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Price elasticity of fuel demand: an econometric approach

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Abstract

The purpose of this paper is to quantify, through the use of Bayesian VAR (BVAR) econometric models, the elasticity of demand for automotive fuels (gasoline, diesel and liquid propane gas - LPG) in response to a shock in both their respective prices at the pump and other and other variables that affect the production of these commodities (such oil price, exchange rate etc.).

The data used consist of time series on consumption and prices of the goods described above as of January 2002 for Italy.

First, the existing literature, which focuses mainly on Anglo-Saxon countries, was analysed in order to obtain terms of comparison that would allow a comparison between the results obtained (described below) and the aforementioned similar studies.

Second, after a description of the data used and their contextualization to the Italian case, the econometric approach used to estimate elasticities is described.

The consequences of in terms of policy are interesting, since these are goods with rigid demand, little susceptible to price changes (whether induced by a change in the price of crude oil or a change in the excise rates in force in the country) and substantially characterized by a certain stability over the years.

The analysis displays also the response of the above-mentioned fuels to Brent's price shocks, delivering as additional result that these fuels are very sensitive to the fluctuations of their raw material whose price's increase is capable of generating a bottleneck in the global value chain imposing negative shifts in the quantity consumed and an increase in price of the fuels analysed

Keywords: Elasticity, demand, price, gasoline, diesel.

1. Literature review

There are several ways to estimate elasticities in econometrics, but in general all estimation models are based on the scheme of a multivariate regression model:

$$Y = X\beta + \varepsilon \qquad (1)$$

where in (1) Y is a vector (nx1) containing the independent variables (e.g., gasoline demand), X is a vector (nxm) of explanatory variables, β is the vector (mx1) of estimated

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coefficients and ε is a vector (nx1) of the error term.

This basic model allows to relate the demand (the Y, or fuel consumption) with the explanatory variables (first of all the price), so it is possible to estimate the coefficients (β) that linked the explanatory variables (including the price) to consumption, or elasticities. The elasticity parameters can then be short-term and long-term, as we will see later. The results found in the existing studies in the literature show that the long-run elasticities take higher values than the short-run elasticities; this is consistent with the rational behaviours of consumers, who in fact revise their fuel expenditures according to the change in the relative prices of fuels, so they are also willing to invest in vehicles powered by relatively cheaper fuels, hence resulting in higher long-run elasticities.

There are numerous works in the literature concerning estimates of the price elasticity of energy demand (see, Taylor, 1975, Dahl and Sterner, 1991, Madlener, 1996, Graham and Glaister, 2002b, or Dahl, 2012) but relatively few studies are based on a meta-analysis of these elasticities. In particular, Espey (1996) developed the first meta-analysis to examine the existence of factors that systematically influence gasoline price (and income) elasticity estimates, particularly in the United States. In his work Espey analyses and catalogues the explanatory variables used, data characteristics, model structure, and estimation technique.

In a later version of the paper, Espey (1998) conducted further analysis of existing empirical studies about gasoline demand, again focusing on the distinction between short-run and long-run elasticities, coming to conclusions in line with what was highlighted earlier, namely, higher long-run elasticities than short-run elasticities.

Numerous literature reviews have been conducted to extrapolate the results of multiple studies aimed at quantifying the price elasticity of fuels and many of the most important results can be summarized in the following table.

Table 1: Main results for price elasticity of demand for fuels (literature review)

Study	Period	Papers analyzed	Product	Elasticity
Espey (1996)	1936-1990	41	Gasoline	-0,65 (LT)
Espey (1998)	1929-1993	101	Gasoline	-0,81 (LT)
Hanly et al. (2002)	1929-1991	69	Car fuels	-0,76 (ST) -1,16 (LT)
Graham and Glaister (2002a)	1996-2000	113	Car fuels	-0,25 (ST) -0,77 (LT)
Brons et al. (2008)	1949-2003	43	Gasoline	-0,36 (ST) -0,81 (LT)
Havranek et al. (2012)	1974-2011	41	Gasoline	-0,09 (ST) -0,31 (LT)
Labandeira et al. (2017)	1990-2016	428	Gasoline	-0,23 (ST) -0,77 (LT)

Source: Brons et al. (2008) and various literature
Note: LT, long term; ST, short term; result obtained by using only papers that employ statistical models

The conclusions of these studies can be summarized as follows: short-run price elasticities of energy products included between -0,09 and -0,76, long-run elasticities ranging between -0,23 and -1,16. The values of elasticities also seem to decrease with years, probably due to the joint effect of energy efficiency improvements but also due to the income effect. The studies analysed are very eterogenous, as they include models estimated both by ordinary least squares and by more complex estimation techniques.

The great variety of studies produced also concerns the temporal aspects: in fact, some models have been estimated through the use of time series data, others are based on models for panel data, and this has effects on the final results[2].

It is important to note that elasticities change when substitute fuels, such as ethanol or biodiesel, are also considered in the specification of this demand (Dahl, 1992), or when an indicator related to the cost of public transportation is introduced[3].

It should be kept in mind, however, as will be seen later in the discussion, that the use of petroleum-derived fuels has heavy negative externalities, such as vehicular traffic and air pollution, additional drivers for a progressive reduction in gasoline consumption[4].

The estimates resulting from the meta-analyses conducted by the various authors show a wide range of variability, which of course depends on the basic conditions of the different countries (economic, social and other), the vehicle fleet on the road, as well as, of course, the type of model used.

In general, for long-run elasticities there is a value of about -0,65, a higher value than for short-run elasticities, as already seen.

Finally, significant differences persist between the various commodities, such as diesel fuel (which turns out to have lower elasticities) and natural gas (which, on the contrary, has higher elasticities).

Another factor that has a decisive impact is the evolution of the price of the raw material that is used for the production of fuels, namely crude oil.

As will be described in the appropriate section in the econometric model presented in this study, the price of oil plays a key role in determining the elasticity of demand to fuel prices.

2. The data

The analysis covers the time frame from January 2002 to February 2020, which is immediately before the lockdown that affected the entire country (and the rest of the world) due to the Covid-19 pandemic.

The pandemic period was purposely excluded from the analysis because the data itself, being a particularly large and prolonged disturbance, would have invalidated the results of the econometric model[5].

Analysing the data shows, particularly for gasoline, the existence of an inverse relationship between consumption and the average price at the pump (including both fuel excise and value-added tax).

Indeed, the historical data series shows a decline in gasoline consumption and an increase in diesel consumption: this may be due to the growing popularity of diesel-

[2] Consequently, the variables used in the various models also play a different role: in the models for macro-type aggregate data it was a matter of using some more macroeconomic indicators as regressors (such as gross domestic product, or resident population, etc.), while in panel models other more specific quantities were also used at the demographic level, but also at the socio-economic level.

[3] On this aspect, some authors such as Goodwin (1992) show that if there is an increase in public transport fares there is a reduction in its use, so there are spillover effects on private vehicle transportation, showing a certain degree of substitutability between the two modes of transportation.

[4] These aspects deserve special attention because the health effects of an increase of 10 µg/m3 (micrograms per cubic meter) of particulate matter (pm10) generate a significant increase in the prevalence of respiratory diseases, with consequent effects in terms of mortality (Cropper et al., 1997; Lozano, 2004).

[5] As a future development, it would be interesting to use a different modelling framework (such as switching VARs) that can adequately model the effects caused by a shock such as that caused by Covid-19 on the economy, and thus be able to return elasticity parameters that take these effects into account.

powered vehicles (driven by the increasing efficiency of diesel engines and the relative convenience of this type of fuel instead of gasoline).

At the same time, LPG consumption has also grown over the years.

Analysing in detail the consumption and prices of diesel fuel, there is a growth in consumption itself due to what has been said (substitution effect toward gasoline) against a growth/substantial stability of the price at the pump.

Table 2: prices and consumptions gasoline, diesel and LPG

Year	Gasoline price	Diesel price	LPG price	Gasoline cons.	Diesel cons.	LPG cons.
	euros	*euros*	*euros*	*thousands liters*	*thousands liters*	*thousands liters*
2002	1,046	0,855	0,520	21.953.552	25.761.677	2.323.894
2003	1,058	0,878	0,540	21.090.164	26.808.383	2.139.823
2004	1,125	0,939	0,539	19.889.344	28.783.234	1.957.522
2005	1,219	1,107	0,570	18.465.847	29.258.683	1.821.239
2006	1,284	1,164	0,648	17.312.842	30.486.228	1.750.442
2007	1,298	1,162	0,626	16.245.902	31.395.210	1.670.796
2008	1,379	1,342	0,681	15.087.432	31.179.641	1.776.991
2009	1,232	1,081	0,563	14.491.803	30.407.186	1.945.133
2010	1,363	1,214	0,660	13.646.175	30.396.407	2.157.522
2011	1,555	1,448	0,755	12.837.432	30.658.683	2.251.327
2012	1,786	1,706	0,823	11.464.481	27.477.844	2.398.230
2013	1,749	1,659	0,806	10.963.115	26.826.347	2.720.354
2014	1,713	1,610	0,770	10.812.482	29.901.931	2.768.142
2015	1,535	1,405	0,613	10.694.221	30.440.602	2.916.814
2016	1,444	1,282	0,564	10.392.669	30.454.034	3.001.770
2017	1,529	1,385	0,634	9.981.254	30.421.619	2.950.442
2018	1,599	1,488	0,673	10.030.480	31.734.025	2.856.637
2019	1,574	1,479	0,632	10.039.713	31.301.388	2.925.664
* 2020	1,568	1,464	0,637	1.520.821	4.696.085	470.796

* only a bimester for 2020

Own elaborations on Economic Development Ministry

The price of crude oil (Brent) shows a fluctuating trend, with a peak around 2008 and the years immediately following (probably triggered by the economic crisis), and then following a seemingly erratic trend until 2014, the year from which prices remained at a substantially lower level.

Inflation, as measured by the Whole Community Index Number (NIC, 2015 = 100), is rising, as is logical, and does not show any particular surge.

Finally, the euro-dollar exchange rate fluctuates around parity, with periods when the European currency appreciates/depreciates against the U.S. currency.

In parallel with the data used in the model, it may be useful to analyse the evolution of the vehicle fleet in Italy (years from 2005 to 2020, source ACI, Automobile Club Italia). The data show that the number of cars on the road has grown, from 34,5 million in 2005 to about 39,8 in 2020, as well as trucks have gone from about 4,2 million in 2002 (adding together both those used for freight transport and special transport) to about 5 million in 2020.

Table 3: Circulating vehicle fleet in Italy (years 2005 - 2020)

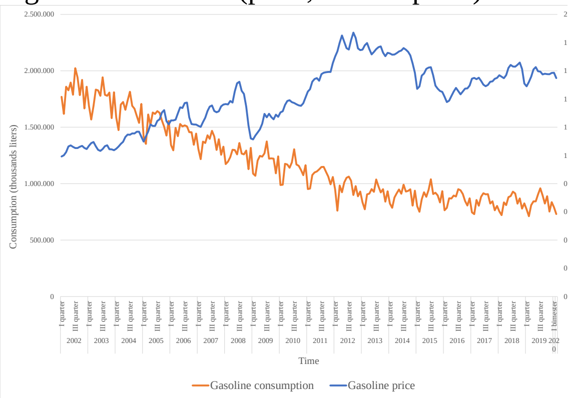
Years	Motorcycles	Wheeler-van	Cars	Bus	Trucks for goods	Trucks special	Tractors	Other	**Total**
2005	4.938.359	344.827	34.667.485	94.437	3.637.740	541.919	148.173	812.161	45.185.101
2006	5.288.818	310.555	35.297.282	96.099	3.763.093	568.654	151.704	852.939	46.329.144
2007	5.590.183	305.666	35.680.097	96.419	3.842.995	594.642	153.912	867.432	47.131.346
2008	5.859.094	300.890	36.105.183	97.597	3.914.998	619.706	157.007	882.463	47.936.938
2009	6.118.098	296.104	36.371.790	98.724	3.944.782	639.428	157.807	408.345	48.035.078
2010	6.305.032	291.757	36.751.311	99.895	3.983.502	656.880	158.289	415.735	48.662.401
2011	6.428.476	287.650	37.113.300	100.438	4.022.129	671.445	159.766	426.497	49.209.701
2012	6.482.796	282.463	37.078.274	99.537	3.989.009	678.409	154.757	427.997	49.193.242
2013	6.481.770	276.743	36.962.934	98.551	3.938.026	680.860	149.563	424.693	49.013.140
2014	6.505.620	272.074	37.080.753	97.914	3.930.858	686.309	150.086	426.852	49.150.466
2015	6.543.612	267.822	37.351.233	97.991	3.943.964	694.888	153.858	435.125	49.488.493
2016	6.606.844	264.529	37.876.138	97.817	4.018.708	707.291	162.092	448.456	50.181.875
2017	6.689.911	260.059	38.520.321	99.100	4.083.348	722.089	173.057	463.462	51.011.347
2018	6.780.733	255.009	39.018.170	100.042	4.130.291	736.491	183.732	477.902	51.682.370
2019	6.896.048	250.234	39.545.232	100.149	4.178.066	751.005	190.303	490.262	52.401.299
2020	7.003.618	246.651	39.717.874	99.883	4.221.718	764.737	195.469	500.389	52.750.339

Source: ACI (Automobile Club Italia)

This shows that the road transport market is still growing and it follows that, despite being in the presence of technological innovations that reduce unit consumption, the demand for fuel still tends to rise.

Figure 1.a and 1.b: Distribution vehicle fleet circulating in Italy (years 2005 / 2020)
Source: own elaborations on data ACI (Automobile Club Italia)

Figure 2.a Gasoline (price, consumption)

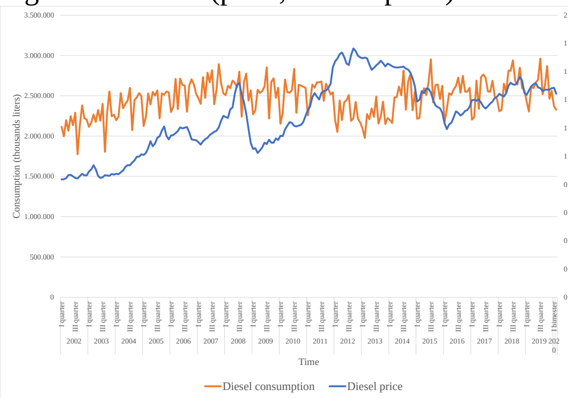


Own elaborations

Figure 2.d Crude oil (price, US dollars)

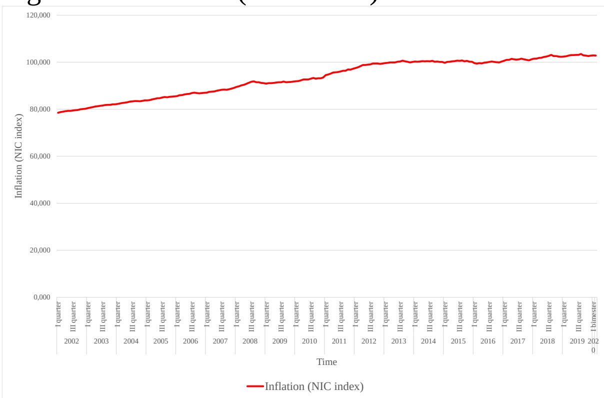
Own elaborations

Figure 2.b Diesel (price, consumption)



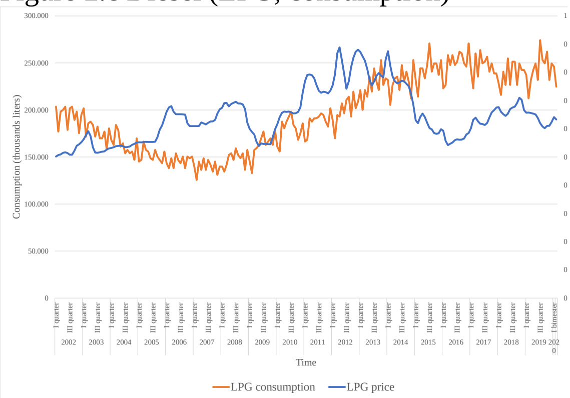
Own elaborations

Figure 2.e Inflation (NIC index)



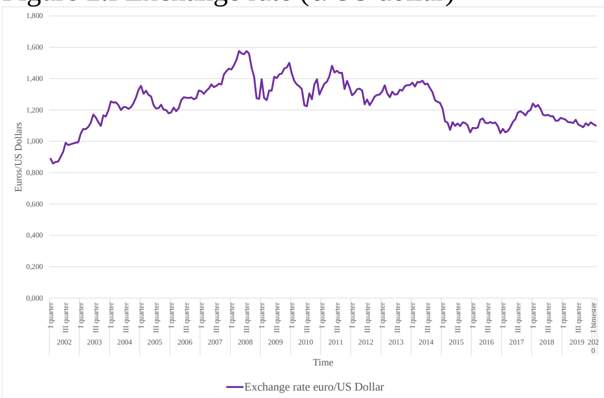
Own elaborations

Figure 2.c Diesel (LPG, consumption)



Own elaborations

Figure 2.f Exchange rate (€/US dollar)



Own elaborations

3.1 The model

As described in section 1 in order to evaluate the elasticities by an econometric approach, there are two main alternatives: panel data or time series analysis. Considering that energy commodities data are observable for a reasonable time span and that NIC indicator is typically a macro variable, a time series approach has been chosen since in the framework of applied macroeconomics this kind of analysis is often preferred to the panel approach which is more useful to deal with micro data.

The principal problem of performing the estimation of elasticities by a time series analysis approach is overcoming the so-called Lucas critique (Lucas 1976), on autoregressive models. An autoregressive model, which is the most immediate approach to model a stochastic process evolving through time, has the following general specification:

$$y_t = \delta + \varphi y_{t-1} + u_t \qquad (2)$$

The observable y at time t is modelled through its autocorrelation to the past, u_t is the prediction error or residual at time t, the autocorrelation coefficient φ in order to avoid an explosive pattern for t approaching to infinity has to be smaller than one in absolute value. Lucas in his contribution of 1976 has criticized also this kind of models to the extent that they are not considering the rationality of individual which may not react to unexpected shocks as they did in the past, in other words modelling economic variable by a model where parameters are only referring to past values of the observables would lead to neglect the contemporaneous correlation among economic variables, which can be considered as a structural relation, crucial in order to infer the behaviour of rational economic agents. The equation below of a VAR (Vector Auto Regression models the ideal type of multivariate model for this type of approach) of lag order p represents the so-called reduced form of the model.

$$Y_t = \delta + \Sigma_1^P A_i Y_{t-i} + u_t \qquad (3)$$

Is possible to notice that in this dynamic system there are no contemporaneous relations between the m observables, the real data generating process allowing for rational economic agents should be represented as structural VAR, the SVAR approach:

$$A_0 Y_t = \delta + \Sigma_{i=1}^P A_i Y_{t-i} + u_t \ (4)$$

The SVAR approach proposed by Sims in 1981 is still one of the most solid strategies to overcome Lucas critique and estimate the structural parameters of a dynamic economic system. In order to estimate the structural parameters of an m dimensional VAR a minimum set of m(m-1)/2 restrictions on the m^2 parameters of interest are required.

The idea of Sims is basically to retrieve from the variance covariance matrix of a multivariate autoregressive model useful information in order to identify the structural relation among economic observables:

$$Y_t = \Sigma_{i=1}^P A_i \ Y_{t-1} + u_t \qquad (5)$$

The reduced form residuals vector u_t, which is usually characterized by non orthogonal residuals in real data, can be factorized as the product of an orthogonal vector of residuals e_t and the Cholesky factor matrix whose notation is $\boldsymbol{A_0^{-1}}$.

$$Y_t = \Sigma_{i=1}^{P} A_i \, Y_{t-i} + \boldsymbol{A_0^{-1}} e_t \qquad (6)$$

The Cholesky factor $\boldsymbol{A_0^{-1}}$ of the variance covariance matrix Σ is a lower triangular matrix with the following properties:

$$\begin{gathered} \boldsymbol{\Sigma_t = u_t u_t{}'} \\ \boldsymbol{u_t u_t{}' = A_0^{-1} e_t \, e_t{}' A_0^{-1}{}'} \\ \boldsymbol{u_t u_t{}' = A_0^{-1} \, I A_0^{-1}{}'} \\ \boldsymbol{u_t u_t{}' = A_0^{-1} \, A_0^{-1}{}'} \qquad (7) \end{gathered}$$

This transformation (7) which relates the residuals of the reduced form to the residuals of the structural form, allows to estimate the contemporaneous relation matrix $\boldsymbol{A_0}$ of t recovering the m(m+1)/2 non redundant information from the matrix $\boldsymbol{\Sigma_t}$, the minimal set of restriction which make the system identified is obtained by construction from the lower triangular form of the Cholesky factor.

Thus, once obtained the Cholesky decomposition of the variance covariance matrix is possible to recover the structural form of the model simply by pre-multiplying the reduced form by the inverse of the Cholesky factor matrix:

$$\begin{gathered} \boldsymbol{u_t = A_0^{-1} e_t} \\ A_0 \, Y_t = A_0 \, A_1 \, Y_{t-1} + A_0 \, \boldsymbol{A_0^{-1} e_t} \\ A_0 \, Y_t = A_{\boldsymbol{1}}^{*} Y_{t-1} + e_t \quad (8) \end{gathered}$$

The Cholesky decomposition which is a known transformation in matrix algebra as already said allows to recover m(m+1)/2 structural parameters from the variance covariance matrix, in order to obtain an identified system of equation for the contemporaneous correlation. The procedure is almost fully a-theoretical, the sensibility of the econometrician is needed only in the ordering of the variables in the model since the lower triangular structure of the matrix A_0 would deliver different set of the m(m-1)/2 restrictions needed according to the different variables ordering proposed.

In this kind of models the elasticities can be considered as the impact of unexpected shocks of the observables which may take several periods to be reabsorbed, in order to study these dynamical aspects of the series, it’s possible to use the so-called impulse response analysis (IRF analysis), since the shocks in this framework are defined as forecast errors, if the SVAR lagged polynomial, as can be demonstrated, is inverted in a VMA (Vector Mobile Average) model by using the lag operator than is possible to forecast h steps ahead obtaining the IRFs by using VMA to predict $Y_{t+1}, Y_{t+2}, \dots, Y_{t+h}$:

$$\begin{gathered} A_0 Y_t = \Sigma_{i=1}^{P} A_i Y_{t-i} + e_t \\ A_0 Y_t - \Sigma_{i=1}^{P} A_i Y_{t-i} = e_t \\ A(L) Y_t = e_t \\ Y_t = B(L) e_t \qquad (9) \end{gathered}$$

3.2 The identification

The identification strategy applied is an update of the one proposed by Manzo et al.[6] (2010), where the estimate was based on time series data for the period from January 1997 to December 2005. The estimation of the cited author was the position of the price index and the exchange rate has been inverted, because the homogeneous currency area of euro the exchange rate is not guided by the national price index anymore. Moreover, the identification applied in this analysis include the Brent crude oil price as a fully exogenous variable in time t, and we consider the multiproduct case, by evaluating the elasticities of demand of gasoline, diesel and LPG.

Since the diesel consumption has most of its shares in the trucking industry, we consider the price and the quantity of diesel exogenous to the other products, and since the consumption of gasoline is higher than the other products, it's reasonable to think that gasoline shocks of price and quantity are affecting the LPG ones.

Table 4: Identification scheme

	P brent	**e** €/$	**NIC**	**P** diesel	**P** gasoline	**P** LPG	**Q** diesel	**Q** gasoline	**Q** LPG
P brent	1	0	0	0	0	0	0	0	0
e €/$	a 71	1	0	0	0	0	0	0	0
NIC	a 21	a 22	1	0	0	0	0	0	0
P diesel	a 31	a 32	a 33	1	0	0	0	0	0
P gasoline	a 41	a 42	a 43	a 44	1	0	0	0	0
P LPG	a 51	a 52	a 53	a 54	a 55	1	0	0	0
Q diesel	a 61	a 62	a 63	a 64	a 65	a 66	1	0	0
Q gasoline	a 71	a 72	a 73	a 74	a 75	a 76	a 77	1	0
Q LPG	a 81	a 82	a 83	a 84	a 85	a 86	s 87	a 88	1

The parameters of interest for the main purpose of the analysis are a_{64}, a_{75}, and a_{86}, they can be considered the price elasticities demand of the three commodities analysed (diesel, gasoline and LPG), since the generic coefficient of this matrix a_{ij} can be interpreted as the response of the i-th variable to j-th shock. Moreover the responses of both the prices and the quantities of the commodities analysed and of course the response of the domestic price index NIC are of interest in order to determine the impact of a bottleneck on the supply chain in the energy market.

4.1 Results

The table below displays the impact elasticities a_{64}, a_{75}, and a_{86}, discussed in the previous paragraph. The elasticities estimated are coherent with M. Espey 1996 the medium fuel elasticity is -0,26 , considering the estimation by single commodity the diesel

[6] Dal Savio G., Dari G., Manzo M. (2010) "Gli effetti della politica fiscale sulla domanda di benzina e di gasolio: un approccio SVAR", Agenzia delle Dogane, working paper no. 4/2010.

elasticity is characterized by the specific contingency that diesel consumption has a significant share in trucking industry, this feature contributes significantly in increasing the rigidity of diesel demand respect to gasoline one which is 2% points more elastic to price shocks, the PLG demand is characterized for being more reactive to price of 5% points respect to medium elasticities, is worth noticing that by weighting the medium elasticity on the commodities consumption levels the medium elasticity is even lower, a possible narrative explanation of the higher elasticity of PLG demand can be can be exploited by considering it as a particular fuel selected by a restricted member of consumers with specific peculiarities that are slightly different from the behaviour of the average gasoline consumer.

Is important to point out that in the monthly horizon is not possible to notice any substitution effects between fuels, since an increase in price of a particular fuel in that horizon reflects only an increase in demand or a decrease in supply due to the short term scenario where consumer adjust their demand to the conjunctural conditions, in order to to study cross elasticities would necessary to run an error correction model, in order to obtain the long run elasticities, which may display a substation effect in the long run between different kind of fuels.

An additional interesting result of the analysis[7] is characterized by the very large responses of both price and quantity of the three fuels analysed to the brent oil price shocks.

The increases in prices of the three commodities are very persistent and never fully vanished in the dynamic simulation, at least for their median values. The quantity of both gasoline and diesel decreases significantly, it’s very evident how the consumption of fuel is way more reactive to shocks which are uncorrelated with the final consumption but with supply shocks in the primary commodities market.

Price shocks in the oil market are affecting the supply chain in the fuel market having a significant impact in the behaviour of consumption which are forced to respond to the international crisis capable of reducing the national economies purchasing power of fuel stocks. Price shocks in the oil market can be seen in though as negative supply shocks in the fuel market, since the decrease in quantity is followed by an increase of the fuels’ price, which can be interpreted as a negative shift of a positive sloped supply curve.

Table 5: short run elasticities

identification order: diesel, gasoline, LPG

short run elasticities	coefficient	lower buond	impact elasticity	upper buond
gasoline	a75	-0,405	-0,248	-0,089
diesel	a64	-0,355	-0,221	-0,090
LPG	a86	-0,420	-0,308	-0,193

Own elaborations

The graphs shown in Figure 3 illustrate the trends in IRFs for all variables in the model; of particular interest are the impulse responses of diesel, gasoline and LPG consumption in response to shocks in their respective prices.

[7] The lower bound and upper bound values shown in the table refer to the "credible set" (the equivalent of confidence intervals in classical inferential statistics) at 68 percent, as is customary in BVAR models (see Killian and Lüktepohl *Structural Vector Autoregressive Analysis*, 2017).

Price shocks have a negative effect on consumption, as might be expected, and the previous patterns of consumption growth themselves are reached, on average, about 12 months after the relative price shock.

Interestingly, crude oil price shocks always have a non-negligible effect.

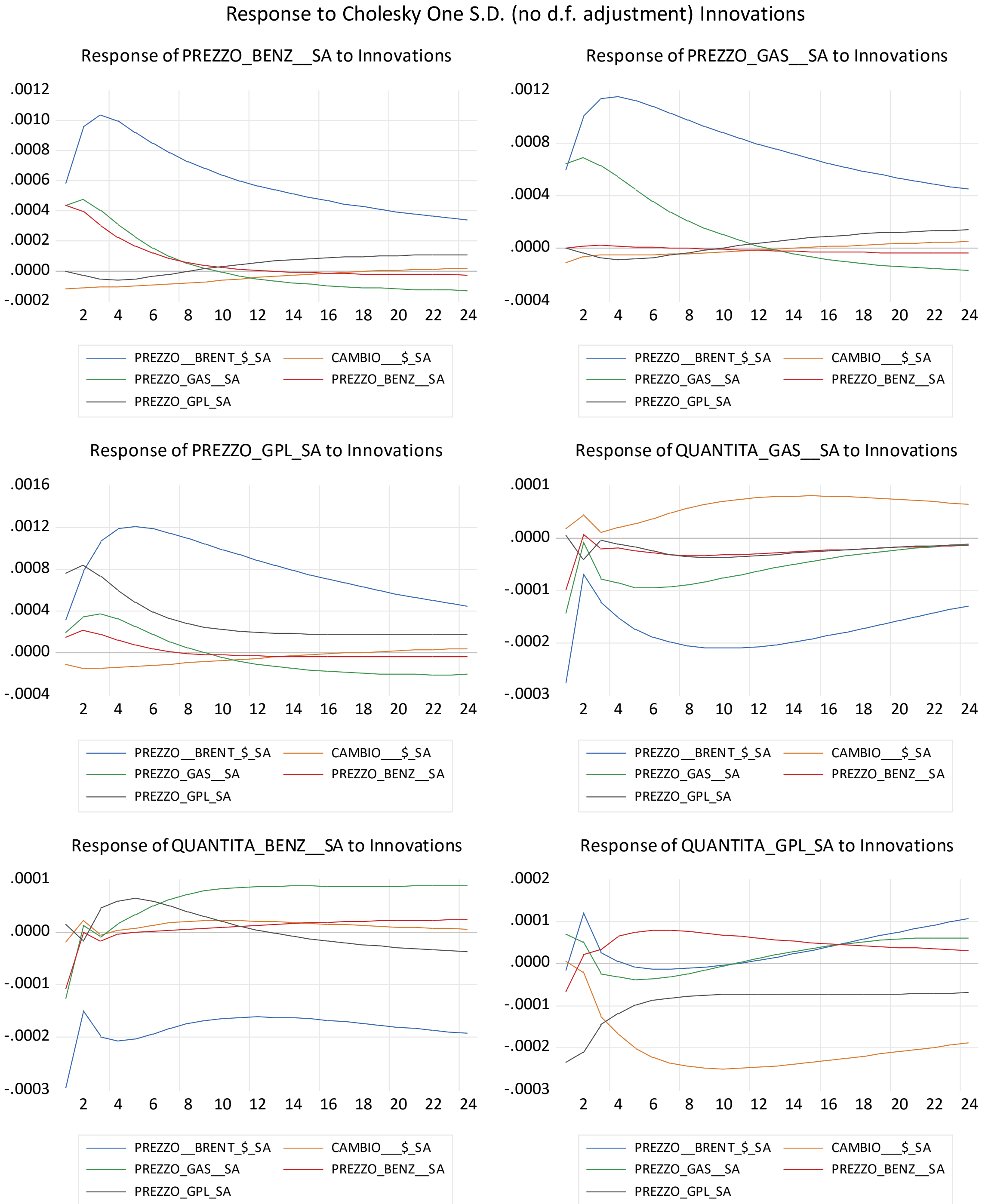


Figure 3: Impulse response functions (IRFs)
Source:own elaborations

4. Robustness check

In order to check the stability of coefficients estimates we run an alternative identification by considering the amplitude of vehicle fleet, which as showed in section 3 is mainly composed by gasoline vehicles then by diesel vehicles and eventually by LPG vehicles.

Thus we inverted the ordering of gasoline and diesel in the table below the results of the alternative specification model are displayed.

Table 6: short run elasticities (alternative specification)

identification order: gasoline, diesel, LPG

model 2	coefficient	lower buond	impact elasticity	upper buond
gasoline	a64	-0,394	-0,280	-0,168
diesel	a75	-0,253	-0,067	0,123
LPG	a86	-0,426	-0,311	-0,193

Source:own elaborations

The results of the alternative model for gasoline and LPG are robust with our main result, on the other hand, with regard to diesel elasticities, the results obtained with this alternative identification are not significative, because the value of the upper bound is positive, while that of the lower bound is negative, implying that this range includes zero, so the sign of the estimated elasticity is not unequivocally negative (as it should be).

This motivate us to elict the model presented in the main results section as the best possible structural model to identify jointly the elastictities of the three fuels analysed under the assumptions of the study under review, i.e., absence of structural changes in the economic system caused by unpredictable events (Covid-19 pandemic, war in Ukraine etc.) and under the other assumptions presented at the beginning of this paper, i.e., the focus on short-term elasticities while leaving out medium- to long-term adjustments (changes in the composition of the vehicle fleet according to various fuels, increasing introduction of electric and hybrid vehicles, change in consumers' mobility habits in response to significant changes in public transportation supply etc.).

5. Conclusions

This paper is part of a strand of literature oriented toward quantifying the relationships between motor fuel prices and their effects on consumption. An interesting evidence of the analysis[8], obtained by introducing spill-over effects in the identification framework, is the very large sensitiveness of both price and quantity of the three fuels analysed to the Brent oil price shocks.

The increases in prices of the three commodities are very persistent and the quantity of both gasoline and diesel decreases significantly, it’s very evident how the consumption of fuel is way more reactive to shocks which are uncorrelated with the final consumption but with supply shocks in the primary commodities market.

[8] The lower bound and upper bound values shown in the table refer to the "credible set" (the equivalent of confidence intervals in classical inferential statistics) at 68 percent, as is customary in BVAR models (see Killian and Lüktepohl *Structural Vector Autoregressive Analysis*, 2017).

Price shocks in the oil market are affecting the supply chain in the fuel market having a significant impact in the behaviour of consumption which are forced to respond to the international crisis capable of reducing the national economies purchasing power of fuel stocks. Price shocks in the oil market can be seen in though as negative supply shocks in the fuel market, since the decrease in quantity is followed by an increase of the fuels' price, which can be interpreted as a negative shift of a positive sloped supply curve. This issue can be addressed by a proper stock procurement policy in order to sterilize transitory spill-over effects on final consumption.

The analyses conducted, specifically for the Italian case, have shown that these goods have a substantially inelastic demand, at least in the short run, in line with the results obtained from similar studies on the subject (both in Europe and in the United States).

In fact, the parameters of elasticity, estimated with a BVAR model, settle on values that oscillate between -0,22 and -0,31 based on the type of fuel considered. This demonstrates that the substantially rigid demand is not particularly influenced by price shocks, and that in any case such shocks are reabsorbed in a relatively short period, 12 months at the most.

This has important implications in terms of transport policies, since a change in the price of fuels (which can also derive from an increase in excise duty rates decided by the Government) does not have much impact on consumption and, consequently, it is not easy to discourage the use of the private vehicle in favour of public transport (in particular for urban travel).

It follows that the modal shift between private and public transport may not be significantly influenced by price policies aimed at discouraging the use of the car, this as regards the movements of single subjects as "private" citizens.

More generally, the inelasticity of diesel consumption for motor vehicles with respect to the price (the lowest value among those estimated, i.e. -0,22) is even more representative of the phenomenon: in the face of price variations, diesel consumption remains practically constants, and this affects freight transport in particular.

In a country like Italy, where over 85% of goods travel by road (against a European average of 75%, Eurostat data), this means that road/motorway congestion remains at high levels, transport costs remain high and environmental pollution continues to be one of the main causes of the lowering of air quality, particularly in large urban centres.

It has already been anticipated in the discussion that the use of petroleum-derived fuels has significant environmental impacts, in addition to the negative effects due to vehicular traffic (particularly in large urban centers), but it is also true that the use of gasoline, diesel, etc. is still essential to modern economic systems.

In addition, the use of these fuels is even higher in many Latin American countries, and it is conceivable that in these areas (but also in other numerous developing regions, such as Southeast Asia) such consumption may even grow in the coming years, with the resulting repercussions in terms of externalities.In the long run, should electric vehicles really become competitive with traditional vehicles powered by fossil fuels, we could see a more marked reduction in fuel consumption and, at the same time, we could find ourselves faced with relatively higher demand functions elastic.

At present, both hybrid and fully electric vehicles still represent a marginal market share; in particular, electric cars represent just over 4% of the market, a still low value and far from the target of 6 million vehicles ambitiously set for 2030. The not particularly significant growth of hybrid and electric vehicles may also depend on the significant maintenance costs of the vehicles themselves (particularly for replacing the battery pack at the end of its useful life), it is to be hoped that reasonable market shares can be achieved in the future with new technologies.

This would be particularly important because it would reduce, at least in part, Italy's energy dependence on oil used for fuel production. In summary, the results confirm what other empirical studies have already shown, namely, a certain rigidity of demand for fuels in the face of more or less marked changes in their prices, so price increases caused by various factors (increase in the cost of crude oil, or price changes associated with increases in excise rates) would not appreciably affect consumption.

From the point of view of Government revenue, this constitutes a plus in that the state can act on the cost of fuels through changes in current excise taxes in order to capture resources, although this politically may not be acceptable.

Future insights from this work could help to investigate the cross-elasticity between fuels in order to show the effects of a (prolonged) increase in the price of gasoline, for example, on the consumption of diesel fuel, but these effects would be over a relatively long period of time. It is more likely that the uptake of electric vehicles will increase in the meantime, and this could be an additional element of consumer choice on the type of vehicle to purchase.

Because of what has been seen so far, one can assume strategies aimed at limiting the use of these fuels, particularly gasoline, through a number of initiatives.

First, a price increase, through fuel excise taxes, in order to discourage excessive consumption of diesel and other motor fuels.

Second, the introduction of even more stringent regulations that would reduce the movement of the most polluting vehicles.

Third, public works aimed at encouraging rail transport should be encouraged, or at least limiting travel by cars, mopeds and motorcycles as much as possible, especially in urban centers.

Fourth, encourage sustainable mobility by creating bicycle paths, pedestrian areas etc. and push all those initiatives aimed at increasing inter-modality in transportation and increasing "green transportation," that is, based on means with low environmental impact.

All this should be done considering that such policies take time to give their results, which is why in fact it has been shown that long-term elasticities are higher than short-term ones, precisely because changes in consumption habits occur slowly, especially as a result of changes in public policies implemented by governments.On the freight transport front, the matter becomes more complex, since in this sense the real competitor should be rail transport, with the completion of the corridors for mobility on the Italian territory in order to interconnect the Italian railway network with the rest of the Europe, but as long as such a strong infrastructural gap remains between the north and south of the country (as in fact it is now) it will be difficult to favor the shift of freight transport from motorways to railways, and this could be one of the future challenges to be faced in the field of transport.

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Appendix

We take a further step toward the inferential procedures used, namely Bayesian estimation methods; in the Bayesian framework the estimation of parameters is based on the concept, brought from the Bayes theorem, of conditional expectation:

$$P(\theta|y) \propto P(\theta)P(y|\theta) \quad \text{(A.1)}$$

The vector θ of model's parameters is the mean of the posterior distribution (i.e. conditional distribution) obtained by integrating the prior distribution $P(\theta)$ and the so-called likelihood $P\big(y|\theta\big)$ which in the Bayesian framework can be assimilated on what usually in frequentist inference is referred as the joint distribution: $\prod_{i=1}^{N} f(y_i\,|\theta)$.

Since the likelihood function is obtained from actual data, the econometrician must be clever in the prior selection; in the Bayesian framework there is a vast literature of possible options for prior selection, for this kind of multivariate parametric models.

For the scope of this analysis the Giannone, Lenza, Primiceri 2012 prior has been selected for its versatility, since this kind of prior performs very well both in out-of-sample estimation and in inference analysis, by mixing the key features of two well-known prior distributions, the famous Minnesota prior proposed by Litterman in 1976, and the dummy variable observation prior, in particular the Minnesota prior has the strength of assigning a parsimonious specification for model observables, which are initialized as unit root processes, this feature allows to obtain an invertible representation of the VAR and SVAR model even if the observables are not stationary in mean[9].

The Giannone Lenza Primiceri prior can be so defined as:

$$\theta|\Sigma_e \sim \mathrm{N}(\theta_0, \Sigma_e \otimes H_0) \qquad \text{(A.2)}$$

$$\Sigma_e^{-1} \sim \mathrm{W}(v_0, S_0^{-1}) \qquad \text{(A.3)}$$

Where the matrix H0 displayed in (A.2) is a convolution of the OLS estimate of ∑e and a set of hyperparameters, whence the posterior distribution is:

$$\theta^p \sim \mathrm{N}(\tilde{\theta}, V_\theta) \qquad \text{(A.4)}$$

$$\tilde{\theta} = vec[(H_0^{-1} + x'x)^{-1}\,(H_0^{-1}\,\theta_0 + x'y)] \qquad \text{(A.5)}$$

$$V_\theta = \Sigma_e \otimes (H_0^{-1} + x'x)^{-1} \qquad \text{(A.6)}$$

We will not go further into the mathematical details of this formulation, for which we refer to the vast existing literature in econometrics.

[9] This prior can be seen as a refinement of the Minnesota prior by adding to afore mentioned Litterman prior a penalty for model complexity, making it more suitable for large datasets.