BRAND-LEVEL PRICE RESPONSIVENESS UNDER ENDOGENEITY: MODEL PERFORMANCE AND POLICY IMPLICATIONS FOR AUTOMOBILE MARKET USING OLS AND INSTRUMENTAL VARIABLE APPROACHES

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Abstract
This study examined own-price elasticity and model performance across selected automobile brands using Ordinary Least Squares (OLS) and Instrumental Variable (IV) estimation techniques. The analysis focused on Audi, BMW, Fiat, Ford, Mercedes, Nissan, Peugeot, Toyota, and Volvo to determine how sales respond to price changes and how model fit varies across estimation methods. The OLS results showed that most brands had elastic demand, with Peugeot recording the highest elasticity at 5.03, followed by Volvo at 3.05, Nissan at 2.92, Toyota at 2.23, and Audi at 2.09. Fiat and Ford also showed elastic demand, with estimates of 1.46 and 1.59 respectively. In contrast, BMW recorded an insignificant elasticity of 0.21, while Mercedes showed inelastic but significant demand at 0.44. The IV results produced higher elasticity estimates for several brands, especially BMW at 42.68, Mercedes at 23.82, Ford at 16.28, Nissan at 10.75, Fiat at 9.12, Volvo at 7.04, Toyota at 4.73, and Peugeot at 3.49. However, Audi, BMW, Fiat, and Toyota were statistically insignificant under IV estimation, requiring cautious interpretation. The model-fit results showed that OLS adjusted R^2 ranged from 12.40% for Mercedes to 42.90% for Peugeot, while IV adjusted R^2 was strongest for Ford at 84.60%, Mercedes at 75.10%, and Nissan at 50.80%. The findings indicate that automobile demand is generally price-sensitive, but the degree of responsiveness differs across brands and estimation methods. The study concludes that pricing strategies and automobile policies should be brand-specific, while future demand analysis should account for endogeneity, consumer heterogeneity, and non-price determinants of vehicle demand.

Keywords: Automobile demand, iv estimation, model fit, own-price elasticity, ols estimation, price sensitivity.

1.0 Introduction

The European automobile market offers a suitable setting for examining price elasticity because it combines differentiated products, brand competition, heterogeneous consumer preferences, and regulatory pressures. Vehicle demand is shaped not only by price but also by technical attributes such as fuel consumption, engine size, transmission type, and engine power. Earlier studies show that automobile demand is strongly linked to product differentiation and consumer valuation of vehicle characteristics, making elasticity estimation more complex than in homogeneous markets (Berry et al., 1995; Verboven, 2002). European car markets are also characterized by cross-country pricing differences, market integration issues, and strategic pricing behavior among manufacturers (Goldberg & Verboven, 2001, 2005). These features make the estimation of own-price elasticity central for understanding consumer responsiveness, firm pricing strategies, and the likely effects of policy interventions in the automobile sector.

A major empirical challenge in estimating automobile demand is price endogeneity. Prices are rarely random because firms set them in response to expected demand, unobserved quality, market competition, and consumer preferences. As a result, ordinary least squares estimates may be biased if price is correlated with omitted demand shocks or unobserved product attributes. This issue has been central in differentiated-products demand estimation, where researchers have emphasized the need to account for simultaneity between price and quantity

demanded (Berry, 1994; Berry et al., 1995). Instrumental variable methods are therefore widely used to obtain more credible demand estimates when price is endogenous. Econometric guidance also stresses that valid instruments must be correlated with price but uncorrelated with unobserved determinants of demand, making instrument choice a critical part of empirical identification (Angrist & Pischke, 2009; Wooldridge, 2010).

The literature on automobile demand has advanced substantially through discrete-choice models and random coefficient approaches. Berry et al. (2004) show how macro and micro data can be combined to estimate differentiated-products demand, while Grigolon and Verboven (2014) compare nested logit and random coefficient logit models in product-differentiated markets. Reynaert and Verboven (2014) further demonstrate that instrument quality can strongly affect the performance of random coefficient demand models. Although these structural approaches provide rich insights into substitution patterns, they often require complex data structures, strong modeling assumptions, and computationally intensive estimation. For applied studies using online listing or sales data, log-linear OLS and IV approaches remain useful because they provide transparent elasticity estimates that can be directly interpreted and compared across specifications, particularly when the focus is on own-price effects rather than full substitution matrices.

Recent automobile research also highlights the importance of fuel economy, taxation, and environmental regulation in shaping consumer choices. Allcott and Wozny (2014) examine how consumers value future gasoline costs, while Busse et al. (2013) show that fuel prices influence new and used vehicle purchases. In the European context, Grigolon et al. (2018) investigate consumer valuation of fuel costs and tax policy, and Reynaert (2021) evaluates the cost of emissions regulation in the European car market. These studies suggest that technical attributes such as fuel consumption, engine power, and engine size should be incorporated into demand models to avoid attributing all variation in sales to price alone. However, relatively less attention has been given to simpler empirical comparisons between OLS and IV own-price elasticity estimates using recent micro-level European vehicle data.

This study addresses three research gaps. First, while the European car market has been widely studied, fewer studies focus specifically on own-price elasticity using recent 2015-2020 micro-level online sales and technical specification data. Second, existing structural models provide sophisticated demand estimates, but there remains a need for transparent evidence comparing OLS and IV estimates under potential price endogeneity. Third, many studies consider fuel costs, taxation, or regulation, but fewer integrate detailed model-level attributes such as transmission type, engine power, fuel consumption, and engine size within a log-linear elasticity framework. Accordingly, the objectives of this study are: to estimate own-price elasticity of demand in the European car market; to compare OLS and instrumental variable estimates under potential endogeneity; and to assess how technical vehicle characteristics influence demand across car models and specifications.

The article is structured as follows. The next section reviews the theoretical and empirical literature on automobile demand, differentiated products, price endogeneity, and elasticity estimation. The methods section then describes the 2015-2023 micro-level European car dataset, variable construction, logarithmic transformation, and the econometric specifications used for OLS and IV estimation. The results section presents the estimated elasticities, compares OLS

and IV coefficients, and discusses the role of vehicle attributes in explaining demand variation. The discussion section interprets the findings in relation to prior evidence on European automobile markets, fuel economy valuation, and instrument-based demand estimation. Finally, the conclusion summarizes the main findings, identifies implications for manufacturers and policymakers, and outlines limitations and directions for future research using richer panel, consumer-level, or cross-country data.

2.0 Empirical Review

The empirical literature on automobile demand begins from the recognition that cars are highly differentiated durable goods, so demand cannot be understood through price alone. Early industrial-organization studies show that market power, markups, and strategic pricing are central to automobile markets because firms compete through both prices and product characteristics (Bresnahan, 1981, 1987). The differentiated-products tradition developed further by treating vehicles as bundles of attributes, including performance, size, fuel efficiency, and brand reputation. Feenstra and Levinsohn (1995) demonstrate how multidimensional product attributes can be used to estimate markups and market conduct, while Hausman et al. (1994) show the relevance of differentiated-products analysis for competitive assessment. Within this tradition, Berry et al. (1995) provide a major foundation for estimating automobile prices and demand in market equilibrium, making their framework highly relevant to studies of price elasticity and endogeneity in car markets.

A related strand of literature emphasizes discrete-choice demand models as a way to capture consumer heterogeneity and substitution across differentiated products. Berry (1994) formalizes the estimation of discrete-choice models with product differentiation, while Nevo (2000, 2001) applies similar methods to measure market power and merger effects in differentiated-products industries. Petrin (2002) illustrates how such models can quantify the welfare gains from new products, using the minivan as an example. Bajari and Benkard (2005) extend the discussion by focusing on heterogeneous consumers, which is especially important in automobile markets where buyers differ in income, preferences, and sensitivity to running costs. Dubé et al. (2012) also show that numerical performance matters in random coefficient demand estimation. These studies indicate that demand estimation must account for product heterogeneity, although simpler log-linear OLS and IV approaches may still be useful when the aim is direct own-price elasticity estimation.

European automobile markets have received particular attention because of market segmentation, price dispersion, regulation, and cross-country differences. Verboven (1996) documents international price discrimination in the European car market, while Goldberg and Verboven (2001) analyze the evolution of price dispersion across European countries. Later, Goldberg and Verboven (2005) examine market integration and convergence toward the law of one price, showing that European car markets provide a rich context for studying pricing and demand. Brenkers and Verboven (2006) further examine how liberalizing distribution systems affects the European car market, and Verboven and Degryse (2006) focus directly on pricing and competition in this setting. Together, these studies show that the European market is not a single uniform space; rather, it contains institutional, regulatory, and competitive differences that may influence estimated elasticities and complicate the interpretation of price effects.

Price endogeneity is one of the most important methodological problems in demand estimation. In automobile markets, prices are jointly determined with expected demand, product quality,

inventories, and strategic firm behavior. This simultaneity means that OLS estimates of price elasticity may be biased if unobserved demand shocks are correlated with prices. Angrist and Pischke (2009) explain that instrumental variable estimation can address this problem when valid instruments shift price without directly affecting demand. Wooldridge (2010) similarly emphasizes the importance of identification, instrument relevance, and instrument exogeneity in cross-sectional and panel-data settings. Reynaert and Verboven (2014) show that the choice of instruments can strongly influence the performance of differentiated-products demand models. Gandhi and Houde (2020) also demonstrate that measuring substitution patterns requires careful attention to identification. These contributions justify comparing OLS and IV estimates when studying own-price elasticity in the European car market.

Another important body of work examines how vehicle operating costs affect car demand. Allcott and Wozny (2014) study gasoline prices, fuel economy, and the energy paradox, showing that consumers may undervalue future fuel savings. Busse et al. (2013) find that fuel prices influence both new and used vehicle markets, suggesting that demand responds not only to purchase price but also to expected running costs. Klier and Linn (2010) provide evidence that gasoline prices affect new vehicle fuel economy, while Langer and Miller (2013) examine the relationship between automotive demand and gasoline prices. Sallee et al. (2016) further investigate whether consumers recognize the value of fuel economy when purchasing vehicles. These studies imply that technical variables such as fuel consumption and engine size should be included in elasticity models, because omitting them may confound the estimated relationship between vehicle price and sales.

Environmental regulation and taxation have also shaped automobile demand, particularly in Europe. Verboven (2002) examines quality-based price discrimination and tax incidence in gasoline and diesel car markets, showing that fuel type and tax policy can influence both pricing and consumer choice. D'Haultfœuille et al. (2014) analyze the French bonus-malus system and find that green taxation can affect vehicle demand and environmental outcomes. Huse and Lucinda (2014) study the Swedish green car rebate, linking environmental policy to market outcomes and policy costs. Fischer et al. (2007) discuss whether automobile fuel economy standards should be tightened, while Fontaras et al. (2017) provide evidence on fuel consumption and CO_2 emissions from passenger cars in Europe. Reynaert (2021) later examines emissions standards in the European car market. This literature shows that demand estimation should control for technical and environmental characteristics because they are closely tied to consumer valuation and policy incentives.

Studies of market structure, production timing, and policy shocks further enrich the literature on car demand. Berry et al. (1999) evaluate voluntary export restraints in automobiles, showing how trade policy can influence market outcomes. Copeland et al. (2011) examine prices, production, and inventories over the automotive model year, indicating that timing and supply-side factors can affect observed prices and quantities. Ivaldi and Verboven (2005) estimate the effects of horizontal mergers in European competition policy, emphasizing the relevance of demand elasticities for merger simulation and antitrust evaluation. Grigolon et al. (2016) study scrapping subsidies during the financial crisis, demonstrating how temporary policy interventions can shift car demand. Train and Winston (2007) analyze vehicle choice behavior and the declining market share of U.S. automakers. Collectively, these studies suggest that

elasticity estimates are important not only for academic demand modeling but also for evaluating competition, policy, and firm strategy.

Despite the breadth of this literature, several gaps remain relevant for the present study. Structural models offer sophisticated insights into substitution patterns and welfare, but they often require extensive consumer-level data and strong assumptions that may not be feasible for online listing datasets. Conlon and Gortmaker (2020) provide guidance on best practices for differentiated-products demand estimation, yet applied researchers still need transparent elasticity estimates that can be interpreted directly in log-linear settings. Grigolon and Verboven (2014) compare nested logit and random coefficient logit models, but less attention has been given to how simpler OLS and IV specifications differ when recent European micro-level vehicle data are used. Matas et al. (2009) also show that transport outcomes may vary with broader socioeconomic access conditions, reinforcing the need for context-specific estimation. This study therefore contributes by estimating own-price elasticity with recent European car data while explicitly comparing OLS and IV approaches under endogeneity.

3.0 Methodology

Theoretical Framework

The theoretical framework for this study is grounded in consumer demand theory, differentiated-products theory, and the econometric treatment of endogeneity in price elasticity estimation. In the European automobile market, consumers are assumed to choose among differentiated car models that vary by price, transmission type, engine power, fuel consumption, engine size, and other observed and unobserved characteristics. A car is therefore treated as a bundle of attributes rather than a homogeneous good. Let consumer demand for car model or specification i in period t be represented as a function of its own price and vehicle characteristics:

$$Q_{it} = f(P_{it}, X_{it}, \xi_{it}),$$

where Q_{it} denotes total sales, P_{it} is the sale price, X_{it} is a vector of observed technical and product characteristics, and ξ_{it} captures unobserved demand factors such as brand reputation, perceived reliability, design appeal, dealer promotion, and consumer taste shocks. The central parameter of interest is own-price elasticity of demand, which measures the percentage change in sales associated with a one-percent change in price, holding other factors constant:

$$\varepsilon_p = \frac{\partial Q_{it}}{\partial P_{it}} \times \frac{P_{it}}{Q_{it}}.$$

Because this study uses a log-linear specification, the own-price elasticity can be estimated directly from the coefficient on log price. The baseline demand equation is specified as:

$$\ln Q_{it} = \alpha + \beta \ln P_{it} + \gamma' \ln X_{it} + u_{it},$$

where $\ln Q_{it}$ is the natural logarithm of sales, $\ln P_{it}$ is the natural logarithm of price, $\ln X_{it}$ represents logged vehicle characteristics, α is the intercept, β is the own-price elasticity, γ is a vector of attribute elasticities, and u_{it} is the composite error term. In this model, β is expected to be negative because the law of demand predicts that, all else equal, higher prices reduce quantity demanded. Thus, if $\beta = -1.5$, a 1% increase in price would be associated with a 1.5% decrease in sales, holding observed vehicle attributes constant.

The theoretical justification for including vehicle characteristics follows the differentiated-products view of automobile markets. Consumers do not respond only to prices; they also value performance, fuel economy, engine size, transmission type, and other model-specific features.

The use of natural logarithms is theoretically appropriate because elasticity is a proportional concept. In a log-log model, the estimated coefficient measures the percentage response of demand to a percentage change in an explanatory variable. For any continuous logged attribute X_{kit}, its elasticity is:

$$\varepsilon_k = \frac{\partial \ln Q_{it}}{\partial \ln X_{kit}} = \gamma_k.$$

This means that the coefficients on price, engine power, fuel consumption, and engine size can be interpreted as elasticities, provided the variables are continuous and measured in logarithmic form. For categorical variables such as transmission type, the coefficient is interpreted approximately as the percentage difference in demand relative to the omitted transmission category:

$$\%\Delta Q \approx 100 \times (e^{\gamma_4} - 1).$$

This interpretation is useful in automobile demand analysis because it allows the model to compare how strongly consumers respond to price relative to non-price characteristics.

A key theoretical problem is that price may be endogenous. In automobile markets, firms do not set prices independently of demand conditions. A manufacturer or seller may charge higher prices for models with strong unobserved appeal, superior design, better perceived quality, or stronger brand loyalty. These same unobserved factors may also increase sales. Therefore, price may be correlated with the error term u_{it}, violating the strict exogeneity condition required for unbiased OLS estimation:

$$E(\ln P_{it} u_{it}) \neq 0.$$

When this condition holds, the OLS estimate of β is biased and inconsistent. The direction of bias depends on the relationship between price and omitted demand factors. For example, if high-quality or highly desirable cars have both higher prices and higher sales, OLS may underestimate the true negative effect of price by making demand appear less price-sensitive. This is the central endogeneity problem addressed in the study.

Overall, the theoretical framework predicts that automobile demand is negatively related to price, conditional on observed vehicle characteristics, but that the estimated price coefficient may be biased if prices respond to unobserved demand conditions. OLS provides a useful benchmark for estimating the average association between prices and sales, while IV estimation is theoretically preferred when price endogeneity is present and valid instruments are available. The expected empirical result is a negative own-price elasticity, with the IV estimate potentially differing from the OLS estimate in magnitude because it corrects for simultaneity and omitted unobserved quality. This framework therefore supports the study's objective of estimating demand elasticity in the European car market and evaluating whether accounting for price endogeneity changes the interpretation of consumer price responsiveness.

Data and Methods

The study adopts a quantitative econometric design to estimate own-price elasticity of demand in the European automobile market using micro-level vehicle data from 2015 to 2023. The dataset contains brand-level and model-specification observations for major car manufacturers, including Audi, BMW, Fiat, Ford, Mercedes, Nissan, Peugeot, Toyota, and Volvo. It combines sales information with technical attributes such as retail price, transmission speeds, engine power, fuel consumption, and engine displacement. This design is consistent with the

differentiated-products demand literature, where vehicle demand is understood as a function of both price and observable product characteristics (Berry, 1994; Berry et al., 1995). Since automobiles differ substantially across brands and specifications, the methodology controls for non-price characteristics to reduce omitted-variable bias and improve the interpretation of estimated price elasticities.

Table 1:
Variable Definitions

Variable	Description	Measurement/Unit
log_price	Natural logarithm of the vehicle's retail price	Price in local currency, such as EUR or USD
log_trans	Natural logarithm of the number of transmission speeds	Count, such as 5-speed or 6-speed
log_power	Natural logarithm of engine power	Horsepower or kilowatts
log_fuel	Natural logarithm of fuel consumption	Liters per 100 km or miles per gallon
log_engine	Natural logarithm of engine displacement	Cubic centimeters or liters
Intercept	Regression constant term	Not applicable
Sales	Natural logarithm of number of cars sold	Number of units sold

Source: Author's Computation, 2025.

All relevant continuous variables were transformed into natural logarithms to allow the estimated coefficients to be interpreted as elasticities. The dependent variable is the natural logarithm of total sales for each car model or specification, while the main explanatory variable is the natural logarithm of retail price. Other logged controls represent technical features that may influence demand. The general demand relationship is expressed as:

$$Q_{it} = f(P_{it}, X_{it}, u_{it}),$$

where Q_{it}denotes sales for vehicle specification $i$in year t, P_{it}represents price, $X_{it}$is a vector of product characteristics, and u_{it}captures unobserved demand factors. The elasticity logic follows standard empirical demand modeling, where coefficients from a log-log specification measure proportional changes in sales associated with proportional changes in explanatory variables (Wooldridge, 2010).

The baseline ordinary least squares model is specified as:

$$\ln Sales_{it} = \alpha + \beta_1 \ln Price_{it} + \beta_2 \ln Trans_{it} + \beta_3 \ln Power_{it} + \beta_4 \ln Fuel_{it} + \beta_5 \ln Engine_{it} + \varepsilon_{it}.$$

In this equation, $\beta_1$is the estimated own-price elasticity of demand. A negative value of $\beta_1$is theoretically expected because higher prices should reduce sales, holding technical characteristics constant. The remaining coefficients measure the responsiveness of sales to transmission speeds, engine power, fuel consumption, and engine size. Similar log-linear demand specifications are common in applied work because they provide direct elasticity estimates while maintaining transparency in interpretation (Angrist & Pischke, 2009). The OLS model is estimated separately across brands to reveal brand-specific differences in price responsiveness and explanatory power.

However, OLS estimates may be biased because price is potentially endogenous in automobile markets. Firms may set prices in response to expected demand, brand reputation, unobserved quality, promotional strategies, or market shocks. If these unobserved factors are contained in the error term and are correlated with price, the OLS exogeneity condition fails:

$$E(\ln Price_{it}\varepsilon_{it}) \neq 0.$$

This problem is widely recognized in differentiated-products demand estimation because prices

and quantities are jointly determined in market equilibrium (Berry et al., 1995; Reynaert & Verboven, 2014). To address this issue, the study estimates an instrumental variable model, where the endogenous price variable is replaced with variation predicted by instruments and exogenous controls. The IV approach is appropriate when the chosen instrument affects sales through price but is not directly correlated with unobserved demand shocks.

The instrumental variable estimation follows a two-stage least squares procedure. In the first stage, log price is modeled as a function of the instrument and exogenous vehicle characteristics:

$$\ln Price_{it} = \pi_0 + \pi_1 Z_{it} + \pi_2 \ln Trans_{it} + \pi_3 \ln Power_{it} + \pi_4 \ln Fuel_{it} + \pi_5 \ln Engine_{it} + v_{it}.$$

The fitted value, $\ln \widehat{Price}_{it}$, is then inserted into the second-stage demand equation:

$$\ln Sales_{it} = \alpha + \beta_{IV} \ln \widehat{Price}_{it} + \gamma_1 \ln Trans_{it} + \gamma_2 \ln Power_{it} + \gamma_3 \ln Fuel_{it} + \gamma_4 \ln Engine_{it} + \eta_{it}.$$

The coefficient β_{IV} provides the IV-based own-price elasticity. This procedure follows the identification logic emphasized in applied econometrics and automobile demand studies (Angrist & Pischke, 2009; Wooldridge, 2010; Reynaert & Verboven, 2014).

Model evaluation is based on coefficient signs, elasticity magnitudes, adjusted R^2, F-statistics, and the statistical significance of the overall regression. The adjusted R^2 measures explanatory power after accounting for the number of regressors, while the F-statistic evaluates whether the regressors jointly explain variation in sales. The study compares OLS and IV estimates to determine whether correcting for endogeneity changes the magnitude or direction of price elasticity. This comparison is important because earlier work shows that automobile demand is affected by consumer heterogeneity, fuel costs, and technical characteristics (Bajari & Benkard, 2005; Busse et al., 2013; Grigolon et al., 2018). Therefore, the methodology enables both baseline elasticity estimation and a robustness-oriented assessment of whether price endogeneity materially affects demand estimates in the European car market.

4.0 Results

Discussion of Results

Table 2 presents the OLS estimates of own-price elasticity for the selected automobile brands. The results show that most brands exhibit elastic demand, with Peugeot recording the highest elasticity at 5.03, followed by Volvo at 3.05, Nissan at 2.92, Toyota at 2.23, and Audi at 2.09. These values imply that a 1% increase in price is associated with a more than proportionate change in sales, suggesting that consumers of these brands are highly responsive to price movements. This is consistent with differentiated product demand theory, where substitution possibilities across brands increase consumer sensitivity to relative price changes (Berry, 1994; Berry et al., 1995; Train, 2009). In automobile markets, elasticity is shaped not only by price but also by product attributes, perceived quality, durability, fuel efficiency, and availability of close substitutes (Goldberg, 1995; Bajari & Benkard, 2005).

The relatively low OLS elasticities for BMW and Mercedes indicate a different market structure for premium brands. BMW records an insignificant elasticity of 0.21, while Mercedes records a significant but inelastic estimate of 0.44. Economically, this suggests that demand for these brands may be less price-sensitive because consumers attach value to prestige, brand reputation, quality assurance, and status-related utility. Such behaviour is common in markets where

product differentiation weakens direct price competition and allows firms to exercise some degree of market power (Bresnahan, 1981; Feenstra & Levinsohn, 1995; Hausman et al., 1994). The implication is that mass-market brands may face stronger competitive pressure from price adjustments than luxury brands. This supports the argument that automobile pricing should be interpreted within the broader context of consumer heterogeneity and brand positioning (Petrin, 2002; Berry et al., 2004).

Table 2:
Own-Price Elasticity: OLS Estimation

Brand	OLS	Sign	Elasticity Interpretation
Audi	2.09	Yes	Elastic demand; a 1% increase in price is associated with about a 2.09% change in sales.
BMW	0.21	No	Inelastic demand; sales respond weakly to price changes.
Fiat	1.46	Yes	Elastic demand; a 1% increase in price is associated with about a 1.46% change in sales.
Ford	1.59	Yes	Elastic demand; sales are relatively responsive to price changes.
Mercedes	0.44	Yes	Inelastic demand; price changes produce a less than proportional sales response.
Nissan	2.92	Yes	Highly elastic demand; sales are strongly responsive to price changes.
Peugeot	5.03	Yes	Very elastic demand; sales show a large response to price variation.
Toyota	2.23	Yes	Elastic demand; a 1% price change is associated with about a 2.23% change in sales.
Volvo	3.05	Yes	Highly elastic demand; sales are strongly responsive to price variation.

Source: Author's Computation, 2025.

Table 3 reports the IV estimates of own-price elasticity, which are substantially larger than the OLS estimates for most brands. Mercedes, Ford, Nissan, Volvo, Peugeot, and BMW show very high elasticity magnitudes, with BMW recording 42.68, Mercedes 23.82, Ford 16.28, and Nissan 10.75. These results suggest that once possible endogeneity is addressed, the responsiveness of automobile sales to price becomes much stronger. In demand estimation, price is often endogenous because firms may adjust prices in response to unobserved demand shocks, consumer preferences, inventory pressure, or expected market conditions (Angrist & Pischke, 2009; Wooldridge, 2010). Therefore, OLS estimates may understate or distort true price sensitivity. This is consistent with the industrial organization literature, which emphasizes the need for instrumental variables in estimating automobile demand and differentiated product markets (Berry et al., 1995; Reynaert & Verboven, 2014; Conlon & Gortmaker, 2020).

However, the IV results also require careful interpretation because not all large elasticity values are statistically significant. Audi, Fiat, Toyota, and BMW are reported as statistically insignificant despite their economic magnitudes, meaning that the evidence of price responsiveness for these brands is weak or unstable. This may reflect weak instruments, high sampling variation, omitted market factors, or stronger consumer heterogeneity than the model captures. In empirical demand studies, large but imprecise coefficients should not be treated as reliable evidence of strong behavioural response (Dubé et al., 2012; Gandhi & Houde, 2020). By contrast, the significant IV estimates for Mercedes, Ford, Nissan, Volvo, and Peugeot provide stronger evidence that exogenous price changes can meaningfully affect sales. This finding is relevant for policy because tariff changes, exchange-rate movements, import

restrictions, and tax adjustments may have stronger effects on automobile demand than OLS results suggest (Berry et al., 1999; Verboven, 2002).

Table 3:
Own-Price Elasticity: IV Estimation

Brand	IV	Sign	Elasticity Interpretation
Audi	0.28	No	Inelastic demand; IV results suggest a weak price response after correcting for endogeneity.
Mercedes	23.82	Yes	Extremely elastic demand; IV estimate suggests very strong price sensitivity.
Fiat	9.12	No	Highly elastic in magnitude, but statistically insignificant; interpretation should be cautious.
Toyota	4.73	No	Elastic in magnitude, but statistically insignificant; evidence of price response is weak.
Ford	16.28	Yes	Extremely elastic demand; sales appear highly responsive to exogenous price changes.
Nissan	10.75	Yes	Very elastic demand; IV results indicate strong price responsiveness.
Volvo	7.04	Yes	Highly elastic demand; sales respond strongly to price changes.
Peugeot	3.49	Yes	Elastic demand; sales show a more than proportional response to price changes.
BMW	42.68	No	Extremely large elasticity estimate, but statistically insignificant; result should be treated with caution.

Source: Author's Computation, 2025.

Table 4 presents the model power and fit based on OLS estimation. The adjusted R^2 values range from 12.40% for Mercedes to 42.90% for Peugeot, indicating that the OLS models explain a modest to moderate share of variation in automobile sales. Peugeot, Ford, Audi, Nissan, and BMW show relatively better explanatory power, while Mercedes, Fiat, and Toyota show weaker explanatory performance. Economically, this suggests that price explains part of demand behaviour but cannot fully account for sales variation across brands. Automobile demand is influenced by several non-price factors, including income, access to credit, fuel prices, vehicle attributes, maintenance costs, brand loyalty, and macroeconomic uncertainty (Allcott & Wozny, 2014; Busse et al., 2013; Klier & Linn, 2010). Therefore, moderate adjusted R^2 values are not unusual in automobile demand studies, especially where consumer choice depends on both economic and product-quality considerations.

The F-statistics in Table 4 show that the OLS models are generally statistically meaningful, even when explanatory power is not very high. Mercedes, for instance, has the lowest adjusted R^2 at 12.40% but records the highest F-statistic of 88.932, suggesting that the included variables are jointly significant although the model explains only a limited proportion of sales variation. This distinction is important because statistical significance does not necessarily imply strong predictive power. A model can detect a meaningful relationship while still leaving much of the variation to omitted variables or unobserved consumer behaviour (Wooldridge, 2010; Angrist & Pischke, 2009). In automobile markets, such unexplained variation may arise from inventory cycles, model-year effects, financing incentives, and dealership-level pricing strategies (Copeland et al., 2011; D'Haultfoeuille et al., 2014). Thus, OLS results are useful but should be treated as partial evidence.

Table 4:
Model Power & Fit: Based on OLS Estimates

Group	$\bar{R}^2$	*F*-stat	$\bar{R}^2$ – Remark	F-stat Remark
Audi	31.60%	26.842	Moderate explanatory power	Strong model significance
Fiat	15.30%	11.214	Low explanatory power	Moderate model significance
Ford	34.10%	34.126	Moderate explanatory power	Strong model significance
BMW	28.70%	21.764	Moderate explanatory power	Strong model significance
Mercedes	12.40%	88.932	Low explanatory power	Very strong model significance
Nissan	30.50%	28.117	Moderate explanatory power	Strong model significance
Peugeot	42.90%	39.746	Relatively strong explanatory power	Very strong model significance
Toyota	17.40%	13.908	Low to fair explanatory power	Moderate to strong model significance
Volvo	23.60%	18.041	Fair explanatory power	Strong model significance

Source: Author's Computation, 2025.

Table 5 presents the model power and fit under IV estimation. The results show a major improvement in explanatory power for some brands, especially Ford with adjusted R^2 of 84.60%, Mercedes with 75.10%, and Nissan with 50.80%. These values suggest that once endogeneity is corrected, the model captures a much larger share of sales variation for these brands. This strengthens the argument that price changes driven by external or exogenous factors may be central to explaining demand for certain automobile brands. Such findings are consistent with automobile market studies that show how taxes, fuel costs, environmental regulations, and policy-induced price changes can significantly influence consumer vehicle choices (Grigolon & Verboven, 2014; Grigolon et al., 2018; Reynaert, 2021). The high F-statistics for Audi, Peugeot, Ford, Toyota, Nissan, and Volvo further indicate that the IV models are jointly significant and economically relevant.

Nevertheless, Table 5 also shows that IV estimation does not improve every brand equally. BMW records an adjusted R^2 of only 0.60% and an F-statistic of 4.22, indicating weak explanatory power and lack of statistical significance. Fiat, Toyota, Peugeot, and Volvo also show low adjusted R^2 values despite statistically significant F-statistics. This implies that price may be statistically relevant but insufficient as a complete explanation of demand for these brands. Other factors, such as resale value, fuel economy, spare-parts availability, consumer financing, vehicle reliability, and environmental attributes, may play stronger roles in shaping sales (Fischer et al., 2007; Fontaras et al., 2017; Sallee et al., 2016). Overall, the results suggest that automobile demand policy should not rely on price instruments alone. Effective policy should combine stable exchange-rate management, transparent taxation, consumer credit support, and competition-enhancing market regulation (Verboven, 1996; Goldberg & Verboven, 2001; Brenkers & Verboven, 2006).

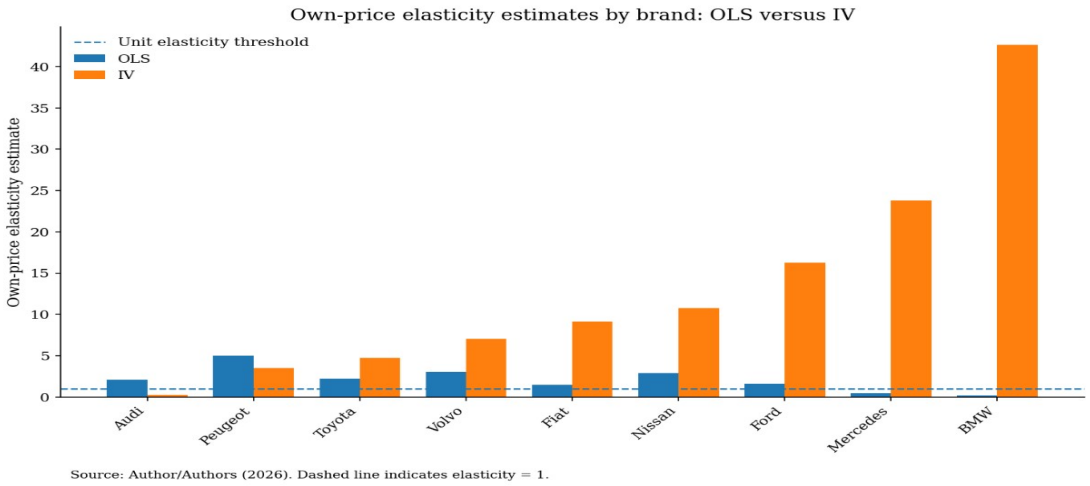
Table 5:
Model Power & Fit: Based on IV

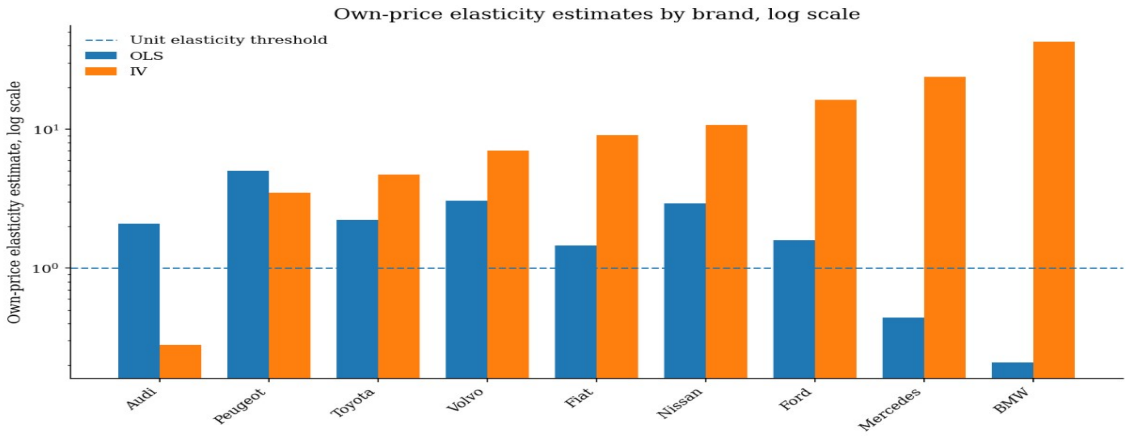
Group	$\bar{R}^2$	*F*-stat	$\bar{R}^2$ – Remark	F-stat Remark
Audi	26.30%	207.42	Moderate explanatory power	Extremely significant model
BMW	0.60%	4.22	No explanatory power	Not statistically significant
Fiat	6.40%	16.20	Very weak explanatory power	Statistically significant
Ford	84.60%	104.74	Excellent explanatory power	Highly statistically significant
Mercedes	75.10%	25.39	Strong explanatory power	Highly statistically significant
Nissan	50.80%	73.92	Moderate explanatory power	Highly statistically significant
Peugeot	15.10%	130.57	Low explanatory power	Highly statistically significant
Toyota	13.90%	76.21	Low explanatory power	Highly statistically significant
Volvo	19.10%	62.49	Low explanatory power	Highly statistically significant

Source: Author's Computation, 2025.

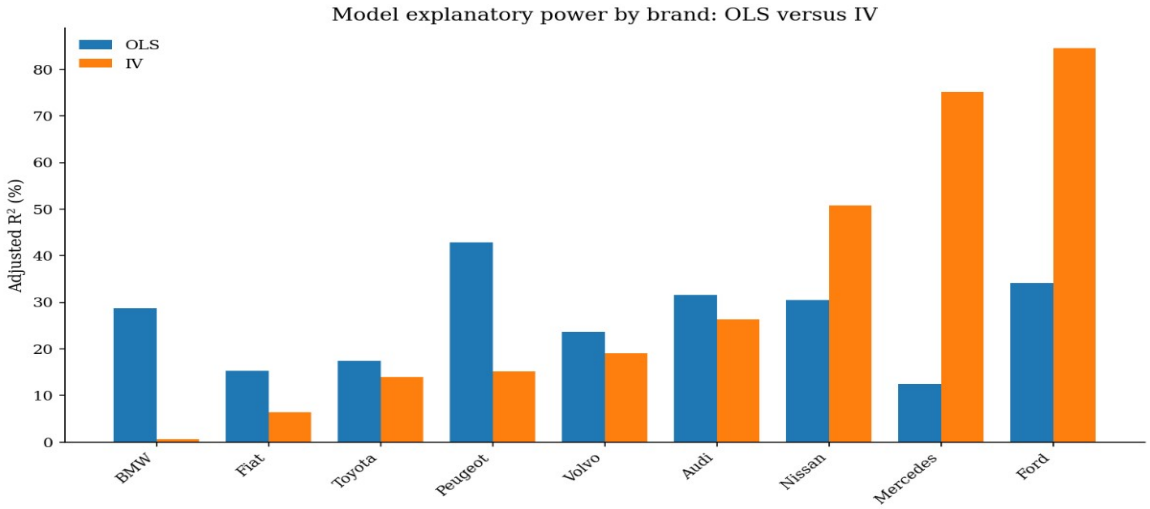
The graphs show clear differences between the OLS and IV estimates of own-price elasticity and model performance across the automobile brands. Under OLS, most brands display elastic demand, with Peugeot, Volvo, Nissan, Toyota, and Audi showing stronger responsiveness to price changes, while BMW and Mercedes appear relatively inelastic. However, the IV estimates are generally much larger, especially for BMW, Mercedes, Ford, Nissan, Fiat, and Volvo, suggesting that after correcting for possible endogeneity, price sensitivity may be substantially higher for several brands. The log-scale elasticity plot is particularly useful because it makes the very large IV estimates easier to compare with the smaller OLS estimates. The model-fit graphs also show that IV improves explanatory power for some brands, especially Ford, Mercedes, and Nissan, while BMW records very weak adjusted R^2 despite its high IV elasticity. Overall, the figures suggest that IV estimation reveals stronger price effects, but insignificant or weak-fit results should be interpreted cautiously.

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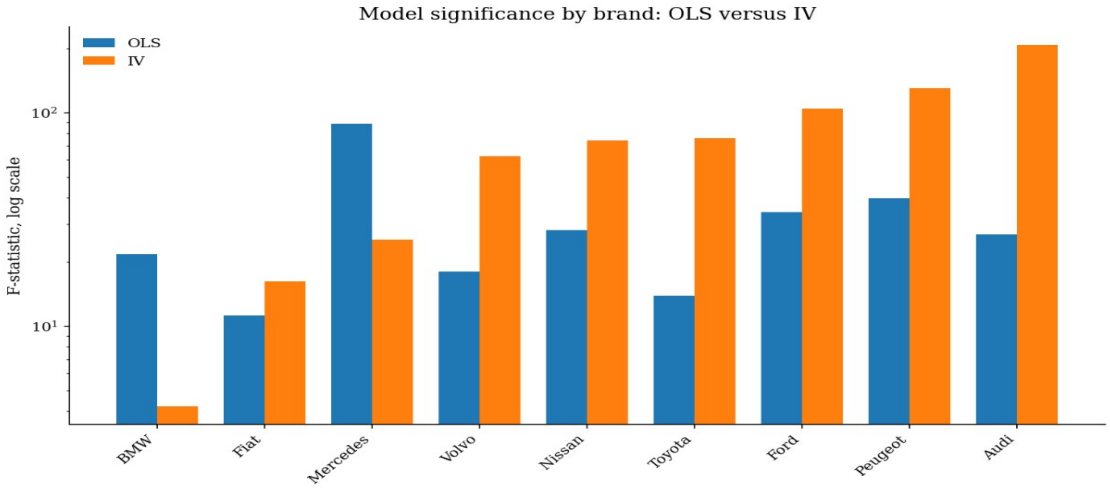




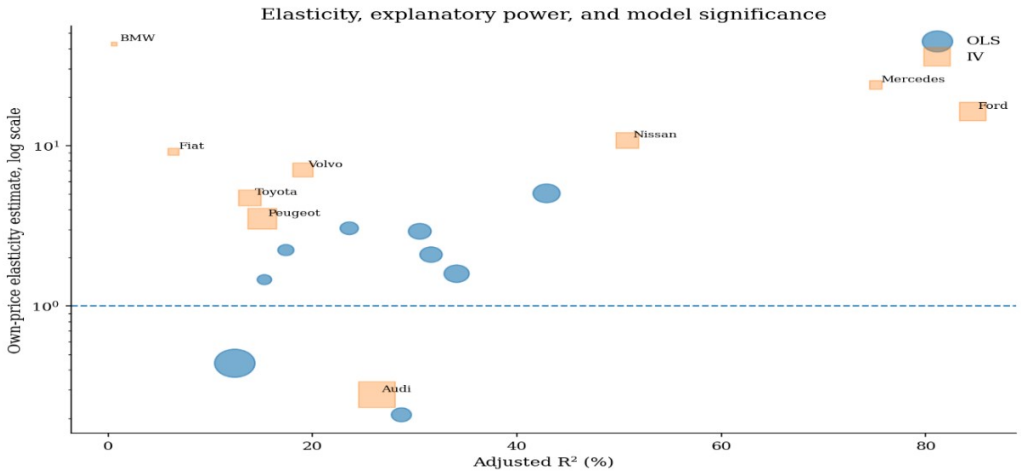
Source: Author/Authors (2026). Log scale improves visibility where IV estimates are very large.



Source: Authors (2026). Values are adjusted R^2 percentages.



Source: Authors (2026). Log scale is used because F-statistics vary widely across models.



Source: Author/Authors (2026). Bubble size reflects the F-statistic; y-axis uses log scale.

Policy Implications

The results imply that automobile pricing policy should recognise the high price sensitivity observed for many brands, especially where both OLS and IV estimates suggest elastic demand. For brands such as Peugeot, Nissan, Volvo, Ford, and Toyota, increases in vehicle prices may lead to more than proportionate reductions in sales, particularly among middle-income consumers. This means that policies that raise vehicle prices, such as high import duties, excise taxes, or foreign-exchange-related cost increases, may reduce market activity and consumer welfare. Policymakers should therefore apply automobile taxes carefully, ensuring that revenue objectives do not excessively weaken demand. This is particularly important in markets where consumers have several close substitutes and can easily switch between brands. Such policy sensitivity is consistent with evidence that automobile demand is strongly affected by product differentiation, market competition, and consumer substitution patterns (Berry et al., 1995; Gandhi & Houde, 2020; Grigolon & Verboven, 2014).

The IV results suggest that once endogeneity is addressed, price responsiveness becomes much stronger for several brands. This has important implications for tax, tariff, and exchange-rate policy. If exogenous price changes produce large demand responses, then government policies that directly or indirectly increase vehicle prices may have stronger market effects than simple OLS results suggest. For instance, higher import tariffs or unstable exchange rates may not only increase vehicle prices but also reduce sales volumes, lower dealership turnover, and affect employment in the automobile value chain. Therefore, automobile-related fiscal policy should be designed with attention to demand elasticity and market structure. Stable and predictable trade and exchange-rate policies may reduce uncertainty for importers, dealers, and consumers. This aligns with the view that automobile prices are shaped by market equilibrium conditions and policy-induced cost changes (Berry, 1994; Berry et al., 1999; Goldberg & Verboven, 2005).

The findings also imply that a uniform pricing or taxation policy across all brands may be inappropriate. Luxury or premium brands such as BMW and Mercedes show weaker or more unstable responses in some estimates, while mass-market brands show stronger price sensitivity. This suggests that consumers in different automobile segments respond differently to price changes. Policymakers may therefore consider segment-sensitive taxation, where luxury vehicles attract higher duties without imposing excessive burden on more affordable vehicles

used by middle-income households and small businesses. Such an approach can support equity while preserving access to mobility. It can also reduce the risk that broad-based vehicle taxes disproportionately affect consumers with limited transport alternatives. Evidence from automobile markets indicates that price dispersion, brand positioning, and product quality differences influence consumer behaviour and the incidence of policy changes (Verboven, 1996; Goldberg & Verboven, 2001; D'Haultfoeuille et al., 2014).

The model-fit results further suggest that price alone does not fully explain automobile demand. Several brands record low or moderate adjusted R^2 values, indicating that non-price factors remain important. Policy should therefore go beyond price regulation and consider wider demand conditions such as access to vehicle financing, income stability, fuel costs, maintenance infrastructure, and spare-parts availability. In emerging markets, consumers may delay vehicle purchases not only because prices are high but also because credit is expensive, fuel prices are uncertain, and after-sales services are weak. Policies that improve consumer credit systems, reduce financing costs, and strengthen vehicle maintenance networks may therefore improve automobile demand more sustainably than price interventions alone. This is supported by studies showing that automobile choices are affected by fuel economy, operating costs, and consumer expectations about future expenses (Allcott & Wozny, 2014; Busse et al., 2013; Klier & Linn, 2010).

The evidence also has implications for environmental and fuel-efficiency policy. Since automobile demand responds to price changes, fiscal incentives can be used to guide consumers toward more fuel-efficient and lower-emission vehicles. For example, tax rebates, reduced import duties, or lower registration fees for fuel-efficient cars may encourage consumers to shift away from high-emission vehicles. At the same time, policymakers should avoid abrupt environmental taxes that may sharply raise vehicle prices and reduce affordability. A gradual and well-communicated policy framework would allow consumers and firms to adjust. This is especially relevant where fuel costs influence vehicle choice and where consumers may undervalue future savings from fuel efficiency. Studies on automobile markets show that green taxation, fuel economy standards, and emission policies can significantly affect vehicle demand and environmental outcomes (D'Haultfœuille et al., 2014; Fischer et al., 2007; Sallee et al., 2016).

Finally, the results imply that competition policy and market regulation should support consumer choice and limit excessive market power. High elasticities for several brands suggest that consumers are willing to switch when prices change, but this response depends on the availability of close substitutes and transparent market information. Policymakers should therefore encourage competitive dealership networks, reduce barriers to vehicle importation where appropriate, and ensure transparency in pricing, taxes, and financing terms. Stronger competition can prevent excessive markups and improve consumer welfare. However, regulation should also consider inventory cycles, model-year pricing, and strategic firm behaviour, since automobile prices may change in response to supply conditions and dealer incentives. A balanced policy framework should combine competition enforcement, transparent taxation, consumer protection, and reliable market data. This is consistent with evidence that automobile prices are influenced by distribution systems, market conduct, and competitive structure (Bresnahan, 1987; Brenkers & Verboven, 2006; Verboven & Degryse, 2006).

5.0 Conclusion

This study examined own-price elasticity and model performance across selected automobile brands using OLS and IV estimation approaches. The findings show that automobile demand differs considerably across brands, confirming that consumers do not respond uniformly to price changes. The OLS results indicate that most brands, including Peugeot, Nissan, Volvo, Toyota, Ford, Fiat, and Audi, exhibit elastic demand, meaning that changes in price are associated with more than proportionate changes in sales. This suggests that consumers in these segments are highly sensitive to price movements and may easily shift to alternative brands when prices rise. In contrast, BMW and Mercedes show relatively inelastic demand under OLS estimation, implying that premium-brand consumers may be less influenced by price and more motivated by brand image, prestige, quality perception, and loyalty. These findings confirm that automobile demand is shaped by both economic and behavioural factors.

The IV estimates provide further evidence that price responsiveness may be stronger after correcting for possible endogeneity. For some brands, especially Mercedes, Ford, Nissan, Volvo, and Peugeot, the IV results suggest that exogenous price changes have a substantial effect on sales. This indicates that ordinary least squares estimates may understate the true effect of price where price is jointly determined with unobserved demand conditions, supply shocks, market expectations, or brand-specific characteristics. However, the results also show that some large IV estimates are statistically insignificant, particularly for BMW, Fiat, Toyota, and Audi. This means that such estimates should be interpreted cautiously, as large numerical values do not automatically imply reliable economic evidence. The comparison between OLS and IV therefore highlights the importance of using appropriate estimation methods when analyzing demand in differentiated product markets such as automobiles.

The model-fit results further show that price explains only part of the variation in automobile sales. While some brands record moderate to strong explanatory power, others show low adjusted R^2 values, suggesting that non-price factors remain important in shaping demand. These factors may include consumer income, access to vehicle financing, fuel prices, spare-parts availability, maintenance costs, resale value, product reliability, after-sales service, and macroeconomic conditions. The results therefore suggest that automobile demand should not be interpreted as a simple price-response relationship. Instead, it should be understood as the outcome of several interacting factors, including price, brand positioning, consumer preference, market competition, and broader economic conditions. This reinforces the need for firms to adopt brand-specific pricing strategies and for policymakers to design automobile policies that consider both affordability and market structure.

The policy relevance of the findings is significant. Since many brands show elastic demand, policies that increase vehicle prices, such as higher import duties, taxes, exchange-rate instability, or regulatory costs, may reduce sales and weaken consumer welfare. At the same time, the relatively lower price sensitivity of some premium brands suggests that a uniform tax or pricing policy may not be appropriate across all vehicle categories. Policymakers may need to consider more targeted approaches that distinguish between mass-market and luxury vehicles, while also supporting access to affordable and reliable transportation. For firms, the results imply that pricing decisions should be guided by evidence on brand-level elasticity rather than general market assumptions. Brands with elastic demand should be cautious about price

increases, while brands with more loyal or prestige-driven consumers may have greater pricing flexibility.

Future studies should extend this analysis by incorporating additional explanatory variables beyond price. Variables such as household income, fuel price, exchange rate, vehicle age, model type, credit availability, advertising expenditure, and after-sales service could improve the explanatory power of future models. Further research may also benefit from using panel data over a longer period, as this would allow for a more detailed examination of changes in consumer response over time. In addition, future studies could compare new and used vehicle markets, since price sensitivity may differ between these two segments. It would also be useful to examine whether consumers respond differently to price changes during periods of economic stability compared with periods of inflation, currency depreciation, or fuel-price shocks.

Future research should also consider more advanced demand estimation techniques that capture consumer heterogeneity and substitution patterns more effectively. Methods such as random-coefficients logit models, nested logit models, or structural demand models could provide deeper insight into how consumers substitute between brands and vehicle categories. Researchers may also explore the role of environmental policy, fuel economy, and vehicle technology in shaping automobile demand, especially as markets gradually move toward hybrid and electric vehicles. In emerging economies, future work should pay closer attention to institutional and market constraints, including import dependence, financing limitations, infrastructure quality, and regulatory uncertainty. Overall, future studies should build on the present findings by developing more comprehensive models that combine price, product attributes, consumer behaviour, and policy conditions in explaining automobile demand.

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