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Research article

Dynamic behavior of transport fuel demand and regional environmental policy: The case of Portugal

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Abstract: Despite the increase in electric mobility, fossil fuels still dominate the transport sector. For a sustainable management of these fuels, environmental policy plays a significant role. It is key to know if higher taxes are effective to moderate demand, which will depend on demand elasticities. While price elasticities determine the effectiveness of higher taxes, income elasticities are important for macroeconomic policy considerations. Furthermore, in dynamic societies and economies, it is possible that elasticities change over time or as a response to certain events, determining the need to adjust policies. We study the case of a small, open economy, highly dependent on fuel imports: Portugal. Our estimation of price and income elasticities for gasoline and diesel demand control for breakpoints and uses a dynamic perspective. The period covered (1995–2015) includes important macroeconomic events, such as the fuel market liberalization and a severe economic crisis. Results for the whole period show that long-run price elasticities are −0.368 for diesel and −0.911 for gasoline. Hence, taxes are more effective to moderate gasoline demand than diesel demand. Long-run income elasticities are 2.338 for diesel and 0.877 for gasoline, demonstrating the strong dependence of diesel consumption on the level of economic activity. The breakpoint analysis indicates that contrarily to the fuel market liberalization process, the economic crisis impacted elasticities. Furthermore, we find variability in elasticities around the period of the economic crisis, which justifies the need for a flexible policy. Dynamic policies can use specific periods as opportunities to promote technical and behavioral desirable changes.

Keywords: fuel demand; price and income elasticities; structural breaks; dynamic analysis; environmental policy

Abbreviations: LPG: Liquefied Petroleum Gas; ARDL: Autoregressive Distributed Lag Model; BIC: Schwarz Bayesian Criteria; DGEG: General Direction of Energy and Geology; ECM: Error Correction Model; GDP: Gross Domestic Product; INE: National Statistics Institute; US: United States of America

1. Introduction

Fuel demand increased greatly over the last decades due to factors such as continuous economic growth, global integration leading to higher transportation needs, and increased access to private cars. Despite the recent increase in electric mobility, traditional fuels are expected to dominate at least until 2050 [1] which raises environmental concerns. To mitigate climate change, the need to reduce fuel consumption, namely for road transport, remains unquestionable. Hence, governments worldwide continue to implement policies to efficiently manage fuel demand. To design environmental policy, it is vital to properly understand fuel demand determinants, namely its response to price and income changes, and its variability over time.

The study of fuel demand responses to price and income changes has been common in the literature, especially after the 1970's oil crisis. The abundance of studies induced surveys and meta-analysis to understand different results (e.g., [2–5]). The fact that estimates for price and income elasticities of fuel demand vary according to the methodology used, the country under analysis, the period covered, the variables included in the model, among other aspects [4], makes the process of understanding fuel demand harder and often country specific. Hence, the determinants of fuel demand are still poorly understood [6].

An important distinctive aspect in the literature is the type of fuel under analysis. Generally, diesel demand is less sensitive to price changes and more sensitive to income changes than gasoline consumption since this fuel is used both for domestic and freight transport purposes [7]. As referred by Frondel and Vance [8], most existing studies focus on gasoline demand (e.g., [9–14]). However, the increasing share of diesel-powered passenger cars [9] encouraged authors to also consider diesel demand in their analysis (e.g., [7,15–17]). Table 1 provides a summary of selected relevant studies in the literature.

Table 1. Selected studies of the literature.

Reference	Fuel type	Country	Period	Method	Price elasticity		Income elasticity	
					Short-run	Long-run	Short-run	Long-run
[7]	Gasoline, diesel and jet fuel	South Africa	1982–2010—quarterly data	ARDL model		[−0.44; −0.59] for gasoline; −0.21 for diesel		[0.62; 0.82] for gasoline; 1.56 for diesel
[9]	Gasoline	14 European countries	1990–2004	Several dynamic panel methods	[−0.029; −0.19]	[−0.314; −0.84]	[0.036; 0.155]	[0.166; 0.614]
[10]	Gasoline	South Africa	1978–2005	ARDL bound testing and cointegration		−0.47		0.36
[12]	Gasoline and total fuel	Switzerla nd	1970–2008—quarterly data	Cointegration	−0.092 for gasoline; −0.082 for total fuel	−0.339 for gasoline; −0.267 for total fuel	0.025 for gasoline; 0.103 for total fuel	0.673 for gasoline; 0.755 for total fuel
[13]	Gasoline	Brazil	1974–1999	Cointegration	−0.092	−0.465	0.122	0.122
[14]	Gasoline	China	1980–1999	Cointegration and error correction	−0.19	−0.56	1.64	0.97
[15]	Gasoline, diesel and total fuel	Spain	2000–2007	Several methods	−0.264 for gasoline; [−0.231; −0.243] for diesel	[−0.558; −0.815] for gasoline; [−0.88; −1.667] for diesel	[0.058; 0.069] for gasoline; [0.217; 0.3] for diesel	[0.122; 0.228] for gasoline; [1.086; 1.564] for diesel
[16]	Gasoline and diesel	Spain	1998–2006	Several dynamic panel methods		[−0.292; −0.417] for gasoline; [−0.027; −0.083] for diesel		Non-significant variable

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Reference	Fuel type	Country	Period	Method	Price elasticity		Income elasticity	
					Short-run	Long-run	Short-run	Long-run
[17]	Gasoline and diesel	Spain	1999–2015	Several methods	[−0; −0.067] for gasoline; [−0.015; −0.071] for diesel	[−0; −0.191] for gasoline; [−0.043; −0.203] for diesel	[0.015; 0.257] for gasoline; [0.018; 0.318] for diesel	[0.043; 0.734] for gasoline; [0.051; 0.91] for diesel
[19]	Gasoline	Lebanon	2000–2010—monthly data	Cointegration techniques	[−0.258; −0.623]		[0.309; 0.815]	

Furthermore, a flexible policy design requires understanding how demand responses change over time. Price and income elasticities may react to specific events by presenting structural breakpoints in the long-run [17]. This can happen due to an economic crisis, or even due to unexpectable events such as the recent COVID-19 situation. Even though these breaks have deep policy implications and often require policy updates and adjustments, only few studies acknowledge elasticities fluctuations over time [5]. Regarding the existence of breakpoints, mixed results appear in the literature. For example, Bentzen and Engsted [18] found no structural breakpoint on energy demand due to the 1973–74 oil shock in Denmark. Bakhat et al. [17] realized that the 2008 economic crises in Spain resulted in a slight increase in price elasticities and a slight decrease in income elasticities for gasoline and diesel demand. Some authors searched for endogenous breakpoints in data, e.g, Boshoff [7] for South Africa and Ben Sita et al. [19] for Lebanon. Both authors found that breakpoints existed and their inclusion improved model adjustments. Mixing the two approaches, Baranzini and Weber [12] tested the data for endogenous structural breakpoints and studied the impacts of the oil shocks and changes in the mineral oil tax. The authors concluded that those events created breakpoints in elasticities. Hughes et al. [20] investigated the existence of a shift in short-run elasticities of gasoline demand for the U.S., because of specific events. Without testing for structural break points, the authors contrasted estimations for the periods 1975–1980 and 2001–2006. Results showed that price elasticity was significantly different for the two periods while income elasticities was not. Rare studies implemented methodologies to test for time-varying elasticities. Exceptions include Park and Zhao [11] and Neto [21] which both focused on gasoline. Park and Zhao [11] used a cointegration regression and found evidence of time-varying price and income elasticities of gasoline demand in the U.S. for the period 1976–2008. Neto [21] used a methodology based on Chebyshev time polynomials with quarterly data from 1973 to 2010 and found time varying gasoline demand elasticities for Switzerland.

Our contribution to the literature is twofold. Firstly, we study the dynamic behavior of both gasoline and diesel demand elasticities, combining structural breakpoint analysis and estimation of time-varying elasticities with the rolling windows methodology. We focus on the impacts of relevant events (the fuel market liberalization and the economic crisis) providing a breakpoint analysis and time-varying estimations of elasticities. To the best of our knowledge, this is the first study covering the dynamic behavior of both gasoline and diesel demand elasticities. The methodology used can be extended to other case studies. Secondly, we provide updated estimates of price and income gasoline elasticities for Portugal, and the first estimations for diesel demand elasticities. Fuel elasticities were rarely calculated for Portugal. The two exceptions are Sterner et al. [22] and Sterner [23]. The case of a small, open economy, totally dependent on fuel imports is relevant due to regional specificities [17]. Focusing on periods of change, such as economic crises and fuel market liberalization can be relevant, not only for the country under analysis, but also for other similar countries and for other events such as the unexpected COVID-19 crisis. Hence, our results intend to shed some light into the desired temporal evolution of policy instruments, such as fuel taxes, which can be applied to any country experiencing periods of macroeconomic change.

The remaining of the paper is organized as follows: after this Introduction, Section 2 presents the data and the model used in our study, Section 3 depicts our main results, and finally, Section 4 concludes the article and provides some policy implications.

2. Material and methods

2.1. The Portuguese case

Portugal is 100 *per cent* dependent on transport fuel imports despite its fragile economic situation. It has one of the highest levels of fuel taxes in Europe despite its low economic growth and average income levels [23]. Commercial road transport is vital due to its peripheral location in the Iberian Peninsula and limitations of alternative transport means. Hence, the number of commercial vehicles increased from 152000 in 1974 to 1313219 in 2015, while the number of passenger vehicles increased from 692000 in 1974 to 5970710 in 2015 (National Statistics Institute—INE)[1]. This can be partly explained by the weak public transportation network. Furthermore, an increasing share of the private fleet works on diesel, which is referred in the literature as the 'dieselization' process [9,16]. According to the Automobile Association of Portugal (ACAP), regarding passenger vehicle sales, the diesel share increased from 45.6% in 2003 to 67.5% in 2015, while the gasoline share decreased from 54.3% to 29.8% in the same period. The share of other types of vehicles (LPG, hybrid and electric) increased from 0.1% in 2003 to 2.7% in 2015.

Over the last decades, Portugal faced important macroeconomic changes. The fuel market liberalization process was concluded on the 1st of January 2004. As a result, the maximum retail price for fuels was eliminated. Sellers could set their prices freely, despite the obligation to communicate weekly average prices to the General Direction of Energy and Geology (DGEG). Additionally, new commercial retailers entered the fuel market. This liberalization process occurred in many European countries, but its effect on consumers' behavior has never been studied in detail. Additionally, Portugal faced a critical budgetary imbalance and a severe economic crisis, with the financial intervention of

[1] https://www.ine.pt/xportal/xmain?xpgid=ine_main&xpid=INE&xlang=pt

the European Commission, the Central European Bank, and the International Monetary Fund. This intervention was also designated Troika intervention. It started in 2011 and finished in 2013. During this period, Portugal received financial support from the three designated institutions and as a counterpart the country had to comply with several restrictive policies following a fiscal contraction and structural reforms. To the best of our knowledge, the impact of all these economic phases in fuel demand responses has never been studied for Portugal.

2.2. Data

We use data on gasoline and diesel consumption per capita (tons), Real Gross Domestic Product (GDP) per capita (€), and fuel real prices (€). Fuel consumption and prices were from DGEG, while GDP data was from INE. We cover a long period, 1995–2015, where important behavioral and technological changes occurred. We use quarterly data, which allows capturing short-term variations and faster speed of adjustment to shocks [7,12,19]. Figure 1 depicts the variables related to gasoline and diesel consumption. It is visible that gasoline consumption decreased over the years, while diesel consumption slightly increased. Gasoline prices are higher than diesel prices, but present similar fluctuations.

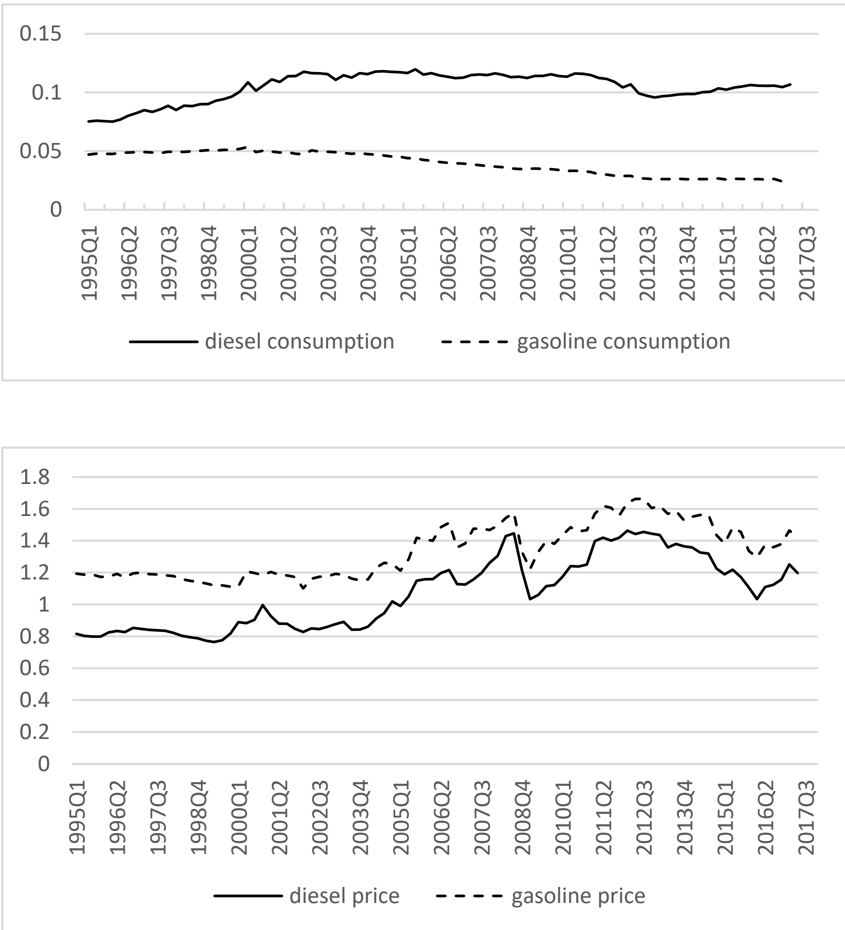

Figure 1. Diesel and gasoline consumption (tons), diesel and gasoline price (€).

The descriptive statistics of the real fuel prices, real income and fuel consumption per capita are presented in Table 2.

Table 2. Descriptive statistics.

Variable	N. of observations	Mean	Max	Min.	Std. dev.
diesel p.c. (tons)	80	0.1045	0.1197	0.0750	0.0127
gasoline p.c. (tons)	80	0.0403	0.05359	0.0256	0.0092
diesel pr. (€)	80	1.0635	1.4635	0.7648	0.2288
gasoline pr. (€)	80	1.3329	1.6632	1.1010	0.1735
gdp p.c. (€)	80	4037.7	4385.8	3366.2	243.19

From Table 2, it is visible that diesel consumption per capita is higher than gasoline consumption per capita, which relates to its commercial use. Additionally, diesel prices are lower (mainly due to lower taxation), which has contributed to the 'dieselization' process. GDP per capita is relatively low in average terms and does not show a large interval between its minimum and maximum.

2.3. Model

To study price and income elasticities of fuel demand, we adopt the Autoregressive Distributed Lag Model (ARDL) proposed by Pesaran and Shin [24], Pesaran et al. [25]. This methodology has also been used in, e.g., Boshoff [7], Akinboade et al. [10]. The ARDL (n_1, n_2, n_3) model is generally defined as follows:

$$q_{i,t} = a_0 + \sum_{j=1}^{n_1} \gamma_{q_{i,j}} q_{i,t-j} + \sum_{j=0}^{n_2} \gamma_{p_{i,j}} p_{t-j} + \sum_{j=0}^{n_3} \gamma_{z_j} z_{t-j} + \epsilon_t \quad (1)$$

where t is the time subscript, $q_{i,t}$ stands for fuels consumption where the subscript i can be g for gasoline or d diesel, p is fuel price and z is GDP. a_0 is the constant term, $\gamma_{q_{i,j}}$ are the coefficients for the lags of the consumption variable, $\gamma_{p_{i,j}}$ and γ_{z_j} are the coefficients for the lags of prices and GDP, respectively. The residuals, ϵ_t, are assumed to be spherically distributed and white noise. The lag orders n_1, n_2 and n_3 are obtained using an information criteria (either the Akaike (AIC) or Bayesian (BIC)).

The model is reparametrized in a conditional error-correction representation:

$$\Delta q_{i,t} = a_0 - \varphi\left(q_{i,t-1} - \theta_p p_{t-1} - \theta_z z_{t-1}\right) + \sum_{j=1}^{n_1-1} \omega_{q_{i,j}} \Delta q_{i,t-j} + \sum_{j=0}^{n_2-1} \psi_{p_{i,j}} \Delta p_{i,t-j} + \sum_{j=0}^{n_3-1} \phi_{z_j} \Delta z_{t-j} + \epsilon_t \quad (2)$$

where Δ is the first difference operator. The first part of Eq 2 indicates the long-run or equilibrium relationship, while the second part (coefficients $\omega_{q_{i,j}}$, $\psi_{p_{i,j}}$ and ϕ_{z_j}) represents the short-run dynamics. The coefficient $\varphi = 1 - \sum_{j=1}^{n_1} \gamma_{q_{i,j}}$ denotes the speed of adjustments to the long run equilibrium and $\theta_p = \sum_{j=1}^{n_2} \gamma_{p_{i,j}} / \varphi$ and $\theta_y = \sum_{j=1}^{n_3} \gamma_{z_j} / \varphi$ are the long-run coefficients of price and income, respectively.

3. Results

3.1. Statistical results

3.1.1. Stationarity tests

Table 3 shows the results for several unit root tests for the variables in levels and after the first difference. In general, all tests indicate that variables have one unit root and become stationary after the first difference. These results validate the necessity to use our ARDL model.

Table 3. Stationarity results.

Variable	ADF	lags	DFGLS	lags	Phillips-Perron, Zp	lags/bandwidth	KPSS	lags/bandwidth
q_g	1.054	0	−2.5762	0	1.05	4	1.05***	7
Δq_g	−10.267***	0	−10.773***	0	−10.203***	5	0.53**	5
p_g	−1.037	2	−1.6984	2	−1.441	2	0.95***	7
Δp_g	−9.757***	1	−9.687***	1	−8.272***	1	0.14	13
z	−3.756***	1	−2.3815	1	−3.509**	3	0.78***	6
Δz	−11.634***	0	−12.484***	0	−11.271***	5	0.62**	4
q_d	−3.131**	3	−1.8401	1	−2.697*	4	0.49**	7
Δq_d	−3.382**	2	−11.692***	0	−10.708***	5	0.54**	5
p_d	−1.614	1	−2.3702	1	−1.418	2	1.01***	7
Δp_d	−6.767***	1	−6.7684***	1	−6.603***	2	0.12	1

*Notes: ***, **, * denotes a t-ratio significant at the 1, 5, 10% level*

For ADF tests, the number of lags was selected on the basis of the AIC, BIC and HQIC; For KPSS and Phillips-Peron tests, the number of lags was selected by automatic bandwidt selection, and autocovariances weighted by Bartlett kernel

3.1.2. Model selection and cointegration results

We started by selecting the adequate lags for each variable. These results can be seen in Table 4 where, additionally, we show the bounds tests for cointegration. The optimal lag length is selected according to using the Schwarz Bayesian Criteria (BIC). As can be observed, the computed F-statistics supports (at 5% significance level) the existence of a long-run cointegrating relationship among all variables.

Table 4. Model selection and cointegration results.

	Diesel	Gasoline
Explanatory variables	q_t, p_t, z_t	q_t, p_t, z_t
Selected model (optimum lag order):	(2, 0, 2)	(3, 0, 4)
F-statistic	5.380	14.040
Critical values (5%)		
Upper bounds	3.88	3.88
Lower bounds	3.235	3.235

Notes: the optimum lag order is obtained according to the Akaike Information Criterion (AIC)

The optimal lag number is higher for gasoline consumption than for diesel consumption, meaning that households take longer to respond to price and income changes than firms. Interestingly, the optimal lag number for prices is zero for both fuels, hence, consumption only responds to contemporaneous price changes.

Table 5 depicts the main estimates concerning the ARDL long-run estimates and the results for several robustness tests.

Table 5. ARDL estimates.

	Diesel	Gasoline
Variable	Coefficient	Coefficient
Const.	−4.362**	−2.167***
	(0.328)	(0.861)
p_t	−0.074***	−0.223***
	(0.023)	(0.033)
y_t	0.932***	0.461***
	(0.192)	(0.162)
q_{t-1}	0.516***	0.389***
	(0.111)	(0.107)
z_{t-1}	−0.209	0.005
	(0.246)	(0.188)
q_{t-2}	0.283***	0.219*
	(0.104)	(0.111)
z_{t-2}	−0.254	−0.037
	(0.218)	(0.200)
q_{t-3}		0.147
		(0.097)
z_{t-3}		−0.457***
		(0.185)
z_{t-4}		0.243
		(0.161)
Trend	0.000	−0.002***
	(0.000)	(0.001)
Adj.R^2	0.9749	0.9962
χ^2_{SC}	2.092	2.817
	(0.719)	(0.589)
Ramsey's RESET	0.048	0.031
	(0.827)	(0.862)
Jarque-Bera	1.382	2.389
	(0.501)	(0.326)
χ^2_H	18.595	9.3607
	(0.010)	(0.498)
F_{Bounds}		
Long Run:		

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	Diesel	Gasoline
Variable	Coefficient	Coefficient
β_p	−0.368	−0.911
	(0.142)	(0.182)
β_z	2.338	0.877
	(0.249)	(0.253)

Notes: Robust standard errors in parenthesis.

***, **, * denotes de t-ratio significant at the 1%, 5% and 10% respectively

χ^2_{SC}—Breusch- Godfrey Serial Correlation LM test

χ^2_H—White Heteroskedasticity test

F_{Bounds}—Bounds based F test

β_p is long-run price elasticity and β_z is long-run income elasticity

In general, our model passes the diagnostic tests for serial correlation (LM statistic), heteroscedasticity (Breusch-Pagan-Godfrey), normality of residuals (Bera-Jarque statistic), and functional form (Ramsey's RESET) at the 5% statistical level. Estimated coefficients have the expected signs and show that long-run price elasticities are −0.368 for diesel and −0.911 for gasoline while long-run income elasticities are 2.338 for diesel and 0.877 for gasoline. The relatively high long-run value encountered for gasoline demand price elasticity may be explained by the relatively low disposable income in Portugal, since as referred by Baranzini and Weber [12], higher income countries may be less sensitive to price changes while lower income ones respond more to price changes. Additionally, diesel demand is highly responsive to income changes, reflecting the strong effect of economic activity on (commercial) diesel demand.

Our coefficient of the time trend is zero and statistically non-significant for diesel (as in Polemis [26]) and is negative and statistically significant for gasoline (as in Bakhat et al. [17]). Technical changes and other modifications have slightly decreased gasoline consumption but had no effect on diesel demand.

The results for the Error Correction Model (ECM) regressions are provided in Table 6.

Table 6. ECM regressions.

	Diesel ARDL (2,0,2)	Gasoline ARDL (3,0,4)
Variable	Coefficient	Coefficient
Const.	−4.362***	−2.169***
	(0.922)	(0.282)
$\Delta q(-1)$	−0.283***	−0.366***
	(0.096)	(0.091)
$\Delta q(-2)$		−0.147
		(0.088)
Δp		
Δz	0.932***	0.461***
	(0.174)	(0.146)
$\Delta z(-1)$	0.254	0.251
	(0.206)	(0.154)

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	Diesel ARDL (2,0,2)	Gasoline ARDL (3,0,4)
Variable	Coefficient	Coefficient
$\Delta z(-2)$		0.214
		(0.157)
$\Delta z(-3)$		−0.243
		(0.151)
ecm_{t-1}	−0.201***	−0.245***
	(0.042)	(0.032)

Notes: Robust standard errors in parenthesis.

***, **, * denotes de t-ratio significant at the 1%, 5% and 10% respectively

The coefficient of the error term (ecm_{t-1}) is statistically significant and has a negative sign, supporting evidence about the established long-run relationship among fuel consumption per capita, income per capita and prices. The importance of price and income to explain fuel demand is also confirmed in the short-run. The coefficient associated with ecm_{t-1} can be interpreted as the speed of adjustment of demand towards its long-run level after a certain shock. This is frequently calculated in the literature. In our model, adjustment speed, i.e., the adjustment that occurs in the first quarter after a shock, is 20.1% for diesel and 24.5% for gasoline. Hence, after a shock, fuel demand adjusts to its long-run equilibrium approximately within the first year. In Baranzini and Weber [12] these values were 37% and 27% for diesel and gasoline, respectively, while in Boshoff [7] they were of 48% and 20%, respectively. From the presented cases, ours is the only one where gasoline adjusts faster than diesel. This can be explained by the higher flexibility of households´ behavior when compared to firms' behavior. Given these fast responses, some authors defend that high frequency data such as our quarterly data (rather than annual data) is more suitable for this type of analysis [19]. On the other hand, authors using annual data frequently conclude that only a small part of the adjustment takes place in the first year (e.g., Eltony and Al-Mutairi [27]).

3.2. Structural breakpoints

In this sub-section, we test for endogenous structural breakpoints in our data. Using a trimming of 15% of the observations, we apply the Quandt-Andrews breakpoint test for one or more unknown structural breakpoints in the sample period (1995Q1–2015Q4). The three statistic measures for LR and Wald F-statistic clearly reject the null hypothesis of no structural breaks. Results show (Table 7) that diesel and gasoline consumption have a breakpoint in 1999Q4 and 2011Q3, respectively. Contrarily to Wu et al. [28] and Fattouh et al. [29], who found significant effects of the fuel market liberalization in the countries under analysis, we found no such evidence for Portugal, since there is no breakpoint around 2004. The breakpoint found for gasoline may, to a certain degree, be related to the economic crisis, which determined the need for the financial intervention of Troika in 2011. The breakpoint for diesel can be related to some new legislations in the fuel market, namely, the compromise of the prime minister to not increase the diesel price for a certain period, but it is also relevant that Portugal started using the euro in this year. Besides the change in currency, which is likely to have influenced agents´ behavior, there were important economic boosts such as increases in investment and decreases in borrowing costs.

Table 7. Structural Breakpoints.

	Diesel	Gasoline
Date	1999Q4	2011Q3
Maximum LR F-statistic	1115.933 (0.000)	87.763 (0.000)
Exponential LR F-statistic	53.927 (0.000)	40.785 (0.000)
Average LR F-statistic	35.733 (0.000)	27.246 (0.000)

Note: Robust standard errors in parenthesis

Distributions of statistics are provided by Andrews (1993).

Dates for maximum statistics are in line "Date"

3.3. Rolling Estimation

Now, we study the dynamic behavior of elasticities. We use the rolling ARDL to gain further insights on the long-run fuel demand determinants and time-varying elasticities. Rolling ARDL estimates were carried out on moving windows with a length of 60 quarters since a reasonably long period of data may be necessary to capture the presence of long-term relationships. Optimal lags were obtained in each iteration using the BIC criteria.

In line with, e.g., Park and Zhao [11], our dynamic estimations show some variability in time-varying elasticities. Figure 2 shows the results for price elasticities, where the vertical lines represent the beginning and the end of the financial intervention in Portugal, also designated Troika intervention. During that period Diesel demand price elasticity is relatively steady around −0.5. From 2011Q2 to 2013Q3, it increases in absolute value, i.e., consumption became more sensitive to price changes during the period of the economic crisis and the Troika intervention. This is consistent with studies for other countries [17] and makes economic sense, because when faced with financial restrictions economic agents pay more attention to price changes. Gasoline demand price elasticity evolves around the mid value of −0.75. Until 2012Q3, values are relatively stable, but after that, they become irregular and face some peaks. Our results indicate that, with a certain delay, gasoline consumption also appears be affected by the economic crisis. However, the effect is not as predictable as in the diesel case. These results are in line with the findings for Spain [17] which showed higher effects for diesel than for gasoline. The explanation is probably related to the fact that households have more flexible behaviors, which can be erratic at times. In general, firms have a more stable and predictable behavior. For both cases, the higher sensitivity to fuel price fluctuations is justifiable since the economic crisis decreases disposable income and affects agents' expectations.

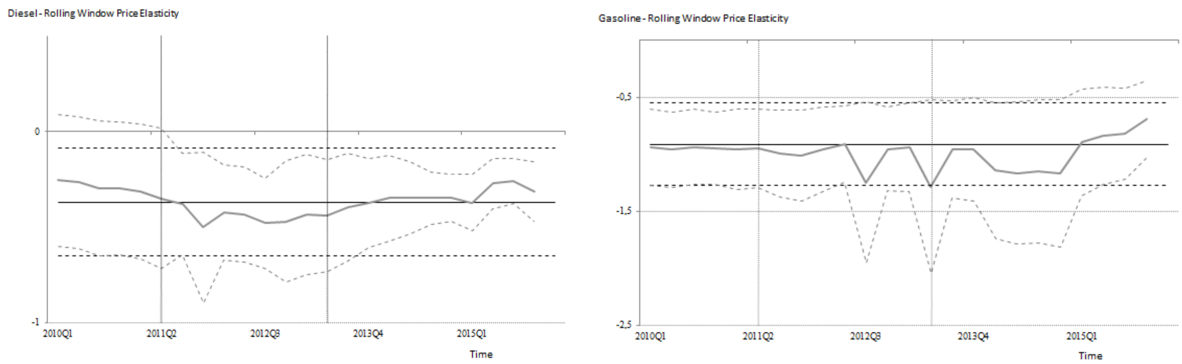

Figure 2. Price elasticity for diesel (left) and gasoline (right) using rolling windows (*Notes: Dashed lines are 2SE bands*).

Figure 3 shows that a similar pattern is observed for income elasticity for diesel during the same period, i.e., consumption became more sensitive to price changes. After 2013Q4, this elasticity decreases probably due to the crisis since diesel is highly used for commercial purposes. Gasoline income elasticity evolves around 1 with a certain degree of variability, despite not necessarily associated with the period of the economic crisis and not as accentuated as for diesel. After the economic crisis, a decrease in income elasticities appears to exist, i.e., gasoline consumption became less responsive to income changes. A tendency that affected Portugal and may have affected other southern European countries (e.g., Spain according to Bakhat et al. [17]).

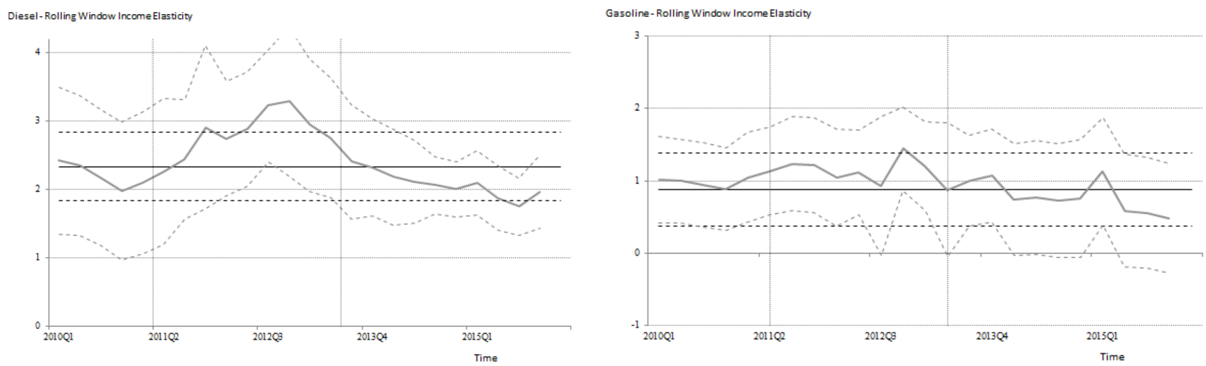

Figure 3. Income elasticity for diesel (left) and gasoline (right) using rolling windows (*Notes: Dashed lines are 2SE bands*).

4. Conclusions and policy implications

Predicting fuel demand responses to price and income changes is fundamental for a proper environmental policy analysis. The transport sector is responsible for a large share of polluting emissions and it is urgent to implement measures to mitigate this problem. The usual static analysis may lead to inadequate results since it does not anticipate changes in demand responses due to specific events, such as an economic crisis. That approach does not consider fluctuations in price and income elasticities over time and it does not provide hints for a flexible and efficient policy design. To explore this issue, we estimate gasoline and diesel price and income elasticities for Portugal covering the period from 1995 to 2015. We give special emphasis to the dynamic behavior of elasticities combining structural breakpoint analysis with time-varying estimations.

Our ARDL model shows evidence of a long run cointegration relationship between gasoline/diesel consumption per capita, prices, and income per capita. Results indicate that long-run price elasticity is −0.911 for gasoline and −0.368 for diesel. Gasoline consumption is more sensitive to price changes than diesel, which is directly related to diesel use for commercial purposes. Households have more transport options and can adopt more flexible behaviors when gasoline price increases. Long-run income elasticity is 0.877 for gasoline and 2.338 for diesel. The higher sensitivity of diesel consumption to income changes is also according to the literature and has the same explanation as for price elasticities [5]. Hence, fuel taxes are more effective to moderate gasoline than diesel demand. Diesel is strongly used for commercial purposes and is, therefore, very dependent on economic conditions. Furthermore, results show that technical changes and other modifications slightly decreased gasoline consumption but had no effect on diesel demand.

Regarding the structural breakpoint analysis, we find no evident effect of the market liberalization in Portugal. Our dynamic estimations show some fluctuations in time-varying elasticities. There is evidence that the economic crisis affected diesel and gasoline demand elasticities, since after the crises, consumers appeared to become more sensitive to price and income changes. This can be seen as a reaction to lower disposable income. The variability in elasticities suggests a need to adjust policy tools, specially at times of economic stress and can also be an opportunity to implement desirable changes. Considering a static analysis is therefore not enough to predict policy effects. For instance, during periods of economic crisis, fuel taxes will have a stronger impact on fuel demand. It is then advisable to adjust taxes periodically which requires updated and dynamic estimates of elasticities. Governments can take advantage of these times to promote necessary behavioral and technical changes. When agents become more responsive to price changes, higher taxes combined with, e.g., promotion of better public transportation systems, or incentives to electric vehicles, can lead to important long-term changes, such as a transition to a less fuel intensive transport sector. Also, agents can be incentivized to adopt fuel saving driving behaviors. Tax revenues can be used to finance those environmental purposes.

In sum, our results highlight the importance of considering time-varying elasticities for policy design, not only after an economic crisis, but also after any other impacting event such as, for example, the recent COVID-19 crisis. The challenges brought by this period can be used as opportunities to, with the best policy combinations, contribute to the desirable energy transition.

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Conflict of interest

The authors declare no conflict of interest.

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