoline demand



delicate equilibrium between supply and consumption of gasoline and of petroleum products in general (Wooldridge, 2012). The country's oil production trend is falling making this equilibrium even more fragile. To meet gasoline consumption as projected in this study, some recommendations can be made to the Government of Cameroon:

1. Cameroon is located in the Gulf of Guinea. This geographical area is particularly rich in proven oil reserves as reported by British Petroleum (2015). This report reveals that the reserves-to-production ratio of Nigeria, Gabon, Chad and Equatorial Guinea are 42.4 years, 41.2 years, 33.7 years, and 17.1 years respectively. Hence, new exploration permits should be granted by the Government for it is likely that Cameroon's proven oil reserves are as large as those of its neighbors. Explorations should focus on the boarder of Lake Chad and the off shores of South-Western Cameroon for these regions are potentially rich in light crude oil.
2. The national refinery (SONARA) built 20 years ago is already dilapidated and its processes are outdated. In order to be less dependent on external supplies, SONARA should be expanded and modernized. This point which is already under study by the ministry of water resources and energy should be accelerated and implemented. The aim is to convert SONARA from a simple type topping refinery to a complex refinery thereby increasing its refining capacity from the current 2.1 million metric tons to 3.5 million metric tons.
3. Rural areas are not well served because of seasonal roads and this is aggravated by the rugged topography. In order to facilitate the distribution of gasoline throughout the territory, the Ministry of transports should modernize transport logistics, develop and expand current modes of transport. Moreover, new licenses should be granted to increase the number of concession holders and private outlets.
4. The hydrocarbon price stabilization fund should regulate and subsidize gasoline price at the pump in view of large distances between petroleum deposits and petrol stations. This measure will improve the presence of petrol stations in rural areas especially in the Northern part of the country.
5. The country's storage capacity is approximately 265 988 m^3 for 13 deposits. These deposits are found in 7 of the 10 regions of the country. Gasoline deposits should be built in the remaining three regions where they are nonexistent and existing storage capacities should be increased. This will secure the country's strategic stocks, prevent any possible shortage, and continue to supply the domestic market.
6. Cameroon has an enormous potential in renewable energy, as well as clear possibilities of developing and using these forms of energy to satisfy national energy needs. With climatic conditions going for drastic reversals, it is proper time for the Government to start exploring a variety of clean fuel alternatives since gasoline and other petroleum products will certainly become scarce in the long-run.

The switch of energy resources will require heavy investments, large resources, manpower, and time. The above recommendations will certainly meet gasoline consumption as projected in this study and help the Government to better implement major energy projects as mentioned in GESP (2009).

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