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How Responsive Are New Car Buyers in India and China to Factors Driving Fuel Consumption?

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Key Points

China and India, the world's two most populous developing economies, are also among the largest automotive markets and carbon emitters. To reduce carbon emissions from the passenger car sector, both countries have considered various policy levers that affect fuel price, car prices and fuel economy. This study estimates the responsiveness of new car buyers in China and India to such policy levers and drivers, including income. Furthermore, we estimate the potential for a rebound effect and the effectiveness of a feebate policy. To accomplish this, we develop a joint discrete-continuous model of car choice and usage based on revealed preference survey data. The data are from approximately 8,000 new car buyers in India and China who purchased cars in 2016 and 2017.

Our results suggest that

- Conditional on buying a new car, fuel consumption in both markets is relatively unresponsive to fuel price and income, with elasticity estimates ranging from 0.12 to 0.15. For both markets, the mean segment-level direct elasticities of fuel consumption relative to car prices and fuel economy range from 0.57 to 0.65.

- The rebound effect on fuel savings due to cost-free fuel economy improvement is found to be 17.1% for India and 18.8% for China. To put this in context, estimates of the rebound effect in the literature range from 5% to 30%.

- A revenue neutral feebate policy, with average rebates and fees of up to approximately 15% of the retail price, result in low fuel savings of 0.7% for both markets. Although the rebound effect of the feebate policy is low (7.3% for India and 1.6% for China), the policy is not an effective fuel conservation policy because of its low fuel savings potential.

Overall, given the limited response to demand-side measures and the need for deep decarbonization and energy security, we must either accept extremely high fuel and vehicle taxes or tolerate lower economic output due to restrictions on new car sales. Given that gasoline prices in both China and India are among the highest in the world, it is uncertain whether additional tax increases can be implemented without provoking public outrage and political fallout. It is thus inevitable that supply-side regulations like performance standards, mandates, and car ownership limitations be considered in both nations. This is despite the literature showing that demand-side measures such as fuel taxes, which directly address externalities, are more cost effective. Moreover, because customers are unaware of the causes of rising automobile costs, supply-side strategies are frequently deemed more politically palatable than government-enforced taxes.

1. Introduction

While China is the world's largest emitter of greenhouse gases (GHGs) and has the largest automobile market, India ranks third in GHG emissions and fourth in vehicle sales globally (Gupta et al. 2018; Timperley 2019; Dua et al. 2021). The transport sector in both countries contributes substantially to GHG emissions. India's transport sector, the third largest emitter nationally, accounted for 11% of the country's carbon dioxide (CO_2) emissions in 2016 (Janssens-Maenhout et al. 2017). With a compound annual growth rate of 8.4%, India's transport-related CO_2 emissions are forecast to rise to 1 billion tonnes annually by 2030 (NITI Aayog and Rocky Mountain Institute 2017a). Locally, vehicle emissions in China contribute 12%-36% of total nitrogen oxide, 10.7% of total PM10 (particulate matter 10 micrometers and smaller) and 16.8% of total PM2.5 (particulate matter 2.5 micrometers and smaller) (Wang et al. 2019). According to the 2020 Environmental Performance Index, China and India are ranked 120 and 168 out of 180 countries, respectively (EPI 2020). Thus, understanding the determinants of transport fuel demand in the world's two most populous and rapidly developing economies has local and global implications.

In the transport sector, the new car market in both countries is expected to increase further given their rapid rates of urbanization and rising income levels. Private vehicle ownership in India is increasing at a compound annual growth rate of 10% (NITI Aayog and Rocky Mountain Institute 2017b). Similarly, vehicle ownership per capita in Chinese cities is increasing at a rate of 10%-25% per year (Darido, Torres-Montoya, and Mehndiratta 2014).

To combat the current and projected increases in GHG emissions from the passenger car sector, both countries have adopted fuel conservation policies. For instance, China first introduced fuel economy standards for light-duty passenger vehicles in 2005, followed by the implementation of its Corporate Average Fuel Consumption (CAFC) target in 2012 to achieve a fuel consumption of 5 liters per 100 kilometers (km) by 2020. Moreover, China introduced a subsidy scheme in 2010 to encourage Chinese automakers to produce vehicles with an engine displacement below 1.6 liters (Chen, Lawell, and Wang 2020). Similarly, India adopted CAFC norms in 2017, which require automakers to reduce the fuel consumption of light-duty vehicles under a curb weight of 3,500 kilograms (kg) to below 130 grams per km of CO_2 by 2022. Another measure considered by policymakers , including NITI Aayog, the Indian government's think tank, is a feebate policy, which reduces the upfront cost of fuel-efficient vehicles and increases it for vehicles with lower fuel economy (NITI Aayog and Rocky Mountain Institute 2017b; Dua et al. 2021; Sheldon and Dua 2020).

The effectiveness of these fuel conservation policies depends mainly on the consequent change in car buyers' preferences to buy fuel-efficient cars and their car usage. For instance, fuel economy standards are likely to increase overall fleet fuel economy. However, the extent to which the induced driving due to low operating costs offsets the fuel consumption savings depends on the combined fuel price elasticity of car choice and usage. This induced travel demand due to a fuel conservation measure is referred to as the rebound effect (Frondel, Ritter, and Vance 2012; Menon and Mahanty 2015). Thus, estimating the car and fuel price elasticity of fuel consumption and the corresponding rebound effects is critical for the *ex ante* evaluation of a fuel conservation policy.

Several studies have explored the effectiveness of fuel conservation policies using combined car preference and usage data in developed countries such as the United States (U.S.) (Bento et al. 2009; Goldberg 1998; Jacobsen 2013; Small and Van

Dender 2007; West 2004) and Japan (Fullerton, Gan, and Hattori 2015). By contrast, applications of joint models in developing countries are limited. The study by Tan, Xiao, and Zhou (2019) is the only Chinese study that simultaneously analyzes car usage and car type preferences to quantify the welfare effects of fuel taxes. However, it estimates separate models for car composition and vehicle kilometers traveled (VKT), leading to inconsistent parameter estimates (see section 2.1 for a detailed discussion). The only study on joint modeling of Indian car buyers' preferences for travel and car types uses data from 2010 (Chugh and Cropper 2017). Some other studies of developing countries rely on modeling the preference for car types or vehicle fleet composition while ignoring the rebound effects due to induced car usage (Chen and Lawell 2020; Xiao and Ju 2014; Yang and Tang 2019), and some use aggregate time-series data to derive elasticities (Dahl 2012; Lin and Zeng 2013).

We bridge this gap by analyzing national data on Chinese and Indian car buyers' sociodemographics and revealed preferences for car types and car usage from 2016 to 2017. These detailed data enable us to estimate a theoretically consistent joint discrete-continuous mixed logit model of car buyers' preferences for car types and usage. Using the parameter estimates of the model, we derive new estimates of the following: i) the fuel price and income elasticity of fuel consumption, ii) the effect of a purchase price reduction and fuel economy improvements on fuel consumption while quantifying the rebound effects and iii) the effect of a revenue-neutral feebate policy on fleet fuel economy and fuel consumption. This study thus presents the first theoretically consistent fuel consumption elasticities for the Chinese automobile market. It also provides new insights into the effectiveness of feebate policies in India and China. Finally, we present the first comprehensive comparison of the results from both countries' automobile markets.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the effectiveness of fuel conservation policies and the corresponding fuel consumption elasticities in China and India. Section 3 describes the specification and estimation of the joint discrete-continuous mixed logit model. Section 4 presents the data collection, summary statistics and empirical model specifications. Section 5 discusses the parameter and elasticity estimates as well as the results of the revenue neutral feebate policy simulation. The final section summarizes the conclusions, implications and limitations of this study.

2. Literature Review

2.1 Chinese Automobile Market

The literature consists of two main streams of studies. The first stream analyzes aggregated time series or panel data using reduced form regression models while correcting for various endogeneity biases. Lin and Zeng (2013) estimate the price and income elasticity of gasoline demand using annual gasoline consumption data for 30 provinces in China from 1997 to 2008. They use regional diesel prices and international crude oil prices as instrumental variables for gasoline prices. The ranges of the intermediate-run price and income elasticity of fuel consumption are [−0.49, −0.20] and [1.01, 1.05], respectively. Sun, Xu, and Yin (2016) show that the gasoline price reform in 2008 led to a 6.25% increase in the fleet fuel economy of new vehicles. The study uses monthly vehicle sales and characteristics data in a fixed-effect regression framework. He, Yang, and Chang (2017) investigate China's fuel demand system by analyzing panel data on vehicle population and use in 306 cities in China from 2002 to 2012 and using the Almost Ideal Demand System (AIDS) model. The estimated ranges of the own-price and expenditure elasticity of fuel consumption for different vehicle models are [−1.22, −0.46] and [0.27, 1.24], respectively.

The second stream of studies uses market- and consumer-level vehicle choice models. Xiao and Ju (2014) apply the popular market-level Berry, Levinson, and Pakes (BLP) model to analyze the effect of consumption and fuel taxes on vehicle sales and fuel consumption. Since they estimate the impacts of tax adjustments on both the demand and supply sides, they can estimate social welfare instead of consumer surplus. The results show that a fuel tax leads to reduced fuel consumption at the expense of social welfare, whereas a consumption tax has no significant effect on any of the measures. Chen and Lawell (2020) also use the BLP model to analyze the effect of fuel conservation policies on vehicle market share and social welfare in the Chinese automobile market. They show that China's CAFC standard restricts the sales-weighted average fuel consumption of vehicles produced by a firm, which is inefficient. Instead, they strongly support the need for stringent fuel economy standards at the vehicle model level.

Some studies have also explored the effect of subsidies on fuel-efficient and new energy vehicles. Yang and Tang (2019) use car registration data for five Chinese cities from 2011 to 2012 and estimate a BLP model to investigate the effectiveness of subsidies. They find that subsidies for fuel-efficient vehicles increase oil consumption and CO_2 emissions but still improve social welfare. Meanwhile, subsidies for new energy vehicles decrease gasoline consumption but raise CO_2 emissions and diminish social welfare. In another study, Sheldon and Dua (2020) explore the cost-effectiveness and impact of China's plug-in electric vehicle subsidy program. To this end, they estimate a consumer-level vehicle choice model using data on new vehicle purchases in 2017. They find that the cost of this plug-in electric vehicle subsidy is $1.90 for each additional liter of gasoline saved. While the aforementioned studies ignore vehicle utilization, Tan, Xiao, and Zhou (2019) simultaneously analyze vehicle choice and usage in the Chinese automobile market. They estimate fleet composition by applying the BLP model on market-level fleet composition and vehicle usage using a fixed-effect regression model on panel data of individuals' VKT from 2009-2010. They find that the fuel price elasticity of vehicle usage is −0.59.

However, Tan, Xiao, and Zhou (2019) adopt a two-stage approach (i.e., they estimate the vehicle demand and VKT models sequentially); this may lead to an inconsistency in the magnitudes and signs of the parameters of both models (Chugh and Cropper 2017). Leveraging household-level data on vehicle choice and usage, we overcome this limitation by jointly analyzing both choices using a discrete-continuous mixed logit model. Following Bento et al. (2009) and Feng, Fullerton, and Gan (2013), we link vehicle demand and usage demand through Roy's identity, which leads to a theoretically consistent single set of parameter estimates. Section 3 provides the details of the model specification.

2.2 Indian Automobile Market

Few studies have explored the effectiveness of fuel conservation policies in India. Chugh, Cropper, and Narain (2011) investigate the fuel economy valuation of Indian car buyers. The fuel economy standard is often preferred as a fuel conservation policy over fuel taxes, if consumers undervalue fuel economy. Using consumer-level data and a hedonic price approach, they find no evidence to support the assumption that Indian car buyers undervalue fuel economy. Bansal et al. (2021) also find similar results by analyzing the preferences of Indian consumers for two-wheelers. They find that Indian two-wheeler buyers are not myopic, i.e., most use a discount rate of 10% or less to find the present value of the future operating cost at the time of purchase. However, none of these studies have considered vehicle usage and rebound effects. Menon and Mahanty (2015) estimate such rebound effects by developing a system-dynamic simulation to analyze the effectiveness of alternative energy policies in conjunction with energy efficiency improvements in India. They find these policies produce more car trips, but the simulation-based analysis is sensitive to the assumptions of the model parameters.

Chugh and Cropper (2017) present the most comprehensive analysis of the Indian automobile market by analyzing household-level car choice and usage data. They offer the first estimates of the price and income elasticity of fuel consumption for the Indian market by applying the theoretically consistent discrete-continuous model that we use in this study. However, their analysis uses data from 2010 and relies on the differences in the retail prices of diesel and petrol. Focusing on the duality of the automobile market was meaningful in 2010 because diesel had historically been cheaper than petrol owing to higher subsidies. However, government-regulated petrol and diesel prices in India were directly linked to international market rates in 2010 and 2014, which led to only small differences between diesel and petrol prices. For instance, in June 2020 the retail price of diesel in the national capital, New Delhi, climbed to \$1.118 per liter, surpassing the petrol price of \$1.117 per liter (Bhardwaj 2020). Buyers are unlikely to alter their preferences based on such minor and temporary differences in the prices of diesel and petrol, barring differences in vehicle fuel economy. This hypothesis is supported by the sharp drop in the market share of diesel vehicles, from 58% in 2013 to 17% in 2021 (Rampal 2021). Further, the higher upfront price premium on diesel cars has been exacerbated by the implementation of the Bharat Stage-VI emission norms (equivalent to Euro 6). The prohibitively high cost of upgrading diesel engines to meet new emission norms has caused leading Indian carmakers, including Maruti Suzuki, to stop making diesel cars (Sasi 2019). Hence, we use household-level vehicle choice and usage data from 2017 and do not distinguish between vehicle alternatives based on fuel type. We also provide new insights into the feasibility of feebate policies in India, new estimates of the price and income elasticity of fuel consumption, and assess the potential for a rebound effect.

3. A Model of New Car Purchases and Usage

The joint modeling of households' preferences for energy products and their usage has been central to estimating energy demand since the seminal work by Dubin and McFadden (1984). However, the two-step approach was popular until the publication of the studies by Bento et al. (2009) and Feng, Fullerton and Gan (2013). These studies use Roy's identity in a static utility maximization framework to derive VKT and achieve a single set of parameters for both choice models. This specification allows for the simultaneous estimation of both choice models using full information maximum likelihood estimation. Both the sub-models and estimators are discussed in detail below.

3.1 Vehicle Choice

According to Bento et al. (2009), the utility of household i, conditional on choosing car j from the J available cars, is

$$v_{ij} = u_{ij} + \varepsilon_{ij} = -\frac{1}{\beta_i} e^{-\beta_i(y_i - r_j) - \gamma X_{ij} - \eta_i} - \frac{1}{\alpha_i} e^{\alpha_i p_j} + \varepsilon_{ij}, \quad (1)$$

where y_i is the annual income of household i; r_j is the annualized purchase price or rental cost of car j; X_{ij} includes the car-specific characteristics, household-specific characteristics and interaction of both characteristics; p_j is the operating cost of car j per km; and η_i is an unobserved normally distributed preference for driving with mean zero and standard deviation σ. We consider α_i and β_i to follow a parametric distribution with the parameters ω_α and ω_β, respectively. To maintain the computational tractability of the model, we assume homogeneous sensitivity of utility relative to other household and car characteristics (i.e., constant γ across households). The common set of identified parameters in the systematic utility is $\Theta = \{\gamma, \omega_\alpha, \omega_\beta, \sigma\}$, and it follows a joint probability density function $f(u|\Theta)$. ε_{ij} is an independent and identically distributed idiosyncratic error term that follows a type 1 extreme value distribution with location parameter zero and scale μ. The probability of household i choosing car j is therefore

$$P_{ij} = \int \frac{e^{\frac{u_{ij}}{\mu}}}{\sum_{k=1}^{J} e^{\frac{u_{ik}}{\mu}}} f(u|\Theta) du. \quad (2)$$

3.2 Driving Distance

Annual VKT can be obtained from Equation (1) using Roy's identity:

$$KM_{ij} = -\frac{\frac{\partial v_{ij}}{\partial p_j}}{\frac{\partial v_{ij}}{\partial y_i}} = e^{\beta_i(y_i - r_j) + \gamma X_{ij} + \alpha_i p_j + \eta_i}. \quad (3)$$

Equations (1) and (3) have the same set of common parameters. Considering the unobserved heterogeneity in systematic utility, the expected value of annual driving distance is

$$E = \int [\beta_i(y_i - r_j) + \gamma X_{ij} + \alpha_i p_j + \eta_i] f(u|\Theta) du. \quad (4)$$

Considering that $ln\, ln\, KM_{ij}$ takes a standard linear regression form with normally distributed error η_i (i.e., preference for driving), the likelihood of observing $\widetilde{KM}_{ij}$, conditional on household i buying car j, is

$$l(\widetilde{KM}_{ij} | l_{ij} = 1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{[lnln\, \widetilde{KM}_{ij} - E(lnln\, \widetilde{KM}_{ij})]}{2\sigma^2}}, \quad (5)$$

where l_{ij} is an indicator that takes 1 if household i buys car j and 0 otherwise, and $E(ln\, ln\, KM_{ij}) = E[\beta_i(y_i - r_j) + \gamma X_{ij} + \alpha_i p_j]$, i.e., Equation (4) without the preference for driving, as its expected value is zero.

3.3 Estimation Strategy

The joint likelihood is the product of the likelihood of household i buying car j and the likelihood of driving that car for $\widetilde{KM}_{ij}$ annually. Thus, the full information likelihood L and log-likelihood LL of a sample of N households are

$$L(\Theta, \mu) = \prod_{i=1}^{N} \prod_{j=1}^{J} \left[P_{ij} l\left(\widetilde{KM}_{ij} | l_{ij} = 1\right)\right]^{l_{ij}}, \tag{6}$$

$$LL(\Theta, \mu) = \sum_{i=1}^{N} \sum_{j=1}^{J} l_{ij} \ln \ln \left[P_{ij} l\left(\widetilde{KM}_{ij} | l_{ij} = 1\right)\right]. \tag{7}$$

Because the log-likelihood does not have a closed-form expression, we approximate it through a simulation using a quasi-Monte Carlo method (Bansal et al. 2021). We also incorporate household-level weights into the analysis. The resulting weighted and simulated full information log-likelihood WLL of the sample is

$$WLL(\Theta, \mu) = \sum_{i=1}^{N} \sum_{j=1}^{J} l_{ij} \left[w_i \ln \ln \left(\frac{1}{R} \sum_{r=1}^{R} P_{ijr} l\left(\widetilde{KM}_{ijr} | l_{ij} = 1\right)\right)\right], \tag{8}$$

where w_i is the weight of household i, P_{ijr}, $\widetilde{KM}_{ijr}$ are the respective quantities for the r^{th} draw from $f(u/\Theta)$, and R is the number of shifted and shuffled Halton draws. We estimate the joint discrete-continuous model by maximizing the weighted simulated log-likelihood by writing our own MATLAB code with the analytical gradient of the log-likelihood. We compute the standard error of the parameters using a robust sandwich estimator. Further, we compute the standard errors of the elasticity estimates. To this end, we take 100 draws from the asymptotic normal distribution of the estimator with the mean as the point estimate and the robust Hessian gradient-based covariance matrix as the covariance. For each draw, the elasticity value is calculated and the standard deviation of the elasticity estimates across the 100 draws is reported as the standard error.

4. Data and Model Specification

4.1 Data for China and India

We use the initial quality survey data collected in India and China by J.D. Power, a global leader in automotive marketing research. Initial quality survey data provide manufacturers with consumer feedback and have remained an industry benchmark for assessing new vehicle quality since 1987. New car buyers who purchased a car between November 2016 and July 2017 for personal use, and had owned them for two to six months, were interviewed. The dataset consists of the attributes of the purchased vehicle, including the brand (make), model, segment (body type), fuel economy and purchase price. It also includes the delivery date, months of ownership, mileage and the vehicle buyers' demographic characteristics (e.g., income, gender and age). J.D. Power also provides us with aggregate sales data on cars to assess how well the individual level sample represents the car market. We also have access to data collected by JATO for China on other vehicle characteristics (e.g., curb weight and vehicle dimensions) at the model level.

Tables 1 and 2 present the sales-weighted means of the segment-level car characteristics for China

Table 1. Sales-weighted mean of the vehicle attributes for China (standard deviations in parentheses).

Segment	Fuel economy (km/liter)	Purchase price (10^5 CNY)	Engine displacement (liters)	Length × width × height (10^{-10} mm^3)	Curb weight (10^{-3} kg)	Number of models	Market Share (%)
Compact	14.74 (0.78)	0.53 (0.08)	1.36 (0.07)	1.03 (0.04)	1.05 (0.05)	3	1.63
Compact basic	14.61 (0.13)	0.53 (0.09)	1.42 (0.02)	1.00 (0.02)	1.00 (0.03)	2	0.16
Compact luxury	11.32 (0.74)	2.92 (0.52)	1.87 (0.17)	1.22 (0.06)	1.57 (0.11)	7	2.63
Compact luxury SUV	11.03 (0.49)	3.13 (0.47)	1.77 (0.12)	1.31 (0.06)	1.64 (0.09)	6	1.42
Compact mini	14.38 (0.00)	1.42 (0.00)	0.99 (0.00)	0.68 (0.00)	0.92 (0.00)	1	0.07
Compact MPV	13.31 (0.25)	0.63 (0.10)	1.49 (0.05)	1.36 (0.08)	1.31 (0.09)	8	5.17
Compact SUV	12.02 (0.64)	1.21 (0.25)	1.63 (0.15)	1.36 (0.10)	1.47 (0.12)	34	11.85
Compact upper	14.33 (0.55)	0.85 (0.02)	1.46 (0.02)	1.05 (0.04)	1.09 (0.02)	6	2.88
Large luxury	10.12 (0.00)	10.15 (0.00)	2.48 (0.00)	1.50 (0.00)	1.97 (0.00)	1	0.10
Large luxury SUV	9.06 (0.23)	8.57 (0.75)	2.78 (0.23)	1.69 (0.04)	2.23 (0.04)	5	0.66
Large MPV	9.54 (0.30)	2.81 (0.25)	2.35 (0.04)	1.64 (0.12)	1.88 (0.03)	3	1.05
Large SUV	10.03 (0.61)	2.71 (0.71)	2.07 (0.35)	1.60 (0.10)	1.89 (0.14)	12	4.16
Midsize	13.15 (0.44)	1.21 (0.18)	1.55 (0.06)	1.21 (0.03)	1.29 (0.04)	25	20.46
Midsize basic	13.74 (0.55)	0.85 (0.11)	1.51 (0.04)	1.17 (0.05)	1.20 (0.09)	24	10.60
Midsize luxury	10.50 (0.44)	4.20 (0.63)	2.08 (0.05)	1.38 (0.03)	1.80 (0.07)	6	2.37
Midsize luxury SUV	10.01 (0.31)	4.40 (0.70)	2.02 (0.07)	1.49 (0.02)	1.90 (0.04)	7	2.01
Midsize MPV	11.26 (0.82)	1.55 (0.53)	1.65 (0.21)	1.56 (0.26)	1.65 (0.20)	3	0.46
Midsize SUV	11.08 (0.46)	1.73 (0.41)	1.80 (0.21)	1.43 (0.06)	1.60 (0.09)	27	12.37
Midsize upper	11.27 (0.45)	2.10 (0.25)	1.83 (0.18)	1.33 (0.03)	1.56 (0.07)	16	6.51
Midsize upper economy	12.57 (0.37)	1.54 (0.21)	1.54 (0.10)	1.24 (0.05)	1.39 (0.07)	12	5.04
Minivan	14.15 (0.39)	0.37 (0.04)	1.24 (0.10)	1.14 (0.06)	1.00 (0.05)	3	0.77
Small SUV	12.95 (0.73)	0.81 (0.12)	1.55 (0.09)	1.29 (0.12)	1.33 (0.11)	23	7.63

Note: MPV = multipurpose vehicle; CNY = Chinese yuan; SUV = sports utility vehicle; mm^3 = cubic millimeters; kg = kilograms.

Table 2. Sales-weighted mean of the vehicle attributes for India (standard deviations in parentheses).

Segment	Fuel economy (km/liter)	Purchase price (10^6 INR)	Engine displacement (liters)	Number of models	Market Share (%)
Luxury	13.08 (1.30)	4.89 (0.65)	2.16 (0.18)	7	0.37
Upper compact	16.16 (0.68)	0.65 (0.05)	1.23 (0.04)	8	8.22
MUV or MPV	15.43 (1.45)	1.09 (0.34)	1.97 (0.51)	9	8.64
Entry midsize	16.51 (0.66)	0.76 (0.05)	1.27 (0.09)	10	12.91
Entry compact	17.58 (0.74)	0.39 (0.04)	0.83 (0.10)	6	11.53
Compact	17.04 (0.64)	0.50 (0.04)	1.03 (0.07)	8	14.90
Premium compact	16.68 (0.73)	0.74 (0.05)	1.23 (0.03)	6	16.66
SUV	15.81 (1.67)	1.19 (0.35)	1.56 (0.34)	14	15.85
Premium SUV	13.10 (1.52)	3.05 (0.01)	2.73 (0.22)	2	0.95
Midsize	16.23 (0.86)	1.09 (0.06)	1.47 (0.10)	6	4.76
Premium midsize	14.71 (1.54)	1.92 (0.08)	1.75 (0.04)	3	0.27
Van	15.21 (0.19)	0.39 (0.06)	1.02 (0.20)	2	4.94

Note: MUV: multi-utility vehicle; INR = Indian rupee; SUV = sports utility vehicle.

Table 3. Correlation between the car-specific attributes

	Fuel economy	Purchase price	Engine displacement	Length × width × height	Curb weight
China					
Fuel economy	1				
Purchase price	−0.70	1			
Engine displacement	−0.81	0.79	1		
Length × width × height	−0.80	0.51	0.68	1	
Curb weight	−0.93	0.77	0.82	0.86	1
India					
Fuel economy	1			-	-
Purchase price	−0.68	1		-	-
Engine displacement	−0.78	0.58	1	-	-

and India, respectively. The data from China and India consist of 234 and 81 models, respectively. The summary statistics indicate that the sales-weighted fleet fuel economy of India is much higher than that of China (16.38 km/liter vs. 12.32 km/liter). This is because sport utility vehicles (SUVs) constitute a substantial share of the Chinese market, whereas the compact and midsize segments dominate the Indian fleet (55% market share). As expected, Table 3 shows a similar and highly negative correlation of fuel economy with engine displacement and other vehicle size indicators (e.g., volume and weight) in both markets.

4. Data and Model Specification

Tables 4 and 5 present the segment-level demographic distributions for China and India, respectively. The India and China samples have 7,894 and 8,951 households,[1] respectively. In China, 42.4% of new car buyers are women, who have higher preferences for the compact basic and luxury segments, compared with just 5% in India. The average household size of Indian car buyers is 4.90 compared with 3.26 for Chinese car buyers. The average car buyer in China is 3.27 years younger than an Indian car buyer. The annual VKT of both market buyers is close to 14,000 km. The VKT for the compact and mini segments, which might not be used for inter-city travel owing to safety and comfort concerns, is much lower. On average, the annual income of an Indian car buyer is much lower than that of a Chinese car buyer ($10,626 vs. $28,268, using 2017 conversion rates).[2] As expected, the luxury and premium car segments attract buyers with much higher incomes and higher ownership rates of cars in both markets.

The population of car buyers is poorly defined because only a fraction of the population is assumed to be financially capable of and willing to buy new cars. Therefore, we adopt choice-based (instead of exogenous demographics-based) sampling weights to obtain consistent parameter estimates. We

Table 4. Mean sociodemographics of Chinese car buyers (standard deviations in parentheses).

Segment	Age (years)	Women (%)	Number of cars	Family size	Annual income (10^5 CNY)	Annual km	Market Share (%)
Compact	32.81 (7.20)	0.44 (0.50)	1.09 (0.28)	3.03 (0.79)	1.35 (0.08)	13,690 (7,412)	1.63
Compact basic	32.17 (7.01)	0.67 (0.48)	1.21 (0.51)	3.17 (0.64)	1.29 (0.06)	10,150 (4,600)	0.16
Compact luxury	33.62 (5.94)	0.45 (0.50)	1.26 (0.44)	3.20 (0.85)	2.82 (0.09)	13,892 (6,976)	2.63
Compact luxury SUV	33.03 (5.71)	0.52 (0.50)	1.30 (0.55)	3.13 (0.80)	2.92 (0.08)	13,192 (6,170)	1.42
Compact mini	29.17 (4.78)	0.50 (0.52)	1.25 (0.45)	3.17 (0.83)	2.19 (0.08)	12,578 (8,949)	0.07
Compact MPV	33.37 (6.64)	0.22 (0.42)	1.06 (0.24)	3.52 (0.94)	1.48 (0.09)	14,286 (7,025)	5.17
Compact SUV	32.65 (6.43)	0.40 (0.49)	1.08 (0.31)	3.20 (0.84)	1.76 (0.08)	13,433 (6,563)	11.85
Compact upper	31.37 (5.70)	0.49 (0.50)	1.05 (0.26)	3.16 (0.76)	1.60 (0.08)	13,284 (6,112)	2.88
Large luxury	32.86 (7.15)	0.57 (0.53)	1.57 (0.53)	2.71 (0.76)	4.50 (0.08)	13,137 (6,803)	0.10
Large luxury SUV	35.68 (6.42)	0.34 (0.47)	1.57 (0.78)	3.31 (0.86)	3.87 (0.09)	14,324 (7,409)	0.66
Large MPV	34.92 (6.65)	0.27 (0.44)	1.22 (0.41)	3.44 (0.88)	2.54 (0.09)	14,343 (7,388)	1.05
Large SUV	34.46 (6.82)	0.36 (0.48)	1.18 (0.54)	3.26 (0.96)	2.44 (0.10)	14,161 (6,906)	4.16
Midsize	32.49 (6.38)	0.45 (0.50)	1.06 (0.24)	3.17 (0.84)	1.66 (0.08)	13,181 (6,540)	20.46
Midsize basic	32.28 (7.10)	0.42 (0.49)	1.07 (0.26)	3.20 (0.88)	1.44 (0.09)	13,010 (6,433)	10.60
Midsize luxury	34.81 (6.48)	0.43 (0.50)	1.27 (0.50)	3.29 (0.79)	3.12 (0.08)	14,048 (6,651)	2.37
Midsize luxury SUV	35.19 (7.05)	0.39 (0.49)	1.40 (0.60)	3.32 (0.86)	3.22 (0.09)	14,688 (7,472)	2.01
Midsize MPV	34.39 (7.33)	0.35 (0.48)	1.04 (0.20)	3.39 (1.11)	2.04 (0.11)	12,332 (5,307)	0.46
Midsize SUV	33.14 (6.60)	0.38 (0.48)	1.10 (0.35)	3.21 (0.82)	1.91 (0.08)	13,959 (6,818)	12.37
Midsize upper	33.15 (6.67)	0.43 (0.49)	1.11 (0.33)	3.20 (0.81)	2.05 (0.08)	13,904 (6,847)	6.51
Midsize upper economy	32.92 (6.82)	0.42 (0.49)	1.07 (0.32)	3.14 (0.80)	1.85 (0.08)	13,934 (7,196)	5.04
Minivan	31.75 (6.55)	0.19 (0.39)	1.06 (0.24)	3.17 (0.73)	1.43 (0.07)	14,486 (9,115)	0.77
Small SUV	32.63 (7.02)	0.40 (0.49)	1.07 (0.31)	3.20 (0.84)	1.53 (0.08)	13,395 (6,804)	7.63
Sample	33.08 (6.92)	0.42 (0.49)	1.13 (.39)	3.26 (0.88)	1.91 (1.05)	13,941 (7,271)	

Note: CNY = Chinese yuan; SUV = sports utility vehicle; MPV = multipurpose vehicle.

Table 5. Mean sociodemographics of Indian car buyers (standard deviations in parentheses).

Segment	Age (years)	Women (%)	Number of cars	Family size	Annual income (10^6 INR)	Annual km	Market Share (%)
Luxury	39.19 (8.78)	0.05 (0.23)	2.38 (0.76)	4.97 (1.19)	1.35 (0.24)	14,021 (10,141)	0.37
Upper compact	36.81 (9.63)	0.06 (0.24)	1.14 (0.45)	4.66 (1.16)	0.66 (0.30)	12,983 (10,468)	8.22
MUV or MPV	37.08 (8.45)	0.03 (0.17)	1.30 (0.59)	5.27 (1.35)	0.76 (0.33)	16,089 (11,790)	8.64
Entry midsize	36.38 (8.77)	0.03 (0.18)	1.16 (0.46)	4.83 (1.29)	0.68 (0.29)	14,034 (11,057)	12.91
Entry compact	36.09 (9.91)	0.07 (0.25)	1.16 (0.44)	4.73 (1.36)	0.56 (0.28)	11,939 (9,935)	11.53
Compact	36.63 (9.90)	0.06 (0.25)	1.14 (0.47)	4.79 (1.37)	0.62 (0.29)	11,754 (8,860)	14.90
Premium compact	34.78 (9.10)	0.07 (0.25)	1.19 (0.52)	4.82 (1.28)	0.69 (0.34)	13,484 (10,217)	16.66
SUV	36.87 (8.42)	0.03 (0.16)	1.32 (0.61)	5.05 (1.33)	0.77 (0.35)	14,644 (10,182)	15.85
Premium SUV	37.80 (8.84)	0.07 (0.25)	1.87 (0.86)	5.48 (1.43)	1.19 (0.35)	16,088 (9,953)	0.95
Midsize	36.44 (8.49)	0.05 (0.23)	1.29 (0.58)	4.86 (1.11)	0.78 (0.35)	13,951 (9,616)	4.76
Premium midsize	38.14 (10.45)	0.03 (0.16)	1.38 (0.72)	4.81 (0.97)	0.89 (0.38)	13,256 (8,635)	0.27
Van	36.92 (9.28)	0.01 (0.08)	1.16 (0.57)	5.16 (1.22)	0.53 (0.28)	12,942 (9,499)	4.94
Sample	36.35 (0.09)	0.05 (0.21)	1.23 (0.55)	4.90 (1.32)	0.69 (0.33)	14,037 (10,985)	

Note: INR = Indian rupee; SUV = sports utility vehicle; MUV = multi-utility vehicle; MPV = multipurpose vehicle.

compute the sampling weights of each make and model such that the choice proportions in the sample are the same as the actual sales proportions. The sampling weight ranges of India and China are [0.21, 8.18] and [0.14, 5.88], respectively.

4.2 Model Specification

We convert the purchase price of a car into the annualized rental cost. We use an inflation-adjusted interest rate of 8.5% and an expected car lifetime of 18 years for the Indian market (Chugh and Cropper 2017). For the Chinese market, we use an inflation-adjusted interest rate of 8% (S&P Global 2019) and an average lifetime of 14.5 years (Hao et al. 2011). The unit operating cost is obtained as the ratio of fuel price to fuel economy. We use the average 2017 fuel price of 6 Chinese yuan (CNY) ($0.888) per liter for China (Ou et al. 2020) and 59 Indian rupees (INR) ($0.9086) per liter for India (ZeeBiz 2017).[3] Because the fuel price remains the same in all the models, the variation in operating costs arises from the heterogeneity in fuel economy across these models.

In addition, we incorporate make- and segment-specific fixed effects to account for unobserved vehicle characteristics. We capture household-level unobserved heterogeneity through log-normal distributions of the coefficient of income minus the rental cost, negative log-normal distribution of operating cost and normal distribution of the preference for driving in indirect utility. The first distributional assumption ensures a positive effect of income on VKT and the positive marginal utility of consuming all other goods. Meanwhile, the second assumption imposes a negative effect of the operating cost on VKT.

We assume that all the households have the same choice set (234 models for China and 81 models for India). Since the data include new car buyers, the surveyed households must decide which car to buy, conditional on having already decided to buy a new car. Owing to this data limitation, we do not consider an ‘outside good’ option of not buying a new car.

5. Results and Discussion

Table 6 presents the parameter estimates (except for the alternative-specific constants) of the joint model for India and China. Most of the parameters are statistically significant at the 1% level, and the the effects are intuitive. Men with higher car ownership rates and larger families drive more in both countries. Car buyers from both countries with larger families prefer larger vehicles (as indicated by the positive interaction between family size and engine displacement in India and volume in China). The coefficients of operating cost and income minus the annual rental cost are used to derive the short-run fuel price and income elasticity of annual VKT. Specifically, fuel price elasticity using Equation (3) is , which we compute at the mean of and the sales-weighted mean operating cost. Income elasticity is computed in the same way.

Table 6 shows that the short-run fuel price elasticity of VKT, considering changes only in vehicle use and not vehicle choice in response to a changing fuel price, is −0.18 for India and −0.28 for China. The

Table 6. Parameter estimates of the demand model and short-run elasticity of VKT.

Variable	India		China	
	Estimates	Standard error	Estimates	Standard error
Fixed parameters (γ)				
Age (year/100)	−0.33***	0.10		
Women	−0.13***	0.040	−0.063***	0.013
Number of cars	0.091***	0.022	0.035**	0.016
Family size	0.035***	0.0070	0.14**	0.080
Length × width × height (10^{-10} mm^3)			−0.0077*	0.0057
Family size × length × width × height (10^{-10} mm^3)			0.064***	0.016
Family size × engine displacement (liters)	0.0028***	0.00038		
Random parameters (α and β)				
Mean				
Income-rental cost (10^5 CNY and 10^6 INR) (β)	−1.68***	0.12	−2.79***	0.10
Operating cost per km (CNY or INR) (α)	−3.83***	0.27	−1.61***	0.13
Standard deviation				
Income-rental cost (and 10^6 INR) (β)	0.45***	0.088	0.31***	0.088
Operating cost per km (CNY/INR) (α)	1.29***	0.11	1.44***	0.063
Preference for driving (σ)	0.64***	0.011	0.40***	0.0071
Scale factor (μ)	9.53***	0.90	1.59***	0.20
Short-run elasticity of VKT				
Income	0.14***	0.0083	0.12***	0.0071
Fuel price or operating cost	−0.18***	0.059	−0.28***	0.049
Number of observations	7,894		8,951	
Number of alternatives	81		234	
Alternative-specific constants	29		89	
Log-likelihood	−39242		−52806	

*p < 10%, **p < 5%, ***p < 1%

Note: This table presents the full information maximum likelihood coefficient estimates (the alternative-specific constants are not shown). The means and standard deviations of the random parameters are presented for the underlying normal distributions. Family size is normalized to 10 in the China data. VKT = vehicle kilometers traveled; CNY = Chinese yuan; INR = Indian rupee; mm^3 = cubic millimeters.

estimates by Chugh and Cropper (2017) are −0.68 and −0.93 for diesel and petrol car owners in India, respectively, but they use data from 2010. As discussed earlier, fuel price regulations have changed radically in India since then. While we are not aware of the short-run fuel price elasticity estimates of VKT for China, Lin and Zeng (2013) find that the short-run elasticity for fuel consumption is not statistically different from zero.[4] The short-run fuel price elasticities of VKT for the U.S. are also below −0.16 (Goodwin, Dargay, and Hanly 2004).

We find that the short-run income elasticity of VKT is 0.14 for India and 0.12 for China. Our estimate for India is lower than the estimate of 0.28 by Chugh and Cropper (2017). An earlier study of the Chinese market by Lin and Zeng (2013) uses time-series data from 1998 to 2007. The study finds that the income elasticity of VKT is not statistically different from zero, even in the intermediate run. A similar low-income elasticity of VKT in the short run is also obtained for the U.S. (Goodwin, Dargay, and Hanly 2004).

5.1 Long-Run Elasticity Estimates: Simulation Analysis

To estimate the long-run elasticity of fuel consumption relative to fuel price and income, we account for the changes in both vehicle choice and usage according to the factors considered. Specifically, we increase fuel price and income by 5% for all car buyers (*ceteris paribus*) and allow consumers to adjust their preferences for car type and usage. The long-run fuel price elasticity of fuel consumption is −0.12 for India and −0.15 for China.[5] The ranges of the existing intermediate/long-run elasticities for India and China are [−0.39, −0.29] (Chugh and Cropper 2017) and [−0.50, −0.20] (Lin and Zeng 2013), respectively. Our estimates of the long-run income elasticity of fuel consumption for India and China are 0.15 and 0.13, respectively. The existing income/expenditure elasticities for India and China are 0.35 (Chugh and Cropper 2017) and [0.27, 1.24] (He, Yang, and Chang 2017), respectively.

We now present the elasticity of fuel consumption relative to the car-specific attributes. We consider two car attributes, car price and fuel economy, and compute the long-run elasticities at the segment level. To compute the long-run own-price elasticity for each car segment, we increase the purchase price of all the models in that segment by 5% from the baseline. We allow consumers to settle for their new preferred cars and new VKTs. We also compute the segment-level fuel consumption in the case of no rebound (i.e., VKT) effect, i.e., assuming that the average model-level VKT is unaffected by changes in the purchase price. We follow the same procedure to determine the own-fuel economy elasticity of fuel consumption (with and without the rebound effect).

The ranges of the segment-level own-price elasticities of fuel consumption for India and China are [–2.07,–0.38] and [–3.47,–0.16], respectively (Table 7). The existing ranges of these estimates for India and China are [–1.86, −0.68] (Chugh and Cropper 2017) and [–1.22, −0.46] (He, Yang, and Chang 2017), respectively. We observe that the impact of car prices on fuel consumption is largely driven by changes in fleet composition, as the segment-level market share elasticities concur with those of fuel consumption. In line with this observation, the purchase price has a low rebound effect in both markets: 0.96% for China and 1.40% for India. The sales-weighted mean of the own-price elasticities of fuel consumption with and without the rebound effect is −0.651 and −0.642 for India and −0.634 and −0.628 for China, respectively.

Table 8 shows the segment-level own-fuel economy estimates of fuel consumption and VKT. The increase in fuel economy affects fuel consumption in three ways: It changes the unit operating cost,

Table 7. Segment-level own-price elasticity.

Segment	Market share elasticity	Fuel consumption elasticity	Fuel consumption elasticity (no rebound)	Market Share (%)	Purchase price (10^5 CNY and 10^6 INR)
India					
Luxury	–1.98	–2.07	–2.00	0.4	4.89
Upper compact	–0.54	–0.54	–0.54	8.2	0.65
MUV/MPV	–0.82	–0.84	–0.83	8.6	1.09
Entry midsize	–0.65	–0.66	–0.65	12.9	0.76
Entry compact	–0.38	–0.38	–0.38	11.5	0.39
Compact	–0.43	–0.44	–0.43	14.9	0.50
Premium compact	–0.68	–0.69	–0.68	16.7	0.74
SUV	–0.84	–0.87	–0.85	15.8	1.19
Premium SUV	–1.89	–1.96	–1.91	0.9	3.05
Midsize	–0.82	–0.84	–0.82	4.8	1.09
Premium midsize	–0.88	–0.91	–0.89	0.3	1.92
Van	–0.39	–0.39	–0.39	4.9	0.39
Sales-weighted average	**–0.640**	**–0.651**	**–0.642**		
China					
Compact	–0.23	–0.24	–0.23	1.6	0.53
Compact basic	–0.19	–0.19	–0.19	0.2	0.53
Compact luxury	–1.21	–1.23	–1.22	2.6	2.92
Compact luxury SUV	–1.23	–1.24	–1.23	1.4	3.13
Compact mini	–0.50	–0.50	–0.50	0.1	1.42
Compact MPV	–0.30	–0.30	–0.30	5.2	0.63
Compact SUV	–0.46	–0.47	–0.46	11.8	1.21
Compact upper	–0.37	–0.38	–0.37	2.9	0.85
Large luxury	–3.43	–3.47	–3.43	0.1	10.15
Large luxury SUV	–3.04	–3.07	–3.04	0.7	8.57
Large MPV	–1.17	–1.19	–1.17	1.1	2.81
Large SUV	–1.10	–1.12	–1.11	4.2	2.71
Midsize	–0.46	–0.46	–0.46	20.5	1.21
Midsize basic	–0.34	–0.35	–0.34	10.6	0.85
Midsize luxury	–1.74	–1.76	–1.75	2.4	4.20
Midsize luxury SUV	–1.74	–1.76	–1.74	2.0	4.40
Midsize MPV	–0.60	–0.60	–0.60	0.5	1.55
Midsize SUV	–0.69	–0.70	–0.70	12.4	1.73
Midsize upper	–0.85	–0.86	–0.85	6.5	2.10
Midsize upper economy	–0.65	–0.65	–0.65	5.0	1.54
Minivan	–0.16	–0.16	–0.16	0.8	0.37
Small SUV	–0.34	–0.34	–0.34	7.6	0.81
Sales-weighted average	**–0.626**	**–0.634**	**–0.628**		

Note: All the elasticity estimates are statistically significant at the 1% level; INR = Indian rupee; CNY = Chinese yuan; SUV = sports utility vehicle; MPV = multipurpose vehicle.

Table 8. Segment-level own-fuel economy elasticity.

Segment	Market share elasticity	Fuel consumption elasticity	Fuel consumption elasticity (no rebound)	VKT elasticity	Market Share (%)	Fuel economy (km/liter)
India						
Luxury	0.39	–0.44	–0.58	0.53	0.4	13.1
Upper compact	0.30	–0.55	–0.67	0.42	8.2	16.2
MUV/MPV	0.31	–0.54	–0.66	0.43	8.6	15.4
Entry midsize	0.28	–0.57	–0.69	0.40	12.9	16.5
Entry compact	0.26	–0.59	–0.70	0.38	11.5	17.6
Compact	0.26	–0.59	–0.70	0.38	14.9	17.0
Premium compact	0.25	–0.60	–0.72	0.37	16.7	16.7
SUV	0.28	–0.57	–0.69	0.40	15.8	15.8
Premium SUV	0.38	–0.45	–0.58	0.53	0.9	13.1
Midsize	0.31	–0.54	–0.66	0.43	4.8	16.2
Premium midsize	0.35	–0.49	–0.62	0.48	0.3	14.7
Van	0.32	–0.52	–0.64	0.45	4.9	15.2
Sales-weighted average	**0.277**	**–0.571**	**–0.687**	**0.398**		
China						
Compact	0.21	–0.63	–0.76	0.33	1.6	14.7
Compact basic	0.21	–0.63	–0.75	0.34	0.2	14.6
Compact luxury	0.25	–0.56	–0.71	0.41	2.6	11.3
Compact luxury SUV	0.26	–0.55	–0.70	0.42	1.4	11.0
Compact mini	0.21	–0.62	–0.75	0.34	0.1	14.4
Compact MPV	0.21	–0.62	–0.75	0.35	5.2	13.3
Compact SUV	0.22	–0.60	–0.74	0.37	11.8	12.0
Compact upper	0.21	–0.63	–0.75	0.34	2.9	14.3
Large luxury	0.29	–0.52	–0.68	0.45	0.1	10.1
Large luxury SUV	0.31	–0.49	–0.66	0.49	0.7	9.1
Large MPV	0.30	–0.50	–0.67	0.47	1.1	9.5
Large SUV	0.28	–0.53	–0.69	0.44	4.2	10.0
Midsize	0.18	–0.65	–0.78	0.32	20.5	13.1
Midsize basic	0.20	–0.63	–0.76	0.33	10.6	13.7
Midsize luxury	0.27	–0.54	–0.69	0.43	2.4	10.5
Midsize luxury SUV	0.28	–0.52	–0.68	0.45	2.0	10.0
Midsize MPV	0.26	–0.55	–0.70	0.42	0.5	11.3
Midsize SUV	0.23	–0.58	–0.73	0.39	12.4	11.1
Midsize upper	0.25	–0.57	–0.72	0.40	6.5	11.3
Midsize upper economy	0.23	–0.60	–0.74	0.37	5.0	12.6
Minivan	0.21	–0.62	–0.75	0.35	0.8	14.1
Small SUV	0.22	–0.61	–0.75	0.36	7.6	12.9
Sales-weighted average	**0.220**	**–0.603**	**–0.743**	**0.366**		

Note: All the elasticity estimates are statistically significant at the 1% level; SUV = sports utility vehicle; MPV = multipurpose vehicle; VKT = vehicle kilometers traveled.

fleet composition and VKT. If we consider all three effects, a 1% increase in fuel economy would, on average, reduce fuel consumption by 0.571% in India and by 0.603% in China. However, if we ignore the third effect (i.e., the VKT effect), these estimates are 0.689% for India and 0.743% for China. Thus, the rebound effect of fuel economy improvements on fuel consumption is 17.1% for India and 18.8% for China. Such rebound effects cannot be captured in studies that do not model VKT using car preferences.

5.2 Assessment of a Revenue-Neutral Feebate Policy

The estimated joint discrete-continuous model is used to predict how a revenue-neutral feebate policy would affect fleet fuel economy and fuel consumption in India and China.[6] Table 9 summarizes the specifications and main results of the feebate policies. We use the sales-weighted average fleet fuel economy as the anchor point (16.38 km/liter for India and 12.32 km/liter for China). To achieve revenue neutrality, we use a fee rate of $1,846.2 per km/liter and a rebate of $1,407.7 per km/liter for India. The fee rate and rebate values are $1,938.4 and $1,627.7 per km/liter, respectively, for China. We convert the fee rates into the proportion of the retail price. Thereafter, we find that, in China, the sales-weighted mean proportion of fees is much lower than that of rebates (7.41% vs. 14.56%) because expensive luxury cars have lower fuel economies.[7]

The differences in total fees and rebates range from $1 million to $3 million, implying that the simulated feebate design is revenue neutral. This revenue-neutral feebate policy leads to 0.812% and 0.795% improvements in the sales-weighted fleet fuel economy for India and China, respectively, translating into fuel savings of 0.703% and 0.688%, respectively. If the effect of the change in car prices on VKT is ignored (i.e., the rebound effect), the fuel savings are slightly higher (0.758% for India and 0.699% for China). These results imply that the rebound effect associated with the feebate policy is 7.3% for India and 1.6% for China.[8]

Table 10 analyzes the change in the segment-level market share due to the feebate policy. The results indicate that the feebate policy works as expected; i.e., the market shares of those segments with fuel

Table 9. The impact of a revenue-neutral feebate policy.

Variable	India	China
Anchor (km/liter)	16.38	12.32
Rebate (US$ per km/liter)	1,407.7	1,627.7
Fees (US$ per km/liter)	1,846.2	1,938.4
Rebate (% retail price)	15.37	14.56
Fees (% retail price)	15.24	7.41
Fuel economy increase (%)	0.812	0.795
Fuel savings (%)	0.703	0.688
Fuel savings (%, no rebound)	0.758	0.699
Original fuel consumption (liter)	1.8980E+09	2.2819E+10
Final fuel consumption (liter)	1.8847E+09	2.2662E+10
Final fuel consumption (no rebound, liter)	1.8836E+09	2.2660E+10
Total rebate (million US$)	1.776E+03	2.0570E+04
Total fees (million US$)	1.773E+03	2.0569E+04

Note: US$= United States dollar.

Table 10. Segment-level effect of the feebate policy.

Segment	Market share change (%)	Fuel consumption change (%)	Fuel consumption change (%) (no rebound)	Fuel economy (km/liter)	Purchase price (10^5 CNY and 10^6 INR)	Market share (%)
India						
Luxury	–14.2	–15.3	–14.8	13.1	4.89	0.4
Upper compact	–2.2	–2.4	–2.4	16.2	0.65	8.2
MUV/MPV	–7.8	–8.9	–8.8	15.4	1.09	8.6
Entry midsize	**0.8**	0.7	0.6	**16.5**	0.76	12.9
Entry compact	**11.6**	11.6	11.3	**17.6**	0.39	11.5
Compact	**5.8**	5.7	5.6	**17.0**	0.50	14.9
Premium compact	**1.1**	1.0	0.9	**16.7**	0.74	16.7
SUV	–3.9	–5.2	–5.1	15.8	1.19	15.8
Premium SUV	–21.4	–23.1	–22.6	13.1	3.05	0.9
Midsize	–1.0	–1.3	–1.3	16.2	1.09	4.8
Premium midsize	–7.5	–8.5	–8.2	14.7	1.92	0.3
Van	–14.1	–14.1	–14.1	15.2	0.39	4.9
China						
Compact	**13.2**	13.1	13.0	**14.7**	0.53	1.6
Compact basic	**9.9**	10.0	9.9	**14.6**	0.53	0.2
Compact luxury	–5.3	–5.5	–5.5	11.3	2.92	2.6
Compact luxury SUV	–6.4	–6.5	–6.5	11.0	3.13	1.4
Compact mini	**8.6**	8.7	8.6	**14.4**	1.42	0.1
Compact MPV	**5.7**	5.8	5.7	**13.3**	0.63	5.2
Compact SUV	–1.7	–1.8	–1.8	12.0	1.21	11.8
Compact upper	**10.5**	10.5	10.4	**14.3**	0.85	2.9
Large luxury	–9.6	–9.7	–9.6	10.1	10.15	0.1
Large luxury SUV	–14.7	–14.9	–14.7	9.1	8.57	0.7
Large MPV	–14.3	–14.5	–14.4	9.5	2.81	1.1
Large SUV	–11.9	–12.1	–12.0	10.0	2.71	4.2
Midsize	**4.5**	4.5	4.4	**13.1**	1.21	20.5
Midsize basic	**7.4**	7.4	7.3	**13.7**	0.85	10.6
Midsize luxury	–9.8	–9.9	–9.9	10.5	4.20	2.4
Midsize luxury SUV	–11.6	–11.7	–11.6	10.0	4.40	2.0
Midsize MPV	–4.9	–5.2	–5.2	11.3	1.55	0.5
Midsize SUV	–7.2	–7.3	–7.3	11.1	1.73	12.4
Midsize upper	–5.7	–5.9	–5.8	11.3	2.10	6.5
Midsize upper economy	**1.3**	1.2	1.2	**12.6**	1.54	5.0
Minivan	**9.1**	9.2	9.1	**14.1**	0.37	0.8
Small SUV	**3.4**	3.2	3.2	**12.9**	0.81	7.6

Note: Segments with fuel economy above the pivot point (i.e., average fleet fuel economy) are in bold. SUV = sports utility vehicle; MPV = multipurpose vehicle; VKT = vehicle kilometers traveled.

economy above the anchor point increase under the feebate policy. However, the increase in the actual market share of fuel-efficient vehicles due to the feebate policy is not substantial because their fuel economy is close to the anchor point. These results indicate that the fleet structure and low purchase price elasticity in both countries make the feebate less effective as a fuel conservation policy.

6. Conclusion

The effectiveness of a fuel conservation policy rests on whether consumers will purchase fuel-efficient cars and drive less. While several studies have considered both factors to evaluate the fuel conservation policies in developed countries, limited evidence exists for such behavioral changes in developing countries such as India and China. This study jointly analyzes household-level data on the vehicle preferences and VKT of new car buyers from India and China who purchased new cars in 2016 and 2017. To this end, it estimates a discrete-continuous structural econometric model. Model parameters are then used to estimate the various elasticities and rebound effects. Further, a revenue-neutral feebate policy is simulated to investigate its effectiveness in developing countries.

The short-run VKT elasticities relative to fuel price and income are –0.18 and 0.14 for India and –0.28 and 0.12 for China, respectively. Similarly, the long-run fuel price and income elasticity of fuel consumption are –0.12 and 0.15 for India and –0.15 and 0.13 for China, respectively. While the own-price elasticity of fuel consumption varies substantially across the car segments, the own-fuel economy elasticity is less heterogeneous. The sales-weighted direct (i.e., own) price and fuel economy elasticities of fuel consumption are –0.651 and –0.571 for India and –0.634 and –0.603 for China, respectively. The purchase price has a low rebound effect in both markets. Meanwhile, the fuel consumption elasticity relative to fuel economy reduces by 17.1% for India and 18.8% for China because of the rebound effect (i.e., induced travel caused by lower operating costs).

Introducing a revenue-neutral feebate policy could improve the sales-weighted mean fleet fuel economy in India and China, but only by 0.811% and 0.795%, respectively, with fuel savings of 0.701% and 0.688%, respectively. The negligible sensitivity of VKT relative to the purchase price translates into a low rebound effect for the feebate policy; this makes it an ineffective fuel conservation policy in India and China.

Given their low responsiveness, none of the demand-side policies considered in this study are effective at reducing fuel consumption and, thus, carbon emissions, especially to the extent required to meet countries' long-term temperature goals, while maintaining new car sales. Low responsiveness, combined with the need for deep decarbonization, would result in either tolerating extremely high fuel and car taxes or accepting lower economic output due to fewer new car sales. Given that fuel prices in both countries are already among the highest in leading oil-consuming nations (Jacob 2018), it is unclear whether there is much room for a further tax increase without risking a public outcry, which could have serious political repercussions. Indeed, India was recently forced to reduce consumer taxes on petrol and diesel after the rising cost of crude oil drove fuel prices to record highs (BBC 2021). Thus, policymakers in both countries have no choice but to implement supply-side policies such as performance standards, mandates and vehicle ownership restrictions. Such supply-side policies are typically less cost-effective than demand-side policies such as fuel taxes, which can directly reduce fuel consumption (Karplus et al. 2013). However, because the reasons for the increase in car prices owing to such supply-side policies remain largely unknown to consumers, they are often considered to be more politically acceptable than government-enforced taxation.

Our results should be interpreted by considering two caveats. First, we do not consider an 'outside good' option because the consumers in the sample have to make the decision as to which car to buy instead of whether to buy a car. This restriction leads to a constant number of cars in the system (i.e., a fall or rise in car sales in the elasticity calculations), meaning that a feebate policy simulation could not be considered. Second, the study does not consider the used car market due to data limitations. Given that the used car market is as large as the new car markets in China (Yingying 2021) and India (Saleem 2019), future studies should account for the interactions between the used and new car markets. Third, this study only evaluates the response of traditional combustion engine car users to a feebate policy because of a lack of data on new energy vehicle customers.

Endnotes

[1] We take a random subsample of 40% of the observations from the dataset originally collected from China to make the estimation computationally tractable. With 234 alternatives and over 100 parameters, the estimation time of one model specification is around 50 hours for the China subsample considered. Since we use choice-based sampling weights, using this randomly selected subsample does not affect the consistency of the estimator.

[2] GDP per capita (current US dollars) for India and China in 2017 was $1,981 and $8,817, respectively

[3] We use the market share of diesel and petrol in 2017 to compute a weighted average of the respective fuel prices (Rampal 2021). We use prices from the middle of the year in Delhi, India's capital city (ZeeBiz 2017).

[4] Previous intermediate/long-run estimates of the fuel price elasticity of VKT for China are [−0.88, −0.58] (Lin and Zeng 2013) and −0.59 (Tan, Xiao, and Zhou 2019).

[5] Since we do not have an 'outside good' option, the long-run elasticity relative to variables that change for the entire vehicle fleet (i.e., fuel price and income) might be underestimated. Specifically, since the total number of cars remains the same in the system, the effects of changes in fuel price/income on vehicle fleet composition are biased. Chugh and Cropper (2017) also acknowledge this limitation.

[6] The feebate design considered is (i) based on the fuel efficiency of the vehicle, (ii) revenue neutral, (iii) size neutral and (iv) technology agnostic, consistent with the prerequisites suggested by the Society of Indian Automobile Manufacturers (SIAM 2018).

[7] We did not find such an effect for India because of the low market share of luxury vehicles in India compared to China.

[8] The rebound effect is higher for India (7.3%) than for China (1.6%) because of the higher fees (% retail price) in India.

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Notes

Notes

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About the Project

Promoting the adoption of energy-efficient vehicles has become a key policy imperative in both developed and developing countries. Understanding the impacts of various factors on adoption rates forms the backbone of KAPSARC's efforts in the light-duty vehicle demand field. These factors include (i) consumer-related factors – demographics, behavioral, and psychographics; (ii) regulatory factors – policies, incentives, rebates, and perks; and (iii) geo-temporal factors – weather, infrastructure and network effects. Our team is currently developing models at different levels: micro-level models using large-scale data comprising new car buyers' profiles, and macro-level models using aggregated adoption data to understand and project the effects of various factors affecting the adoption rate of energy-efficient vehicles.