Econometric Analysis of Demand for Petrol in India, 1966-2019

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Abstract

This study uses single-equation dynamic models to estimate petrol demand in India. Estimated long-run elasticities are higher than their short-run counterparts, which is in line with expectations based on the existing literature. We find price elasticities of -0.418 (long-run) and -0.189 (short run), which indicates that when price increases by 10%, demand tends to reduce by approximately 4% as consumers adjust their consumption behaviour. Prices appear to be more elastic in India rather than USA where studies estimate petrol elasticities to be in the range of -0.02 to -0.04 in the short term. We further find evidence that long-run elasticities are not as high as estimated elsewhere. We address issues around modelling of habit formation, habit persistence, and unobserved heterogeneity. Results are essential for transportation policymaking, especially in the context of taxation, understanding price stability, estimating the effects of duty increases on demand, and the potential implications for carbon taxes. The results are also important for wider policy considerations such as climate protections goals, reducing local emissions, dependency on fossil fuels, and strategic energy security.

Keywords: Energy modeling, Econometric modeling
JEL Classification: Q41; Q42; Q48.

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Contents

List of Figures

List of Tables

1. Introduction and summary of relevant literature

This study addresses transport petrol consumption in India. Specifically, we estimate price and income elasticities, both in the short-run and and in the long-run. We then make use of recent developments in the econometric literature to examine and address issues around modelling of habit formation, habit persistence, and unobserved heterogeneity.

Consumption of petrol (and related and petroleum products) is a well-studied topic, not least because it has important implications for economic policy. This is true especially in the context of price stability, the effects of petrol duty changes on demand, and the implications for carbon taxes.

There are a number of challenges with estimation, not least uncertainty of estimation caused by the complex and changing nature of petrol demand. Demand is a function of a number of human decisions that do not necessarily depend on cost, but also on unobservable preferences. Travel decisions are related to both professional and household decisions, which are highly dependent on context and habits.

Price and income elasticities of petrol demand are crucial if we are to capture demand response of consumers against a change in income or a change in price of oil. For policymakers this is of importance since it is possible to understand the the potential social welfare implications of energy pricing schemes, expected effects of rising energy prices on consumers, and related policy outcomes. The problem for researches is that the complex nature of petrol demand can introduce significant uncertainty of estimation. Petrol demand can be driven by various different decisions and factors. For example, travel decisions are strongly related to various household decisions, such as budget allocation, work and geographical preferences, weather conditions, situational factors such as trip purpose, passengers to carry, etc.

Related studies can be broadly separated according to two main dimensions. The first dimension is the region of interest. The second dimension is whether they use disaggregate or aggregate data sources. Studies that have used United States disaggregated data include Archibald and Gillingham (1980, [1]) Kayser (2000, [44]), Puller and Greening (1999, [51]), West and Williams (2007, [64]), and Wadud et al. (2010, [62]). US studies that use aggregated data include Hirota et al (2003, [30]), Austin and Dinan (2005,[3]), Hughes et al. (2008, [34], [35]), Hymel et al. (2010, [38],[39]), Lin and Prince (2013, [45]), Sentenac-Chemin (2012, [55]), Wadud et al. (2009, [61]. Examples of disaggregated data studies for European countries include Brannlund and Nordstrom (2004, [7]), Burguillo et al. (2017, [10]), and Romero-Jordan et al. (2010, [52]). Examples of aggregated data studies for European countries include Odeck and Johansen (2016, [48]), and Breunig and Gisz (2009, [8]). From US data, we can see that estimated short-term elasticities of petrol demand range from -0.03 to -0.51, whilst long-term elasticities range from -0.239 to -0.473. From global data, we can see that estimated short-term elasticities of petrol demand range from -0.09 to -0.36, whilst long-term elasticities range from -0.2 to -0.81. Table 1 presents a brief summary of related literature.

Table 1: Review of relates studies on elasticities of petrol demand

Source	Observation period	Geographic region	Elasticity, Short term	Elasticity, Long term
Breunig and Gisz (2009)c	1966-2006	Australia	-0.13	-0.2
Odeck and Johansen (2016)	1980–2011	Norway	-0.26	0.09
Burguillo et al. (2017)	1998–2005	Spain	-0.35 to -0.49e	
Romero-Jordán et al. (2010)	1998–2001	Spain	–	-0.55
Brännlund and Nordström (2004)	1985–1992	Sweden	–	-0.98
Austin and Dinan (2005)	2001	USA	–	-0.39
Hughes et al. (2008)b	1975–1980	USA	-0.275	–
Hughes et al. (2008)b	2001–2006	USA	-0.056	–
Hymel et al. (2010)	1966–2004	USA	-0.075	-0.361
Hymel et al. (2010)b	2004	USA	-0.055	-0.285
Lin and Prince (2013)c	1990–2012	USA	-0.03	-0.239
Sentenac-Chemin (2012)c	1978–2005	USA	–	-0.3
Wadud et al. (2009)	1984–2003	USA	-0.266	–
Archibald and Gillingham (1980)	1972–1973	USA	-0.43	–
Kayser (2000)b	1981	USA	-0.23	
Puller and Greening (1999)	1980–1990	USA	-0.35	–
Wadud et al. (2010a)	1997–2002	USA		-0.473
West and Williams (2007)	1996–1998	USA	-0.51	–
Brons et al. (2008)a	1972–1999	Worldwide	-0.36	-0.81
Burke and Nishitateno (2013)c	1995–2008	Worldwide	–	-0.2 to -0.5
Dahl (2012)a,c	1954–2005	Worldwide	-0.15	-0.55
Dahl (2012)a,d	1954–2005	Worldwide	-0.10	-0.33
Goodwin et al. (2004)	1981–1991	Worldwide	-0.16	-0.43
Goodwin et al. (2004)a	1974–1981	Worldwide	-0.35	-0.93
Havranek et al. (2012)a,c	1974–2011	Worldwide	-0.09	-0.31
Hirota et al. (2003)	1990–2002	Worldwide	-0.195	–

a = Meta study (otherwise primary study). b = Focus on periods with high petrol price variation. c= Analysis based on gasoline consumption only. d = Analysis based on diesel consumption only. e = Estimated mixture of short- and long-run elasticities.

2. Empirical strategy

Single-equation studies have their origin in dynamic demand models of 1960's a la Balestra-Nerlove ([4]) and Houthakker-Taylor ([31],[33]). Demand for durable goods in this context is examined using a partial adjustment mechanism where both stockpiling and habit-forming play a role. This leads to a general dynamic theory of utility maximisation. In such models, the stock of a durable good is a function of the gap between past stock and current (desired) stock levels; see See Taylor et al [32] for an extensive survey.

Such models have been fruitfully applied to petrol consumption. For example, Baltagi and Griffin ([6]) use the idea of partial adjustments driven by a fixed vehicle stock as follows:

$$\nu_t^* \equiv \left(\frac{V^*}{N}\right)_t = k_1 \left(\frac{P_g}{P}\right)_t^{k2} \left(\frac{Y}{N}\right)_t^{k3} \left(\frac{Car}{N}\right)_{t-1}^{k4} \epsilon_t \tag{1}$$

where ν_t^* corresponds to consumption of petrol per capita at time t, Car corresponds to the stock of cars, N is the population, Y is real income, P is the aggregate price level, P_g is the price of petrol, V^* is the desired volume of petrol consumption, and ϵ_t is the error term, assumed to be white noise i.i.d.

Since the adjustment is not necessarily instantaneous, we model it as follows:

$$\nu_t = (\nu_t^* (\nu_t^*)^\theta (\nu_{t-1})^{1-\theta} \tag{2}$$

when $\theta = 1$ then $\nu_t^* = \nu_t$ i.e. there is instant adjustment of desired to actual consumption. In the case of petrol this is possible but unlikely, since there exist a number of factors which determine the "stickiness" of demand. If we consider transportation-related factors alone, then these can include e.g. commuting habits and geographic dispersion of residential property, which in the short run tends to be fixed. We are able to re-arrange and combine equations 1 and 2 to yield a useful model for observed petrol consumption per person

$$\nu_t = k_1^{\theta}\left(\frac{P_g}{P}\right)_t^{k2\theta}\left(\frac{Y}{N}\right)_t^{k3\theta}\left(\frac{Car}{N}\right)_{t-1}^{k4\theta}\nu_{t-1}^{1-\theta}\epsilon_t^{\theta} \tag{3}$$

We further fix the notation of equation 3 individual for real variables and per-individual and take logs, which yields the well-utilised in the literature specification (e.g. [5], [20], [6], [24], [17], [42], [15], see [28] for a survey):

$$\nu_t = k_1^{\theta}\left(p_t\right)_t^{k2\theta}\left(y_t\right)_t^{k3\theta}\left(car_{t-1}\right)_{t-1}^{k4\theta}\nu_{t-1}^{1-\theta}\epsilon_t^{\theta} \tag{4}$$

If we impose a restriction where $\beta_c = 0$[1] then we obtain

$$\begin{aligned} ln(\nu_t) = \theta ln(k_1) + \theta k_2 ln(p_t) + k_3\theta ln(y_t) + k_4\theta ln(car_{t-1}) + (1-\theta)ln(\nu_{t-1}) + \theta ln(\epsilon_t) \\ = \beta_0 + \beta_p ln(p_t) + \beta_y ln(y_t) + \beta_\nu ln(\nu_{t-1}) + \beta_c ln(car_{t-1}) + \epsilon_t \end{aligned} \tag{5}$$

We then extend model 5 as per [8] by including lagged values of ν_t in order to account for the possibility that adjustment of actual to desired consumption may last greater than single period. We can then estimate the following model:

$$ln(\nu_t) = \beta_0 + \beta_p ln(p_t) + \beta_y ln(y_t) + \sum_{j=1}^{q}\beta_{\nu q} ln(\nu_{t-q}) + \epsilon_t \tag{6}$$

Model 5 has a limitation, which is its inability to capture persistence of current consumption habits ([54], [45]). On the other hand, it is possible to address this issue by incorporating moving average terms. But on the other hand, this would make standard OLS estimation inconsistent. Model 6 also has a limitation, which relates to price reversibility. The implication here is that demand response to a rise in prices is identical to demand response to a fall in prices. This assumption may be too strong to aceept. We follow [8] and address this constraint with a relatively enhanced specification.

2.1. Controlling for unobservable stock effects in the demand function.

We have derived a model which depends on relative prices and real income. Now let us consider a model for petrol consumption at a given time t which is a function of not only real income and relative prices and real income, but also some unobservable stock parameter, s^*_{t-1}. This parameter captures habitual (i.e. psychological) determinants of petrol consumption. It also captures physical determinants, such as commuter dispersion, and vehicle efficiency. We are able to state a new specification as follows:

$$ln(\nu_t) = \alpha_1 + \alpha_2 ln(p_t) + \alpha_3 ln(y_t) + \alpha_4 s^*_{t-1} + w_t \tag{7}$$

Urban layouts, habits, and other such determinants evolve according to

$$\Delta s^* \equiv s^* - s^*_{t-1} = ln(\nu_t) - \delta s^*_{t-1} \tag{8}$$

[1] In other words, we assume that stocks of vehicles are constant.

Equation 8 is essentially identical to a standard capital equipment model, where δ would correspond to the rate of depreciation. However, in our specification we use the parameter δ to control for the speed at which the determinants of petrol consumption adjust. Setting $\delta = 1$ is the same as setting $\theta = 1$ in model 2.

By setting $\delta = 1$, model 7 collapses to model 5. Estimating 5 is equivalent to imposing an assumption that there exist no 'stock effects' (either habitual or physical) to past consumption that affect current consumption. For petrol consumption this is assumption is not realistic because we know that habits exhibit a strong effect on consumption. These can include the following channels, some of which can be persistent ([56, 34]):

In the short-run:

- Behavioural habits. Demand is determined by trip frequency, vehicle upkeep, driving style, and car-pooling.

In the long-run:

- Location choice. Considerations regarding where to work and live determine commuting distance.
- Vehicle choice. Considerations regarding petrol efficiency determine petrol consumption.
- Availability of cycling paths, public transport, etc.

To mitigate for this restrictive assumption, we aim to rewrite the Houthakker-Taylor model.

2.2. Augmenting Houthakker and Taylor (1966) with moving average errors.

We reparametrise equation 7 by writing $\Delta ln(\nu_t)$, substituting equation 8, adding a lag to equation 7, and replacing s^*_{t-2} in $\Delta ln(\nu_t)$.

$$ln(\nu_t) = \alpha_1\delta + \alpha_2\delta ln(p_{t-1}) + \alpha_2\Delta ln(p_t) + \alpha_3\delta(y_{t-1}) + w_t - (1-\delta)w_{t-1} \tag{9}$$

After further rearranging model 10 we get model 11. The benefit of doing this is that we get a model with a moving average component:

$$ln(\nu_t) = \gamma_0 + \gamma_p ln(p_{t-1}) + \gamma_{\Delta_p}\Delta ln(p_t) + \gamma_y ln(y_{t-1}) + \gamma_{\Delta_y}\Delta ln(y_t) + \gamma_\nu ln(\nu_{t-1}) + u_t \tag{10}$$

Stock adjustment may take longer than one period. Hence, we replace model 8 with the below specification.

$$s^* = ln(\nu_t) + (1-\delta)s^*_{t-1} + \sum_{j=2}^{q}\delta_j s^*_{t-j}. \tag{11}$$

And finally, we combine models 7 and 11 to get

$$ln(\nu_t) = \gamma_0 + \sum_{j=1}^{q}\gamma_{pj} ln(p_{t-j} + \gamma_{\Delta_p}\Delta ln(p_t) + \sum_{j=1}^{q}\gamma_{yj} ln(y_{t-j} + \gamma_{\Delta_y}\Delta ln(y_t) + \sum_{j=1}^{q}\gamma_{\nu j} ln(\nu_{t-j} + u_t \tag{12}$$

The above model has the advantage of being flexible in the sense that the parameters which determine the short-run and the long-run elasticities are estimated separately. This is in direct opposition of model 6.

2.3. Modeling price reversibility

Following [17], we aim to identify different effects on consumption of price decreases and vs increases. To do this we replace introduce three constructed price series in the above equations

$$ln(p)_t^+ = \sum_{s=2}^{t} \Big[(ln(p)_s - ln(p)_{s-1}) - (ln(p)_s^{max} - ln(p)^(max)_{s-1}\Big]\mathbb{1}(ln(p)_s > ln(p)_{s-1})$$

$$ln(p)_t^- = \sum_{s=2}^{t} \Big[ln(p)_s - ln(p)_{s-1}]\mathbb{1}(ln(p)_s > ln(p)_{s-1})$$

$$ln(p)_t^{max} = \begin{cases} ln(p)_1 & \text{if } t = 1 \\ ln(p)_t & \text{if } ln(p)_t > ln(p)_s \forall s < t \\ ln(p)_{t-1} & \text{if } ln(p)_t = ln(p)_{t-1} \end{cases} \quad (13)$$

where $\mathbb{1}(\cdot)$ is an indicator function which equals unity if the expression in brackets is true, zero if it is not. $ln(p)_t^+$ / $ln(p)_t^-$ / $ln(p)_t^{max}$ corresponds to the cumulative series of sub-maximum price increases / price decreases / max historical prices respectively. Using the following property,

$$ln(p)_t = ln(p)_t^+ + ln(p)_t^- + ln(p)_t^{max} \quad (14)$$

we get specification 15, which is our final model to be estimated

$$ln(\nu_t)_t = \beta_0 + \beta_{pmax} ln(p)_t^{max} + \beta_{p+} ln(p)_t^+ + \beta_{p-} + ln(p)_t^- + \beta_y + ln(yt) + \beta_\nu + ln(\nu_{t-1}) + \epsilon_t \quad (15)$$

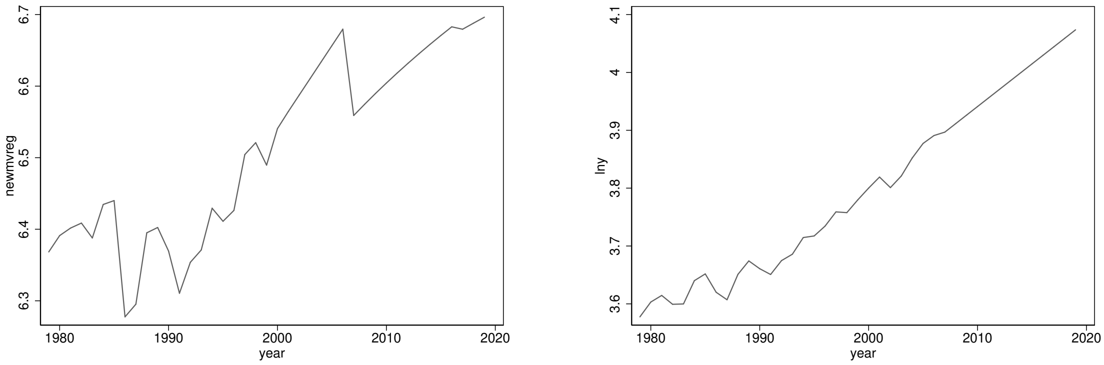
3. Data

We make use of data from Indian Ministry of Road Transport and Highways, BP Statistical Review of World Energy, IMF Government Finance Statistics, and World Bank national accounts data. Obtaining more nuanced data of this kind has posed some minor challenges which forced some modelling choices. For example, it could be interesting to reparametrise equations 1 and 2 in order to capture effects of heterogeneity of vehicles where our model could incorporate parameters relating to the current stock of cars, such as age, vehicle utilisation, CO2/particulates emissions, or petrol efficiency. To this extend, we made enquiries to the Indian Civil Service so that we could obtain these data. However, this request was not successful. Apparently, the Ministry of Petroleum and Natural Gas was earlier part of Ministry of Chemicals and Fertilisers and this departmental change affected the way historical data is collated and archived. Table 5 outlines the main data sourced for this study. Reliable petrol price data were not obtainable prior to the start of our sample period.

3.1. Augmented Dickey-Fuller test

We conduct a Augmented Dickey-Fuller test for unit root. The data shows a clear upward trend, we use the trend option with dfuller to include a constant and time trend (consumption grows over time) in the augmented Dickey-Fuller regression. Results show that we can overwhelmingly reject the null hypothesis of a unit root at all common significance levels. From the regression output, the estimated β of -.63002 implies that $\rho = (1 - .6300) = 0.37$. Experiments with fewer or more lags in the augmented regression yield analogous conclusions.[2]

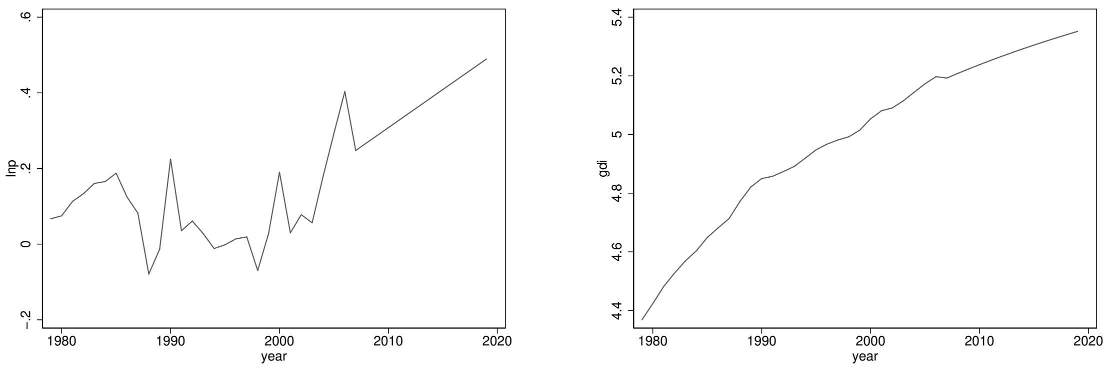
[2] As the ADF test is underpowered, we conduct a KPSS test with the null of stationarity against the alternative hypothesis of a unit root. Results do not change.



(a) Number of total vehicles. (Index, 1966 = 100).

(b) Aggregate income - wages and profits. (Index, 1966 = 100).

Figure 1: Number of total vehicles and wages.



(a) Petrol Price Index (Index, 1966 = 100).

(b) Aggregate income - wages and profits. (Index, 1966 = 100).

Figure 2: Petrol price index and GDI.

3.2. Johansen's test

This test has a limitation in the sense that it relies on asymptotic properties and sensitive to specification errors in limited samples. After plotting logged consumption vs price index, it is clear that our variables indicate trend together. We now perform a unit root test to see if our data are stationary at same level. We use AIC as the lag selection criteria. The results show that all the variables exhibit non-stationarity in level (at 1% significance level) but they show stationarity for the first difference. We conclude that our variables of interest are I(1)[3].

As as an entry point to further analysis, we fit a basic vector autoregressive (VAR) model and graph the orthogonalised impulse-response functions (OIRFs). Figure 3 shows this simple reduced-form VAR without constraints. The graph of impulse-response functions (IRFs) indicates that shocks are likely to correlated. We then use AIC as a lag order selection statistic for a series of vector autoregressions of order $1, \ldots, 10$. Our information criterion shows that the appropriate lag is 1.

When we apply Johansen approach [41], we need to select the deterministic elements of the model in order to recognise if deterministic components (constant or a time trend), are included in levels or cointegration equation. Clearly, cointegration tests are specification-sensitiveand the distribution of the test statistics varies for each combination. In this regard, we can make the following test choices.

- Model 1: no deterministic trend in data and no intercept or trend in cointegration equation (CE);
- Model 2: no linear trend in data but an intercept (no trend) in CE;
- Model 3: a linear trend in data and intercept (no trend) in CE;
- Model 4: a linear trend in data, while intercept and trend exist in CE;
- Model 5: a quadratic deterministic trend in data, intercept and trend in CE.

We only consider 2 (most restrictuve), 3, and, 4 (least restrictive). After we determine the appropriate lag length, we start from the most and continue to least restrictive model (Pantula principle), comparing the rank statistic is compared with its concordant critical value.

Since λ_{trace} at $r = 0$ exceeds its critical value at 5% level, we reject the null of no cointegration equations. But since at $r = 1$, the λ_{trace} is less than its critical value at 5% level, we thus fail to reject the null that only one cointegration equations exist. In other words, the Johansen procedure indicates that a cointegration relationship exist between petrol prices and volume of petrol consumed. We were able to find one analysis in the literature that in this regard is close to this study, specifically [43] investigate cointegration among petrol demand, real price of petrol, and real GDP for India for the period 1971-1972 and 2012-2013. They also estimates short-run and long-run elasticity of petrol demand with respect to its price and GDP. Johansen-Juselius and ARDL bounds test methods establish that petrol demand, petrol price, and GDP are cointegrated. Regime shift cointegration tests with endogenous structural breaks, confirm cointegration between gasoline demand and GDP. We note this result but in line with other studies in the literature, and in light of our univariate unit root test results, we do not feel the need to amend the econometric specification beyond the adjustments which were already discussed earlier in Section 2.

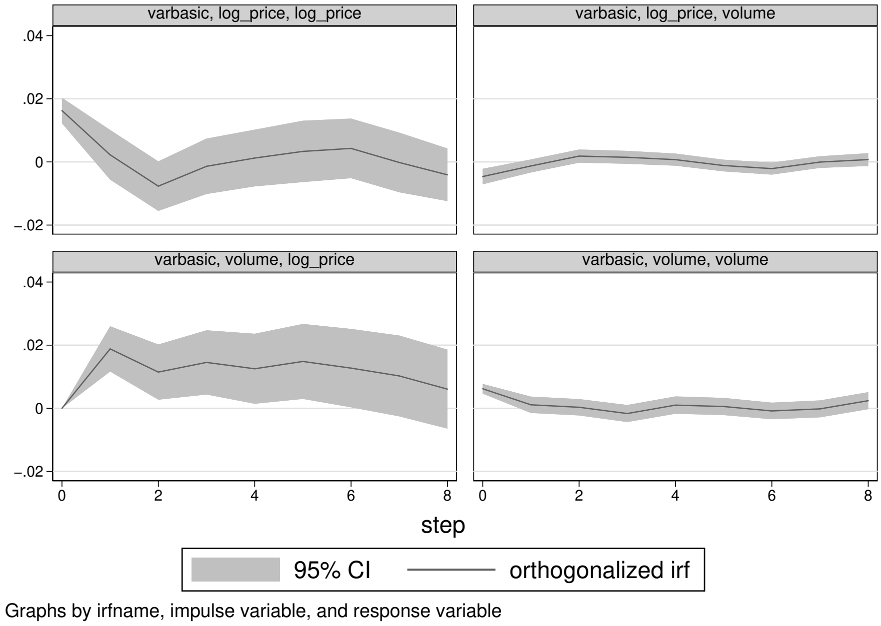
In line with other studies in the field of energy economics ([2, 3, 7, 9, 12, 13, 25, 26, 35, 8], etc), we also consider the impact of the crude oil shocks in the late 1970s. One such shock was the 1979 Oil Crisis, which was caused by the Iranian Revolution. To test the hypothesis of unit root on pre-1978 and post- 1979 data we would ideally like to have more observationa. Regrettably, we were not able to obtain quarterly data from the Indian Civil Service and the best we could rely on was annual-frequency data. Analogously, data from such public sources as World Bank, BP Statistical Review, and IMF is only available on an annual frequency.

[3] We conducted the KPSS test to remove the suspicion that our time-series is fractionally integrated (that is, neither I(1) nor I(0)).

3.3. Granger causality (Toda-Yamamoto specification)

Next, we look at Granger causality. In line with our theoretical expectations, the Toda-Yamamoto ([59]) specification of the Granger causality test indicates long-term unidirectional (Granger) causality from real income to petrol consumption.

Figure 3: Fitting a basic VAR model and graphing the orthogonalised IRFs



4. Point estimates of price elasticities using the Delta method.

We make use of Stata's 'nlcom' command that implements the delta method to convert the confidence intervals to those obtained directly from the least squares regression. The delta method approximates the expectation of some function $g(\cdot)$ of a r.v. x by taking a (truncated) Taylor expansion. It can be shown ([1]) under relatively weak conditions for any parameter θ that is approximately Gaussian in its sampling distribution with variance σ^2/n, the sampling distribution of $g(\theta)$ is also approximately normal with variance $[g'(\theta)]^2\sigma^2/n$. This is because $g(\cdot)$ is approximately linear around θ. Stata's function *nlcom* is used for this purpose.

5. Results

Table 2: Estimates from basic models. Models with and without time trends

	Model (6) no trend	Model (15)-(a) no trend	Model (15)-(b) no trend	Model (6) with trend	Model (15) with trend
β_p	-0.101**			-0.189***	
	-0.036			-0.032	
β_y	0.016	0.189	0.03	0.222*	0.192
	-0.038	-0.128	-0.117	-0.097	(0.148)
β_{v1}	0.176	0.474*	0.285		
	-0.261	-0.209	-0.215		
β_{v2}	0.194	0.206	0.22		
	-0.228	-0.297	-0.278		
β_{v4}	0.593**	0.073	0.379+	0.279	0.399
	-0.177	-0.286	-0.205	-0.194	(0.301)
β_{pmax}		0.181*			-0.216
		-0.071			(0.176)
β_{p+}		-0.142**	-0.132**		-0.150***
		-0.043	-0.043		(0.034)
β_{p-}		-0.096**	-0.127***		-0.203**
		-0.033	-0.033		(0.071)
Post-1978 dummy variable				0.288**	0.255*
				-0.088	(0.106)
Pre-1979 time trend				0.013*	0.007
				-0.006	(0.012)
Post-1978 time trend				-0.003**	-0.007
				-0.001	(0.006)
β_0	0.162	0.696**	0.531+	2.988**	2.477+
	-0.202	-0.253	-0.284	-1.013	(1.432)
Observations	53	53	53	53	53
R^2	0.941	0.954	0.949	0.964	0.954
Long-run income elasticity	0.0157	0.181*	0.0295	0.222*	0.192
	(0.41)	(2.55)	(0.25)	(2.28)	(1.29)
Long-run price elasticity	-0.101**			-0.189***	
	(-2.77)			(-5.99)	
Long-run price elasticity to maximums		0.189			-0.216
		(1.47)			(-1.23)
Long-run price elasticity to increases			-0.132**		-0.150***
			(-3.04)		(-4.36)
Long-run price elasticity to decreases			-0.127***		-0.203**
			(-3.84)		(-2.87)
AIC	-251.991	-261.706	-257.189	-276.803	-259.506

All models are estimated by OLS with White-Huber robust standard errors. Lags in columns (a), (b), and (c) are selected by AIC. Using standard model selection criteria, Model (b) is preferred to models (a) or (c), while model (d) is preferred to model (e). +, *, ** *** indicate statistical significance levels at 10%, 5%, 1%, and 0.1% respectively. The irreversible model is rejected in favour of the standard reversible model once time trends are included in the model.

Table 3: Estimates from basic models. Models with and without time trends

	Model (6) no trend	Model (15) no trend	Model (6) time trend	Model (15) time trend
β_p	-0.120**		-0.151**	
	-0.037		-0.048	
β_y	-0.022	0.063	0.219	0.155
	-0.045	-0.151	-0.19	(0.251)
β_{v1}	0.450*	0.503*	0.440*	0.505*
	-0.181	-0.206	-0.184	(0.208)
β_{v4}	0.13	0.156	0.128	0.150
	-0.19	-0.224	-0.199	(0.294)
β_{pmax+}		-0.118$^+$		
		-0.059		
β_{p-}		-0.101*		-0.134$^+$
		-0.039		(0.079)
Post-1978 time trend			-0.003	-0.004
			-0.002	(0.005)
β_{pmax}				-0.097
				(0.156)
β_{p+}				-0.112$^+$
				(0.057)
β_0	2.43	1.707	1.679	1.422
	-1.482	-1.606	-1.429	(1.656)
Observations	41	41	41	41
R^2	0.882	0.856	0.892	0.857
Long-run income elasticity				0.155
				(0.62)
Long-run price elasticity				
Long-run price elasticity to maximums				
Long-run price elasticity to increases		-0.118		-0.112
		(-2.00)		(-1.97)
Long-run price elasticity to decreases		-0.101*		-0.134
		(-2.61)		(-1.69)
AIC	-221.959	-211.828	-223.559	-208.188

Column (*b*) includes the restriction $\beta_{pmax} = \beta_{p+}$. All models are estimated by OLS with White-Huber robust standard errors. Lags in columns (a), (b), and (c) are selected by AIC. Using standard model selection criteria, Model (a) is preferred to models (b), while model (c) is preferred to model (d). $^+$, *, ** *** indicate statistical significance levels at 10%, 5%, 1%, and 0.1% respectively. As in Table 2, the irreversible model is rejected in favour of the standard reversible model once time trends are included in the model.

Table 4: Estimates from basic models. Models with and without time trends

	Model (12)-(a)	Model (12)-(b)	Model (12)-(c)
γ_{p1}	-0.042	-0.065	-0.073*
	-0.031	-0.048	(0.034)
$\gamma_{\Delta 1}$	-0.392***	-0.373***	-0.418***
	-0.065	-0.069	(0.058)
γ_{y1}	-0.367*	-0.262	-0.252
	-0.172	-0.207	(0.156)
$\gamma_{\Delta y}$	-0.337	-0.223	-0.395^{+}
	-0.218	-0.291	(0.211)
γ_{p3}	-0.033	-0.031	
	-0.028	-0.031	
γ_{y3}	-0.054	-0.01	
	-0.189	-0.215	
γ_{p4}	-0.003	0.001	-0.020
	-0.021	-0.022	(0.020)
γ_{y5}	0.427*	0.395*	0.332*
	-0.181	-0.184	(0.161)
γ_{v1}	0.716***	0.687***	0.642***
	-0.119	-0.14	(0.114)
γ_{v3}	-0.197	-0.239	
	-0.191	-0.209	
γ_{v4}	0.16	0.174	0.110
	-0.159	-0.168	(0.142)
Post-1978 time trend		-0.001	-0.001
		-0.002	(0.001)
γ_0	1.786	1.707	1.129
	-1.364	-1.494	(1.248)
Observations	41	41	41
R^2	0.951	0.952	0.947
Long-run income elasticity	-0.367*	-0.223	-0.395
	(-2.13)	(-0.77)	(-1.87)
Long-run price elasticity	-0.392***	-0.373***	-0.418***
	(-6.07)	(-5.40)	(-7.22)
AIC	-244.033	-242.974	-244.769

All models are estimated by OLS with White-Huber robust standard errors. Lags in columns (a), (b), and (c) are selected by AIC. Using standard model selection criteria, Model (a) is preferred to models (b), while model (c) is preferred to model (d). $^{+}$, *, ** *** indicate statistical significance levels at 10%, 5%, 1%, and 0.1% respectively.

6. Conclusion

India's oil demand has soared over the last few years, reaching an average figure for oil demand growth y/y of 0.40 mb/d in 2018, compared with 0.1–0.15 mb/d over the previous decade. This rise in demand could have implications for India's recently acquired status as a net exporter of petroleum products. In comparison, China's oil demand has slowed to around 0.30 mb/d from levels of 0.50 mb/d in the previous decade.

To shed light on this crucial area, we uses single-equation dynamic models to estimate petrol demand in India using a data set compiled from Indian Ministry of Road Transport and Highways (and augmented national accounts data). We find price elasticities of -0.418 (long-run) and -0.189 (short run), which indicates indicates that when price increases by 10%, demand reduces by approx 4% in a reasonably long period of time that allows the consumers to adjust their consumption behaviour.

Estimated long-run elasticities are higher than their short-run counterparts, which is in line with expectations based on the existing literature. We find price elasticities of -0.418 (long-run) and -0.189 (short run), which indicates indicates that when price increases by 10%, demand reduces by approx 4% in a reasonably long period of time that allows the consumers to adjust their consumption behaviour. Prices appear to be more elastic in India rather than say USA where studies estimate petrol elasticities to be in the range of -0.02 to -0.04 in the short term.

We find similar evidence for short-term demand elasticities as elsewhere in the literature ([2, 3, 7, 9, 12, 13, 25, 26, 35, 37]). On the other hand, we find evidence that long-run elasticities are not as high as estimated elsewhere. For example, Oxford Institute for Energy Studies [2, 3] estimates the long-run demand elasticities for petrol and gasoline to be around 1. Our finding support previous estimates by Burke and Nishitateno [12] who estimate the worldwide petrol demand elasticities to be between -0.2 to -0.5.

Our testing indicates long-term unidirectional (Granger) causality from real income to petrol consumption. The direction matters. If there was unidirectional Granger causality running from petrol consumption to economic growth, then reducing petrol consumption could put downward pressure on national income. Alternatively, if there was evidence of unidirectional Granger causality running from economic growth to petrol consumption then one could suggest that reducing consumption through energy conservation and demand side measures would not be a detriment on economic growth.

Table 5: Data used in sample, years 1966-2019.

Variable	Source
Petrol consumption	bp Statistical Review of World Energy 2020
Male and female average earnings	International Monetary Fund, Government Finance Statistics
GNP (current US$)	World Bank national accounts data
Population	United Nations Population Division's World Population Prospects: 2020 Revision.
CPI	International Monetary Fund, International Financial Statistics and data files.
Petrol Price Index	Ministry of Petroleum & Natural Gas, Government of India. https:/ppac.gov.in
Registered Motor Vehicles in India	Indian Ministry of Road Transport and Highways. https://data.gov.in
Petrol consumption	Ministry of Petroleum & Natural Gas, Government of India

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