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THE MICROECONOMIC IMPACT OF FUEL PRICE AND TAX INCREASES ON PROFESSIONALS' TRANSPORT MODE CHOICES IN SRI LANKA

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ABSTRACT

Sri Lanka's recent economic crisis, marked by steep fuel price increases and higher income taxation, has eroded disposable incomes and significantly increased commuting costs. Professionals (ISCO-88) represent a critical commuter group in Colombo due to their high value of time and reliance on private transport; however, limited empirical research examines how simultaneous fuel price and income tax shocks influence their mode choices. This study investigates the microeconomic impact of these shocks on mode choice using a stated-preference experiment with 42 respondents across five scenarios reflecting variations in fuel prices, commuting distances, and taxation-induced income reductions. Alternative-specific travel costs and times were derived using calibrated functions to ensure realistic trade-offs among cars, motorcycles, staff transport, and public transport, and responses were analysed using an alternative-specific conditional logit model. The results indicate a clear substitution pattern under increasing cost pressures: motorcycle usage declines sharply with income reductions, car use decreases more gradually, staff transport acts as an intermediate adjustment mechanism, and public transport absorbs the largest share of demand. These responses reflect short-run adjustments to cost shocks driven by changes in relative generalised costs rather than permanent preference shifts. The findings highlight how combined fuel price and income tax shocks reshape commuting behaviour in the short run, emphasising the need to align fuel taxation with investments in public and employer-supported transport to ensure sustainable urban mobility.

Keywords: *Fuel prices, taxation, transport model choice, stated-preference, alternative-specific conditional logit model*

1. INTRODUCTION

Sri Lanka's economy has only recently begun to recover from its most severe economic crisis in history, characterised by sharp increases in fuel prices, higher income taxation, and a substantial erosion of real incomes [1]. These developments have significantly increased the cost of living, with transportation costs emerging as one of the most visible and immediate burdens on households. For urban commuters, particularly professionals, rising fuel prices and taxation jointly affect both the direct cost of travel and the disposable income available for commuting, thereby altering travel behaviour through both price and income channels. Although macroeconomic stabilisation efforts under the IMF-supported Extended Fund Facility (EFF), launched in 2023, provided some relief, the cost of living remains elevated. Fuel prices, in particular, have persisted at high levels despite the introduction of formula-based pricing, increasing by 259% during 2021–2022 before stabilising at Rs. 309 per litre for Octane 92 and Rs. 286 per litre for auto diesel in December 2024. By the end of 2025, these prices were adjusted slightly to Rs. 299 and Rs. 283, respectively [2]. Fiscal reforms, including the introduction of the 18% VAT in 2024 and new excise duties added to the 2023 budget, improved government revenue but simultaneously reduced disposable household income by increasing transport costs.

The Western Province, Sri Lanka's most urbanised and economically active region, exemplifies this challenge. In 2023, 39.3% of Sri Lanka's total vehicle fleet of 8.38 million was concentrated in the Western Province [3]. This includes private motorised vehicles, such as cars and motorcycles, which dominate commuting patterns among professionals. However, this concentration of private vehicle ownership significantly contributes to congestion and fuel demand in Colombo. Incorporating modal share data further highlights the imbalance in urban transport use, where private modes continue to dominate, despite increasing costs. The 2019 Household Income and Expenditure Survey reported that 14.2% of monthly household spending was devoted to transport and communication, a proportion that has risen sharply owing to inflation and tax increases [4]. Real wage contractions between 16.9% and 22% between 2021 and 2024 further constrained affordability and intensified commuting pressures [1].

These economic conditions primarily influence short-run micro-level behaviour, as commuters adjust their mode choices in response to immediate changes in relative costs and disposable income. However, in the long run, such behavioural adjustments may be partially reversible as incomes recover or as individuals reoptimize their commuting preferences. During the 2022 crisis, when many commuters shifted to carpooling, overcrowded buses, and ride-hailing services, they often compromised comfort and reliability to reduce costs.

Professionals who live and/or work in Colombo constitute a critical group whose commuting decisions significantly influence traffic congestion, fuel demand, and public transport utilisation. Despite their importance, there is limited empirical evidence on how fuel prices and taxation pressures shape their transport mode choices. This knowledge gap restricts policymakers' ability to anticipate behavioural responses and design equitable and effective fiscal and transport policies, particularly in contexts where demand estimation becomes more complex owing to rapidly changing economic conditions and behavioural responses. This study addresses this gap by examining the following research question: What is the impact of increases in fuel prices and taxes on professionals' transportation mode choice in Sri Lanka? This study aims to analyse how rising fuel prices and taxation influence the commuting choices of professionals who live and/or work in Colombo, identify substitution pathways between private and collective modes under varying cost pressures, and provide empirical evidence to inform policymakers, transport planners, employers, and transport providers.

2. LITERATURE REVIEW

Consumer and random utility theories provide the primary theoretical foundations for analysing transport mode choice behaviour. Under the framework of random utility maximisation, individuals are assumed to choose the transport mode that yields the highest utility, which depends on observable attributes such as travel cost and time, as well as unobservable factors [5]. Within this framework, changes in fuel prices and taxation affect travel decisions through multiple economic mechanisms, including the price elasticity of demand, income effects, and substitution effects. An increase in fuel prices raises the marginal cost of private transport, leading to a movement along the demand curve (price effect), whereas higher income taxation reduces disposable income, shifting demand toward lower-cost alternatives (income effect). These combined effects generate substitutions across transport modes, particularly from private to collective modes, depending on the relative generalised costs, service quality, and individual preferences [6]. This theoretical structure is particularly relevant in the Sri Lankan context, where professionals face binding budget constraints and high opportunity costs. A growing body of international literature examines how fuel price fluctuations and fiscal measures influence transportation behaviour. Studies in both developed and developing economies find that increases in fuel prices lead to reduced private vehicle usage and increased reliance on public or shared transport, although the magnitude of these effects depends on service quality, income levels, and urban structure [7]. Empirical evidence also highlights the role of income heterogeneity, where higher-income individuals exhibit lower price sensitivity, whereas middle-income groups demonstrate stronger substitution toward cost-efficient modes [8]. These findings provide a useful comparative foundation for analysing transport behaviour in Sri Lanka, where similar economic pressures have emerged in a more constrained environment.

The empirical literature shows that transport mode choice is influenced by the interaction of economic, financial, and household factors, with professionals responding differently to changes in fuel prices, taxes, and disposable income [5], [9]. Increases in fuel prices or taxes raise the generalised cost of private travel and tend to encourage shifts toward public or active modes, although such responses depend heavily on service quality, travel time, and crowding [10]. There is a hierarchy of transport needs in which travellers prioritise safety, time, cost, and comfort, explaining why factors such as reliability, convenience, and cost strongly influence modal decisions [11]. Professionals in Sri Lanka choose among private vehicles, public transport, employer-supported transport, and shared mobility, with choices influenced by fuel prices, travel distance, parking availability, comfort, and reliability [12], [13]. Although public transport becomes more attractive when private transport costs rise [14], its effectiveness in drawing commuters depends on service quality; international studies have revealed that higher fuel prices lead to increased bus or rail use when travel time and reliability are acceptable [15], [16], [17], [18]. Sri Lankan evidence shows income, vehicle ownership, safety, comfort, trip distance, and total cost as major determinants of mode choice [19], [20] consistent with findings from Malaysia and Japan, where income, service reliability, and comfort significantly influence preferences [21], [22].

Income and disposable income further influence mode choice by affecting both affordability and the value placed on travel time [23]. Higher income taxation reduces disposable income and intensifies cost sensitivity, encouraging shifts to lower-cost modes through income, value of time, and financing channels [14], [24], [25], [26]. Although higher-income households are generally less responsive to fuel price increases [27], middle-income professionals in Sri Lanka show greater substitution toward public transport or motorcycles during price hikes [13], whereas vehicle ownership increases with income [28]. During the 2022–2023 economic crisis, rising fuel prices and increased income taxes significantly reduced the purchasing power of professionals, causing shifts toward buses, trains, and ridesharing [29], [30]. Behavioural adaptations, such as reducing trip frequency, trip chaining, or shortening trip distances, also emerged during fuel shortages [31], [32], [33]. Distance, travel time, and last-mile connectivity remain critical constraints on public transport use [34], [35], [36], whereas commuters respond strongly to rising per-trip costs by reassessing discretionary travel [12], [37]. However, poor reliability and overcrowding limit modal shifts even when fuel prices rise [19], [38], and higher income professionals are less sensitive to such costs [5], [39]. Parking costs and availability also significantly influence private vehicle use, with higher fees reducing car trips and encouraging public transport or shared options [28], [40], [41], [42].

Despite the broad body of literature, there is limited evidence on how combined fuel prices and income tax shocks affect professionals in low- and middle-income countries. Post-2022 Sri Lankan studies remain scarce, even though rising fuel prices, reduced disposable income, and limited public transport quality have reshaped commuting behaviours in Colombo. Existing studies do not sufficiently account for distributional differences within the professional segment or the role of employer-provided transportation. This study addresses these gaps by examining how fuel prices and tax increases influence the transport mode choices of professionals in Sri Lanka.

3. METHODOLOGY

This study investigates the microeconomic effects of fuel price increases and income taxation–induced reductions in disposable income on the commuting mode choices of professionals in Sri Lanka. The methodological framework is grounded in random utility theory, which assumes that individuals choose the transport mode that maximises their utility, consisting of a systematic (observable) component and a random (unobserved) component [5], [43]. Within this framework, changes in travel costs and income conditions alter the relative utility of the available alternatives, thereby inducing substitution across transport modes. The design is a within-respondent repeated-choice experiment in which each participant faces five policy scenarios characterised by systematic variations in commuting distance (12–20 km), fuel price (Rs. 320–450 per litre), and taxation-induced income reductions (0%–15%), as shown in Table 2. Each scenario specifies the same four commuting alternatives, differentiated only by travel time and monetary cost, which vary systematically across the scenarios. This design balances realism (through plausible distances and fuel price levels) and experimental control through consistent alternatives across the respondents. The SP framework ensures that all respondents evaluate identical scenarios, which enables a comparative analysis and strengthens the internal validity of the design. As recommended by [44], attributes were selected based on policy relevance, interpretability, and realism.

The analytical strategy is based on the alternative-specific conditional logit (ASCL) model. In this framework, utility is expressed as a function of mode-specific attributes (time and cost) and case-specific variables (income reduction), which interact with alternatives to capture heterogeneous effects. Public transport serves as the base alternative, and alternative-specific constants (ASCs) capture unobserved baseline preferences for cars, motorcycles, and staff transport relative to public transport. The ASCL model is particularly suitable because it allows the estimation of substitution effects among a fixed choice set while incorporating both alternative- and case-specific attributes [5].

3.1. Methods of Analysis

This section specifies the analytical framework, estimation strategy, and post-estimation procedures used to quantify the effects of fuel prices and taxation-induced income reductions on professionals' mode choices. The analysis follows random utility maximisation [43] and the established practice for stated preference (SP) transport studies [5], [9], [44].

3.1.1. Model foundation and identification

Decision maker i faces a finite choice set C = {Car, Motorcycle, Staff, Public} in scenario s = 1,…,5. The utility of alternative j ∈ C

$$\mathrm{Uijs} = \mathrm{Vijs} + \varepsilon\mathrm{ijs} \quad \text{---} \ (1)$$

where Vijs is the systematic component, and εijs is an i.i.d. Type I extreme value error. To achieve identification, one alternative-specific constant (ASC) is normalised; public serves as the base (αPublic = 0). The scale is identified by the variance of εijs the logit scale factor), so coefficients are interpreted relative to that scale.

3.1.2. Systematic utility specification

Attributes enter the model as alternative-specific time and cost, and as a case-specific measure of income reduction. To enhance numerical stability and interpretability, time and cost were scaled as time10 = minutes / 10 and cost100 = Rs / 100.

$$\mathrm{Vijs} = \alpha\mathrm{j} + \beta\mathrm{t}.\,(\mathrm{timeijs}/10) + \beta\mathrm{c}.\ (\mathrm{costijs}/100) + \delta\mathrm{Car}\cdot 1[\mathrm{j} = \mathrm{Car}]\cdot \mathrm{inc\_redpctis} + \delta\mathrm{Moto}\cdot 1[\mathrm{j} = \mathrm{Motorcycle}]\cdot \mathrm{inc\_redpctis} + \delta\mathrm{Staff}\cdot 1[\mathrm{j} = \mathrm{Staff}]\cdot \mathrm{inc\_redpctis} \quad \text{---} \ (2)$$

with α Public = 0. The parameters βt and βc capture the marginal disutility of time and cost, respectively. The δ coefficients allow income-reduction pressure to differentially shift the utilities of Car, Motorcycle, and Staff relative to Public. This parameterisation is empirically motivated by preliminary estimations that indicate heterogeneous responses across modes and by the theory that private modes bear higher effective cost pressure when disposable income falls [9], [45]. The interaction terms (δCar, δMoto, and δStaff) capture how income reductions differentially affect the utility of each mode relative to public transport. A negative coefficient indicates that an increase in income reduction lowers the relative attractiveness of that mode, whereas a positive coefficient suggests a relative increase in attractiveness.

Under the logit assumption, the choice probability is

$$\mathrm{P}\,(\mathrm{yis} = \mathrm{j} \mid \mathrm{xis}\,) = \frac{\exp(\mathrm{Vijs})}{\sum \mathrm{k} \in \mathrm{c}\, \exp(\mathrm{Viks})} \text{ -- (3)}$$

3.1.3. Empirical construction of attributes

$$\mathrm{Timejs} = \frac{\mathrm{ds}}{\mathrm{speedj}} \times 60 \text{ -- (4)}$$

The speeds were as follows: motorcycle 35 km/h, car 30 km/h, staff 24 km/h, and public 20 km/h (effective speeds that embed typical Colombo congestion and dwell times). Alternative-specific costs (Rs/trip) are computed from transparent, mode-specific linear rules calibrated to maintain a realistic cost ordering (Car > Staff > Motorcycle > Public) and the expected fuel-price pass-through;

CostCar,s = 1200 + 50(ds −12) + 2(ps−320),

CostStaff,s = 800 + 30(ds−12) + 1(ps−320),

CostMoto,s = 500 + 20(ds−12) + 0.5(ps−320),

CostPublic,s = 300 + 10(ds−12).

3.1.4. Estimation strategy

The model is estimated by maximum likelihood on long-format data with one row per alternative per scenario, per respondent. The likelihood of respondent iii is the product of the scenario-specific probabilities of the chosen alternatives. The log-likelihood is maximised, subject to parameter constraints. Cluster-robust (respondent-level) standard errors were used to account for within-person correlation across repeated scenarios, a standard remedy for panel SP designs [9]. Alternative-specific constants were included for cars, motorcycles, and staff; public transport was the reference. The final specification adopted the interaction form shown above. An equivalent specification treats inc_redpct as a case-level variable (i.e., a variable that varies across choice scenarios but not across alternatives) and allows it to have alternative-specific coefficients. This is observationally equivalent to the interaction specification given Public as the base, and the interaction parameterisation was retained as it facilitates the direct interpretation of fiscal pressure effects relative to Public.

3.1.5. Post-estimation predictions and market-share simulation

To translate parameter estimates into policy-relevant outcomes, predicted choice probabilities are computed for each respondent–scenario–alternative.

$$P^{ij_s} = \frac{\exp(V^{ij_s})}{\sum_{k\in C}\exp(V^{ik_s})} \text{ --- (5)}$$

Scenario-level expected market shares are then obtained by averaging the responses across respondents.

$$\widehat{S}_J^{\,s} = \frac{1}{N}\sum_{i=1}^{N} P^{ij_s} \text{ -- (6)}$$

These shares summarise the aggregate mode-shift trajectory as fuel prices and taxation rise and are particularly informative when individual time/cost coefficients are estimated imprecisely due to design collinearity. In the present application, the simulated shares displayed a monotonic decline in cars and motorcycles and a concomitant rise in public transport (and a sustained role for staff), matching the observed SP frequencies and reinforcing face validity.

$$\mathrm{VoT}\left(\frac{\mathrm{Rs}}{\mathrm{hour}}\right) = \frac{\beta_t}{\beta_c} \times 60 \text{ -- (7)}$$

3.1.6. Monetary valuation: Value of Time (VoT)

The VOT is derived as the marginal rate of substitution between time and cost.

$$\mathrm{VoT} = \left|\frac{\widehat{\beta_t}}{\widehat{\beta_c}}\right| \times 6\ (\mathrm{Rs/hour}) \text{ -- (8)}$$

where the factor 60 converts 10-minute units to hours. With both time and cost entering as disutility (negative coefficients), the ratio is reported without a leading negative sign to ensure positive monetary valuation. In the empirical application, the VoT is approximately Rs 272/hour, which is economically plausible for Colombo professionals and is consistent with benchmark ranges reported in the literature for commuting (often one-third to one-half of the relevant hourly wage) [9], [45]. Because time and cost are correlated by design, the VoT is interpreted as indicative rather than a precise valuation.

3.2. Sources of Data

This study focuses on professionals employed in the Colombo District. Colombo is the economic and administrative hub of Sri Lanka, with the densest concentration of jobs, highest income levels, and greatest exposure to commuting-related congestion and fuel-price fluctuations. Professionals in this district constitute a population segment of particular policy interest because their travel patterns disproportionately influence congestion and fuel demand, and their opportunity cost of time makes them highly responsive to generalised cost changes [45].

3.3. Sampling

A purposive sampling method was employed to capture professionals in the Colombo District through a multistage recruitment process. Purposive sampling is widely used in SP studies when the research objective is to analyse the behaviour of a clearly defined subgroup rather than generalising to the entire population [44]. Sampling was conducted through three primary channels: professionals were reached through professional associations, employer networks, and alumni lists. The Colombo District was selected purposively because of its unique concentration of commuting professionals and because policy shocks in this region are likely to have outsized national effects. Out of the 50 questionnaires distributed, 42 usable responses were obtained after excluding incomplete or inconsistent submissions (e.g. partially answered choice tasks or internally inconsistent selections across scenarios), yielding a response rate of 84 per cent. The sample comprised 42 professionals, each responding to five scenarios, resulting in 210 choice sets and 840 observations in the long format. This structure meets the established guidelines for stated-preference discrete choice experiments, where multiple choice tasks per respondent improve parameter reliability even with relatively modest sample sizes [9], [44].

Data Collection Method

Data were collected using a structured online questionnaire administered through Google Forms. The instrument consisted of three main sections.

- Section A: Demographics. Socio-economic data were collected, including age, gender, household size, income bracket, occupation, sector, and education level.
- Section B: Hypothetical choice tasks. Respondents were presented with five scenarios, each varying in fuel price, taxation-induced income reduction, and commuting distance. In each scenario, respondents selected one preferred commuting mode from car, motorcycle, staff transport, or public transport.
- Section C: Additional information. Supplementary data on generalised costs (e.g. typical tolerance for delay, departure times) and perceptions relevant for calculating the VOT were collected.

The questionnaire design followed the best practices in SP research by balancing clarity and simplicity with policy relevance. Short-answer and single-choice formats were used, along with limited open-ended items for qualitative perspectives. The dataset was structured in a long format with four rows per respondent scenario combination. Table 1 summarises the key variables used in this analysis.

Table 1: Variables and their definitions

Variable	Description
Id	Respondent identifier
Scenario	Scenario index (1–5)
Alternative	Mode alternative: Car, Motorcycle, Staff, Public
Choice	Binary outcome: 1 if chosen, 0 otherwise
Distance (d)	Commuting distance (km): 12, 14, 16, 18, 20
Fuelprice (p)	Fuel price (Rs./L): 320, 360, 400, 430, 450
Inc_redpct	Income reduction due to taxation (proportion: 0–0.15)
Time_min	Alternative-specific travel time (minutes)
Time10	Travel time scaled in 10-minute units
Cost_rs	Alternative-specific cost (Rs.)
Cost100	Cost scaled in 100 Rs. units
Demographics	Age, gender, occupation, income bracket, household size, education

Source: Compiled by Author

3.3.1. Scenario specification

Table 2 presents the five policy scenarios used in this study.

Table 2: Scenario attributes

Scenario	Distance (km)	Fuel price (Rs./L)	Income reduction (%)
1	12	320	0
2	14	360	5
3	16	400	10
4	18	430	12
5	20	450	15

Source: Compiled by Author

3.3.2. Cost and time calculations

Travel time was calculated using the following assumed average effective speeds: motorcycle, 35 km/h; car, 30 km/h; staff transport, 24 km/h; and public transport, 20 km/h. These values reflect the effective peak-period speeds in Colombo, incorporating congestion delays, stop-and-go conditions, and dwell times rather than free-flow speeds. Although actual speeds may vary across routes and time periods, the selected values are consistent with the observed urban traffic conditions reported in prior transport studies in Sri Lanka and comparable urban contexts. To ensure robustness, the analysis focused on relative differences in time and cost across modes rather than absolute values. As such, moderate variations in the assumed speeds do not materially alter the substitution patterns observed in the model, as these are primarily driven by relative generalised costs rather than exact travel times. The coefficients used in the cost functions represent calibrated marginal costs under Colombo's urban conditions: 50 Rs/km and 2 Rs/Re. for cars reflect higher fuel intensity (~10 km/L) and additional distance-related operating costs; 30 and 1 for staff transport capture lower per-kilometre and moderate fuel sensitivity due to cost sharing; 20 and 0.5 for motorcycles reflect higher fuel efficiency (~35 km/L) and lower non-fuel costs; and 10 for public transport represents regulated fare increments largely independent of fuel price.

d = commuting distance in kilometres
p = fuel price in Sri Lankan Rupees per litre

1. **Car**

$$\mathrm{CostCar} = 1200 + 50(\mathrm{d} - 12) + 2(\mathrm{p} - 320) \quad \text{----------------------------------} (9)$$

Baseline trip (12 km, Rs. 320 fuel) = Rs. 1200. Distance increment = Rs. 50/km; fuel increment = Rs. 2 per Re.

2. **Staff transport**

$$\mathrm{CostStaff} = 800 + 30(\mathrm{d} - 12) + 1(\mathrm{p} - 320) \quad \text{---------------------------------} (10)$$

Baseline = Rs. 800; lower distance sensitivity than car; moderate fuel sensitivity.

3. **Motorcycle**

$$\mathrm{CostMoto} = 500 + 20(\mathrm{d} - 12) + 0.5(\mathrm{p} - 320) \quad \text{-----------------------------} (11)$$

Baseline = Rs. 500; fuel-efficient, hence smaller increments.

4. **Public transport**

$$\mathrm{CostPublic} = 300 + 10(\mathrm{d} - 12) \quad \text{---} (12)$$

Baseline = Rs. 300; increments depend only on distance; fares are assumed to be insulated from short-run fuel price fluctuations.

These assumptions ensured a consistent cost hierarchy across scenarios: cars > staff > motorcycles > public. Combined with time rankings (motorcycles < cars < staff < public), they generate plausible trade-offs that reveal how respondents substitute modes under different levels of policy-induced cost pressure.

4. ANALYSIS, RESULTS AND DISCUSSION

Building on the stated-preference design and model specification outlined in the methodology, this section presents the empirical analysis of Sri Lankan professionals' transport mode choices under varying fuel prices and taxation scenarios. The analysis began with descriptive statistics to provide an overview of the respondent characteristics and confirm that the experimental design offered a realistic and sufficiently broad range of attribute levels. The sample comprised 42 professionals, yielding a response rate of 84 per cent. The gender distribution comprised 19 females (45.2%) and 23 males (54.8%), indicating a reasonably balanced sample size. The average age of respondents was 40.5 years (SD = 9.2), ranging from 27 to 57 years, thereby covering both younger and more experienced professionals. Reported monthly incomes ranged from LKR 76,000 to LKR 580,000, with an average of LKR 234,667 (SD = 135,611) and a median of LKR 187,500, reflecting participation from low-, middle-, and high-income groups. Collectively, these demographics suggest sufficient diversity in gender, age, and income, providing a solid foundation for the subsequent econometric estimation.

Although household size was collected as part of the survey, preliminary analysis did not indicate a strong or systematic influence on the mode choice within the present sample. This may reflect the relatively homogeneous nature of the considered professional group. However, household characteristics may play a more significant role in broader populations, and future research should explore these effects using larger and more diverse samples.

As shown in Table 3, each scenario comprised 42 observations (one per respondent), yielding a total of 210 choices. For each scenario, the top row presents the raw counts, and the bottom row displays the percentages. In Scenario 1 (baseline: fuel Rs. 320, no income reduction, 12 km distance), cars (34%) and motorcycles (40%) dominated, whereas staff transport (13%) and public transport (9%) accounted for smaller proportions. This reflects a strong baseline preference for private modes when operating costs are low. In Scenario 2 (fuel Rs. 360, 5% income reduction, 14 km distance), car use remained steady at 34 per cent, while motorcycle use rose to 47 per cent, becoming the most popular mode. Public (≈9%) and Staff (12%) shares were largely unchanged, suggesting that under modest fuel price increases, some car users substituted motorcycles as a cheaper private alternative rather than transitioning directly to collective modes. In Scenario 3 (fuel Rs. 400, 10% income reduction, 16 km distance), motorcycle use collapsed to 0 per cent, car use declined to 15 per cent, and collective modes became dominant: public transport accounted for 26 per cent and staff transport for 23 per cent. This marks a critical threshold where rising costs undermine the viability of private modes, redirecting demand toward collective alternatives. In Scenario 4 (fuel cost Rs. 430, 12% income reduction, 18 km distance), public and staff transport shares increased further to 27 per cent each, while car use fell to 9 per cent and motorcycle use remained marginal at 7 per cent. In Scenario 5 (fuel cost Rs. 450, 15% income reduction, and 20 km distance), public transport emerged as the dominant mode (30%), with staff transport also retaining a substantial share (25%). Car use declined to 8 per cent, while motorcycle use stagnated at 7 per cent. In this highest-pressure scenario, the collective modes absorbed more than half of the total demand. Aggregating across all scenarios, cars accounted for 65 choices (31%), motorcycles for 15 (7%), public transport for 70 (33%), and staff transport for 60 (29%). The overall trend highlights the steady erosion of private mode dominance and the corresponding rise in collective modes under sustained cost pressure.

Table 3: Distribution of respondents' mode choices across the five stated-preference scenarios

Scenario	Car	Motorcycle	Public Transport	Staff Transport	Total
1	22	6	6	8	42
	33.85%	40.00%	8.57%	13.33%	20.00%
2	22	7	6	7	42
	33.85%	46.67%	8.57%	11.67%	20.00%
3	10	0	18	14	42
	15.38%	0.00%	25.71%	23.33%	20.00%
4	6	1	19	16	42
	9.23%	6.67%	27.14%	26.67%	20.00%
5	5	1	21	15	42
	7.69%	6.67%	30.00%	25.00%	20.00%
Total	**65**	**15**	**70**	**60**	**210**
	100.00%	100.00%	100.00%	100.00%	100.00%

Source: Compiled by author based on the survey data

The alternative-specific conditional logit model (Table 4) provides further insights into these substitution dynamics. As expected, both travel time and cost entered with negative coefficients, consistent with random utility theory [5] [43], which posits that individuals maximise utility subject to budgetary and time constraints. However, neither coefficient was statistically significant ($p > 0.30$). This reflects the compact structure of the stated-preference experiment, in which time and cost were tightly linked to fuel prices and distances, producing multicollinearity and limiting independent variation [44]. In such designs, coefficients often point in the theoretically expected direction but lack precision, as respondents respond to bundled policy shocks (fuel and tax changes) rather than marginal changes in the attributes. Similar challenges have been noted in SP studies that prioritise realism over strict orthogonality [9].

Table 4: Alternative-specific conditional logit model

Choice	**Coef.**	**Robust Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval] Lower**	**[95% Conf. Interval] Upper**
alt_time10	-5.50	5.41	-1.02	0.31	-16.11	5.10
alt_cost100	-1.21	1.18	-1.03	0.30	-3.53	1.10
Car_inc_redpct	-3.48	22.40	-0.16	0.88	-47.38	40.43
Car__cons	6.01	5.11	1.18	0.24	-3.99	16.01
Motorcycle_inc_redpct	-52.72	23.73	-2.22	0.026	-99.22	-6.21
Motorcycle_cons	-5.28	5.97	-0.88	0.38	-16.98	6.42
Staff_inc_redpct	4.57	13.98	0.33	0.74	-22.82	31.96
Staff__cons	3.07	3.06	1	0.32	-2.93	9.06
Public	Base Alternative					

Number of obs = 840
Case variable: caseid Number of cases = 210
Alternative variable: alt Alts per case: min = 4
avg = 4.0
max = 4
Log pseudolikelihood = -242.61134
Wald chi2(5) = 61.21
Prob > chi2 = 0.0000
(Std. Err. adjusted for 42 clusters in id)

Note: caseid is the variable identifying each unique choice scenario (one per respondent–scenario combination), used to group the four alternatives (Car, Motorcycle, Staff Transport, Public Transport) into a single choice set for estimation in the conditional logit model. alt is the variable identifying the four alternatives within each choice set.

Source: Compiled by author based on the survey

Income reduction has heterogeneous effects across modes. For Motorcycles, the coefficient was large and negative (–52.7, $p = 0.026$), indicating strong vulnerability to fiscal pressures. This aligns with the observed collapse of motorcycle choices between Scenarios 2 and 3 and is consistent with prior findings that middle-income commuters abandon motorcycles when affordability declines [39], [46]. For Cars, the coefficient was negative (–3.5) but insignificant ($p = 0.877$), reflecting the relatively short-run inelasticity of car use, particularly among higher-income earners [45]. For Staff transportation, the coefficient was positive (+4.6) but insignificant ($p = 0.744$), suggesting that employer-provided services may buffer professionals under fiscal strain. The alternative-specific constants indicated baseline preferences for cars and staff over public transport, with motorcycles being disadvantaged, although none were statistically significant. This mirrors the commuting culture in Sri Lanka, where private and semi-private modes retain prestige and convenience advantages relative to public transport. Overall, while statistical insignificance limits coefficient-level inference, the model captures the broad substitution pathways observed in the raw data: motorcycles collapse quickly, cars decline more gradually, staff transport offers an intermediate option, and public transport ultimately absorbs most of the demand.

To complement the regression results, the predicted choice probabilities were calculated using Stata's post-estimation routines (Table 5). These probabilities represent the model-simulated likelihood that each transport mode is chosen under a given scenario based on the estimated coefficients. In other words, while individual coefficients may be difficult to interpret directly, the predicted probabilities translate the model outputs into expected market shares, allowing for a straightforward comparison across alternatives and scenarios.

Table 5: Predicted choice probabilities-Stata's post-estimation routines

Scenario	Predicted Car	Predicted Motorcycle	Predicted Public Transport	Predicted Staff Transport
1	0.569467	0.182462	0.105907	0.142164
2	0.437327	0.088982	0.224854	0.248838
3	0.259906	0.033582	0.369444	0.337068
4	0.166494	0.028769	0.462355	0.342382
5	0.114425	0.023349	0.504107	0.358119

Source: Compiled by author based on the survey

In baseline Scenario 1, the model predicts that cars will capture 57 per cent of choices, motorcycles 18 per cent, staff transport 14 per cent, and public transport 11 per cent. This indicates that, under low fuel costs and no income reduction, private modes are strongly preferred, particularly cars.

When moving to Scenario 2, with a moderate fuel price increase and a 5 per cent income reduction, the predicted car share falls to 44%, and motorcycles decline sharply to 9 per cent, while public and staff transport increase to 23 and 25 per cent, respectively. This shift suggests that even modest fiscal pressures redistribute demand toward collective modes. In Scenario 3, where fuel prices and income reductions intensify, cars are predicted to fall further to 26 per cent, motorcycles nearly vanish at 3 per cent, and both Public and Staff transport become dominant at 37 and 34 per cent, respectively. This reflects a turning point in commuter behaviour, where collective options start to overtake private vehicles as the most viable choice. Finally, in Scenario 5, the model projects cars at only 11 per cent and motorcycles at 2 per cent, while public transport absorbs 50 per cent of the demand and staff transport 36 per cent. This outcome suggests that under the highest-pressure conditions, collective transport modes together capture over 85 per cent of the commuting market, confirming the strong substitution away from private vehicles in response to sustained cost increases. The VOT was estimated at Rs. 271.78 per hour, reflecting respondents' implicit willingness to pay for one hour of travel time savings. Although derived from imprecise coefficients, this estimate is consistent with professional wage levels in Colombo and aligns with international benchmarks, suggesting that VOT values often fall within one-third to one-half of the hourly wages for commuting trips [9], [45].

Taken together, the evidence from observed distributions, model results, predicted probabilities, and the VOT estimate paints a coherent picture of behavioural adjustment under fuel price and taxation pressures. Professionals initially favour private modes, particularly Cars and Motorcycles, but rising costs rapidly undermine these options. Motorcycles collapse first, cars decline more gradually, staff transport emerges as an intermediate solution, and public transport ultimately absorbs the majority of the demand. These findings have several policy implications. Rising energy and fiscal costs will likely accelerate modal shifts toward Public and Staff transport. This shift may reduce congestion and fuel imports but will also strain Sri Lanka's already overstretched public transport infrastructure. Enhancing the frequency, reliability, and safety of buses and trains will be critical to accommodate the new demand. The sharp vulnerability of motorcycle users suggests the need for targeted interventions, such as credit support for electric two-wheelers or subsidised staff transport access, to prevent mobility deprivation. The relative resilience of staff transport highlights the importance of employer- and institution-provided mobility solutions; policies incentivising firms to expand such services could facilitate smoother transitions away from private vehicles. Finally, while public transport eventually absorbs most of the demand, cultural preferences and affordability considerations imply that mode shifts occur gradually. Therefore, policy requires a combined approach: pricing instruments (fuel taxation and parking charges) alongside supply-side improvements (modernised fleets, integrated ticketing, and staff transport support).

This study has several limitations that must also be acknowledged. The modest sample size constrained the statistical power, contributing to the insignificance of some parameter estimates despite their theoretically expected signs. The stated-preference design emphasised realism by linking distance, fuel price, cost, and time, thereby introducing multicollinearity, which limited the precision in isolating marginal effects [9]. In addition, income reduction was modelled uniformly, whereas, in practice, fiscal impacts vary across households, sectors, and coping strategies. Future research could address these limitations by employing larger and more diverse samples, designing orthogonal or efficient SP experiments to reduce attribute correlation, and integrating revealed-preference data to validate stated-preference findings [5], [9]. Extensions using mixed logit or latent class models would also illuminate heterogeneity across professional subgroups, further enhancing the policy relevance of discrete-choice analyses in the Sri Lankan context.

5. CONCLUSION

This study examined the microeconomic impacts of fuel price increases and income reductions on the commuting mode choices of professionals in Sri Lanka using a stated-preference experiment and an alternative-specific conditional logit framework. The analysis demonstrated a clear and consistent substitution pathway: Cars and Motorcycles, initially dominant under baseline conditions, progressively lost ground as fuel and tax pressures intensified. Motorcycles proved particularly vulnerable, collapsing rapidly under income reduction, whereas cars declined more gradually. Staff transport emerged as a transitional buffer, especially for middle- and high-income professionals, whereas public transport ultimately absorbed the largest share of demand under the most severe policy scenarios. Although some parameter estimates were statistically insignificant due to sample size constraints and collinearity in the design, the aggregate substitution patterns, predicted choice probabilities, and the Value of Time estimate (Rs. 272/hour) provided a coherent and theoretically consistent narrative. These results not only validate the responsiveness of professionals to generalised cost changes but also underscore the economic plausibility of the observed behavioural adjustments.

These findings have significant policy implications. Rising fuel prices and taxation are likely to accelerate the demand for collective modes, particularly public transport, placing increased pressure on Sri Lanka's already constrained system. Simultaneously, the resilience of staff transport highlights the potential role of employer- and institution-based mobility solutions in supporting smoother transitions away from private vehicles. Therefore, policymakers must adopt a balanced approach that combines pricing instruments with investments in public transport infrastructure, service quality, and employer partnerships to ensure equitable, efficient, and sustainable mobility under rising energy costs. Ultimately, this study contributes to the growing body of evidence on transport mode choice under fiscal and energy constraints in developing economies. It provides a framework for understanding how professionals adjust to cost pressures, highlights the importance of Public and Staff transport as adaptive mechanisms, and points to the need for an integrated, forward-looking transport policy in Sri Lanka. This study primarily captures short-run behavioural responses to fuel prices and taxation shocks. Future research incorporating longitudinal data or revealed preference approaches would be valuable for assessing the persistence of these effects over time.

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