Fuel demand, carbon tax and electric vehicle adoption in India's road transport

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Abstract

To reduce oil import dependence and carbon emission from road transport, the study estimates the demand for gasoline, high-speed diesel and electric vehicles (EV) in India using non-linear cointegration techniques. The data spans from November 2014 to April 2022. Gasoline, high-speed diesel and EV demand are found to be asymmetric in mean and quantiles, exhibiting extreme tail dependence. Gasoline and high-speed diesel demand are price inelastic, which means that taxation is an ineffective policy instrument to reduce their demand and carbon emissions. However, such taxation could increase the demand for EV. A decrease in electricity prices would also increase the demand for EV while negatively impacting high-speed diesel demand. The study recommends that reducing electricity prices and imposing an additional carbon tax on gasoline and high-speed diesel could encourage electric mobility, eventually reinforcing India's 'net zero' target by 2070. Future studies could focus on forecasting EV demand under different scenarios.

Keywords: Electric vehicles; Asymmetry quantile cointegration; Demand elasticity; India; Carbon Tax

1. Introduction

Electric mobility is the backbone of the world's transition to a green economy. Many countries have set targets to increase the penetration of electric mobility and reduce the dependence on fossil fuels by the year 2030 as part of their collective resolution to limit the global warming temperature below 1.5-degree centigrade (Anika et al., 2022; Morgenthaler et al., 2021). Countries across the globe have initiated various policy interventions like providing financial incentives, rebates on road tax, subsidy on the purchase or manufacturing the electric vehicles (EV) (IEA, 2021a; Jin et al., 2022; Liu et al., 2022; Martins et al., 2023; Srivastava et al., 2022; Wangsa et al., 2023; Wappelhorst et al., 2020; Yang et al., 2022). The prime objectives of all such policy interventions are to reduce the number of fossil fuel-driven vehicles and replace these with EV(Breschi et al., 2023; Glyniadakis and Balestieri, 2023; Hosein et al., 2023; Williams et al., 2023). A list of policy interventions by major advanced and developing economies to promote electric mobility is summarized in Table A1 (Appendix).

Till now, the transportation sector has been heavily dependent on two major petroleum products, namely Gasoline and high-speed diesel (HSD) (EIA, 2021). HSD is only the type of diesel which is used as transportation fuel. Light Diesel Oil is used in India for industrial applications (PPAC, 2023); hence, it is excluded from the scope of the current study. India is the third-largest carbon emitter and the second-largest importer of crude oil. The country has set an ambitious target to reduce its oil import dependence by replacing petroleum-driven vehicles with EV and producing more and more electricity from renewable and other clean energy sources to achieve a net zero target by 2070. India is expected to meet 50% of its energy requirements from renewable energy by 2030 and reduce its excessive reliance on fossil fuels(Media Center, 2021).

To what extent an emerging economy like India would be able to reduce the demand for gasoline and HSD depends primarily on their price and income elasticity. Low price elasticity implies limited maneuverability to lessen the demand despite a price increase. Inelastic demand also suggests that imposing a carbon tax on gasoline and HSD has a marginal impact on carbon emission reduction (Erdogdu, 2014; Neto, 2012; Romero-Jordán et al., 2010; Sun et al., 2022). Income elasticity, on the other hand, would determine whether gasoline and HSD are luxury or necessary goods. Besides income and own price elasticity, cross-price elasticity would help us to establish whether EV can replace petroleum-driven vehicles and, if so, up to what extent (Brito et al., 2020; Fridstrøm and Østli, 2021; Sheldon and Dua, 2019). To the best of our knowledge, there is no such study available in the literature which has studied the impact of the growing penetration of electric mobility on the demand for gasoline and HSD in India. The current research tries to bridge the gap by estimating income, own and cross-price elasticity of gasoline and HSD demand for India using non-linear cointegration techniques, which address asymmetry in mean and quantiles. As a robustness check, the study estimates the demand for gasoline and HSD-driven vehicles and extends the study further by estimating the demand for EV. India imports around 80% of crude oil due to a stagnation in domestic production (Figure 1). India's oil import has increased from 184795 million tons (MT) in the financial year 2012 to 211980 MT in 2021(PPAC, 2022). The country is vulnerable to oil supply and price shocks, which significantly dent India's foreign exchange reserve and jeopardise its energy security. In India, petroleum refining has a capacity of 188.57 million tons and produces various petroleum products. Figure 2 depicts the consumption of various petroleum products, with gasoline and HSD being the main products consumed in transportation. Almost all the gasoline (99.6%) and 70% of HSD are consumed in the transportation sector (Ministry of Petroleum & Natural Gas, 2022). HSD is also used for power generation with 589 MW of utility-level capacity (Ministry of Power GoI, 2023). Additionally, diesel generators also provide backup power for various sectors. Estimates for the total capacity of diesel generators range from 72 to 90 GW (Singh Sarita, 2016; IEA, 2021)

Figure 1. Domestic production and import of crude oil

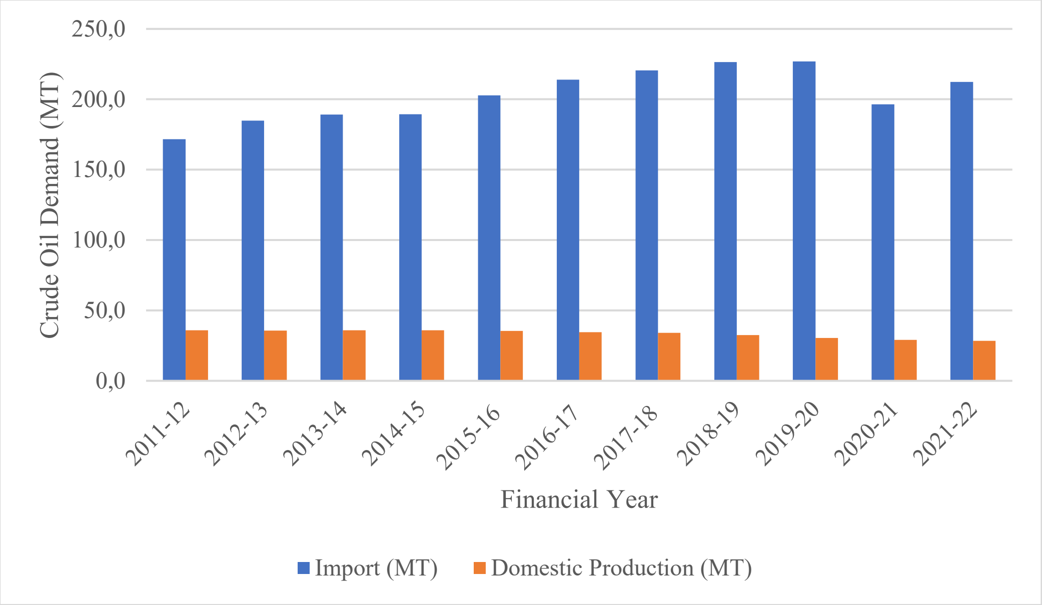

Figure 2: Consumption of petroleum products in the financial year 2021-22

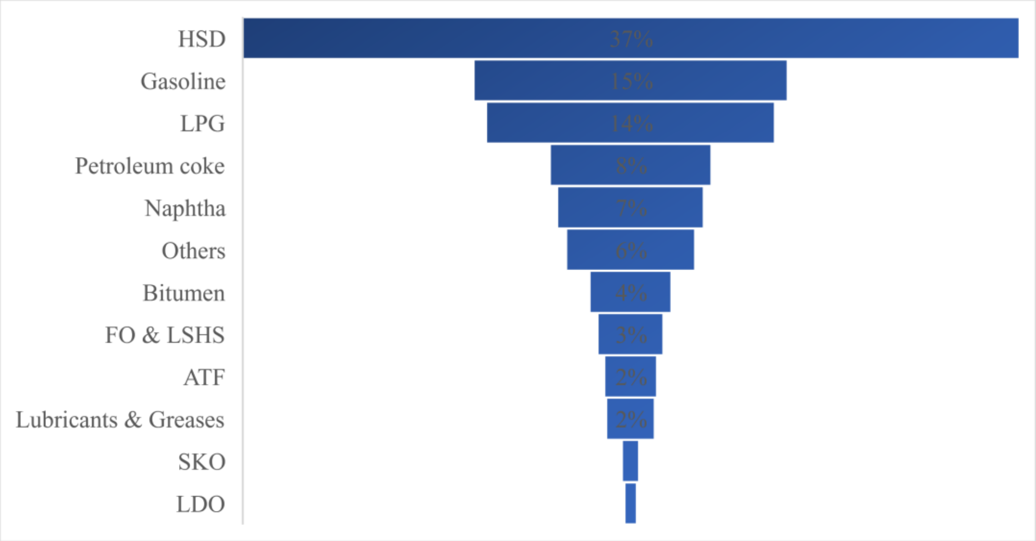

Table A2 (Appendix) lists major policy interventions witnessed by India’s petroleum sector in recent years. As far as the retail pricing of gasoline and HSD is concerned, before deregulation, they were administered by ‘trade parity pricing (TPP)’ comprising 80% import parity and 20% export parity price at the refinery gate. However, at retail levels, prices were fixed by the government. Public sector oil marketing companies were confronted with the vast recoveries, the difference between the trade parity price and the realised price at the refinery gate fixed by the central government (Ghosh Sajal and Kanjilal Kakali, 2013; Ghosh Sajal and Prasad Rohit, 2012). The retail price of gasoline and HSD were further inflated by heavy taxes imposed by central and state governments[1].

In the financial year 2021-22, India's expenditure on crude oil imports amounted to USD 120.6 billion, a significant increase from the USD 62.2 billion and USD 101.3 billion spent in the financial years 2020-21 and 2019-20, respectively(PPAC, 2021). The promotion of EV is being regarded as a dual solution capable of curbing the escalating import expenses while simultaneously mitigating tailpipe emissions within the transportation sector. India has also introduced several policy interventions to incentivize the manufacturing and purchase of EV (Table A2). In the "National Electric Mobility Mission" plan, the government of India (GOI) introduced a policy for "Faster Adoption and Manufacturing" of EV (FAME-I) in April 2015 (MHIPE, 2015). FAME policy framework, which has been extended twice till March 2024 with an enhanced financial outlay of Rs 10,000 Cr, is intended to push EV penetration in public transport. The GOI offers an upfront subsidy as a component of FAME-II, aimed at narrowing the price difference between the initial purchase cost of EV and internal combustion engine (ICE) vehicles. These policy interventions have catalyzed a substantial increase in EV sales, propelling the numbers from under 1,000 in April 2015 to approximately 77,000 by March 2022 (see Figure 3). Figure 3 also suggests that India may be nearing a significant tipping point, where electric vehicles account for 5% or more of new car sales, signifying the onset of mass adoption. However, by adopting the FAME-II policy (MHIPE, 2019), the GOI has aimed to achieve a target of 30% EV penetration for private cars, 70% for commercial cars, 40% for buses and 80% for two -and three-wheelers by the year 2030. As per a report released by NITI Aayog (Srivastava Pradeep et al., 2022), a government think tank, it anticipates 100% penetration of electric two-wheelers in the Indian market by the financial year 2026–27 under

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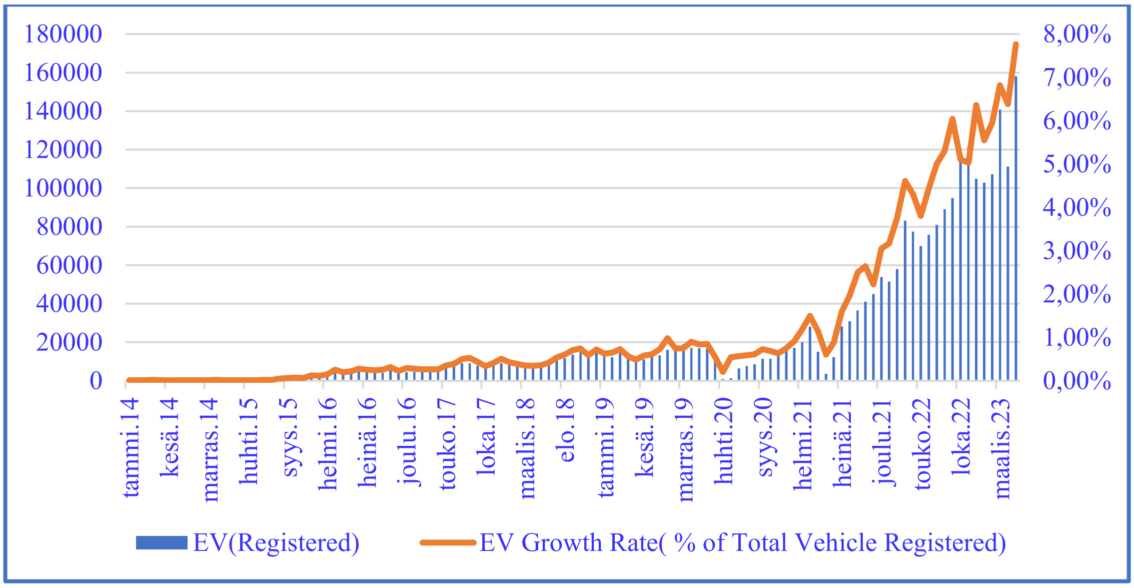
[1] Total tax imposed on gasoline and HSD were around 37% and 33% respectively in April 2022.

an optimistic scenario. In an alternative scenario driven by technology advancements and the withdrawal of current incentives by 2024, the report forecasts a 72% penetration rate by 2031.

Figure 3: Number of registered EV and the market penetration rate in India



Source: (National Informatics Centre, 2022)

Since EV come with almost zero tailpipe emission of air pollutants, they can tremendously contribute to decarbonising the transportation sector when electricity is generated from renewable energy sources (Arcentales et al., 2023; Jenn, 2023; Lau, 2022; Requia et al., 2018). India has an ambitious plan to install 500 Giga-watt (GW) of non-fossil fuel power plants by 2030 thereby reducing the reliance on coal, the dirtiest fossil fuel used for producing most of India's electricity. The transition to EV fueled by renewable energy should also reduce India's dependence on gasoline and HSD. Such inter-fuel substitution should significantly reduce the carbon footprints in India's transportation sector and cut India's import dependence on crude oil.

Thus, India's energy sector, in general, and the transportation sector, particularly, have witnessed several disruptions in recent years. Several reforms have been initiated in India to reduce the demand for gasoline and HSD and encourage EV penetration (Table A2). Moreover, the post-COVID economic stimulus package provided by many governments, including India, places a larger share of EV in the transportation sector (Kim and Karpinski, 2020). Under such circumstances, it is critical to revisit the elasticity estimates with recent data and the deployment of appropriate econometric methodologies that can capture the idiosyncratic nature of constituents of demand functions. Our study aims to address these intricate matters.

Studies that estimate the demand for gasoline and HSD in various countries, including India, are summarised in Table A3 (Appendix). The demand is price inelastic, though there are significant variations in elasticity estimates. Income elasticity, on the other hand, indicates that fuel (gasoline/HSD) is a necessary good (<1) for some countries and a luxury good (>1) for the rest. Despite HSD being the largest consumed oil product in India, the study related to its elasticity estimates is limited to (Ghosh, 2010), though there are recent studies that explore the dynamics between HSD price and inflation (Ghosh, 2022; Pradeep, 2022). In comparison, studies by (Kanjilal and Ghosh, 2017; Ramanathan, 1999; Sentenac-Chemin, 2012) have estimated the demand responsiveness of gasoline with changes in income and price (Table A3). Table A3 also reveals that all the India-specific studies use annual data, and the data span used in these studies cannot capture the impact of external and internal influences witnessed in recent years on elasticity estimates. Moreover, annual data employed in the previous studies fail to retain information on seasonality and the dynamic complexities of time series variables. It is also important to note that the small sample size arising from the annual data makes statistical inferences unreliable (M¨uller and Watson, 2019). Hence, increasing the data granularity from annual to monthly should capture the external and internal influences more preciously, leading to a robust elasticity estimate. The current study uses monthly data from November 2014 to April 2022 to capture the most critical periods of policy changes, e.g., deregulation of prices of HSD (Oct 2014), daily revision of price of gasoline and HSD (July 2017), adoption of the FAME policy framework for faster adoption and manufacturing of EV and COVID pandemic (Table A2).

So far as the choice of econometric model is concerned, earlier studies, barring a few (Kanjilal and Ghosh, 2018; Lee and Olasehinde-Williagasoline, 2021; Mukhtarov et al., 2020) use a linear framework to estimate static or time-invariant elasticity values of gasoline and HSD (Table A3). This assumption of constant price and income elasticity is highly unrealistic, which may yield misleading elasticity estimates. According to (Lee and Olasehinde-Williagasoline, 2021), assuming a constant elasticity in estimating the demand for gasoline and HSD is flawed. This is because there are general nonlinearities in demand caused by factors such as changes in policy formulation, technological advancements, and geopolitical reasons. So, the modelling strategies for estimating the elasticity must be carefully selected. While evaluating the income, own, and cross-price elasticity of gasoline and HSD demand for India, this study addresses the non-linearity issue in the demand equation from two angles. First, it examines how the demand function responds on average to positive and negative variations in price and income. The Nonlinear Auto-Regressive Distributed Lag (NARDL) model of cointegration (Shin et al., 2014) relaxes the linearity framework of (Pesaran et al., 2001) by inducting an asymmetric adjustment process of the independent variables. Second, this study evaluates the distributional asymmetry in price and income elasticity of gasoline and HSD demand for India. The quantile-dependent property is investigated by allowing cointegrating coefficients to vary across quantiles of the demand function (Cho et al., 2015; Xiao, 2009). This model investigates a strong possibility that gasoline and HSD demand for India may differ across quantiles and respond asymmetrically to positive or negative changes in determinants of demand.

The novelty of our study can be summarized as follows:

1. We re-estimate the income and price elasticity of gasoline and HSD demand for India using nonlinear cointegration techniques, shedding light on the asymmetric mean and quantile dependency of these fuels' elasticity. One of the unique contributions of this study is that, unlike previous studies, the MS or HSD demand functions do not

necessarily react similarly to the increase or decrease in its determinants. Moreover, the demand functions are allowed to respond differently as the demand of MS or HSD changes its states from low to medium or high.

2. Our study utilizes recent monthly data, in contrast to many previous studies that rely on annual data, ensuring a more accurate representation of rapidly changing internal and external factors.
3. In addition to estimating income and own-price elasticity, we also calculate cross-price elasticity for gasoline and HSD demand. This is the first instance in the literature where we explore the possibility of substitution between electricity and gasoline/HSD.
4. As a robustness check, we employ non-linear cointegration models to estimate the demand for gasoline and HSD-driven vehicles.
5. Finally, our study estimates the demand for Electric Vehicles (EV) to evaluate the increasing focus on green mobility in India.

Our empirical outcomes uncover the asymmetries in mean and quantiles in the demand functions of gasoline, HSD, and EV. This signifies that the demand function responds differently in mean and its extreme tails to the increase or decrease in determinants of demand. We find that an increase in the prices of gasoline and HSD has an insignificant impact on their respective demand functions, which indicates the rise in taxation is an ineffective policy instrument to curtail the demand for these fuels and hence their carbon emission. We also establish that gasoline is a complementary good to HSD as the fall (rise) in gasoline price results in the increase (decrease) in demand for HSD in anticipation of the decline(escalation) in HSD price. But, HSD is a substitute for gasoline as the rise in gasoline prices leads to increased HSD demand. This outcome can be attributed to the relative price differential advantage enjoyed by the HSD users over gasoline, where HSD price has historically maintained a lower price markup, although the HSD price deregulation in late 2014 brought down the relative price spread between gasoline and HSD. Another important discovery of our analysis is that both gasoline and HSD are substitutes for EV. Thus, the number of registered EV increases with the gasoline and HSD prices. Electricity and EV are found to be complementary as the fall (rise) in electricity prices leads to an increase(decrease) in EV penetration, although the decline in electricity prices has a much stronger impact on the number of EV registered than its increase. Thus, to enhance EV penetration, GOI should incentivise the fall in electricity prices through increased penetration of renewable energy mix. Further, an increase in prices of gasoline and HSD also helps the consumer to adopt EV.

The rest of the paper is organised as follows: section 2 describes the theoretical framework and data description. Section 3 summarises the materials and methods. Sections 4 and 5 analyze the results. Section 6 concludes the study, highlighting major policy prescriptions. Section 7 summarises the managerial implications of the study.

2. Theoretical Framework & Data Description

Several earlier studies had considered the demand for energy as a function of its price and income. Further, some other studies have also stated that the demand for energy depends on other factors like population, levels of urbanization, number of vehicles etc. (Eleyan et al., 2021; Gao et al., 2021; Liddle et al., 2020; Liddle and Parker, 2022; Wang and Lee, 2022; Xiuzhen et al., 2022). Govt of India (GOI) introduced the deregulation of prices of Gasoline in June 2010(Ministry of Petroleum & Natural Gas, 2010) and that of HSD in October 2014 (CCEA, 2014) due to the burgeoning economic burden of subsidies on the sales of these fuels. Prior to deregulation, prices of gasoline and HSD were controlled; hence, they did not reflect the actual market-determined prices. As part of the current study, the demand for gasoline and HSD is considered a function of income and own price for the post-deregulation period. Since gasoline and HSD are used as transportation fuels, there is a possibility of substitution or complementarities between these two fuels. Thus, to test interdependency, the demand functions of gasoline and HSD are estimated to accommodate the cross-price impact of gasoline and HSD. We have also considered electricity price as one of the predictors in these demand equations to assess whether electricity will impact the demand for these fuels. To validate the findings of our models regarding the demand for gasoline and HSD, we have estimated the sales of gasoline and HSD-driven vehicles. Given the fact that a significant portion of gasoline (approximately 99.6%) and HSD (around 70%) in India is consumed by the transportation sector(Ministry of Petroleum & Natural Gas, 2014), we expected that the demand functions for gasoline-driven vehicles and HSD-driven vehicles should generate directionally similar outcomes.

The study estimates the following Marshallian demand functions.

$$Y_t = \alpha + \beta * (Income_t) - \gamma * (Own\_Price_t) \pm \delta * (Cross\_\mathrm{Price}_t) \qquad (1)$$

where Y_t = demand for HSD or MS

α = constants

β= income elasticity of crude oil import demand

γ = own-price elasticity of crude oil import demand

δ= cross price-elasticity

2.1 Data Description

The data span ranges from November 2014 to April 2022. It covers important events such as the HSD deregulation, daily price revisions of gasoline and HSD, FAME I & II policy for EV penetration, aggressive expansion of renewable energy, and the COVID pandemic. The HSD deregulation was implemented on 18 October 2014, which dictates our sample's starting point (Table A2).

The prices of gasoline and HSD vary significantly across different Indian states. Factors such as transportation costs, state and central taxes can affect the prices of these fuels, leading to substantial price differences. This lack of uniformity in pricing makes it challenging to establish a single national-level price for gasoline and HSD. Furthermore, the prices of these fuels can also vary significantly among cities within the same state. For example, the price of gasoline in Mumbai is different from that in Pune, which is another city in the same state of Maharashtra. Similar trends are observed in the case of electricity prices. The cost of electricity generation in India is determined by several factors, including the source of power generation (such as coal, gas, hydro, nuclear, solar, and wind), transportation costs, and the charges imposed by the regulators. Additionally, the nature of the end-users (whether they are industrial, commercial, domestic, agricultural, etc.) can also influence electricity prices. Electricity prices can exhibit significant variations, not just among various states in India but also within cities located in the same state. Moreover, agricultural electricity tariffs (price) are often subsidized by industrial and commercial tariffs. It is also important to note that the frequency of electricity tariff revisions in India varies depending on the state, and there is no uniform policy across the country. Some states, such as Delhi and Tamil Nadu, revise electricity tariffs every six months, while others, like Maharashtra, Gujarat, and Uttar Pradesh, revise tariffs annually. In certain states such as Bihar, Jammu and Kashmir, and Odisha, tariff revisions take even longer. None of the Indian states have a policy of revising tariffs on a quarterly or monthly basis. Hence, the study uses the Wholesale Price Index (WPI) of gasoline, HSD[2] and electricity as a proxy for pan-India prices following earlier works (Dasgupta and Sarangi, 2021; Pal and Mitra, 2016; Tiwari and Menegaki, 2019). Since the data used in the current study is at a monthly granularity, it is not possible to use the Gross Domestic Product (GDP), which is published quarterly in India, as a representation of income for demand models. Therefore, to address this issue, the study uses monthly data on IIP as a proxy for GDP[3] , which has also been used as a substitute for GDP in previous studies such as those conducted by (Gaur and Dash, 2015; Mishra et al., 2020; Moody et al., 1993). Table 1 describes the variables used while mentioning their sources.

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[2] We have collected the monthly price of gasoline and HSD in four metro cities and taken the average value as a proxy for the pan-India price of gasoline and HSD though the series suffer from missing observations. We then converted the nominal (pump) price to real series and check if these prices share a long-run relationship with the WPI of gasoline and HSD. Since both the series are I(1) in nature, we conducted (Søren Johansen and Juselius, 1990) cointegration tests. Results suggest that the series are cointegrated, which means WPIs could be used as proxies for gasoline and HSD prices.

Johansen-Juselius cointegration tests

	WPI_MS & Avg_gasoline_real		***WPI_HSD & Avg_HSD_real***	
Null Hypotheses	**Trace Statistic**	**Max-Eigen Statistic**	**Trace Statistic**	**Max-Eigen Statistic**
$r = 0$ $(No\ cointegration)$	18.283**[0.01]	17.327***[0.00]	28.411***[0.00]	27.554***
$r \leq 1$ $(at\ most\ one\ cointegrating\ relation)$	1.315 [0.25]	1.315 [0.25]	0.011[0.91]	0.011[0.91]

Notes: *, **, *** signify 10%, 5%, and 1% levels of significance.

[3] To confirm that IIP can be used as a suitable proxy for GDP, we conducted an investigation to determine if the two variables share a long-term or cointegrating relationship over the duration of our data. As GDP is only available at a quarterly frequency, we first converted the data to monthly GDP by using quadratic interpolation. Unit root tests indicate that GDP is a non-stationary series of order one, or I(1), while IIP is a stationary series, as also demonstrated in Table 3. Given the differing orders of integration, we applied both ARDL and NARDL bounds tests for cointegration. The results in the table below show that both series are cointegrated, which validates the use of IIP as a proxy for GDP.

Models	**ARDL**	**NARDL**
$\boldsymbol{GDP = f(IIP)}$: **F statistic**	2.19	9.39***
$\boldsymbol{IIP = f(GDP)}$: **F statistic**	4.27**	62.03***
5% critical value [LB, UB]	*[3.62, 4.16]*	*[3.1, 3.87]*
1% critical value [LB, UB]	*[4.94, 5.58]*	*[4.13,5]*

Notes: *, **, *** signify 10%, 5%, and 1% level of significance.

Table 1: Description of variables

Data Description	After logarithmic transformation	Source
Index of industrial production	*IIP*	https://mospi.gov.in/web/iip/home
Monthly consumption of gasoline in	*MS*	https://www.ppac.gov.in/content/147_1_ConsumptionPetroleum.aspx
Monthly consumption of HSD	*HSD*	https://www.ppac.gov.in/content/147_1_ConsumptionPetroleum.aspx
Monthly sales of all gasoline-driven vehicles in India	*VMS*	https://vahan.parivahan.gov.in/vahan4dashboard
Monthly sales of all HSD-driven vehicles in India	*VHSD*	https://vahan.parivahan.gov.in/vahan4dashboard
Monthly sales of all electric vehicles in India	*VEV*	https://vahan.parivahan.gov.in/vahan4dashboard
Wholesale price index of gasoline	*Pr_MS*	https://eaindustry.nic.in/
Wholesale price index of HSD	*Pr_HSD*	https://eaindustry.nic.in/
Wholesale price index of electricity	*Pr_ELEC*	https://eaindustry.nic.in/

2.2. Descriptive analysis

Table 2 summarizes the statistical properties where all variables depart from normality with positive excess kurtosis. For example, IIP has the highest double-digit positive excess kurtosis of 24.42 (=27.42-3) followed by VHSD, VMS, HSD, and MS, suggesting that these variables have heavy right tails. It also indicates the presence of an excess leptokurtic pattern in these series. Price variables show an excess kurtosis of 2.6, 1.1, and 0.93 for Pr_ELEC, Pr_MS, and Pr_HSD, respectively, exhibiting a heavy tail pattern. VEV has the least excess kurtosis (0.73). As India's economy has been growing rapidly, it has experienced significant non-linear growth in both average and per capita income. This non-linear relationship between energy consumption and economic growth has been established by (Ghosh and Kanjilal, 2020; Kanjilal and Ghosh, 2021). Substantial growth in per capita income has, in turn, been accompanied by a significant increase in the sales of vehicles in road transport in India. An increase in vehicle sales has thereby raised the demand for fuels like MS and HSD. These instances of non-linear growth are among the likely factors contributing to the high kurtosis observed in the variables selected for our study. Moreover, during the study period, gasoline and HSD prices underwent deregulation, resulting in an uneven distribution of fuel prices. So, the review of descriptive statistics reveals that the demand functions cannot be modelled in a linear framework that estimates constant elasticity values.

Table 2: Descriptive statistics

	IIP	*HSD*	*VHSD*	*Pr_HSD*	*MS*	*VMS*	*Pr_MS*	*VEV*	*Pr_ELEC*
Mean	4.81	8.77	12.14	4.49	7.69	14.09	4.44	8.75	4.69
Median	4.82	8.78	12.23	4.49	7.72	14.12	4.42	9.11	4.67
Maximum	5.00	8.96	12.56	5.12	7.98	14.51	5.06	11.27	4.91
Minimum	3.99	8.09	9.70	3.92	6.88	12.17	4.05	5.15	4.59
Std. Deviation	0.12	0.12	0.39	0.22	0.18	0.32	0.20	1.44	0.06
Skewness	-3.86	-1.99	-3.80	0.41	-1.20	-3.68	0.95	-1.03	1.51
Kurtosis	27.42	11.67	20.83	3.93	6.07	20.67	4.10	3.73	5.60
Jarque-Bera test *(p-value)*	2459.4** *(0.00)*	340.9** *(0.00)*	1408.5** *(0.00)*	5.7* *(0.06)*	57.1** *(0.00)*	1373.9** *(0.00)*	18.1** *(0.00)*	17.9** *(0.00)*	59.3** *(0.00)*

Notes: ** represents 5%, and * indicates 10% level of significance.

2.2 Unit root tests

The study uses ADF and Bai & Perron unit root tests (Bai and Perron, 2003, 1998) with structural breaks to check the stationarity properties of the time series variables. Both tests recommend the presence of structural breaks in most variables apart from IIP (Table 3). Thus, the unit root tests reveal that the variables display a combination of I(0) and I(1) features, which further suggests the suitability of applying non-linear cointegrating models (NARDL and QNARDL) models in estimating demand functions.

Table 3: Tests for non-stationarity

Series	**ADF**	**Bai and Perron**
	Level (intercept and trend)	
IIP	-4.74**	-6.53**
HSD	-1.86	0.45: Break Date: 2020M08
VHSD	-1.55	-0.05: Break Date: 2021M01
Pr_HSD	-2.50	-3.30: Break Date: 2021M01
MS	-2.11	-4.29: Break Date: 2016M02
VMS	-1.47	0.79: Break Date: 2020M12
Pr_MS	-2.43	-3.56: Break Date: 2021M01
VEV	-2.26	-3.20: Break Date: 2015M08
Pr_ELEC	-1.20	-4.69**: Break Date: 2021M07
	First difference (intercept and no trend)	
IIP	NA	NA
HSD	-10.37**	-13.14**
VHSD	-9.28**	-10.25**
Pr_HSD	-6.50**	-6.94**
MS	-12.13**	-18.51**
VMS	-10.37**	-10.66**
Pr_MS	-5.98**	-5.93**
VEV	-9.13**	-10.38**
Pr_ELEC	-5.72**	-8.52***

Note: This table shows the results of ADF and Bai & Perron unit root tests.'***' and '**' imply a significance level of 1% and 5%, respectively. The breakpoints in the Bai Perron tests are indicated in parentheses.

3. Materials and methods

This section briefly discusses NARDL and QNARDL methodologies for estimating demand functions. Linear cointegration models (Engle and Granger, 1987; Soren Johansen and Juselius, 1990; Pesaran et al., 2001) have been widely applied in empirical research to investigate cointegrating relationships. (Pesaran et al., 2001)'s method of Autoregressive-Distributed lag (ARDL) bounds tests also investigates linear cointegration, but it overcomes the limitations of earlier models that enable the investigation of the long-run link of variables having different order of integration, i.e. $I(0)$ or $I(1)$. However, this approach does not take into account possible asymmetries in the variables.

(Shin et al., 2014) 's NARDL extends the work of (Pesaran et al., 2001)'s ARDL model that introduces non-linearity by adding asymmetric effects of regressors. This makes the NARDL model suitable for examining the relationship of variables with a combination of I(1) and I(0) properties, which seems to be the case in the current context. By considering potential nonlinearities and asymmetries in the relationship between variables, the NARDL model offers a flexible approach for empirical research, allowing for a more nuanced analysis of cointegrating relationships.

3.1 NARDL model

Shin et al. (2014)'s general form of the NARDL model is defined as

$$\Delta Z_t = C_0 + \delta_1 Z_{t-1} + \delta_2^+ X_{t-1}^+ + \delta_2^- X_{t-1}^- + \delta_3^+ Y_{t-1}^+ + \delta_3^- Y_{t-1}^- + \sum_{i=1}^{p} \emptyset_i \Delta Z_{t-i} + \sum_{j=1}^{q1}(\alpha_j^+ \Delta X_{j-1}^+ + \alpha_j^- \Delta X_{j-1}^-) + \sum_{l=1}^{q2}(\beta_l^+ \Delta Y_{l-1}^+ + \beta_l^- \Delta Y_{l-1}^-) + \epsilon_t \qquad (2)$$

Δ is the first difference operator, Z_t is the dependent variable, X_t and Y_t are the dependent variables, δ_1, δ_2, δ_3 are long-term coefficients, α, ø, β are short-run coefficients. δ_1 is the speed of adjustment towards long term equilibrium of dependent variable.

X_{t-1}^+/Y_{t-1}^+, X_{t-1}^-/Y_{t-1}^- are the partial sums of positive and negative changes in the variables X/Y, and expressed as below:

$$X_t^+ = \sum_{i=1}^{t} \Delta X_i^+ = \sum_{i=1}^{t} Max(\Delta X_i, 0)$$

$$X_t^- = \sum_{i=1}^{t} \Delta X_i^- = \sum_{i=1}^{t} Min(\Delta X_i, 0)$$

$$Y_t^+ = \sum_{i=1}^{t} \Delta Y_i^+ = \sum_{i=1}^{t} Max(\Delta Y, 0)$$
$$Y_t^- = \sum_{i=1}^{t} \Delta Y_i^- = \sum_{i=1}^{t} Min(\Delta Y_i, 0)$$

The following hypotheses determine the cointegration relationship of equation (2),

$$\text{Ho: } \delta_1 = \delta_2^+ = \delta_2^- = 0\,;\ \delta_1 = \delta_3^+ = \delta_3^- = 0;\ \delta_1 = \delta_4 = 0$$
$$\text{Ha: } \delta_1 \neq \delta_2^+ \neq \delta_2^- \neq 0\,;\ \delta_1 \neq \delta_3^+ \neq \delta_3^- \neq 0\,;\ \delta_1 \neq \delta_4 \neq 0$$

Long-run elasticity for positive and negative shocks to exogenous variables is estimated as follows:

$$\omega_2^+ = -\frac{\delta_2^+}{\delta_1};\ \omega_2^- = -\frac{\delta_2^-}{\delta_1};\ \omega_3^+ = -\frac{\delta_3^+}{\delta_1};\omega_3^- = -\frac{\delta_3^-}{\delta_1};\ \omega_4 = -\frac{\delta_4}{\delta_1}$$

$\alpha_j^+, \alpha_j^-, \beta_j^+, \beta_j^-, \gamma,$ are used to capture the short-term elasticity of the independent variables.

Wald tests are used to test the long-and short-term asymmetries in independent variables. The Following hypotheses are used for Wald tests:

Long Term:

$$\text{Ho:}\quad \omega_2^+ = \omega_2^-;\ \omega_3^+ = \omega_3^-$$
$$\text{Ha:}\quad \omega_2^+ \neq \omega_2^-;\ \omega_3^+ \neq \omega_3^-$$

Short Term:

$$Ho = \sum_{j=1}^{q1} \alpha_j^+ = \sum_{j=1}^{q1} \alpha_j^- ; \sum_{j=1}^{q2} \beta_j^+ = \sum_{j=1}^{q2} \beta_j^-$$

$$Ha = \sum_{j=1}^{q1} \alpha_j^+ \neq \sum_{j=1}^{q1} \alpha_j^- ; \sum_{j=1}^{q2} \beta_j^+ \neq \sum_{j=1}^{q2} \beta_j^-$$

3.2 QNARDL model

This study also employs the QNARDL model, which is a combination of NARDL and QARDL developed by (Cho et al., 2015) to understand the location asymmetries in the short and long-term adjustments.

The model can be defined as follows:

$$Q_{\Delta Yt} = \rho_0(\tau) + \rho_Y(\tau)Y_{t-1} + \rho_s^+(\tau)X_{t-1}^+ + \rho_s^-(\tau)X_{t-1}^- + \sum_{i=1}^{p-1} \alpha_i(\tau)\Delta Y_{t-1} + \sum_{i=0}^{q-1}(\theta_i^+(\tau)\Delta X_{t-1}^+ + \theta_i^-(\tau)\Delta X_{t-1}^- + \varepsilon_t(\tau) \qquad (3)$$

where Y is the dependent variable, and τ represents k^{th} quantile of Y ranging between 0 and 1. Seven quantile brackets, 5%, 10%, 15%, 50%, 85%, 90%, and 95%, are selected following the distribution of Y. QNARDL model tests short- and long-run asymmetric impact for the defined quantiles. Table 3.1 has descriptions of variables used in the above QNARDL equation.

Smaller quantiles are associated with the economic crisis, and larger quantiles are associated with economic expansion(Hashmi et al., 2022). Since energy consumption is cointegrated with income (Kanjilal and Ghosh, 2021), in the context of the current study, a smaller quantile of demand for gasoline is associated with a period of economic crisis and a higher quantile of demand is linked with a period of economic expansion.

The below table summarize a list of variables used to estimate demand functions using NARDL and QNARDL models.

Table 3.1: Description of variables used for estimating demand functions by the NARDL and QNARDL models.

Demand Equation number	Endogenous Variable	Exogenous variables		
	Z	X	Y	W
4.1	HSD	Pr_HSD	Pr_ELEC	IIP
4.2	HSD	Pr_HSD	Pr_MS	IIP
4.5	MS	Pr_MS	Pr_ELEC	IIP
4.6	MS	Pr_MS	Pr_HSD	IIP
4.3	VHSD	Pr_HSD	Pr_ELEC	IIP
4.4	VHSD	Pr_HSD	Pr_MS	IIP
4.7	VMS	Pr_MS	Pr_ELEC	IIP
4.8	VMS	Pr_MS	Pr_HSD	IIP
5.1	VEV	Pr_ELEC	Pr_HSD	IIP
5.2	VEV	Pr_ELEC	Pr_MS	IIP

4. Results and Discussion

Descriptive analysis and unit root test results have guided us to examine non-linearity in the demand functions using NARDL and QNARDL models.

4.1 Estimation of HSD demand through NARDL and QNARDL models

For HSD demand, the following demand functions have been estimated[4].

$$HSD = f(IIP, Pr\_HSD, Pr\_ELEC) \quad (4.1)$$

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[4] To validate the demand for HSD, we have also estimated the demand for HSD-driven vehicles. Since there are significant variations in the price of HSD-driven vehicles and no price index is available, we use the following functional forms:

$$VHSD = f(IIP, Pr\_HSD, Pr\_ELEC) \quad (4.3)$$

$$VHSD = f(IIP, Pr\_HSD, Pr\_MS) \quad (4.4)$$

where $VHSD$ represents the HSD driven vehicles registered.

$$HSD = f(IIP, Pr\_HSD, Pr\_MS) \qquad (4.2)$$

where

IIP = Index of Industrial Production, used as a proxy for income

HSD = Demand for HSD

Pr_HSD = HSD price
Pr_MS = Gasoline price
Pr_ELEC= Electricity price

First, we have estimated HSD demand functions (*Models 4.1* and *4.2*) through the NARDL model. As a precursor to the NARDL model, we first estimate the ARDL model. The estimated F-statistics of ARDL bounds tests are lower than the lower bound, ruling the possibility of linear cointegration in the demand functions of HSD. NARDL Bounds test for cointegration, on the other hand, rejects the null of no cointegration since F-Statistics (14.22, 11.98) are higher than the upper bound (Table 4). It confirms that the cointegrating relationship between *HSD, IIP, Pr_HSD* and *Pr_ELEC* (*Pr_MS* for *Model 4.1*) is asymmetric. Wald tests for long-run asymmetries further validate that the HSD demand is asymmetric (Section III of Table 4).

The statistical significance of the lagged dependent variables representing the speed of adjustment, with a negative sign, indicates the stability of the model. The residuals do not violate the assumptions of 'no auto-correlation' and 'no heteroscedasticity' (Section IV, Table 4).[5] Moreover, CUSUM and CUSUM-SQ tests confirm the stability of estimated coefficients in NARDL models. Hence, the diagnostics favour the selection and estimation of the model.

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[5] The deviation from 'normality' assumption in the *Model 4.1* (Section IV, Table 4) hints at the need to examine the tail ends of demand distribution which is discussed in QNARDL results.

Table 4: NARDL estimation results of HSD demand

Variables	***Model 4.1:*** ΔHSD_t *f(IIP, Pr_HSD$^{(+)}$,Pr_HSD$^{(-)}$,Pr_ELEC$^{(+)}$,Pr_ELEC$^{(-)}$)*	***Model 4.2:*** ΔHSD_t *f(IIP, Pr_HSD$^{(+)}$,Pr_HSD$^{(-)}$,Pr_MS$^{(+)}$,Pr_MS$^{(-)}$)*
Section I: Conditional Error Correction		
	Coeff *(p-value)*	**Coeff *(p-value)***
$Constant$	4.75** *(0.00)*	4.97***(0.00)*
HSD_{t-1}	-1.22 ** *(0.00)*	-1.18***(0.00)*
IIP_{t-1}	1.24** *(0.00)*	1.15**(0.00)
$Pr\_HSD_t^+$	-0.002 *(0.61)*	0.29 *(0.24)*
Pr_HSD^-	-0.07 *(0.13)*	0.11*(0.46)*
$Pr\_ELEC_{t-1}^+$	0.002 *(0.98)*	
Pr_ELEC^-	0.19 *(0.31)*	
$Pr\_MS_{t-1}^+$		-0.34*(0.15)*
$Pr\_MS_t^-$		-0.07*(0.67)*
ΔHSD_{t-1}	0.65** *(0.00)*	0.63***(0.00)*
ΔHSD_{t-2}	0.34***(0.00)*	0.39***(0.00)*
ΔHSD_{t-3}		-0.05*(0.41)*
ΔHSD_{t-4}		0.12***(0.04)*
ΔIIP_t	0.83** *(0.00)*	0.89***(0.00)*
ΔIIP_{t-1}	-0.79***(0.00)*	-0.75***(0.00)*
ΔIIP_{t-2}	-0.53***(0.00)*	-0.54***(0.00)*
$\Delta Pr\_HSD_t^+$	-0.39** *(0.05)*	
$\Delta Pr\_HSD_{t-1}^+$	0.52** *(0.01)*	
$\Delta Pr\_HSD_{t-2}^+$	-0.34**(0.07)*	
$\Delta Pr\_HSD_{t-3}^+$	-0.45***(0.01)*	
$\Delta Pr\_ELEC_t^+$	-0.92***(0.00)*	
$\Delta Pr\_MS_t^+$		-0.82***(0.02)*
$\Delta Pr\_MS_{t-1}^+$		0.32*(0.13)*
$\Delta Pr\_MS_{t-2}^+$		-0.33*(0.14)*
$\Delta Pr\_MS_{t-3}^+$		-0.69***(0.00)*
$\Delta Pr\_MS_{t-4}^+$		0.31*(0.12)*
$\Delta Pr\_MS_{t-5}^+$		-0.53***(0.00)*
Section II: Long-Run Asymmetric Effects		
Variables	**Coeff *(p-value)***	**Coeff *(p-value)***
IIP	1.01** *(0.00)*	0.97***(0.00)*
Pr_HSD^+	-0.02 *(0.54)*	0.24 *(0.25)*
Pr_HSD^-	-0.05* *(0.06)*	0.09 *(0.37)*
Pr_ELEC^+	0.001 *(0.98)*	
Pr_ELEC^-	0.16 *(0.34)*	
Pr_MS^+		-0.28 *(0.15)*
Pr_MS^-		-0.06 *(0.65)*
Section III: Bounds and Long-run (LR) Wald asymmetry tests		
F-stat(ARDL)	2.18	3.06
F-stat(NARDL)	14.22**	11.98**
LR Wald Test Pr_HSD(p-value)	*(0.00)***	*(0.00)***
LR Wald Test Pr_ELEC(p-value)	*(0.00)***	
LR Wald Test Pr_MS (p-value)		*(0.14)*
Section IV: Statistics and Diagnostics		
CUSUM Test	ST	ST
CUSUM-SQ Test	ST	ST
F (Serial Correlation) (p-value)	*(0.48)*	*(0.97)*
F (Heteroscedasticity) (p-value)	*(0.72)*	*(0.17)*
JB (Normal)(p-value)	*(0.00)***	*(0.71)*

Note: Lower and upper band critical values for the bounds test (ARDL): 2.79, 3.67 respectively. Upper band critical values for the bounds test (NARDL) are 2.39 and 3.38 at the 5% significance levels. () shows p-values. * = 10% ;**=5% ***=1% significance levels. ST indicates 'stable'. UST implies 'unstable'.

Investigation of the long-run elasticity of income (IIP), own-price (Pr_HSD), and cross-price (Pr_ELEC or Pr_MS) on the HSD demand (Section II of Table 4), we observe that a 1% decline in HSD price leads to an inelastic increase in its demand by 0.05% for the first model with statistical significance at 10% level. Electricity price also has no significant impact on the HSD demand. Since more than 64% of HSD in India is consumed for freight movement (Infrastructure advisory CRISIL, 2021), it is challenging to reduce this consumption given the current state of technological and charging infrastructure advancements in the country. As a result, the lack of significance of electricity prices on HSD demand is primarily attributed to the skewed distribution of HSD demand towards freight movement. The second model shows an insignificant impact of both HSD and gasoline prices on the HSD demand. This independence of HSD demand on the price of gasoline is likely due to the fact that only around 17% of HSD is used in private cars/commercial taxis compared to around 40% of the gasoline consumption in this fleet segment.

The statistical insignificance of $Pr\_HSD_t^+$ suggests that imposing an additional tax on HSD in the form of a "carbon tax" would not reduce the HSD demand and carbon emission from the fuel. The conclusions drawn are comparable to those of Aklilu (2020), who demonstrated that the current tax system for gasoline and HSD might be insufficient to meet the European Union's emission goals. It also indicates that the government can earn substantial tax revenue by imposing an additional tax on HSD in India. The revenue generated from this tax could be utilized to establish infrastructure for electric mobility or support research and development in emerging energy technologies. (Pradhan and Ghosh, 2022).

The income effect hovers around '1' and is statistically significant in both cases.[6] In the short run, an increase in HSD prices mainly causes a decline in HSD demand where the effect is inelastic and varies between 0.39% and 0.45%. The elasticity estimates are different from Ghosh (2010) due to the choice of models (ARDL versus NARDL), time span, and data frequency (Table A3). As revealed in section-I of Table 4, an increase in short-run gasoline prices leads to a moderately elastic fall in HSD demand in the second demand function. The findings indicate that gasoline is a complement to HSD in the short run. This suggests that perhaps people curtail their mobility for the short run in expectation of a rise in the prices of HSD. We have also observed demand for HSD goes up with an increase in the price of electricity in the short-run. This finding indicates that electricity acts as a substitute for HSD demand in the short run.

For validation purposes, we extended our analysis to estimate 'HSD-driven vehicles registered' as a proxy for HSD demand (as presented in Table A4). We opted to use the same NARDL and QNARDL models for this purpose to maintain empirical consistency. By doing so, we have ensured that our validation process is in line with the original modeling strategy, thereby providing a robust and coherent assessment of the findings. The elastic income effect on the demand for HSD-driven vehicles is affirmed (2.90% and 3.36%, Section II-Table A4). Interestingly, the finding that gasoline acts as a complement to HSD demand is further confirmed. A decline in gasoline prices is a leading indicator for the fall in HSD prices, thereby causing an increase in demand for HSD-driven vehicles by 0.62% (Table A4). This outcome can be attributed to the relative price differential advantage enjoyed by the HSD users over gasoline. Notably, the electricity price has two months lagged effect where a 1% decline in

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[6] The asymmetric effect of *IIP* has an almost similar elastic effect on the HSD demand in both cases, where increases in income drive up the demand for HSD and the decrease in income has a similar impact on the demand in the negative direction. This finding is validated for all demand functions estimated in the study. Hence, the asymmetric effect of *IIP* has been kept outside the scope of this study to save degrees of freedom.

electricity price leads to a very high elastic (3.72%) fall in HSD-driven vehicles registered. In addition, the departure from normality is also witnessed in Table A4, suggesting the influence of extreme tails in HSD demand.

We use the QNARDL model in the next stage to investigate distributional asymmetry. The quantiles ($Q_{0.05}$, $Q_{0.10}$, $Q_{0.15}$, $Q_{0.50}$, $Q_{0.85}$, $Q_{0.90}$, $Q_{0.95}$) are selected to investigate the tail dependence of demand functions.[7] The HSD demand elasticity with distributional asymmetries for the specified quantiles is shown in Table 5. Figures A1 and A2 (Appendix) depict the QNARDL parameter estimates. The lagged dependent variables across all quantiles are significant and negative, affirming the stability of the QNARDL model.

Table 5 shows that income is elastic at the tail ends when the HSD demand is very low and unit elastic when the demand is very high. In *Model 4.1*, higher quantiles depict a slightly more elastic influence of income on the HSD demand. While looking at the impact of HSD price, we observe that both positive and negative changes in HSD price have no significant impact on HSD demand. A similar outcome is also established for *Model 4.2* (Table 5).

So far as electricity price is concerned, the empirical outcomes reveal intriguing policy implications for *Model 4.1* when electricity price declines at the tail end of HSD demand. For instance, when the HSD demand is very high (85th, 90th, and 95th quantiles), for a 1% decline in electricity price, HSD demand falls more than 0.6% (Table 5), thereby suggesting that electricity and HSD are substitutes. This finding remained hidden in NARDL results, and QNARDL unravels an asymmetric and quantile-dependent relationship of HSD demand with the price of electricity.

For *Model 4.2*, when the HSD demand is at the lowest quantile (5th), a 1% increase in gasoline price leads to a 0.87% fall in HSD demand (Table 5). On the contrary, when the demand for

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[7] The elasticity estimates of demand functions being the focus point of the current study, the QNARDL estimation results are kept in the Appendix.

HSD is at the highest quantile end (95th), for a 1% decline in gasoline price, HSD demand rises by 0.39% (Table 5). The findings indicate that since gasoline price always keeps a higher price spread than HSD, an increase in gasoline price acts as an early warning of an increase in HSD price. Similarly, the decline in gasoline price when the HSD demand is at the highest, the demand increases further as HSD prices are expected to also fall in tandem with gasoline prices. So, gasoline behaves more like a complementary product for HSD.

We validate the above results by estimating the demand for HSD-driven vehicles through the QNARDL model (Table A5). For *Models 4.3* and *4.4*, HSD and HSD-driven vehicles are complementary products, which are also quantile dependent. Notably, the rise (decline) in gasoline prices brings an elastic (≥ 1%) decrease (increase) in HSD demand at the lowest and highest quantiles. Thus, HSD demand follows laws of demand with gasoline price, which act as the leading indicator of increase or decrease of HSD prices. The income remains highly elastic across quantiles (Table A5). *Model 4.3* in Table A5 also reveals that a reduction in electricity price would reduce the demand for HSD-driven vehicles at higher quantiles. So, lower electricity prices may replace some HSD-driven vehicles with EV. This finding strengthens the outcomes of HSD demand (*Model 4.1*, Table 5), and we can reasonably conclude that lower electricity price replaces some HSD-driven vehicles and, thereby, reduce the HSD demand.

Table 5: QNARDL elasticity of HSD demand

	Model 4.1: ΔHSD_t: *f(IIP, Pr_HSD*$^{(+)}$*,Pr_HSD*$^{(-)}$*,Pr_ELEC*$^{(+)}$*,Pr_ELEC*$^{(-)}$*)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
IIP_{t-1}	1.275*	1.473	1.047**	0.984**	0.995**	1.011**	1.035**
$Pr\_HSD_t^+$	0.011	-0.233	-0.057	-0.006	0.054	0.072	0.104*
Pr_HSD^-	0.002	-0.157	-0.102	-0.030	-0.062	-0.057	-0.045
$Pr\_ELEC_{t-1}^+$	0.235	0.240	0.155	-0.098	0.167	0.120	0.102
Pr_ELEC^-	0.478*	0.167	0.357	0.028	0.653**	0.621**	0.672**
*Wald test of parameter constancy (p-value) : (0.03)***							
	Model 4.2: ΔHSD_t:*f(IIP, Pr_HSD*$^{(+)}$*,Pr_HSD*$^{(-)}$*,Pr_MS*$^{(+)}$*,Pr_MS*$^{(-)}$*)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
IIP_{t-1}	0.868**	0.825	1.019**	0.943**	1.068**	1.146**	1.094**
$Pr\_HSD_t^+$	0.832	0.503	0.253	0.379	-0.100	-0.182	-0.238
Pr_HSD^-	0.281	0.111	0.164	0.120	0.026	-0.118	0.214
$Pr\_MS_{t-1}^+$	-0.876**	-0.518	-0.323	-0.414	-0.025	0.040	0.086
$Pr\_MS_t^-$	-0.220	-0.030	-0.180	-0.076	-0.159	-0.017	-0.397**
Wald test of parameter constancy (p-value):$(0.06)*$							

Notes: '*,' '**', and '***' imply significance at 10%,5%, and 1% levels, respectively. Elasticity is the ratio of long-run coefficients to the coefficient of lagged dependent variable (Cho et al., 2015). To check the robustness of quantile dependent property of HSD demand elasticity, we run a Wald test with the null of parameter constancy across quantiles which rejects the null of parameter constancy for the overall QNARDL model confirming the heterogeneity of parameters across quantiles.

4.2 Estimation of gasoline demand through NARDL and QNARDL models

Models 4.5 and 4.6 are used to estimate the gasoline (MS) demand[8]

$$MS = f(IIP, Pr\_MS, Pr\_ELEC) \qquad (4.5)$$

$$MS = f(IIP, Pr\_MS, Pr\_HSD) \qquad (4.6)$$

(Table 6) suggest that gasoline demand links to income (*IIP*), its price (*Pr_MS*), and cross-price (*Pr_HSD* or *Pr_ELEC*) in a non-linear and asymmetric way. Wald tests for long-run asymmetries also confirm that gasoline demand is asymmetric (Section III of Table 6). The diagnostic tests of residuals also show favourable results. Moreover, CUSUM and CUSUM-SQ tests also demonstrate coefficient stability in NARDL estimation.

The long-run elasticity estimates reveal that IIP is almost unit elastic and statistically significant at a 5% level (Section II of Table 6). The negative changes in gasoline price have an inelastic but statistically significant effect on gasoline demand (*Model 4.6*), where a 1% decline in gasoline price leads to an increase in gasoline demand by 0.44%. Since a positive change in gasoline price does not affect gasoline demand, like HSD, imposing additional tax will have an insignificant impact on carbon emissions from gasoline. For other India-specific studies (Kanjilal and Ghosh, 2018; Ramanathan, 1999; Sentenac-Chemin, 2012), the income elasticity estimated in this study is less elastic. Own-price elasticity is more inelastic than (Kanjilal and Ghosh, 2018). The HSD price does not significantly impact the gasoline demand in the long run. While analysing the short-run dynamics, we find income is almost unit elastic, and gasoline demand is sensitive to an increase in gasoline prices at a 5% level where demand

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[8] To validate the demand for MS, we have also estimated the demand for gasoline-driven vehicles using the following functional forms:

$$VMS = f(IIP, Pr\_MS, Pr\_ELEC) \qquad (4.7)$$

$$VMS = f(IIP, Pr\_MS, Pr\_HSD) \qquad (4.8)$$

where VMS represent the gasoline-driven vehicles registered.

elasticity varies between 0.44% and 0.50% (Table 6, Section I). Electricity price has no significant impact on the gasoline demand. No cross-price dependency of HSD and electricity is observed on the demand for gasoline. As per the data available on the web portal of GOI, EV, both two-wheelers and four-wheelers electric vehicles constituted around 4% of total gasoline-driven vehicles sold in India in the year 2022 (Vahan Dashboard, 2023). Since the number of gasoline-driven- vehicles is significantly larger than the number of electric vehicles, it justifies the absence of any impact of electricity price on the demand for gasoline.

We validate the above results by estimating the NARDL model for 'gasoline-driven vehicles registered' (Table A6). The findings are similar. The income effect is elastic (2.03% and 2.68%). The gasoline price-fall significantly influences the rise in the demand for gasoline - driven vehicles in *Model 4.8*. Interestingly, the HSD is established as a substitute for gasoline-driven vehicles because a decline in HSD price brings down the demand for gasoline-driven vehicles by 0.59% in the long run. (Table A6, Section II). Additionally, in the short run, the reduction in electricity prices caused a significant fall in gasoline-driven vehicle demand (4.97%) with a two-month lagged effect (Table A6, Section I). These findings establish that HSD and electricity are substitutes for gasoline-driven vehicles. The results are due to the fact that the prices of gasoline are always higher than the prices of HSD in India. Thus, the demand for gasoline-driven mobility is sensitive to the decline in HSD and electricity prices in India. The violation of normality assumptions warrants the investigation of tail dependency in gasoline-driven vehicles.

Table 6: NARDL estimation results of gasoline demand

Variables	***Model 4.5:*** ΔMS_t *f(IIP,Pr_MS$^{(+)}$,Pr_MS$^{(-)}$, Pr_ELEC$^{(+)}$,Pr_ELEC$^{(-)}$)*	***Model 4.6:*** ΔMS_t *f(IIP,Pr_MS$^{(+)}$,Pr_MS$^{(-)}$, Pr_HSD$^{(+)}$,Pr_HSD$^{(-)}$)*
Section I: Conditional Error Correction		
	Coeff ***(p-value)***	**Coeff** ***(p-value)***
$Constant$	1.54** *(0.00)*	1.74***(0.00)*
MS_{t-1}	-0.54***(0.00)*	-0.67***(0.00)*
IIP_{t-1}	0.53** *(0.00)*	0.67***(0.00)*
$Pr\ \_MS_{t-1}^{+}$	-0.002*(0.97)*	0.09 *(0.60)*
Pr_MS^{-}	-0.05 *(0.35)*	-0.299** *(0.03)*
Pr_ELEC^{+}	-0.15 *(0.20)*	
$Pr\ \_ELEC_{t}^{-}$	-0.29* *(0.09)*	
Pr_HSD^{+}		-0.09 *(0.58)*
Pr_HSD^{-}		0.14 *(0.24)*
ΔIIP_{t-1}	0.99** *(0.00)*	1.01***(0.00)*
$\Delta Pr\_MS_{t}^{+}$	-0.50***(0.01)*	
$\Delta Pr\_MS_{t-1}^{+}$	0.33**(0.07)*	
$\Delta Pr\_MS_{t-2}^{+}$	-0.44***(0.01)*	
Section II: Long-Run Asymmetric Effects		
Variables	**Coeff** ***(p-value)***	**Coeff** ***(p-value)***
IIP	0.97** *(0.00)*	1.00** *(0.00)*
Pr_MS^{+}	-0.003 *(0.97)*	0.14 *(0.51)*
Pr_MS^{-}	-0.09 *(0.15)*	-0.44** *(0.01)*
Pr_ELEC^{+}	-0.28 *(0.13)*	
Pr_ELEC^{-}	-0.054 *(0.11)*	
Pr_HSD^{+}		-0.14 (0.50)
Pr_HSD^{-}		0.21 (0.18)
Section III: Bounds and Long-run (LR) Wald asymmetry tests		
F-stat (ARDL)	1.45	1.03
F-stat (NARDL)	6.08**	6.44**
Wald LR Test Pr_MS (p-value)	*(0.00)***	*(0.33)*
Wald LR Test Pr_ELEC(p-value)	*(0.40)*	
Wald LR Test Pr _HSD (p-value)		*(0.00)***
Section IV: Statistics and Diagnostics		
CUSUM Test	ST	ST
CUSUM-SQ Test	ST	ST
F (Serial Correlation) (p-value)	*(0.95)*	*(0.91)*
F (Heteroscedasticity) (p-value)	*(0.55)*	*(0.53)*
JB (Normal) (p-value)	*(0.48)*	*(0.62)*

Note: Lower and upper band critical values for the bounds test (ARDL): 2.79, 3.67 respectively. Upper band critical values for the bounds test (NARDL) are 2.39 and 3.38 at the 5% significance levels. () shows p-values. * = 10% ;**=5% ***=1% significance levels. ST indicates 'stable'. UST implies ‘unstable’.

In the next stage, we estimate *Models 4.5* and *4.6* through QNARDL**.** The distributional asymmetries are observed for gasoline demand for both models (Table 7). Figures A5 and A6 (Appendix) display the QNARDL parameter estimates for gasoline demand.

The income effect shows unit elastic behaviour at the lower and middle quantiles when the gasoline demand is very low or medium for *Model 4.5*. Similar behaviour is depicted in *Model 4.6*. The impact of gasoline price is only observed in *Model 4.6*, where the negative movements of gasoline prices have a statistically significant positive effect on gasoline demand abiding by the 'laws of demand'. But the impact is highly elastic (-1.59%) when the demand is at the lowest quantile (5th). At higher quantiles (85th, 90th, and 95th), the gasoline price elasticity varies from -0.64% to -0.89% (Table 7). Such quantile-dependent asymmetry justifies the application of the QNARDL model for estimating the long-run relationship of gasoline demand. HSD price also shows extreme quantile dependency in impacting the gasoline demand when HSD price changes are negative. At the 5th quantile, when gasoline demand is at the lowest, a 1% decline in HSD price causes a 1.22% decline in gasoline demand. Similarly, at higher quantiles (90th and 95th), gasoline demand reduces by 0.67% and 0.76%, respectively, for a 1% fall in *Pr_HSD*. Thus, HSD appears to be a clear substitute for gasoline, which is also validated by the NARDL outcome of demand for gasoline-driven vehicles (Table A6). The electricity price has no impact on gasoline demand in the long run. These outcomes are further verified by the QNADL model of gasoline-driven vehicles (Table A7). Thus, the above analysis confirms that HSD is a substitute for the fuel of gasoline-driven vehicles. However, the same remained inconclusive for electricity. The income remains highly elastic across all quantiles (Table A7).

Table 7: **QNARDL elasticity of gasoline demand**

	Model 4.5: ΔMS_t: *f(IIP,Pr_MS*$^{(+)}$*,Pr_MS*$^{(-)}$*, Pr_ELEC*$^{(+)}$*,Pr_ELEC*$^{(-)}$*)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
IIP_{t-1}	1.097**	1.002**	0.920**	0.826**	0.225	0.318	0.452
$Pr\_MS_{t-1}^{+}$	-0.015	0.011	0.070	0.093	0.175	0.162	0.011
Pr_MS^{-}	-0.065	-0.071	-0.004	-0.100	-0.142	-0.106	-0.090
Pr_ELEC^{+}	-0.142	-0.126	-0.143	-0.287	-0.165	-0.399	0.057
$Pr\_ELEC_t^{-}$	-0.527	-0.442	-0.468	-0.376	0.076	-0.225	-0.023
*Wald test of parameter constancy (p-value) : (0.03)***							
	Model 4.6: ΔMS_t: *f(IIP,Pr_MS*$^{(+)}$*,Pr_MS*$^{(-)}$*, Pr_HSD*$^{(+)}$*,Pr_HSD*$^{(-)}$*)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
IIP_{t-1}	0.979**	1.075**	1.074**	0.841**	0.680	0.721	0.793
$Pr\_MS_{t-1}^{+}$	-0.059	0.616	0.584	-0.159	-0.359	-0.652	-1.081
Pr_MS^{-}	-1.593**	-0.627	-0.193	-0.237	-0.648**	-0.897**	-0.895**
Pr_HSD^{+}	0.038	-0.646	-0.500	0.180	0.318	0.599	1.028
Pr_HSD^{-}	1.225*	0.297	0.016	0.056	0.409	0.671**	0.760**
*Wald test of parameter constancy (p-value): (0.06)**							

Notes: '*,' '**', and '***' imply significance at 10%,5%, and 1% levels, respectively. Elasticity is the ratio of long-run coefficients to the coefficient of lagged dependent variable (Cho et al., 2015). To check the robustness of quantile dependent property of gasoline demand elasticity, we run a Wald test with the null of parameter constancy across quantiles which rejects the null of parameter constancy for the overall QNARDL model confirming the heterogeneity of parameters across quantiles.

5. Estimation of EV through NARDL and QNARDL models

An important discovery from the estimation of demand for HSD and gasoline is the potential emergence of electricity as a substitute. Given that the majority of HSD (70%) and gasoline (99.6%) are consumed in the transportation sector, the impact of electricity as a fuel in this sector can be attributed to the increasing adoption of EV. As a result, it is crucial to estimate the demand for EV separately using the following functional form

$$VEV = f(\,IIP, Pr\_ELEC, Pr\_MS) \qquad (5.1)$$

$$VEV = \, f(\,IIP, Pr\_ELEC, Pr\_HSD) \qquad (5.2)$$

The data span used for the estimation of VEV is from May 2015 to April 2022 to capture the specific policy interventions by GOI (FAME I & II).

India's heavy reliance on imported Lithium-Ion batteries, constituting 30% to 40% of total EV costs, spurred the Government of India (GOI) to introduce Production Linked Incentive (PLI) initiatives. In May 2021, the GOI initiated a PLI scheme with an Rs 18,100 Crores budget to boost domestic Lithium-Ion battery production. In September 2021, another PLI scheme was introduced, allocating Rs 25,938 Crores to incentivize EV and component manufacturing (Ministry of Heavy Industries, 2022). The GOI has also implemented policies to strengthen charging infrastructure, ensuring secure, accessible, reliable, and cost-effective facilities (Ministry of Power, 2022). Furthermore, several Indian states have launched initiatives to accelerate EV adoption, underscoring both the GOI and state governments' commitment to EV integration in India's transportation sector.

The ARDL and NARDL Bounds test for cointegration reject the null hypothesis of no cointegration (Table 8). Wald tests for long-run asymmetries confirm the statistical significance of differential effects of positive(negative) changes of *Pr_ELEC, Pr_HSD* and *Pr_MS* on demand for EV (Section III of Table 8). So, the electric vehicle demand has a non-linear and asymmetric relationship with income, electricity price and the price of gasoline or

HSD. The violation ‘normality’ and 'heteroscedasticity’ assumption of residuals along with CUSUM & CUSUM-SQ raises a flag to investigate the tail-dependency of demand for electric vehicles.

Table 8: NARDL estimation results of EV demand

Variables	***Model 5.1:*** $\Delta \boldsymbol{VEV_t}$ *f(IIP,Pr_ELEC$^{(+)}$,Pr_ELEC$^{(-)}$, Pr_HSD$^{(+)}$,Pr_HSD$^{(-)}$)*	***Model 5.2*** $\Delta \boldsymbol{VEV_t}$ *f(IIP,Pr_ELEC$^{(+)}$,Pr_ELEC$^{(-)}$, Pr_MS$^{(+)}$,Pr_MS$^{(-)}$)*
Section I: Conditional Error Correction		
	Coeff ***(p-value)***	**Coeff** ***(p-value)***
$\boldsymbol{Constant}$	-1.51 *(0.46)*	-1.816 *(0.38)*
$\boldsymbol{VEV_{t-1}}$	-0.29***(0.00)*	-0.31***(0.00)*
$\boldsymbol{IIP_{t-1}}$	0.84**(0.09)*	0.93**(0.06)*
$\boldsymbol{Pr\_ELEC_t^+}$	-0.87 *(0.20)*	-1.43 *(0.04)*
$\boldsymbol{Pr\_ELEC_{t-1}^-}$	-1.99* *(0.10)*	-2.51***(0.02)*
$\boldsymbol{Pr\_HSD_t^+}$	0.44*(0.14)*	
$\boldsymbol{Pr\_HSD_t^-}$	0.59***(0.03)*	
$\boldsymbol{Pr\_MS_t^+}$		0.63**(0.06)*
$\boldsymbol{Pr\_MS_t^-}$		0.64** *(0.02)*
$\Delta \boldsymbol{IIP_t}$	3.05***(0.00)*	2.95***(0.00)*
$\Delta \boldsymbol{IIP_{t-1}}$	1.07***(0.00)*	1.02***(0.00)*
$\Delta \boldsymbol{Pr\_ELEC_t^-}$	-0.46*(0.79)*	0.32*(0.85)*
$\Delta \boldsymbol{Pr\_ELEC_{t-1}^-}$	-0.82*(0.65)*	0.41*(0.82)*
$\Delta \boldsymbol{Pr\_ELEC_{t-2}^-}$	5.91***(0.00)*	7.12***(0.00)*
$\Delta \boldsymbol{Pr\_MS_t^+}$		0.64*(0.48)*
$\Delta \boldsymbol{Pr\_MS_{t-1}^+}$		0.41*(0.64)*
$\Delta \boldsymbol{Pr\_MS_{t-2}^+}$		-1.68**(0.06)*
$\Delta \boldsymbol{Pr\_MS_{t-3}^+}$		-1.92***(0.03)*
Section II: Long-Run Asymmetric Effects		
Variables	**Coeff** ***(p-value)***	**Coeff** ***(p-value)***
$\boldsymbol{IIP}$	2.88***(0.03)*	2.97*(0.00)*
$\boldsymbol{Pr\_ELEC^+}$	-3.01*(0.23)*	-4.55**(0.06)*
$\boldsymbol{Pr\_ELEC^-}$	-6.84*(0.13)*	-7.98***(0.03)*
$\boldsymbol{Pr\_HSD^+}$	1.52**(0.09)*	
$\boldsymbol{Pr\_HSD^-}$	2.04***(0.05)*	
$\boldsymbol{Pr\_MS^+}$		2.00***(0.02)*
$\boldsymbol{Pr\_MS^-}$		2.03***(0.00)*
Section III: Bounds and Long-run (LR) asymmetry tests		
F-stat (ARDL)	4.88**	4.90**
F-stat (NARDL)	4.17**	4.61**
LR Wald Test Pr_ELEC (p-value)	*(0.40)*	*(0.43)*
LR Wald Test Pr_HSD (p-value)	*(0.05)***	
LR Wald Test Pr_MS (p-value)		*(0.02)***
Section IV: Statistics and Diagnostics		
CUSUM Test	ST	ST
CUSUM-SQ Test	UST	UST
F (Serial Correlation) (p-value)	*(0.38)*	*(0.65)*
F (Heteroscedasticity) (p-value)	*(0.00)**	*(0.02)***
JB (Normal) (p-value)	*(0.00)**	*(0.01)***

Note: Lower and upper band critical values for the bounds test (ARDL): 2.79, 3.67 respectively. Upper band critical values for the bounds test (NARDL) are 2.39 and 3.38 at the 5% significance levels. () shows p-values. * = 10% ;**=5% ***=1% significance levels. ST indicates 'stable'. UST implies ‘unstable’.

Before investigating the tail dependency, we briefly discuss the long-and short-run dynamics of NARDL estimation of the demand for electric vehicles. The income elasticity is beyond 2.8% for both models (*Models 5.1* and *5.2*) and is statistically significant, signalling that electric vehicles fall under luxury goods. The electricity price (increase/decrease) exhibits an inverse relationship with the demand for electric vehicles; hence, as expected, EV and electricity are complementary goods. This is, however, true only for *Model 5.2*. EV demand is susceptible to electricity prices, and a 1% fall in electricity prices increases the demand for EV by 7.98%. Interestingly, HSD and gasoline are highly elastic substitutes for EV demand. For HSD, with a 1% rise (fall) in prices, electric vehicle demand increased (decreased) by 1.52% (2.04%) (Table 8, Section II). The effect of an increase in *VEV* due to the rise in *Pr_HSD* is statistically weaker than the decrease. On the other hand, for gasoline, the impact is consistent in magnitude and statistical significance, where for a 1% increase (decrease) in gasoline prices, *VEV* go up (down) by 2.00% (2.03%). These impacts are statistically significant at a 5% level. The outcomes are the reflection of the government's initiatives of FAME 1 & II.

QNARDL estimation results of EV demonstrate the quantile dependency and distributional asymmetries for the specified quantiles (Table 9). The appendix (Figures A9 and A10) shows QNARDL parameter estimates. The estimation confirms stability as the lagged dependent variable is statistically significant and negative across quantiles for both demand functions.

While investigating the elasticity estimates of income and price (Table 9), we observe that income has no impact on *VEV* for both models. In contrast, the dynamics of electricity, HSD, and gasoline prices are highly fascinating, which NARDL results could not capture. The electricity price has an asymmetric impact on *VEV*. It is highly elastic at the middle quantile (50^{th}). Negative price movements substantially affect both models. For example, a 1% decrease in electricity price leads to an 11 to 12% increase in the demand for electric vehicles. The impact of HSD and gasoline prices on electric vehicles registered shows distributional asymmetries and is highly elastic. For instance, with a 1% increase in *Pr_HSD*, EV demand increased by 4.24% at the 15th quantile (Table 9). In the extreme right tail, when the demand for electric vehicles is the highest (95th), a 1% increase in *Pr_HSD* drives up the electric vehicle demand by 1.89%. The impact at the 85th and 90th quantiles is also elastic but statistically significant at the 10% level. On the other hand, a 1% decrease in HSD price significantly lowers the demand for electric vehicles at lower to middle quantiles, where the elasticity varies from 2.9% (50th quantile) to 5.50% (5th quantile). So, HSD emerges as a potential substitute for electric vehicles at the tail end of demand for electric vehicles. In the second case (*Model 5.2*), we observe that gasoline prices also unfold similar dynamics. With the increase in gasoline prices, EV demand goes up by 2.03% at the highest quantile (95th). The gasoline price decline also reduces EV demand by 2.5% (90th, 95th quantiles).

So, empirical outcomes are insightful, which indicate that both gasoline and HSD consumption can be reduced by strengthening the market for electricity-driven vehicles. Thus, our study demonstrates that electric vehicles are a potential substitute mainly for HSD, which is a unique contribution to the existing literature.

Table 9: QNARDL elasticity of EV demand

	Model 5.1: $\Delta \boldsymbol{VEV_t}$: *f(IIP,Pr_ELEC$^{(+)}$,Pr_ELEC$^{(-)}$, Pr_HSD$^{(+)}$,Pr_HSD$^{(-)}$)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
$\boldsymbol{IIP_{t-1}}$	-6.387	-4.517	-2.439	3.102	1.104	1.047	-0.557
$\boldsymbol{Pr\_ELEC_t^+}$	-4.869	-3.084	-6.109	-6.978*	-0.845	-0.885	-0.820
$\boldsymbol{Pr\_ELEC_{t-1}^-}$	-10.800	-7.079	-11.032*	-12.132**	-0.390	-1.069	-1.748
$\boldsymbol{Pr\_HSD_t^+}$	3.930	3.597	4.248**	2.111	1.770*	1.528*	1.897**
$\boldsymbol{Pr\_HSD_t^-}$	5.508**	4.429	5.669**	2.911**	0.489	0.479	1.089
*Wald test of parameter constancy (p-value): (0.04)***							
	Model 5.2: $\Delta \boldsymbol{VEV_t}$: *f(IIP,Pr_ELEC$^{(+)}$,Pr_ELEC$^{(-)}$, Pr_MS$^{(+)}$,Pr_MS$^{(-)}$)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
$\boldsymbol{IIP_{t-1}}$	0.537	0.629	-1.223	3.736	0.004	-0.580	-0.356
$\boldsymbol{Pr\_ELEC_t^+}$	2.084	-1.743	-6.955	-4.981	-2.575	-1.450	-1.465
$\boldsymbol{Pr\_ELEC_{t-1}^-}$	2.271	0.394	-6.446	-11.031**	-8.068	-4.752	-4.578
$\boldsymbol{Pr\_MS_t^+}$	2.344	3.782	5.595	0.980	1.480	2.011*	2.030**
$\boldsymbol{Pr\_MS_t^-}$	0.942	1.365	3.131*	1.905	2.684	2.550**	2.502**
*Wald test of parameter constancy (p-value):(0.09)**							

Notes: '*,' '**', and '***' imply significance at 10%,5%, and 1% levels, respectively. Elasticity is the ratio of long-run coefficients to the coefficient of lagged dependent variables (Cho et al., 2015). To check the robustness of quantile dependent property of numbers of electric vehicles' demand elasticity, we run a Wald test with the null of parameter constancy across quantiles which rejects the null of parameter constancy for the overall QNARDL model, confirming the heterogeneity of parameters across quantiles.

6. Conclusions

Decarbonizing the transportation sector is crucial for India, given its dependence on fossil fuels. Therefore, the integration of electric mobility into the transportation sector has become a pivotal aspect of India's strategy for transitioning towards cleaner energy sources. This study estimates the demand elasticity of HSD, gasoline, and electric vehicles by employing NARDL and QNARDL models with recent data. As a robustness check, the outcomes of these models are verified through a similar analysis of demand functions of gasoline and HSD-driven vehicles registered.

The empirical outcomes reveal asymmetries in the demand functions of gasoline, HSD, and EV in mean and quantiles. So, the demand function responds differently to the increase or decrease in its determinants. Results show that the rise in gasoline and HSD prices does not impact demand functions. This means an increase in taxation remains an ineffective policy instrument to curtail the demand for these fuels and, hence, their carbon emission. However, taxation can continue to be an effective policy instrument to generate additional revenues, which can be leveraged to finance the green mobility infrastructure. Another important discovery of our analysis is that both gasoline and HSD are substitutes for EV. Thus, the number of registered electric vehicles increases with an increase in gasoline and HSD prices.

We also establish that gasoline is a complementary product to HSD as the fall (rise) in gasoline price results in the increase (decrease) in demand for HSD in anticipation of the decline(escalation) in HSD price. But, HSD is a substitute for gasoline as the rise in gasoline prices leads to an increase in HSD demand. This outcome can be attributed to the relative price differential advantage of HSD over gasoline, where HSD price has historically maintained a lower level due to differential taxation policies.

Electricity and EV are found to be complementary as the fall (rise) in electricity prices leads to an increase(decrease) in EV penetration, although the decline in electricity prices has a much stronger impact on the number of EV registered than its increase. A fall in electricity prices is also found to have a detrimental impact on the demand for HSD and HSD-driven vehicles. A similar effect is observed for gasoline-driven vehicles in the short run. In summary, lowering electricity prices is a key constituent that can increase EV penetration and has a plummeting impact on the demand for HSD and gasoline-driven vehicles. India has an ambitious renewable energy target, and an accomplishment of the target will not only reduce India's carbon emission from the power sector by replacing some of the dirty coal-fired power plants with renewables but also bring down the electricity price (Rahul Agarwal et al., 2019; Jain & Shrimali, 2022). Thus, the government of India must continue its policy interventions to enhance the penetration of renewable energy in the overall electricity mix. The present research suggests that lowering electricity prices and implementing extra carbon taxes could promote the adoption of electric mobility, ultimately strengthening India's aim to achieve a "net zero" status by 2070.

Future studies are recommended to evaluate the demand for all petroleum products in various end-use sectors such as transport, industry, agriculture, and households. Additionally, investigating the demand for petroleum products at the state level using a panel data framework could be explored. It would also be valuable to assess the effectiveness of different government policies to promote the adoption of electric vehicles and forecast their future demand, considering the number of charging infrastructure as one of the exogenous variables.

7. Managerial insights

In light of the Government of India's (GOI) commitment to decarbonize road transportation and achieve net-zero emissions by 2070, addressing the carbon footprint of the Indian road transportation sector is imperative. Previous GOI policy initiatives (Table A2) have led to a surge in demand for electric vehicles (EV).

Our study provides valuable insights. We observe no significant price impact on the demand for gasoline and high-speed diesel (HSD), suggesting that additional carbon taxes alone may not effectively reduce demand and carbon emissions from these fuels. Nevertheless, such taxes can serve as important incentives for the transition to cleaner fuels.

The relationship between gasoline and HSD is intricate, with gasoline complementing HSD in some scenarios while HSD acts as a substitute for gasoline in others. Additionally, electricity and gasoline/HSD-driven vehicles demonstrate substitution effects, as lower electricity prices reduce the demand for gasoline and HSD-driven vehicles, potentially leading to increased electric vehicle (EV) adoption. Conversely, rising fuel prices may drive higher EV adoption rates. Electricity and EV exhibit a complementary relationship, with lower electricity prices facilitating greater EV adoption.

In light of these findings, we propose policy recommendations to help achieve the Government of India's (GOI) target of a 30% EV penetration in total vehicle sales by 2030. This includes implementing carbon or green taxes on gasoline and HSD sales to encourage the transition to cleaner fuels. Prioritizing the expansion of clean and renewable electricity generation, such as wind and solar, can help reduce electricity prices and promote greater EV adoption. Furthermore, utilizing revenue generated from carbon/green taxes to subsidize electricity generated from clean sources will enhance the affordability and accessibility of clean energy for EV users.

These policy recommendations aim to expedite EV adoption and align with India's objectives to decarbonize the road transportation sector, supporting its ambitious sustainability goals.

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Appendix

Table A1: Compilation of policies related to the promotion of EV in top countries regarding EV penetration

Country	% of the sale of EV sales year in 2022 (% of total car sales)	Total sales of EV in the year 2022 (in million)	Target of EV penetration by 2030 (% of new Cars)	List of Policies to enhance penetration of EV's
World	14	10.2		
China	29%	5.9	50%	• Exemption from vehicle purchase tax • Incentivization of charging infrastructure • End sale of gasoline and HSD vehicles by 2030
USA	7.7%	1.9	50%	• Inflation Reduction act: investment of $7.5 B in EV charging infra, $7 B in Battery component, $10 B in the clean transportation sector • 500, 000 EV chargers by year 2030
Germany	31%	0.83	100%	• Grant for the purchase of BEV/FCEV • Eur 900 Incentive per charging point for purchase and installation of EV charger • 10-year tax exemptions for BEV • Target of 10 million EV & 1 million Charging points by 2030
United Kingdom	23%	0.37	100%	• Phasing out sale of ICE vehicles by 2030 • Tax exemptions for BEV • Financial incentives for installation of EV chargers and purchase of EV • 300,000 EV chargers by 2030
France	21%	0.34		• Financial incentives for installation of EV chargers and purchase of EV • No sales of ICE vehicles beyond 2040
Norway	88%	0.166	100% (2025)	• Tax exemption on purchase of EV • Reduced toll taxes for EV on highways • Free parking for EV • Policies to boost charging infrastructure
Korea	9.4%	0.131	33%	• Tax credits for investment in EV production • Subsidy for purchase of EV • Incentives to build charging infrastructure
Sweden	54%	0.163	100% (2025)	• Grant for the purchase of EV and installation of EV charging stations • Free charging of EV
Canada	9.4%	0.114	100% (2035)	• Point of sale incentives of $ 2,500 to $5,000 for purchase of EV • Incentives for the installation of EV charging stations
Netherlands	35%	0.107	100%	• Subsidy to purchase EV • Exemptions from road taxes • Incentives for the installation of EV charging stations
India	1.5%	0.048	30%	• Subsidy to purchase EV • Incentives for the installation of EV charging stations

Note: Authors' compilation from (IEA, 2023a, 2023b; International Energy Agency, 2023)

Table A2: Important policy interventions in the electricity and petroleum sector related to transportation

Time	Policy Brief	Objective
June’2010	Deregulation of the retail price of petrol (gasoline).	In order to reduce the subsidy burden on the Govt as, OMC used to sell Petrol and Diesel at below the market price
January '13	National Electric Mobility Mission Plan (NEMMP) 2020	The principal end objectives of the National Mission for Electric Mobility are National energy security, mitigation of the adverse impact of vehicles on the environment and growth of domestic manufacturing capabilities
October '14	Deregulation of Retail prices of Diesel (HSD)	Govt. allowed OMC to increase the Diesel prices in increments of 40 paise to 50 Paisa per litre in Jan '13, and full deregulation of retail prices became effective in Oct '14.
April '15	FAME- Phase-I	In order to promote the manufacturing of electric and hybrid vehicle technology and to ensure sustainable growth of the same, GOI introduced the FAME-1 policy frame with a total outlay of Rs 895 Crore for the period 1st April '15 to 31st March '19
June '17	Daily Price Revision of Petrol (gasoline) and Diesel (HSD)	GOI introduce daily price revisions of Petrol and Diesel with objectives to make the retail prices more reflective of the current market conditions, minimising the volatility in the RSP of Petrol (gasoline) and Diesel.
July '16	National Green Tribunal	Any registered diesel vehicle more than 10 years old, and petrol (gasoline) vehicles over 15 years old cannot operate in the national capital region (NCR)
Oct '18	Supreme Court of India	
March '19	FAME-Phase-II	GOI introduced Phase-II of the FAME policy framework with an enhanced outlay of Rs 10,000 Cr for the period 1st Apr '19 to 31st March '22 to further penetrate Electric mobility in the country.
March '19	PM-KUSUM (Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyan)Scheme	Scheme to promote the use of renewable energy in the agricultural sector and offer the benefits of solar farming to Indian farmers
June '18	National Policy on Biofuels	The policy is aimed at taking forward the indicative target of achieving 20% blending of biofuels with fossil-based fuels by 2030
Dec '21		An indicative target of 20% blending of ethanol in petrol by 2030 and 5% blending of biodiesel in diesel by 2030.
Feb '22	Ban on Diesel Generators by The Commission for Air Quality Management (CAQM)	It would be illegal to use generator sets fuelled by diesel in Delhi & National Capital Territory (NCR) from October 1, 2022,

Table A3: Elasticity estimates for gasoline and HSD

S.N.	Authors	Country/Region	Energy Type	Study Period	Data Frequency	Methodology	Long Run Price elasticity	Long run income elasticity
1	(Eltony and Al-Mutairi, 1995)	Kuwait	Gasoline	1970-1989	Annual	Engle & Granger	-0.46	0.92
2	(Eltony, 1996)	GCC	Gasoline	1975-1993	Annual	Error Component Model	-0.17	0.48
3	(Alves and de Losso da Silveira Bueno, 2003)	Brazil	Gasoline	1974-1999	Annual	Engle & Granger	-0.464	0.122
4	(Liu, 2004)	OECD	Gasoline	1978-1999	Annual	GMM	-0.99/-0.6	0.37/0.61
5	(Polemis, 2006)	Greece	Gasoline	1978-2003	Annual	Johansen Cointegration	-0.38	0.79
6	(Akinboade et al., 2008)	South Africa	Gasoline	1978-2005	Annual	ARDL	-0.47	0.36
7	Liddle, 2012)	OECD	Gasoline	1978-2005	Annual	OLS, FMOLS, DOLS	-0.43/-0.19	0.2/0.34
8	(Rentziou et al., 2012)	USA	Gasoline	1998-2008	Annual	SURE Panel mode	-0.035/-0.088	0.853
9	(Lin and Zeng, 2013)	China	Gasoline	1997-2008	Annual	Partial Adjustment Model	-0.497 to -0.196	1.01 to 1.05
10	(Mikayilov et al., 2020)	Azerbaijan	Gasoline	2002-2018	Monthly	TVC Cointegration	-0.15	0.1/0.29
12	(Lee and Olasehinde-Williagasoline, 2021)	USA/China/Russia /India/Japan	Gasoline	1995-2008	Annual	Time-Varying Parameter Model	China:-0.182 India:-0.027 USA: -0.018 Russia:-0.029 Japan:-0.02	China: 0.487 India: 0.373 USA: 0.13 Russia:0.096 Japan:0.069
13	(Ghoddusi et al., 2022)	Iran	Gasoline & HSD	April'05 to March'15	Monthly	Dynamic Panel	Gasoline: -0.291 Diesel: -0.116	
India Specific Studies								
1	(Ramanathan, 1999)	India	Gasoline	1972-1993	Annual	Cointegration	-0.32	2.68
2	(Ghosh, 2010)	India	HSD	1972-73 to 2005-06	Annual	ARDL	Not Significant	1.27
3	(Sentenac-Chemin, 2012)	India	Gasoline	1978-2005	Annual	Engel & Granger	-0.58/-0.35	0.65/1.89
4	(Kanjilal and Ghosh, 2018)	India	Gasoline	1971-72 to 2012-13	Annual	ARDL, J-J, HJ	JJ:-2.08 ARDL: -1.92	JJ: 1.36 ARDL:1.49 HJ:1.16
5	(Lee and Olasehinde-Williagasoline, 2021)	India	Gasoline	1990-2018	Annual	TVP	-0.027	0.374

Table A4: NARDL estimation results of HSD-driven vehicles

Variables	*Model 4.3:*$\Delta VHSD_t$ $f(IIP, Pr\_HSD^{(+)}, Pr\_HSD^{(-)}, Pr\_ELEC^{(+)}, Pr\_ELEC^{(-)})$	*Model 4.4:* $\Delta VHSD_t$ $f(IIP, Pr\_HSD^{(+)}, Pr\_HSD^{(-)}, Pr\_MS^{(+)}, Pr\_MS^{(-)})$
Section I: Conditional Error Correction		
	Coeff ***(p-value)***	**Coeff** ***(p-value)***
$Constant$	-1.27**(0.27)	-3.61**(0.00)
$VHSD_{t-1}$	-1.03**(0.00)	-1.03**(0.00)
IIP_{t-1}	3.01**(0.00)	3.48**(0.00)
$Pr\_HSD_t^{+}$	0.08 (0.56)	-0.42(0.36)
Pr_HSD^{-}	0.31**(0.01)	0.75**(0.02)
$Pr\_ELEC_t^{+}$	-0.57 (0.53)	
$Pr\_ELEC_{t-1}^{-}$	0.14 (0.82)	
$Pr\_MS_t^{+}$		0.09(0.84)
$Pr\_MS_t^{-}$		-0.64*(0.06)
$\Delta VHSD_{t-1}$	0.24**(0.00)	0.14**(0.00)
ΔIIP_t	1.76**(0.00)	1.88**(0.00)
$\Delta Pr\_ELEC_t^{-}$	0.51 (0.62)	
$\Delta Pr\_ELEC_{t-1}^{-}$	-0.44 (0.68)	
$\Delta Pr\_ELEC_{t-2}^{-}$	3.71** (0.00)	
Section II: Long-Run Asymmetric Effects		
Variables	**Coeff** ***(p-value)***	**Coeff** ***(p-value)***
IIP	2.90**(0.00)	3.36**(0.00)
Pr_HSD^{+}	0.08 (0.52)	-0.40 (0.23)
Pr_HSD^{-}	0.30**(0.03)	0.72**(0.01)
Pr_ELEC^{+}	-0.55 (0.15)	
Pr_ELEC^{-}	0.13 (0.82)	
Pr_MS^{+}		0.08(0.79)
Pr_MS^{-}		-0.62**(0.05)
Section III: Bounds and Long-run (LR) asymmetry tests		
F-stat(ARDL)	1.82	1.07
F-stat(NARDL)	33.22**	38.40**
LR Wald Test Pr_HSD (p-value)	*(0.17)*	(0.02)**
LR Wald Test Pr _ELEC (p-value)	*(0.41)*	
LR Wald Test Pr_MS (p-value)		*(0.17)*
Section IV: Statistics and Diagnostics		
CUSUM Test	ST	ST
CUSUM-SQ Test	UST	UST
F (Serial Correlation) (p-value)	*(0.63)*	*(0.20)*
F (Heteroscedasticity)(p-value)	(0.00)**	*(0.31)*
JB (Normal) (p-value)	(0.00)**	(0.00)**

Note: Lower and upper band critical values for the bounds test (ARDL): 2.79, 3.67 respectively. Upper band critical values for the bounds test (NARDL) are 2.39 and 3.38 at the 5% significance levels. () shows p-values. * = 10% ;**=5% ***=1% significance levels. ST indicates 'stable'. UST implies ‘unstable’.

Table A5: QNARDL elasticity of HSD-driven vehicles

	Model 4.3: $\Delta \boldsymbol{VHSD_t}$: *f(IIP,Pr_HSD⁽⁺⁾,Pr_HSD⁽⁻⁾, Pr_ELEC⁽⁺⁾,Pr_ELEC⁽⁻⁾)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
$\boldsymbol{IIP_{t-1}}$	2.627	2.724	3.176	2.995**	3.110**	3.261**	2.637
$\boldsymbol{Pr\_HSD_t^+}$	0.123	0.276	0.112	0.064	0.069	0.149	0.230
$\boldsymbol{Pr\_HSD^-}$	0.344*	0.403	0.331	0.243**	0.154	0.219	0.010
$\boldsymbol{Pr\_ELEC_t^+}$	-0.127	-0.448	-0.232	-0.652	-0.582	-1.153	0.143
$\boldsymbol{Pr\_ELEC_{t-1}^-}$	0.666	0.667	0.718	0.039	0.385*	0.213*	1.426
*Wald test of parameter constancy (p-value): (0.00)***							
	Model 4.4: $\Delta \boldsymbol{VHSD_t}$: *f(IIP,Pr_HSD⁽⁺⁾,Pr_HSD⁽⁻⁾, Pr_MS⁽⁺⁾,Pr_MS⁽⁻⁾)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
$\boldsymbol{IIP_{t-1}}$	3.780**	3.569*	3.661**	3.145**	2.936**	2.760**	3.053**
$\boldsymbol{Pr\_HSD_t^+}$	-1.639**	-1.232*	-0.835	-0.089	0.645	0.661	0.840
$\boldsymbol{Pr\_HSD^-}$	-0.063	0.060	0.120	0.522**	0.928**	1.081**	1.168**
$\boldsymbol{Pr\_MS_t^+}$	1.445**	0.952*	0.597	-0.223	-1.054	-1.115**	-1.206
$\boldsymbol{Pr\_MS_t^-}$	0.300	0.087	0.138	-0.374	-0.907**	-1.138**	-1.185*
*Wald test of parameter constancy (p-value):(0.07)**							

Notes: '*,' '**', and '***' imply significance at 10%,5%, and 1% levels, respectively. Elasticity is the ratio of long-run coefficients to the coefficient of lagged dependent variable (Cho et al., 2015). To check the robustness of quantile dependent property of HSD demand elasticity, we run a Wald test with the null of parameter constancy across quantiles which rejects the null of parameter constancy for the overall QNARDL model confirming the heterogeneity of parameters across quantiles.

Table A6: NARDL estimation results of gasoline-driven vehicles

Variables	*Model 4.7*: ΔVMS_t $f(IIP, Pr\_MS^{(+)}, Pr\_MS^{(-)}, Pr\_ELEC^{(+)}, Pr\_ELEC^{(-)})$	*Model 4.8*: ΔVMS_t $f(IIP, Pr\_MS^{(+)}, Pr\_MS^{(-)}, Pr\_HSD^{(+)}, Pr\_HSD^{(-)})$
Section I: Conditional Error Correction		
	Coeff *(p-value)*	**Coeff *(p-value)***
$Constant$	5.76***(0.00)*	1.51*(0.17)*
VMS_{t-1}	-1.24***(0.00)*	-1.09***(0.00)*
IIP_{t-1}	2.52***(0.00)*	2.93***(0.00)*
$Pr\_MS_t^+$		0.12 *(0.81)*
$Pr\_MS_{t-1}^+$	0.27 *(0.15)*	
Pr_MS^-	0.19 *(0.22)*	-0.77***(0.05)*
Pr_ELEC^+	-0.66 *(0.15)*	
$Pr\_ELEC_{t-1}^-$	0.19 *(0.79)*	
Pr_HSD^+		-0.43 *(0.41)*
Pr_HSD^-		0.64**(0.08)*
ΔVMS_{t-1}	0.32** *(0.00)*	0.19***(0.00)*
ΔIIP_t		1.67***(0.00)*
ΔIIP_{t-1}	1.44***(0.00)*	
$\Delta Pr\_MS_t^+$	-0.31*(0.56)*	
$\Delta Pr\_MS_{t-1}^+$	-0.06 *(0.90)*	
$\Delta Pr\_MS_{t-2}^+$	-0.46 *(0.37)*	
$\Delta Pr\_MS_{t-3}^+$	-1.53***(0.00)*	
$\Delta Pr\_ELEC_t^-$	1.43 *(0.22)*	
$\Delta Pr\_ELEC_{t-1}^-$	1.23 *(0.31)*	
$\Delta Pr\_ELEC_{t-2}^-$	4.97***(0.00)*	
Section II: Long-Run Asymmetric Effects		
Variables	**Coeff *(p-value)***	**Coeff *(p-value)***
IIP	2.03** *(0.00)*	2.68***(0.00)*
Pr_MS^+	0.22 *(0.16)*	0.11*(0.79)*
Pr_MS^-	0.15 *(0.22)*	-0.71***(0.05)*
Pr_ELEC^+	-0.53 *(0.17)*	
Pr_ELEC^-	0.15 *(0.79)*	
Pr_HSD^+		-0.39*(0.35)*
Pr_HSD^-		0.59**(0.09)*
Section III: Bounds and Long-run (LR) asymmetry tests		
F-stat (ARDL)	8.34**	6.41**
F-stat (NARDL)	27.74**	26.14**
LR Wald Test Pr_MS(p-value)	*(0.15)*	*(0.10)**
LR Wald Test Pr_ELEC(p-value)	*(0.06)**	
LR Wald Test Pr_HSD(p-value)		*(0.03)***
Section IV: Statistics and Diagnostics		
CUSUM Test	ST	ST
CUSUM-SQ Test	ST	UST
F (Serial Correlation) (p-value)	*(0.15)*	*(0.21)*
F (Heteroscedasticity) (p-value)	*(0.68)*	*(0.75)*
JB (Normal) (p-value)	*(0.06)**	*(0.00)***

Note: Lower and upper band critical values for the bounds test (ARDL): 2.79, 3.67 respectively. Upper band critical values for the bounds test (NARDL) are 2.39 and 3.38 at the 5% significance levels. () shows p-values. * = 10% ;**=5% ***=1% significance levels.. ST indicates 'stable'. UST implies 'unstable'.

Table A7: QNARDL elasticity of demand for gasoline-driven vehicles

	Model 4.7: ΔVMS_t: *f(IIP,Pr_MS*$^{(+)}$*,Pr_MS*$^{(-)}$*, Pr_ELEC*$^{(+)}$*,Pr_ELEC*$^{(-)}$*)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
IIP_{t-1}	1.965**	1.856**	2.009**	2.049**	0.682	0.827	0.727
$Pr\_MS^{+}_{t-1}$	0.045	0.156	0.145	0.236	0.625*	0.550	0.569**
Pr_MS^{-}	0.094	0.165	0.122	0.104	0.226	0.220	0.191
Pr_ELEC^{+}	-0.471	-1.065*	-0.987	-0.579	-0.696	-0.683	-0.640
$Pr\_ELEC^{-}_{t-1}$	-0.223	-0.834	-0.532	0.338	0.473	0.344	0.480
*Wald test of parameter constancy (p-value):(0.06)**							
	Model 4.8: ΔVMS_t: *f(IIP,Pr_MS*$^{(+)}$*,Pr_MS*$^{(-)}$*, Pr_HSD*$^{(+)}$*,Pr_HSD*$^{(-)}$*)*						
Variables	**5%**	**10%**	**15%**	**50%**	**85%**	**90%**	**95%**
IIP_{t-1}	3.011**	2.780**	2.817**	2.854**	1.518	1.466	1.955
$Pr\_MS^{+}_{t}$	1.031	0.558	0.270	-0.367	-0.634	-0.824	-0.593
Pr_MS^{-}	-0.636*	-0.424	-0.303	-0.500	-1.367	-1.310	-1.751**
Pr_HSD^{+}	-1.303**	-0.760	-0.564	0.082	0.546	0.689	0.433
Pr_HSD^{-}	0.501*	0.377	0.187	0.485	1.273	1.177	1.625**
*Wald test of parameter constancy (p-value):(0.10)**							

Notes: '*,' '**' and '***' imply significance at 10%,5%, and 1% levels, respectively. Elasticity is the ratio of long-run coefficients to the coefficient of the lagged dependent variable (Cho et al., 2015). To check the robustness of quantile-dependent property gasoline-driven vehicle demand elasticity, we run a Wald test with the null of parameter constancy across quantiles which rejects the null of parameter constancy for the overall QNARDL model confirming the heterogeneity of parameters across quantiles.

Figure A1: QNARDL Estimation: *Model 4.1 F(HSD / IIP,* $Pr\_HSD^{(+)}$*,*$Pr\_HSD^{(-)}$*,* $Pr\_ELEC^{(+)}$*,*$Pr\_ELEC^{(-)}$*)*

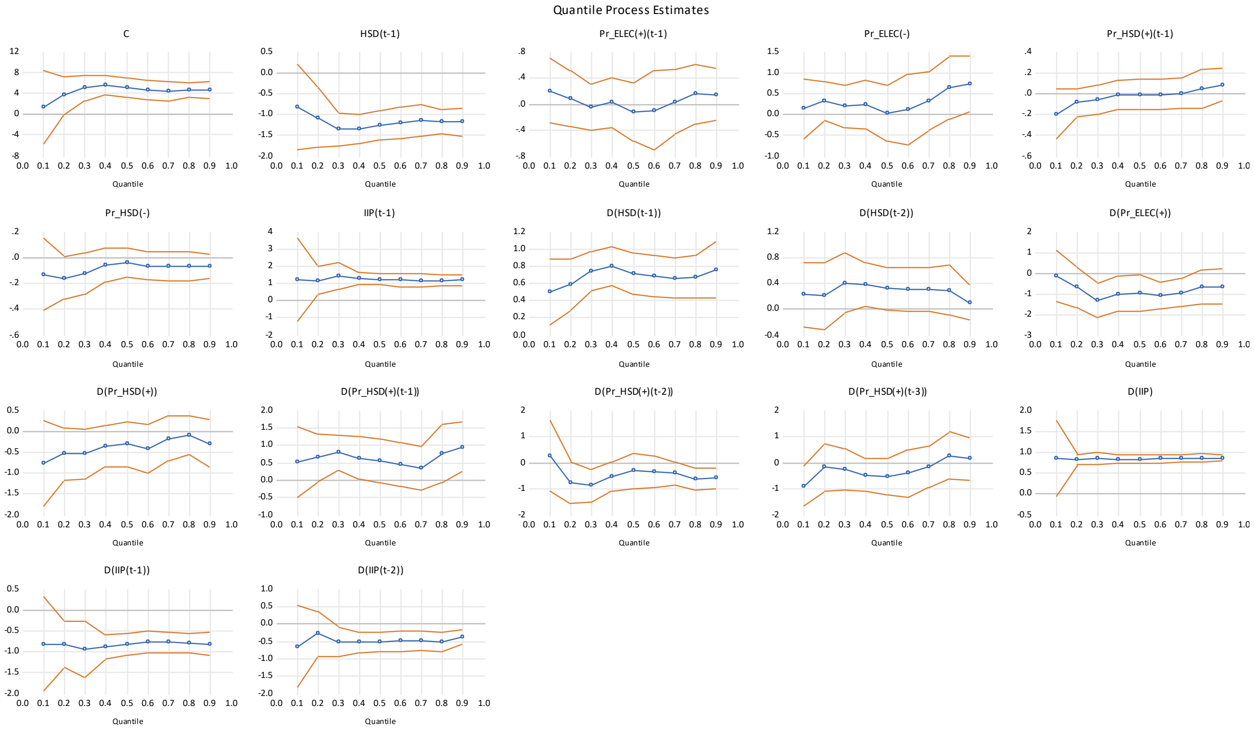

Figure A2: QNARDL Estimation: *Model 4.2* $F(HSD / IIP,\ Pr\_HSD^{(+)}, Pr\_HSD^{(-)},\ Pr\_MS^{(+)}, Pr\_MS^{(-)})$

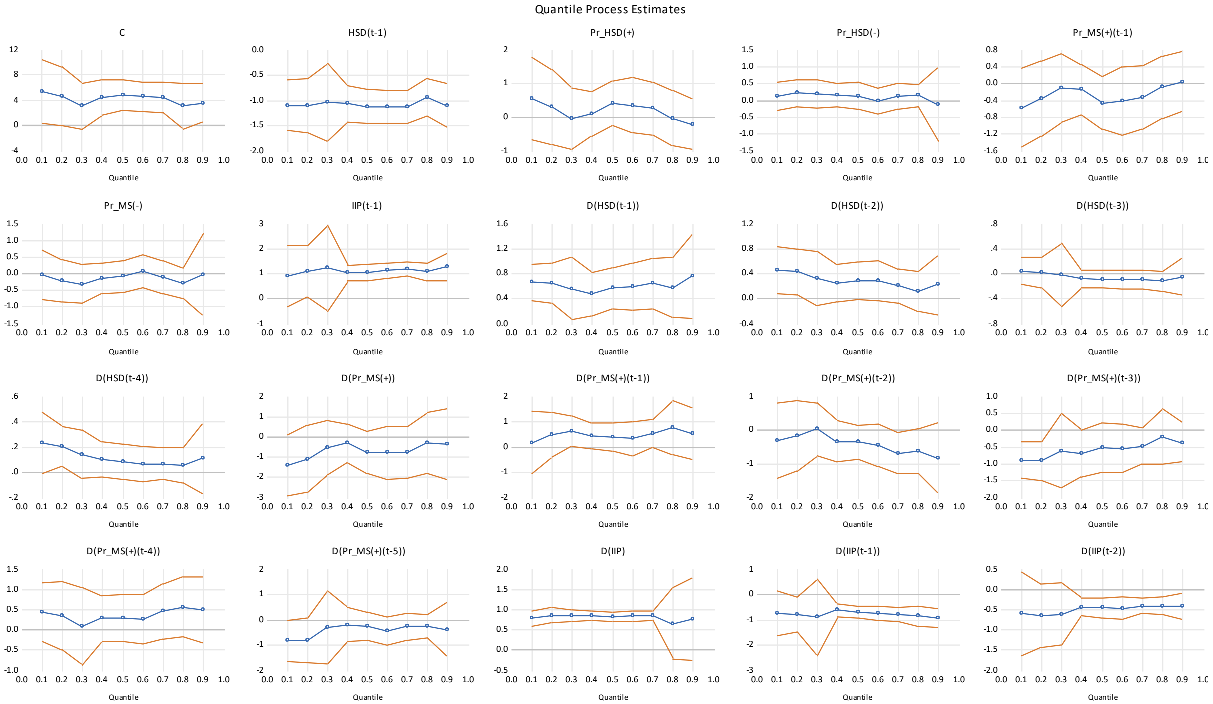

Figure A3: QNARDL Estimation: *Model 4.3 F(VHSD / IIP, Pr_HSD$^{(+)}$,Pr_HSD$^{(-)}$, Pr_ELEC$^{(+)}$,Pr_ELEC$^{(-)}$)*

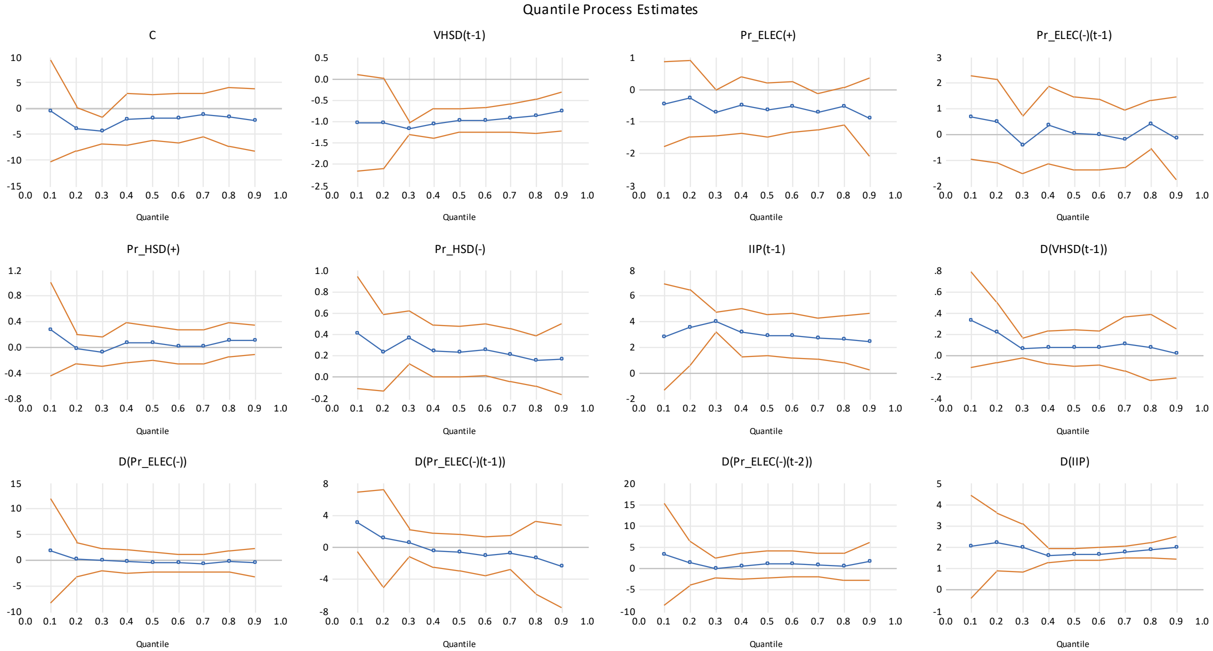

Figure A4: QNARDL Estimation: *Model 4.4 F(VHSD / IIP, Pr_HSD*$^{(+)}$*,Pr_HSD*$^{(-)}$*, Pr_MS*$^{(+)}$*,Pr_MS*$^{(-)}$*)*

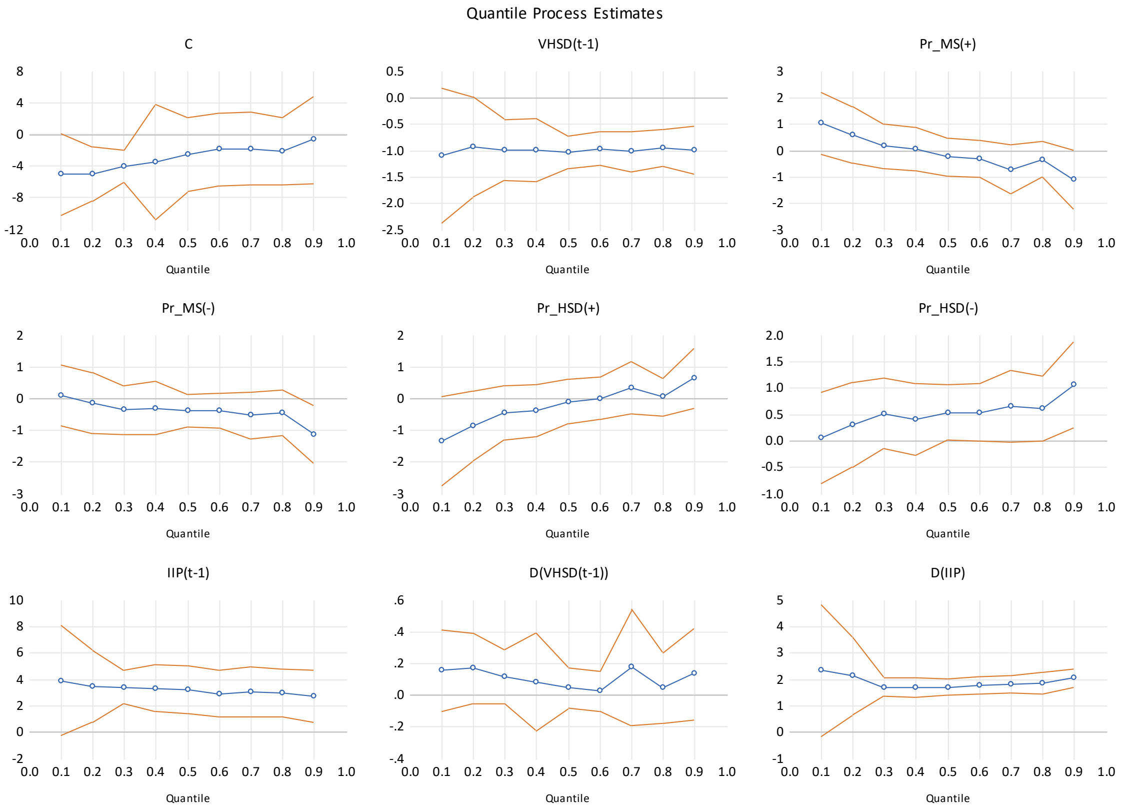

Figure A5: QNARDL Estimation: *Model 4.5* $F(MS / IIP, Pr\_MS^{(+)}, Pr\_MS^{(-)}, Pr\_ELEC^{(+)}, Pr\_ELEC^{(-)})$

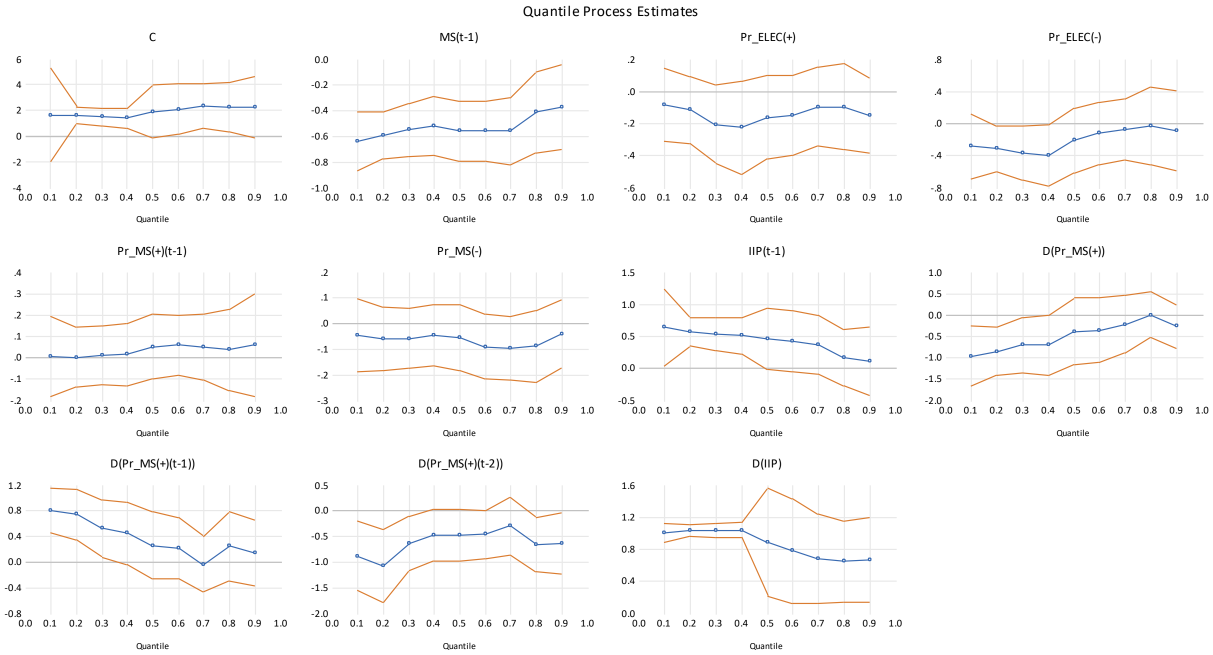

Figure A6: QNARDL Estimation: *Model 4.6* $F(MS / IIP, Pr\_MS^{(+)}, Pr\_MS^{(-)}, Pr\_HSD^{(+)}, Pr\_HSD^{(-)})$

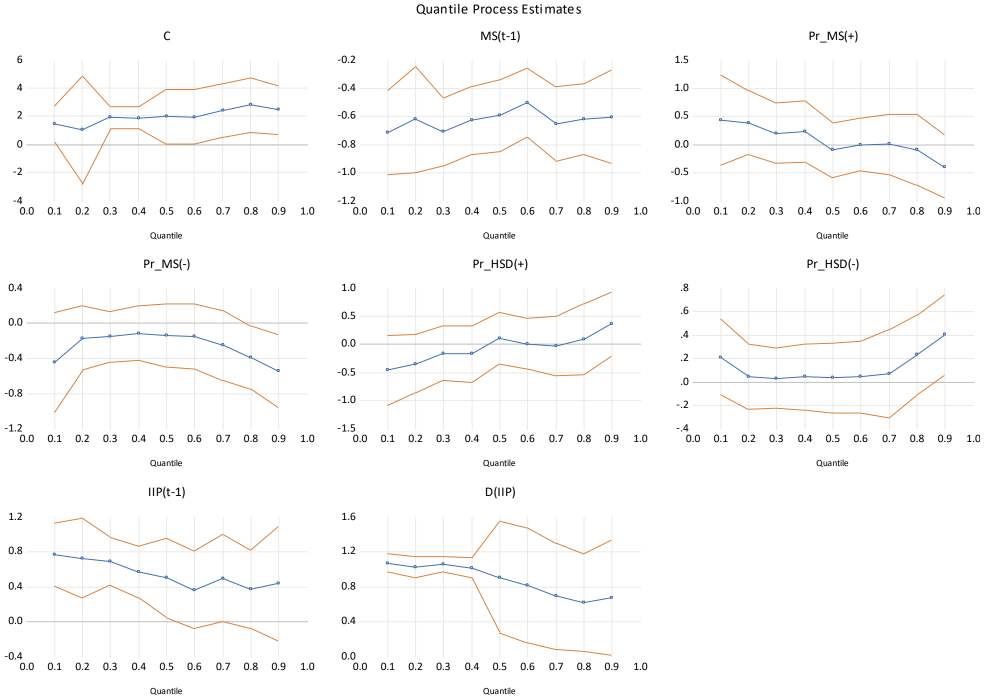

Figure A7: QNARDL Estimation: *Model 4.7* $F(VMS / IIP, Pr\_MS^{(+)}, Pr\_MS^{(-)}, Pr\_ELEC^{(+)}, Pr\_ELEC^{(-)})$

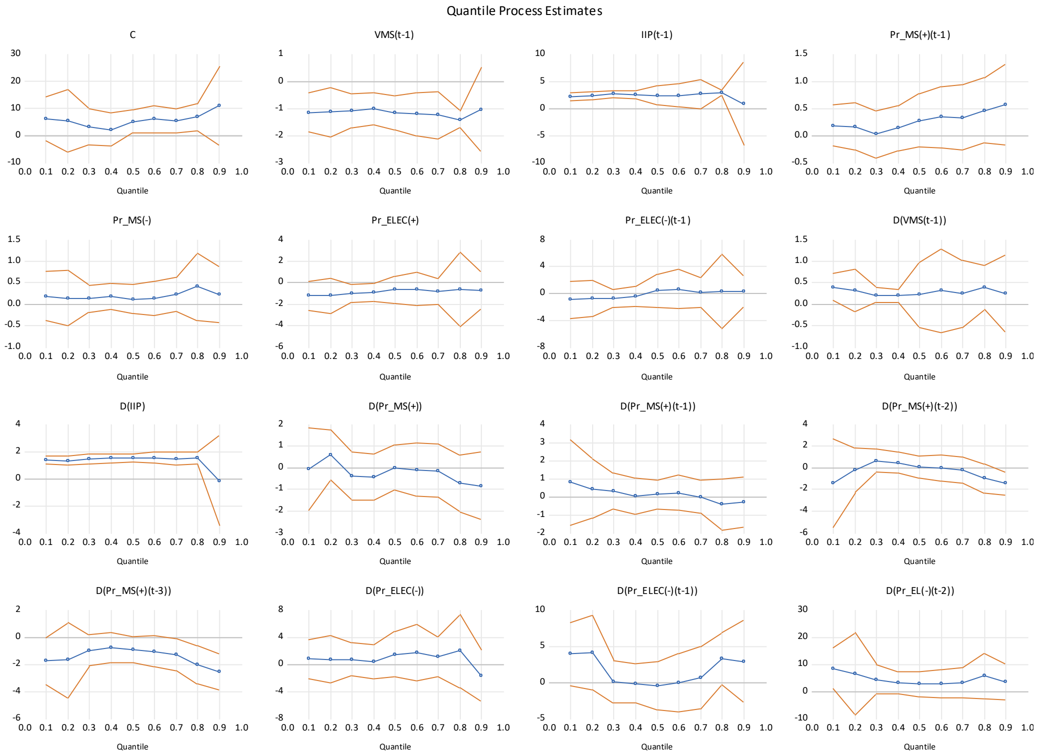

Figure A8: QNARDL Estimation: *Model 4.8 F(VMS / IIP, Pr_MS$^{(+)}$,Pr_MS$^{(-)}$, Pr_HSD$^{(+)}$,Pr_HSD$^{(-)}$)*

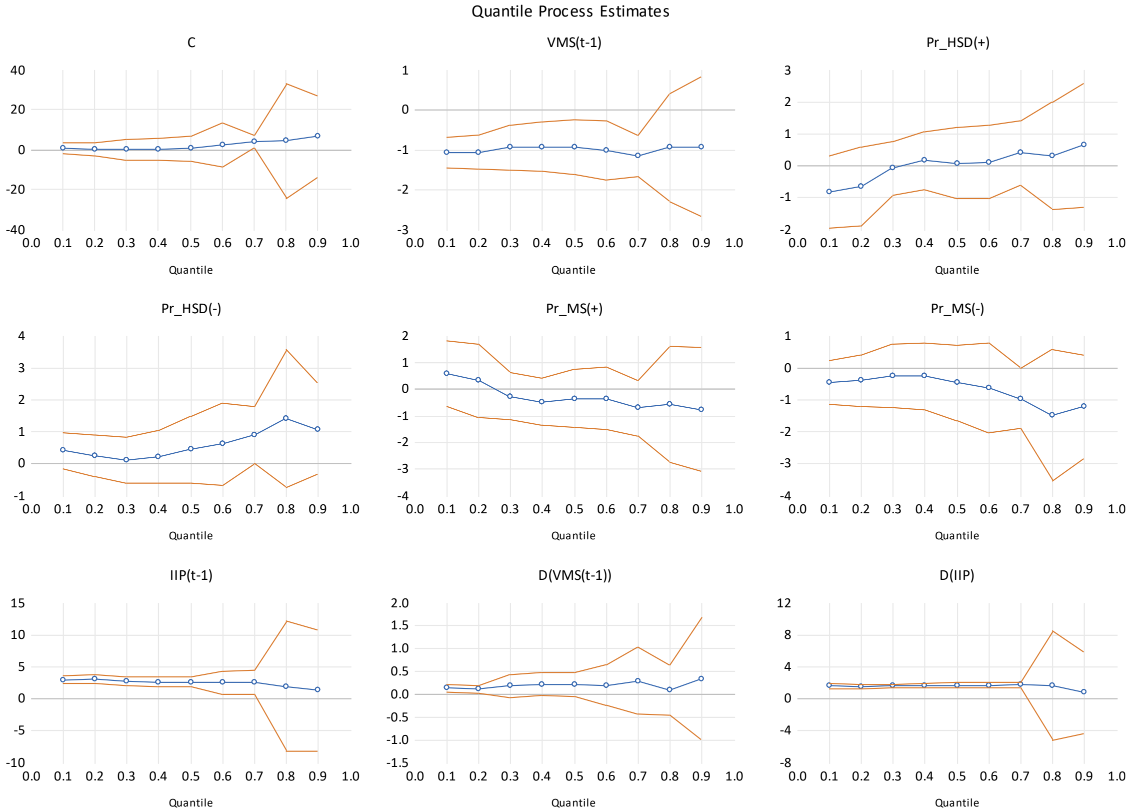

Figure A9: QNARDL Estimation: *Model 5.1 F(VEV / IIP,* $Pr\_ELEC^{(+)}$, $Pr\_ELEC^{(-)}$, $Pr\_MS^{(+)}$, $Pr\_MS^{(-)}$*)*

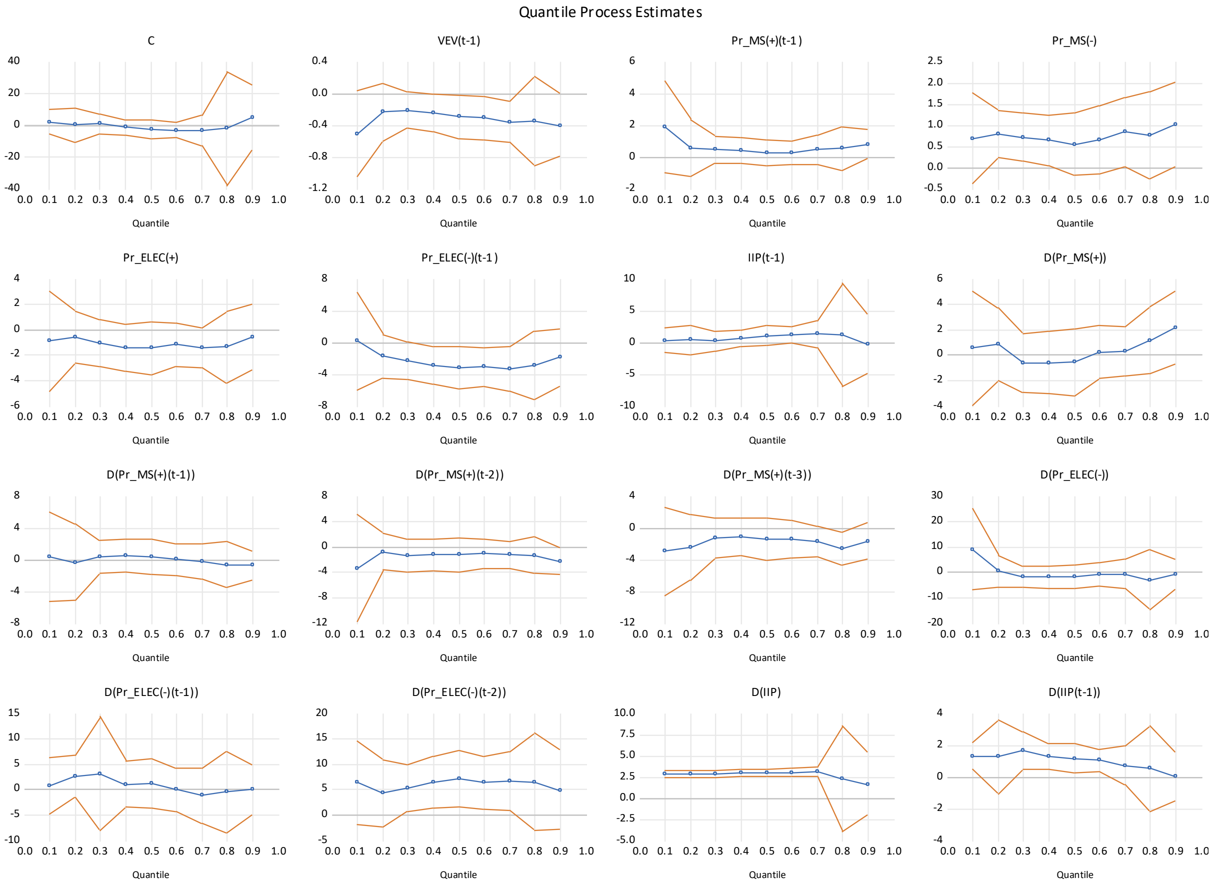

Figure A10: QNARDL Estimation: *Model 5.2 F(VEV / IIP, Pr_ELEC*$^{(+)}$*,Pr_ELEC*$^{(-)}$*, Pr_HSD* $^{(+)}$*,Pr_HSD*$^{(-)}$*)*