

Fuel economy valuation and preferences of Indian two-wheeler buyers



Prateek Bansal^a, Rubal Dua^{b,*}, Rico Krueger^c, Daniel J. Graham^a

^a Transport Strategy Centre, Department of Civil and Environmental Engineering, Imperial College London, UK

^b King Abdullah Petroleum Studies and Research Center (KAPSARC), Saudi Arabia

^c Transport and Mobility Laboratory, École Polytechnique Fédérale de Lausanne, Switzerland

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ABSTRACT

India has experienced exponential growth in sales of two-wheelers due to their high fuel economy and easy manoeuvrability in congested traffic conditions. Understanding Indian consumers' valuation of fuel economy while purchasing a two-wheeler is crucial to evaluate whether Indian two-wheeler buyers are myopic with regards to future fuel costs. However currently, there exists no quantification of the value that Indian two-wheeler buyers ascribe to fuel economy. We address this gap in the literature by analyzing revealed preference survey data from more than 8000 respondents across India, who purchased a new two-wheeler in 2018. Discrete choice models, including standard conditional logit and flexible mixed logit, are used to infer estimates of the discount rate that Indian consumers apply to obtain the present value of future operating cost at the time of two-wheeler purchase. The results of conditional logit indicate that the annual discount rate is below 10% for Indian two-wheeler buyers with monthly household incomes above 15,000 rupees (~US\$215 in 2018; ~73% of the sample). Mixed logit suggests substantial heterogeneity in discount rates across respondents at a given income level. The median of the mixing distribution is close to the conditional logit estimates, which leads to a conclusion that an average Indian two-wheeler buyer ascribes a high value to future fuel cost savings. Besides, our analysis provides various insights into Indian consumers' preferences. For instance, style/looks, fuel economy, comfort, and brand (in decreasing order) are the top four factors that influence two-wheeler purchase decisions of Indian consumers.

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1. Introduction

1.1. Context

India is the world's third-largest emitter of greenhouse gases (GHGs) after China and the US (Timperley, 2019). India's transportation sector is the third-largest contributor to carbon dioxide emissions, accounting for roughly 11% of all carbon dioxide emissions in 2016 (Janssens-Maenhout et al., 2017). Road transport accounts for around 94% of total carbon dioxide emissions of the transport sector (Bhatt, 2019).

The rapid growth of vehicle sales is partly responsible for India's rising share of carbon dioxide emissions. India recently displaced Germany to become the world's fourth-largest market for vehicle

sales (Gupta et al., 2018). Vehicle sales in India are expected to grow further with rising incomes, which has major implications for global carbon dioxide emissions. Estimates from an Indian government policy think tank suggest that both the number of on-road vehicles as well as the passenger mobility-related carbon dioxide emissions may triple by 2030 (NITI Aayog and Rocky Mountain Institute, 2017a).

Two-wheelers dominate the Indian passenger vehicle market. In 2019, the share of two-wheelers in the domestic passenger vehicle market was 84%, as compared to 13% for four-wheeler passenger vehicles and 3% for three-wheelers (SIAM, 2019). Moreover, annual sales of two-wheelers have doubled in the last decade from 11 million in 2010 to 21 million in 2019 (Statistical Research Department, 2020). Given the high share and expected growth rate, various policy levers such as feebate¹ policies are being

* Corresponding author.

E-mail addresses: prateek.bansal@imperial.ac.uk (P. Bansal), rubal.dua@kapsarc.org (R. Dua), rico.krueger@epfl.ch (R. Krueger), d.j.graham@imperial.ac.uk (D.J. Graham).

¹ Feebates involve taxes on fuel-inefficient vehicles and rebates for fuel-efficient vehicles.

considered to reduce the carbon dioxide emissions associated with the Indian two-wheeler sector (IEA, 2020; NITI Aayog and Rocky Mountain Institute, 2017a & 2017b).

From the policy perspective, understanding fuel economy valuation of Indian two-wheeler buyers is crucial to evaluate whether there is an “energy efficiency gap” or “energy paradox”, i.e. whether Indian consumers are myopic and undervalue future operating costs at the time of purchase (Bento et al., 2012; Fuerst and Singh, 2018; Gillingham and Palmer, 2014; Gillingham et al., 2019; Jaffe and Stavins, 1994; Matsumoto and Omata, 2017; Orlov and Kallbekken, 2019; Parry et al., 2007; Yoo et al., 2020). If consumers are found to undervalue fuel economy at the time of vehicle purchase, it is reasonable to implement policies such as fuel economy standards² that will help consumers to save money (Allcott and Wozny, 2014; Chugh et al., 2011). Consumers’ fuel economy valuation has become even more critical given that the Indian government’s recent policy announcements aim to combat energy security issues by increasing the uptake of electric vehicles, which typically have relatively higher upfront costs and lower operating fuel costs (Albrahim et al., 2019; IEA 2020; Kumar and Alok, 2020; Li and Wang, 2019; Zhuge et al., 2020). However, these analyses are difficult to undertake in the Indian context due to data availability challenges. We are only aware of a study by Chugh et al. (2011), in which the authors estimate fuel economy valuation of Indian car buyers using a hedonic price approach. However, studies related to preferences of two-wheelers are rare in a developing country context (Guerra, 2019; Lin et al., 2013; Ye and Wang, 2011).

To the best of our knowledge, this is the first time that fuel economy valuation of two-wheeler buyers is presented for a fast-growing developing market such as India, using large-scale survey data on the revealed preferences of consumers.

1.2. Literature review on the Indian two-wheeler market

There are various reasons for the popularity of two-wheelers in India. Ever since the two-wheeler market opened to international manufacturers, fierce competition has challenged manufacturers to reduce price and improve the quality of the vehicles. As they steadily become fuel-efficient and incur a low maintenance cost, the interest of Indian consumers in two-wheelers has only been growing. Urbanization-induced congestion in cities further incentivize the use of two-wheelers due to compact size and thus, better manoeuvrability (Kathiravanaa et al., 2010). In recent years, automobile manufacturers have started placing a high importance on consumer satisfaction. Their interest in understanding the preferences of two-wheeler buyers has increased to capture more market shares.

We succinctly discuss several studies, which investigate preferences for two-wheelers in India. Sathish and Pughazhendi (2011) use a sample of 125 respondents from a small city in the southern state of Tamil Nadu to understand consumer preferences for two-wheelers. They find a statistically significant correlation between aesthetics and consumer preferences for a two-wheeler model. Similarly, Yasmeen (2015) survey 200 people from Chennai city to understand the key factors determining the preferences for two-wheelers. They find that mileage, price and performance as the most important factors, and colour and style as the least important aspects. Furthermore, Kathiravanaa et al. (2010) analyze a sample of

300 university students to understand consumers’ brand recognition and its association with preferences for two-wheeler attributes. They find that brand is an important factor in the consumer’s purchase intentions and that the post-purchase buyer-manufacturer relationship is a major contributor to gain competitiveness in the long run. Chavan and Changan (2016) analyze preferences of 131 students from Satara city in Maharashtra. They find that popularity, social status and brand loyalty affect students’ preferences for a brand. In a recent study, Khan et al. (2018) use a multiple linear regression model to analyze the satisfaction of 600 two-wheeler buyers from Hyderabad. They find no statistically significant association between consumer satisfaction and demographics. In addition, Rajesh et al. (2018) survey 158 respondents in Kerala to understand their brand awareness. The results of this study indicate that respondents only switch to other brands with a higher price because they assume that higher price implies better quality.

Recent studies on two-wheelers also focus on understanding the perception of female consumers. Murugan and Shanti (2014) survey 400 female consumers in metro cities in India and conduct various ANOVA tests. They find regional variation in preferences and satisfaction levels of female buyers, perhaps due to cultural differences. Mundu et al. (2011) collect data from 115 women from Pune city. Their analysis suggests that women are inclined towards buying automatic two-wheelers due to ease of driving and manoeuvring. Women also value storage space in two-wheelers.

1.3. Research gaps and contributions

Whereas previous studies use advanced behavioural models to understand the car ownership and purchase decisions of Indian consumers (Dash et al., 2013; Chugh and Cropper, 2017), preferences for two-wheelers are often analyzed using simple statistical techniques such as percentage comparisons or ANOVA tests. Moreover, our review suggests that such analyses rely on small-scale surveys in one city, and hence, the ecological validity of these studies is limited.

This study contributes to the literature by analyzing revealed preference survey data from over 8000 respondents who purchased a new two-wheeler in 2018. We provide insights about the association of consumers’ demographic characteristics such as age, income, gender, and car ownership status and their preferences for specific two-wheeler segments. Finally, we estimate the consumers’ valuation for fuel economy of two-wheelers. To this end, we use discrete choice models and estimate the discount rate that Indian consumers use to obtain the present value of the future operating cost at the time of purchase. Appropriate sampling weights are used in the estimation to ensure that the sample represents the population-level sales proportion at the make-model level.

The remainder of this paper is organized as follows: Section 2 describes the formulation of discrete choice models and a procedure to estimate the discount rate; Section 3 summarizes data sources; Section 4 discusses summary statistics, computation of sampling weights, main results, and policy implications; conclusions and future work are presented in Section 5.

2. Discrete choice model formulation

We assume that consumers choose an alternative that maximizes the utility. The indirect utility derived by individual i from choosing alternative j is defined as follows:

² Recent research suggests that similar to a feebate, fuel economy standards impose a constraint on automakers which creates an implicit subsidy for fuel-efficient vehicles and an implicit tax for fuel-inefficient vehicles (Davis and Knittel, 2019).

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \beta_i X_{ij} + \varepsilon_{ij},$$

where V_{ij} is systematic utility and ε_{ij} is an idiosyncratic error term. We assume that V_{ij} is a linear function of the alternative-specific attributes X_{ij} , with a marginal utility vector β_i . Note that individual-specific marginal utility vector captures unobserved preference heterogeneity across decision-makers. The distribution on β_i and ε_{ij} leads to different models. Gumbel distribution on independent error term and $\beta_i = \beta$ leads to the conditional logit (CL) model. After normalizing the scale of the error term, the probability of choosing alternative j by individual i in CL is defined as follows:

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{k \in C_i} e^{V_{ik}}},$$

We note that the CL model suffers from the independence-of-irrelevant-alternatives (IIA) property (Train, 2009). To relax IIA property and account for unobserved heterogeneity in preferences of Indian two-wheeler buyers, we also estimate a mixed logit (MXL) model. We omit mathematical details of CL and MXL for brevity because they are standard models in the choice modeling literature. Interested readers can refer to Train (2009) for the estimation details.

2.1. Discount rate

For decisions involving future cash flows, rational decision-makers can be assumed to calculate the net present value of benefits and costs (Train, 1985). Vehicle choice is one such example because operating cost occurs during life span of vehicle, but the vehicle price is paid at the time of purchasing. Some vehicles can have a higher upfront cost but may yield lower operating cost due to higher fuel economy and vice versa. A rational user would use a discount rate to compute the present value of the operating cost and then would trade-off it with the purchase price and other attributes. To represent this decision rule, we rewrite the systematic part of the indirect utility equation in the context of the case study:

$$\beta_i X_{ij} = \beta_{i,p} price_{ij} + \beta_{i,PVOC} PVOC_{ij} + \beta_{i,z} Z_{ij}$$

where $\beta_{i,p}$ and $\beta_{i,PVOC}$ are marginal utilities of the purchase price and present value of the operating cost (PVOC) for an individual i . Z_{ij} is a vector of other attributes (e.g., top speed and kerb weight), with a marginal utility vector $\beta_{i,z}$ for an individual i .

The computation of $PVOC_{ij}$ requires the knowledge of the discount rate, which is unknown to the researcher. Helfand and Wolverson (2009) and Wang and Daziano (2015) review various methods to estimate the discount rate in vehicle preferences. We briefly describe the endogenous discounting method that we use in this study. If the vehicle life is long enough (i.e., the long vehicle life assumption is tenable for monthly cashflow) and fuel price as well as usage intensity is assumed to be constant,³ $PVOC_{ij}$ can be

computed using the capitalised worth approximation (Train, 1985):

$$PVOC_{ij} \approx \frac{OC_{ij}}{r_i},$$

where OC_{ij} is the uniform monthly operating cost of alternative j and r_i is the monthly discount rate of an individual i . If we define $\beta_{i,OC}$ as the marginal utility of the OC_{ij} , the systematic utility equation becomes:

$$\beta_i X_{ij} = \beta_{i,p} price_{ij} + \beta_{i,OC} OC_{ij} + \beta_{i,z} Z_{ij},$$

where $\beta_{i,OC} = \frac{\beta_{i,PVOC}}{r_i}$. For a rational consumer, under ideal market conditions, $\beta_{i,p} = \beta_{i,PVOC} = -\alpha_i$, where α_i is a marginal utility of the income. Therefore, maximum willingness to pay (WTP) for marginal savings in monthly operating cost can be written as:

$$r_i = \frac{\beta_{i,p}}{\beta_{i,OC}} = \frac{1}{WTP_{i,OC}},$$

We also consider the marginal utility of purchase price to decrease with the increase in household income. This assumption has been used extensively in the literature (Beggs and Cardell, 1980; Choo and Mokhtarian, 2004; He et al., 2012; Lave and Train, 1979; Mannering and Winston, 1985; Mannering et al., 2002). In line with the cited literature, we assume that household income affects vehicle choice making indirectly through affecting consumers' marginal utility for purchase price. It leads to discount rate that varies inversely with the income:

$$r_i = \frac{\beta_{i,p}}{Income_i \times \beta_{i,OC}}.$$

This assumption pivots on two observations (Dubin and McFadden (1984); Hausman, 1979; Train, 1985). First, lower-income households are likely to be less educated, and therefore, are less able to evaluate the future benefits of higher upfront investment in energy-efficient technology. Second, these households have lower liquid capital, which makes them less willing to invest in energy-efficient alternatives even if they perceive future savings in operating cost. The monthly discount rate (r_i) can be converted to an annual discount rate (a_i) using the following expression:

$$a_i = (1 + r_i)^{12} - 1.$$

Thus, the implicit annual discount rate can be obtained as a by-product of the estimation of discrete choice models with covariates $price_{ij}$, OC_{ij} , and $Income_i$. We have a closed-form expression for the discount rate in CL, but the distribution of the discount rate in MXL is obtained through simulation (i.e., by taking draws from mixing distributions of marginal utilities $\beta_{i,p}$ and $\beta_{i,OC}$). A high implicit discount rate implies that two-wheeler buyers care less about future savings or costs, and thus, they associate lower weight to the monthly operating cost (i.e., fuel economy). This phenomenon is also known as the energy paradox (Wang and Daziano, 2015). On the contrary, a low implicit discount rate indicates that two-wheeler buyers are willing to pay higher upfront cost for an alternative which provides savings in future operating cost.

3. Data description

In this analysis, we use a revealed preference survey data of 8159 respondents across India who purchased a new two-wheeler for personal use between March 2018 and October 2018 (i.e., 2–6 months of ownership). Fig. 1 shows the state-wise spatial

³ The assumption of the constant fuel price is standard in studies on consumer preference elicitation for durable goods (Helveston et al., 2015; Hidrue, 2011). A more realistic dynamic model of fuel price expectations can be formulated to relax the constant price assumption. It is worth noting that the assumption of constant vehicle kilometres traveled (VKT) during life cycle ignores the possibilities of the rebound effect, that is the purchase of a more fuel-efficient vehicle encourages consumers to travel more due to lower operating cost (De Borger et al., 2016a; Gillingham et al., 2013; Greening et al., 2000; Hymel et al., 2010; Menon, 2017). The assumption of constant VKT can be relaxed by joint modeling of VKT and two-wheeler choices (Berkowitz, 1990; De Jong, 1990; Fullerton and Gan, 2005; Goldberg, 1998; Mannering and Winston, 1985; West, 2004).

distribution of respondents. The data consist of respondents from 21 states, which constitute around 94% of the Indian population. Mainly, the sample does not include respondents from low-populated states in north and north-east of India. The survey was conducted between September and December 2018. Respondents were contacted through intercepts on the street or at other locations such as petrol stations and shopping malls. Detailed interviews were conducted at a location and time of their convenience.

The dataset was collected and provided by J.D. Power, a global leader in automotive marketing research. J.D. Power collected this data as the part of the initial quality survey (IQS), which provides manufactures with the consumers' feedback on new vehicle quality. IQS has been an industry benchmark for assessing new vehicle quality since 1987. The IQS questionnaire is very detailed as J.D. Power obtains consumers' feedback on over 200 vehicle attributes (see J.D. Power, 2019 press release for details), but we have access to only limited variables. The individual-level dataset contains information on attributes of the purchased two-wheeler such as brand (make), model, segment (defined by engine displacement), fuel economy, and purchase price. Moreover, this dataset also contains the delivery date, months of ownership, mileage on the vehicle, and various demographic characteristics of vehicles buyers (e.g., income, gender, and age). J.D. Power also provided us aggregate sales data of two-wheelers to assess how well the individual-level sample represents the market of interest.

Since we do not have information about the models considered by the respondent during purchase, we need to create the choice set for each respondent. Based on the two-stage characterisation of the choice process of Manski (1977), Ben-Akiva and Boccara (1995) suggest a method to latently generate choice set. However, the method is not scalable to a large number of alternatives, as we have in this study (i.e., 70 make-models). Horowitz and Louviere (1995)

and Swait (2001) also propose another method to generate consideration sets, but these methods also do not work in practice for a large number of alternatives, because they require enumerating all possible choice subsets. In the absence of any practical method to generate choice set, we assume that respondents considered all available models in the market while purchasing a two-wheeler, i.e. all available models in the market are in the choice set of respondents. Due to a substantial variation in the reported purchase price and fuel economy of models, we source data on attributes of each model from the BikeWale platform which offers comprehensive information about the two-wheelers market in India.

4. Results and discussion

4.1. Summary statistics

In this section, we present a descriptive analysis of the vehicle choice and consumer preference data. Table 1 summarizes average attribute values of models in each segment. Clearly, MC-Economy and MC-Executive segments, on an average, have higher fuel economy, higher time to accelerate from 0 to 60 km/h, lower price, lower weight, and lower top speed as compared to other motorcycle segments.

Table 1 also shows the possibilities of a high correlation between make-model-specific attributes. To evaluate the extent of correlation, we present pair-wise correlations between attributes of all 70 make-models in Table 2. The results indicate that the magnitude of all correlations, except with fuel economy, are above 0.75. It is worth noting that the presence of such high correlation between alternative-specific attributes and no variation in choice sets across respondents complicates the estimation of choice models using revealed preference datasets (Haaf et al., 2016; Sheldon and Dua 2018).

We also derive insights about the variation in preferences of different demographic groups for two-wheeler segments in Table 3. In the sample, 5.3 percent buyers are female but almost all of them choose a two-wheeler from SC (i.e., scotty/scooter) segment, perhaps because models in this segment have better storage facility, automatic transmission, and step-through frame which is much more appropriate for women's dressing in India. The sample has 18.8 percent vehicle buyers who have at least one car in their household. As expected, the proportion of car owners is much higher in Premium Plus, Premium and Upper Executive segments. Whereas we see a similar trend for higher income households, proportions of buyers older than 40 years are lesser in these luxury segments. These findings are aligned with the intuition.

The survey also asked respondents about the main reason behind buying the specific two-wheeler. Main reasons and corresponding proportions are presented in Fig. 2. The figure indicates that style, mileage, comfort, brand, and engine performance are the top five reasons (in decreasing order). According to opinions of experts, Bansal and Kockelman (2017) conclude that Indian consumers rank fuel economy, price, engine power, and brand as top features (in decreasing order of importance) while purchasing two-wheelers. Three out of four attributes highlighted by this previous study are among top five factors of the current study. However, the experts interviewed in Bansal and Kockelman (2017) may have overlooked the importance that Indian consumers associate with style/looks of two-wheelers, which turns out to be the most important factor in this study.

We further investigate the segment-specific preferences of respondents who quote one of the top three reasons and results are presented in Table 4. As expected, the respondents who quote style/looks as the most important reason are more likely to buy two-

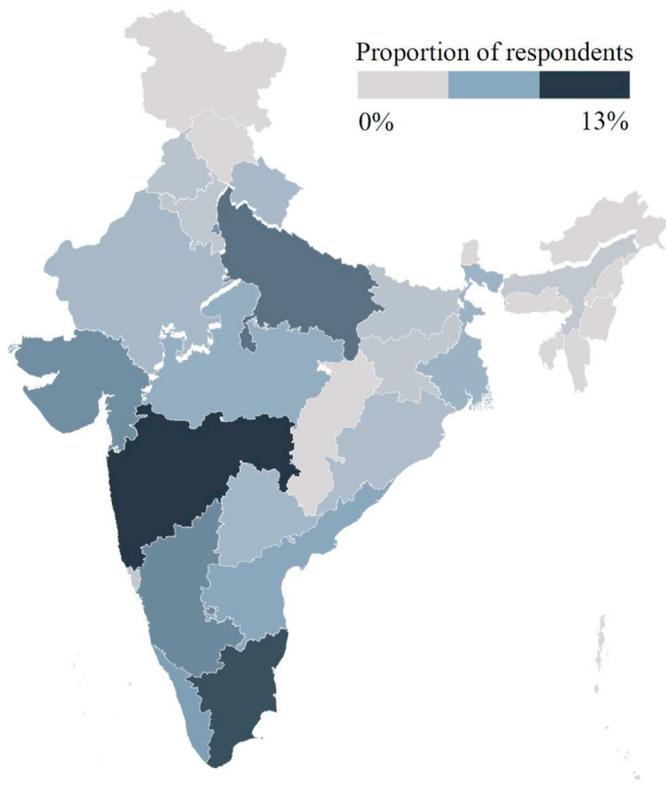


Fig. 1. State-wise spatial distribution of respondents (N = 8159).

Table 1
Mean values of model-specific attributes for segments.

Segments	Model Count	Fuel economy (km/l)	Purchase price (INR)	Time for 0–60 km/h (sec)	Weight (kg)	Engine power (bhp)	Top speed (km/hr)
MC – Economy	15	66	56,133	8.1	112	8.3	89
MC – Executive	7	58	65,571	7.0	121	10.3	95
MC – Premium	14	43	105,773	4.7	148	17.1	119
MC – Premium Plus	5	35	154,400	3.8	184	21.1	123
MC – Upper Executive	9	47	88,411	5.3	142	13.1	112
SC – Economy	1	50	53,000	12.2	93	5.3	70
SC – Executive	14	48	56,000	10.1	106	7.6	83
SC – Upper Executive	5	48	70,800	8.2	110	8.6	89

*MC: motorcycles, SC: scooters; INR: Indian rupee.

Table 2
Correlation between model-specific attributes.

	Fuel economy	Purchase price	Time for 0–60 km/h	Kerb weight	Engine power	Top speed
Fuel Economy	1					
Purchase Price	−0.73	1				
Time for 0–60 km/h	0.42	−0.77	1			
Kerb Weight	−0.61	0.91	−0.82	1		
Engine power	−0.66	0.92	−0.82	0.92	1	
Top speed	−0.59	0.86	−0.88	0.85	0.92	1

* Please refer to Table 1 for units of other variables.

Table 3
Preferences of demographic groups for different segments.

Segment	Female	Car owner	Monthly household income >50,000 Rupees	Age >40 years
MC – Economy	0.3%	12.4%	7.7%	14.2%
MC – Executive	0.0%	15.9%	8.6%	15.2%
MC – Premium	0.4%	24.3%	20.1%	4.2%
MC – Premium Plus	0.7%	39.2%	28.3%	8.2%
MC – Upper Executive	1.2%	18.6%	18.0%	7.8%
SC – Economy	39.8%	9.7%	10.7%	17.5%
SC – Executive	15.8%	18.1%	12.0%	15.6%
SC – Upper Executive	13.7%	20.8%	15.4%	15.4%

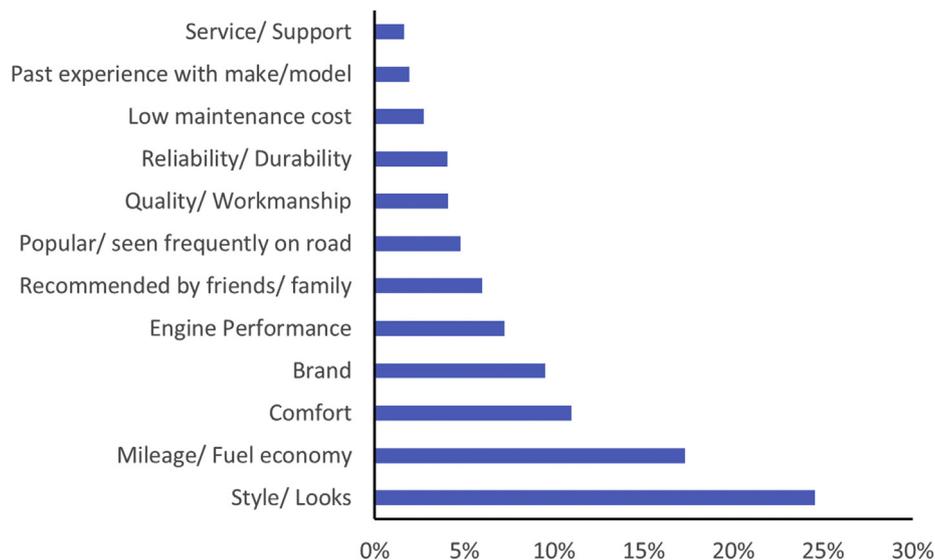


Fig. 2. Frequencies of main purchase reasons.

wheelers from the MC – Premium segment. Moreover, respondents who cite fuel economy as the main reason behind their purchase

prefer the MC-Economy segment, which has the highest fuel economy (see Table 1). Respondents considering comfort do not

show a strong inclination toward any segment but are slightly more inclined to buy two-wheelers from SC-executive segment.

4.2. Sampling weights

The population of two-wheelers buyers is not well defined because only a fraction of the population can be assumed to be willing and financially capable to buy new two-wheelers. Therefore, the use of exogenous sampling weights to mimic the population-level demographic distributions of potential two-wheeler buyers is infeasible, as the true distribution is unknown. For the same reason, we adopt the endogenous (choice-based) sampling weights in our analysis to ensure consistency of the estimates (Manski and Lerman, 1977).

To understand the representativeness of the sample, we first plot the make/brand-level sample and sales proportions in Fig. 3. The plot indicates that the sample mainly underrepresents Hero brand and slightly overrepresents all other makes except Hero and Honda. We compute sampling weights of each make-model such that choice proportions in the sample are the same as the actual sales proportions. The sampling weights vary from 0.14 for the most overrepresented Bajaj Avenger 220 model to 3.09 for the most underrepresented Hero HF Deluxe/Deluxe Eco/Deluxe i3S model.

4.3. Model estimation results

In this section, we discuss the results of discrete choice models. Having access to months of vehicle ownership and mileage enabled us to compute individual-specific monthly operating cost. In the computation of operating cost, we assume a constant petrol price of Indian rupees (INR) 70 per liter based on the petrol price in the national capital during January 2018 (NDTV, 2018). Decreasing marginal utility of the purchase price relative to household income also ensures enough sampling variation in this variable. Given that two-wheelers in executive and economy segments have substantially higher fuel economy, we anticipate that buyers of these alternatives might ascribe higher importance to fuel economy (as also observed in Table 4), and thus, may have lower discount rates. Therefore, we also include the interaction of operating cost with the economy-executive dummy in some specifications. Pairwise correlations between covariates are presented in Table 5.

We also attempted to estimate the willingness to pay of Indian consumers for other performance-based attributes of two-wheelers such as acceleration and top speed, but we encountered an identification issue. After controlling for alternative-specific constants (i.e., fixed effects) at make-model level, these performance-based attributes do not have any variation left to identify their marginal utilities in a linear utility specification because they do not vary across respondents. However, this is not a concern because performance-related attributes are embedded in the alternative-specific fixed effects.

Table 6 summarizes the results of weighted CL specifications.

Table 4
Segment-wise proportion of buyers who quote one of top three reasons behind the purchase.

Segments	Style/Looks	Mileage/Fuel economy	Comfort	Sample proportions
MC – Economy	11.0%	57.4%	22.3%	26.9%
MC – Executive	8.0%	14.6%	13.6%	11.9%
MC – Premium	28.3%	3.5%	12.2%	15.7%
MC - Premium Plus	8.9%	0.8%	3.5%	6.5%
MC - Upper Executive	10.5%	4.3%	6.2%	7.7%
SC – Economy	0.8%	0.7%	3.6%	1.2%
SC – Executive	21.6%	13.7%	29.2%	21.4%
SC - Upper Executive	10.9%	5.0%	9.4%	8.7%

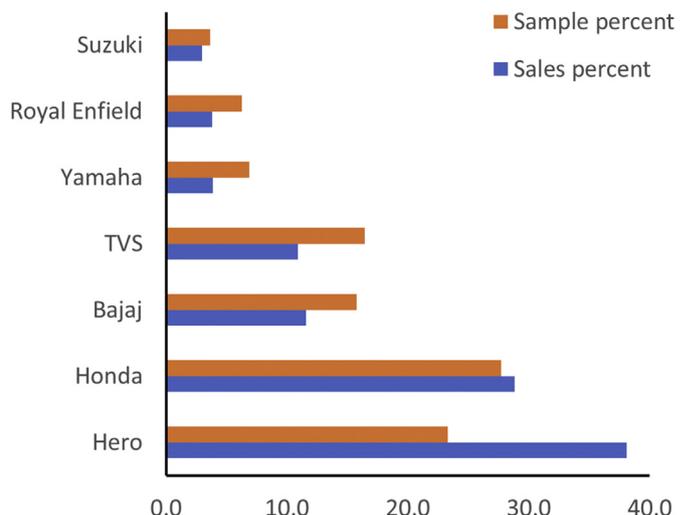


Fig. 3. Sample and sales proportions at make level.

Table 5
Correlation between covariates.

	price/income	OC	OC x EC_EX
price/income	1		
OC	0.15	1	
OC x EC_EX	-0.22	0.23	1

* **Price:** purchase or ex-showroom price (INR); **Income:** monthly household income (INR); **OC:** operating cost per month (INR)/1000; **EC_EX:** dummy which is 1 if the alternative is executive or economy class.

Table 6
Results of the conditional logit model.

Covariates	Specification 1		Specification 2	
	Estimate	z-value	Estimate	z-value
price/income	-0.13	-7.13	-0.13	-7.2
OC	-0.70	-7.18	-0.96	-9.1
OC x EC_EX			-0.31	-6.6
Loglikelihood	-28519		-28497	
McFadden R-square	0.1304		0.1311	
# of observations	8159		8159	

* **Price:** purchase or ex-showroom price (INR); **Income:** monthly household income (INR); **OC:** operating cost per month (INR)/1000; **EC_EX:** dummy which is 1 if the alternative is executive or economy class.

**All specifications have 69 alternative-specific constants, one for each make-model.

Signs of marginal utilities of purchase price, monthly operating cost, and interaction term are as expected. Inclusion of interaction term also does not affect the marginal utility of the purchase price,

because of the low correlation between covariates. Based on these results, we consider weighted CL (specification 2) as the final CL specification.

To ensure that the marginal utility of the cost-related attributes remains negative in MXL estimation, we consider the negative of marginal utilities to be lognormally distributed. This assumption is standard in empirical studies relying on parametric MXL models (Train, 2009). Table 7 presents the results of all considered MXL specifications. The statistically significant standard deviation of the marginal utility of operating cost in specification 1 suggests the presence of preference heterogeneity. The results of specifications 2 and 3 show the presence of heterogeneity in the importance that Indian two-wheeler buyers associate to price (depending on their income). However, very low z-value of the standard deviation of the interaction term in specification 3, and almost identical loglikelihood values of specifications 2 and 3 suggest considering the marginal utility of interaction term to be homogeneous. Thus, we use specification 2 to compute the mixing distribution of the discount rate of Indian two-wheeler buyers.

It is also worth noting that the mean marginal utility estimates of other two covariates with random heterogeneity are robust, i.e. these estimates are close to what we obtained in specification 2 of weighted CL (see Table 6). For instance, whereas mean values of the mixing distribution of marginal utilities for price/income, operating cost, and the interaction term are -0.21, -1.13, and -0.29, respectively, in specification 3 of weighted MXL, these estimates are -0.13, -0.96, and -0.31, respectively, in specification 2 of weighted CL.

4.4. Checking for price endogeneity

Endogeneity arises if the unobserved factors associated with vehicle choice are correlated with observed attributes, such as price. In the presence of endogenous regressors, the coefficient estimates of the observed attributes are inconsistent. In vehicle choice modeling, price endogeneity can be a concern (Haaf et al., 2016). Statistical testing for the existence of endogeneity is not always possible in empirical studies due to unavailability of the required data. However, given that alternative specific constants (ASCs) capture the part of the utility governed by unobserved attributes, measuring the correlation between purchase price and ASCs provides an indication of the extent of price endogeneity (Haaf et al., 2016; Sheldon and Dua 2020b). To check for potential price endogeneity issues, we use the same approach and find a correlation between price and the estimated ASCs of make-models. A low correlation value of -0.06 in specification 2 of the weighted CL and -0.02 in specification 2 of the weighted MXL model show

that the price endogeneity is less likely to be a concern in this analysis.

4.5. Discount rate

Fig. 4 and Table 8 show the variation of the annual discount rate relative to monthly household income for weighted CL and weighted MXL models. For households with a monthly income of INR 15,000, INR 30,000, and INR 100,000, annual discount rate estimates of the weighted CL model for executive and economy segments are 8.6%, 4.2%, and 1.2%, respectively. These values are slightly higher - 11.5%, 5.6%, and 1.7% - for all other segments. Previous studies also obtained similar results regarding a sharp decrease in discount rate with the increase in household income. For instance, while understanding preferences for air conditioners, Hausman (1979) found a decrease in the discount rate from 39% to 8.9% as the annual household income increases from below US\$10,000 to US\$25000-350,000.

Both Fig. 4 and Table 8 show that the median of the mixing distribution of the discount rate from the weighted MXL model is close to the estimates of the weighted CL model, but there is substantial heterogeneity in discount rates of households within specific income groups. For instance, the 20th, 50th, and 80th percentiles of the discount rate for households with a monthly income of INR 15,000 are 6.5%, 15.4%, and 38.6%, respectively. In conclusion, we observe substantial heterogeneity in preferences of Indian two-wheeler buyers, but such low median discount rate values indicate that an average Indian two-wheeler buyer is not myopic and ascribes a comparatively high value to fuel economy.

4.6. Policy implications

We now discuss the importance of our results in the context of feebate policies that the Indian government is considering to expedite the adoption of fuel-efficient vehicles (NITI Aayog and Rocky Mountain Institute, 2017b). The latest report by NITI Aayog, the Indian Government's think tank, mentions that auto buyers apply a high discount rate. In other words, auto buyers are assumed to undervalue expected fuel savings from purchasing higher fuel economy vehicles relative to the upfront costs. This warrants the need for a feebate type policy, which lowers the upfront price of higher fuel economy vehicles by providing rebates and raises the upfront price of lower fuel economy vehicles by applying fees. However, our findings suggest that the average Indian two-wheeler buyer ascribes a comparatively high value to future operating costs relative to upfront costs and is not myopic. Thus, our results do not lend support to the implementation of traditional feebate type

Table 7
Results of the weighted mixed multinomial logit (MXL) model.

Mean	Specification 1		Specification 2		Specification 3	
	Estimate	z-value	Estimate	z-value	Estimate	z-value
price/income	-0.13	-9.0	-0.21	-6.0	-0.21	-6.0
OC	-1.16	-8.1	-1.12	-8.1	-1.13	-8.1
OC x EC_EX	-0.29	-6.2	-0.29	-6.1	-0.29	-6.1
Standard Deviation						
price/income			0.20	2.8	0.20	2.9
OC	1.18	3.2	0.99	3.0	0.99	2.9
OC x EC_EX					0.004	0.02
Loglikelihood	-28491		-28489		-28489	
McFadden R-square	0.1312		0.1313		0.1313	
# of observations	8159		8159		8159	

* **Price:** purchase or ex-showroom price (INR); **Income:** monthly household income (INR); **OC:** operating cost per month (INR)/1000; **EC_EX:** dummy which is 1 if the alternative is executive or economy class.

**All random coefficients are assumed to be lognormally distributed. All specifications have 69 alternative-specific constants, one for each make-model.

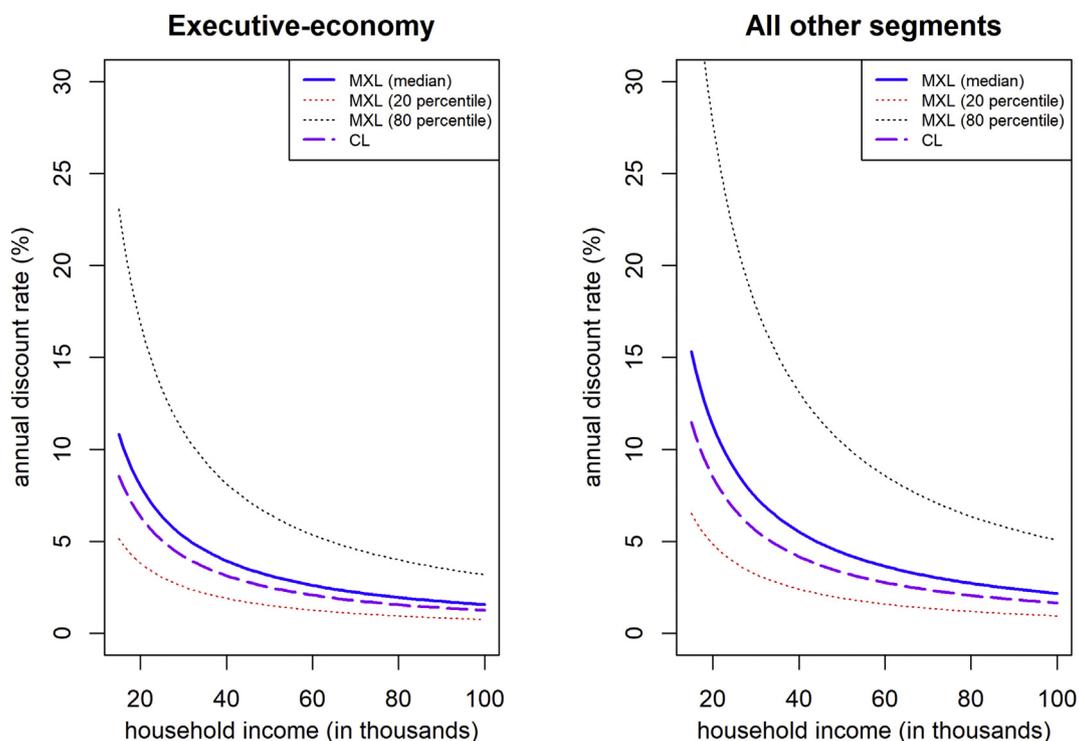


Fig. 4. The estimated discount rates of conditional logit (CL) and mixed logit (MXL) models.

Table 8
Discount rate estimates at different income levels.

Income (INR)	All other segments				Executive-economy segment			
	Conditional logit (CL)	Mixed logit (MXL) percentile			Conditional logit (CL)	Mixed logit (MXL) percentile		
		20th	50th	80th		20th	50th	80th
15,000	11.5%	6.5%	15.4%	38.6%	8.6%	5.1%	10.9%	23.3%
30,000	5.6%	3.2%	7.5%	17.9%	4.2%	2.5%	5.3%	11.1%
50,000	3.3%	1.9%	4.4%	10.4%	2.5%	1.5%	3.2%	6.5%
75,000	2.2%	1.3%	2.9%	6.8%	1.7%	1.0%	2.1%	4.3%
100,000	1.7%	0.9%	2.2%	5.1%	1.2%	0.8%	1.6%	3.2%

policies.

Our results, however, do suggest a substantial degree of heterogeneity in the valuation of operating costs both within and across specific income groups, with lower income buyers being far more myopic than higher income buyers. Thus, a progressive fee-bate policy, involving higher rebates and lower fees for lower income consumers (Sheldon and Dua 2020a), would be helpful in balancing the undervaluation of operating costs relative to upfront costs by lower income groups. Similar progressive rebate designs have also been recently reported in the literature and are currently under either pilot stage testing (California Air Resources Board, 2015; Sheldon and Dua 2019a, 2019b) and/or fully implemented (Colgan 2016).

5. Conclusions and future work

This study uses discrete choice models to analyze Indian consumers' revealed preferences for fuel economy and other attributes of two-wheelers. The results indicate that the majority of Indian two-wheeler buyers, ~73% of the sample, have a discount rate below 10%, i.e. they are not myopic. These estimates are useful in forecasting the demand for new models in the two-wheeler

market, and in understanding the effect of fuel prices on demand for existing make-models. The discount rate estimates can also be directly used as inputs to system dynamics models, which are increasingly used to understand the system-level impacts of energy policies (Menon and Mahanty, 2015). The results of the descriptive analysis are also relevant for vehicle manufacturers. For instance, style/looks and fuel economy are found to be the top two most important factors influencing Indian two-wheeler buyers' purchase decisions.

Our analysis contributes to the literature by taking the first step towards efficient energy policy design for the Indian two-wheeler market. Nonetheless, various other aspects can be considered in future work. First, previous studies have established the existence of the direct rebound effect – induced travel demand due to energy efficiency – among Indian vehicle buyers (Menon and Mahanty, 2012, 2015; Menon 2017). Since the advantages of energy efficiency policies may be offset by increased driving, scrutinising the rebound effect is crucial to identify the true impact of such policies. Readers can refer to Sorrell et al. (2009) for theoretical issue in the rebound effect estimation and Hymel et al. (2010) for an analysis of the rebound effect in road transport. Second, due to the possible presence of a rebound effect, it might be worthwhile to consider

implementing energy efficiency policies in conjunction with policies aiming to encourage two-wheeler sharing⁴ and scrappage. The system-level impact of a combination of multiple policies has been studied in the context of four-wheelers by Menon and Mahanty (2015), and such analyses can be a potential next step for two-wheeler market. Accounting for substitution between four-wheelers and two-wheelers or between two-wheelers within a household would be another critical component of such system-level analyses (De Borger et al., 2016b). Third, supplementing the existing data source with stated preference data can help in reliably estimating willingness to pay of Indian consumers for other performance-related attributes such as engine power (Ben-Akiva et al., 1994). Fourth, we mainly focus on the demand side, but a detailed analysis of various policy interventions can be performed by simultaneously modeling demand and supply sides (Allcott and Wozny, 2014; Chen and Lawell, 2019).

CRedit authorship contribution statement

Prateek Bansal: Conceptualization, Data curation, Formal analysis, Methodology, Writing - original draft. **Rubal Dua:** Conceptualization, Methodology, Writing - review & editing, Project administration, Resources, Supervision. **Rico Krueger:** Conceptualization, Methodology, Writing - review & editing. **Daniel J. Graham:** Conceptualization, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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⁴ With the advent of transportation network companies, two-wheeler sharing is realistic in India (ETAuto, 2017)

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