Influence of Social Network Effect and Incentive on Choice of Star Labeled Cars in India: A Latent Class Approach based on Choice Experiment

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Abstract

To encourage efficient consumption of energy, India has adopted energy consumption labels for electrical equipment and is now considering the introduction of fuel efficiency labels for cars. By means of a Discrete Choice Experiment (DCE), this paper assesses consumer preferences for fuel efficiency labels in New Delhi. A novelty of this study is that half of the respondents are treated by informing them that an environmental regulation would impose restrictions on the number of days cars can ply with the exception of highly efficient labeled cars which would be allowed to ply every day. An additional novelty of this study is that, in order to deepen our understanding on why people prefer cars that are labeled as fuel efficient, we take into account behavioural motives, which we divide into intrinsic motivation, environmental knowledge, extrinsic motivation (social network) and social interaction. We report results of latent class logit model and random parameter logit model. The classes in the latent class model are classified based on respondent's socio-economic characteristics and behavioural motives. The results show that on average, respondents are willing to pay more for the highly efficient labeled car under both control and incentive treatment, however, the willingness to pay for highly efficient labeled car is much higher under the incentive treatment.

Keywords: Choice Experiment; Social Network; Fuel Efficiency Label; Bureau of Energy Efficiency; Latent Class

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1 Introduction

Growing concerns over climate change due to increasing green house gas emissions has increased interest in analyzing ways to reduce emissions. In India, transport sector accounts for 7.3% of the energy consumption in 2015-16 and is a major contributor to green house gas emissions in India (Energy Statistics, 2017). The fuel consumption in India has been increasing rapidly and have reached to 196.48 million (Mn) tons in 2016 (Petroleum Planning and Analysis Cell, 2017). It is forecasted that growth in the energy consumption from the transport sector will outpace growth in other sectors by 2040 (India Energy Outlook, 2015). One of the reasons of increasing energy consumption is increasing vehicle ownership. It is projected that increase in the annual car sales would be over 5.5 Mn per year and total stock of cars would exceed 45 Mn by 2020 (Bureau of Energy Efficiency, 2011). The introduction of fuel economy standards and labels can play a key role in reducing fuel consumption, thereby reducing emissions. The other possible approaches to reduce fuel consumption are fuel taxes, traffic control measures, fiscal incentives etc. (An and Sauer, 2004).

The introduction of fuel labels can affect consumer choices by informing consumers about the fuel consumption of the vehicles and thus overcoming informational asymmetry problem. These labels may appeal more to environmentally conscious consumers or may influence their behaviour. The fuel labels could be effective in nudging people to switch towards high fuel efficient choices (Codagnone et al., 2016). The impact of label on consumer behaviour could depend on what information is provided and how it is presented. In European Union, the labeling directive on car label in terms of CO_2 emissions was implemented by all its member states. But in few of its member states the relevant information was not presented clearly to consumers (Haq and Weiss, 2016). Codagnone (2013) suggested that fuel label is more effective if it indicates running costs per five years and graphic illustration of CO_2 emissions, rather than just presenting information on fuel consumption.

The designing of public policies based on fuel labels was pioneering by mostly developed countries[4]. More recently, countries such as China and India have followed suit. India is currently considering the introduction of fuel labels for cars as part of a wider effort to decrease emissions from the transportation sector[5]. Ministry of Power has issued average fuel consumption standards based on kilometers per litre (kmpl) for the passenger cars in 2015. These norms will be binding for car manufacturers in two phases by 2017 and 2022. The target is to improve fuel efficiency (mileage) by 10% in the first phase and by 30% in the second phase. In addition to the standards, Bureau of Energy Efficiency (BEE) plans to introduce star labels for all the new cars sold in the market. These star labels aim to provide information to consumers on the fuel consumption of the car along with a star rating from one to five stars. The five star refers to the most fuel efficient car and one star refers to the least fuel efficient car.

The labeled car will provide private benefits to consumers in the form of fuel cost savings and public benefits in the form of reducing greenhouse gas emissions. These fuel efficient labeled cars are important for improving air quality, especially for Delhi, which has extremely high air pollution. It will be beneficial to gain insights into whether we should expect fuel labels to be effective and whether consumers would buy fuel efficient vehicles even if they are more expensive, especially in the context of a developing country. There could be behavioural motivations explaining consumer preferences for labeled products. We divide these motivations into intrinsic motivation, environmental knowledge, extrinsic motivation (social network), social interaction and any regulatory incentive.

Intrinsic motivation is based on internal urge to contribute towards the environment or give someone in the act of selflessness as discussed in the concept of warm glow (Andreoni, 1990). In our study, we capture it by environmental concern of individuals. For intrinsic motivation to materialise consumers' knowledge about environment is relevant. Therefore, we have included questions on environmental knowledge. Extrinsic motivation is how be-

[4]United States was first to adopt Corporate Average Fuel Economy (CAFE) standards in 1975 and label in 1980, however its standards are less stringent compared to Japan and European Union (Atabani et al., 2011).

[5]In India, Bureau of Energy Efficiency has already introduced standards and labeling program in 2006 for 21 equipments such as direct cool refrigerator, distribution transformer, air conditioner etc.

haviour of other individual impact purchase decisions of the respondents. In other words, purchase decision might be guided by the social norms that have risen from the network formed by individuals in the society. When network is formed by environmentally concern individuals, it's referred as green network (Brecard, 2013). We capture extrinsic motivation (social network) in terms of peer group influence on respondents' purchase decisions. Social interaction among individuals is an important component for the formation of social network. Social interactions capture how often individuals interact. For these networks to influence individual behaviour the degree of trust among individuals is also important. In addition, policy makers can give a regulatory incentive (i.e., some reward on purchasing highly efficient labeled product) to nudge consumers behaviour. In this study, the regulatory incentive is incorporated in the form of lenient environmental regulation if a consumer chooses a highly efficient labeled car.

This paper aims to assess consumer preferences for fuel efficient star labels in New Delhi by means of a Discrete Choice Experiment (DCE). In a choice experiment, individuals are presented a hypothetical setting and then asked to choose an alternative from several alternatives. Each alternative comprises of different levels of the selected attributes. The good used in our study is cars. The three hypothetical alternatives presented to the respondents are high star labeled car (star 4,5), moderate star labeled car (star 3) and unlabeled car. The attributes presented for these alternatives are price of the car, mileage (kmpl), engine displacement, transmission and social network (market share of family/friends/neighbours/colleagues). We use alternative specific labels so that we are able to infer the preferences for the label. We sample our data from two neighbourhoods in Delhi, viz., South Delhi and East Delhi.

A novelty of this study is that half of the sample were given the treatment in the form of environmental regulation which impose restrictions on the number of days cars can ply with the exception of highly efficient labeled cars which would be allowed to ply every day. This provides an incentive to the users of high efficient labeled cars in the form of a lax environmental regulation. Arguably, those under incentive treatment are more likely to choose cars because of their fuel labels than those respondents who are not.

Many previous studies have documented the preferences for fuel efficient cars or appliances (e.g. Shen and Saijo, 2009; Ward et al., 2011; Hidrue and Parsons, 2015; Datta and Filippini, 2016; Zhou and Bukenya, 2016; Hackbarth and Madlener, 2016). However, these studies have not explored as to why people would prefer cars or appliances that are labeled as efficient. Another novelty of this study is that why people prefer cars that are labeled as fuel efficient and in order to deepen our understanding on this we explore the behavioural motivation of the people. We measure these by including questions in the questionnaire on intrinsic motivation, environmental knowledge, social network and social interaction. We also include questions on trust because for these networks to form trust is also an important factor.

We estimate conditional logit, random parameter logit and latent class logit model. Our preferred specifications are the latent class models because it allows for interpretation in terms of social leaders, social pressure group and non-followers. These models allow us to learn that social leaders (high behavioural motivations, i.e., high intrinsic motivation, high environmental knowledge, average to high social network and high social interaction) and social pressure group (average behavioural motivations) have a higher willingness to pay for labeled cars as compared to non-followers (low behavioural motivations). The results show that the social network effect is significant (for social pressure group) and compared to other attributes (label, price, engine, transmission); the social network effect is small in magnitude. We find that regulatory incentive have an important role in nudging consumer behaviour towards purchasing high fuel efficient cars. The incentivized individuals have higher preference for highly efficient star labeled cars over the non-incentivized individuals. Thus, incentive plays a positive role in influencing consumer preferences towards labeled cars.

The reminder of the paper is structured as follows. The next section describes the literature review, section 3 describes the discrete choice model, data sources and sampling, section 4 describes the empirical methodology used in analyzing discrete choice model, section

5 discusses the results and section 6 contains the concluding remarks.

2 Literature Review

2.1 Fuel efficient vehicles or appliances

A number of studies in the field of environment economics related to transport sector have examined consumer preferences for alternative fuel efficient vehicles such as electric, hybrid, CNG vehicles with respect to gasoline vehicles. The majority of these studies have adopted qualitative research (Axsen and Kurani, 2013; Green et al., 2014) and stated preference techniques (Hidrue et al., 2011; Achtnicht, 2012; Dimitropoulos et al., 2016; Lin and Tan, 2017). Axsen and Kurani (2013) using a design game showed that majority of consumers designed plug in hybrid vehicles as their preference for next new vehicle, small number of consumers designed hybrid or conventional vehicle and very few consumers prefered electric vehicles in California, 2011. Green et al. (2014) suggested that policies focusing on adoption of electric vehicles should focus on niche markets and green consumers using easy accessible loans and targeted incentives. Hidrue et al. (2011) using a choice experiment found that consumers' willingness to pay a premium for electric vehicles ranged from \$6000 - \$16,000 above their willingness to pay for gasoline vehicles in U.S. Hackbarth and Madlener (2016) showed that about one-third of the consumers are inclined towards purchasing at-least one alternative fuel vehicle option in Germany. For the consideration of alternative fuel vehicles by consumers, it is required that vehicle features meet some minimum requirements, for example, fast charging infrastructure.

In addition, literature has analyzed the effects of eco-label on household appliances, food products etc. (Shen and Saijo (2009); McNeil and Iyer (2010); Ward et al. (2011); Chunekar (2014)). McNeil and Iyer (2010) found that standard and labeling program in India is expected to reduce the residential electricity consumption by 55 Terawatt hours (TWh) and total savings of 385 TWh by 2030. Ward et al. (2011) using choice experiment and random parameter logit model showed that consumers on an average are willing to pay $250 - $349 for an U.S. energy star labeled refrigerators. Chunekar (2014) compared standard and labeling program for refrigerator in India, with U.S., China and European Union energy star programs.

The literature on standards and labels for cars (Silitonga et al., 2011; Norhasyima et al., 2013, Zielinski et al., 2016; Haq and Weiss, 2016; Codagnone et al., 2016) is less developed. Silitonga et al. (2011) showed that the introduction of fuel labels for passenger cars in Indonesia is expected to save significant amount of fuel and emissions. Norhasyima et al. (2013) showed that if fuel labels for cars are adopted in Malaysia, there will be positive changes in consumers' purchasing pattern. Zielinski et al. (2016) discusses potential of the U.S. CAFE standards in reaching the goal of average combined fleet-wide fuel economy of 48.7 - 49.7 mpg by 2025. Haq and Weiss (2016) evaluated car labeling scheme in European Union. The paper suggested that labeling scheme on cars can be made more effective by introducing uniform label for cars as mirrors of energy label and by a labeling scale which allows differentiation between plug in and efficient hybrid vehicles. Codagnone et al. (2016) tested the effect of motor vehicle label on cognitive processing and consumers' car purchase decision in randomized control trials in ten European countries. The paper showed that car labels focusing on running costs or fuel economy are more effective in capturing consumers' attention as compared to emissions information.

2.2 Behavioural motivations

Various studies in literature have examined consumers' behavioural motives in influencing their preferences towards environmental friendly products (Menges et al., 2005, Ek and Soderholm, 2008; Coad et al., 2009; Carlsson et al., 2010; Rasouli and Timmermans, 2016). Among behavioural motivations, we first discuss papers on intrinsic motivation, followed by papers on social norms, social network and incentives.

Menges et al., 2005; Koo et al., 2015; Ma and Burton, 2016; Hartmann et al., 2017 are some of the studies which analysed impact of intrinsic motivation in influencing consumer preferences towards green products. Menges et al. (2005) conducted a test for presence of warm glow motivations and consumers' willingness to donate for green electricity in Germany. The paper found that the crowding in effect is expected for electricity contracts having small shares of green electricity, i.e., people donate more for green electricity. While crowding out effects is expected for all or none contracts, i.e., people are willing to spend less on green electricity and want to free ride on others contribution. Hartmann et al. (2017) showed that warm glow effect has a stronger impact on pro-environmental behaviour as compared to altruism. Koo et al. (2015) used partial least squares regression and showed that intrinsic motivations (warm glow) and extrinsic motivation in the form of saving money and legislative pressure, relate to the purchase of smart green IT device.

Ek and Soderholm, 2008; Carlsson et al., 2010; Farrow; 2017; He and Zhan, 2018; Welsch and Kuhling, 2018 are some of the studies which discussed about social norms in influencing consumer preferences towards green products. Ek and Soderholm (2008) showed that if other consumers participate in green electricity consumption, individual will also purchase green electricity to maintain his self-image. Carlsson et al. (2010) discussed whether consumer preferences for environmental friendly goods could be driven by conformity, i.e., desire to follow the social norm in Sweden, 2007. The paper found that women are willing to pay more for ecological friendly coffee and their willingness to pay increased when large number of consumers purchased ecological friendly coffee. Griskevicius et al. (2010) showed that status concerns lead consumers purchase green products over luxurious non green products. Consumers may have interest in purchasing environmental friendly products to show their pro-environmental attitude (Clark et al., 2003). He and Zhan (2018) showed that norms lead to adoption of electric vehicles in China. Welsch and Kuhling (2018) found positive relationship between green self image and life satisfaction across European countries. The benefit of having a green self image is higher in societies which display higher agreement in connection to pro environmental attitudes.

Rasouli and Timmermans (2016) using choice experiment and random parameter logit model, showed that price of the car and vehicle attributes are more important and social network effect, i.e., share of friends, peers, relatives is relatively less important in consumers decision on purchasing electric cars. Except Rasouli and Timmermans, 2016, the studies have not empirically estimated the effect of social network and interactions in consumers' behavioural motives towards green products. For instance, consumers may be willing to pay higher for labeled cars due to network effect. It would be interesting to determine whether individuals take into account behavioural motives while making purchase decisions for labeled cars.

Few studies in literature have incorporated incentive treatment to influence consumer preferences towards green products (Coad et al, 2009; Ziegler, 2012; Dimitropoulos et al., 2016). Coad et al. (2009) showed that providing more information through energy label will encourage intrinsically motivated consumers to buy green cars in Switzerland. However, financial incentives such as subsidies or fines are more effective for extrinsically motivated consumers. Ziegler (2012) using a choice experiment analysed consumer preferences for alternative vehicles types in Germany. The study showed that policy instruments of promotion of research and development, taxes and subsidy could increase social acceptance for alternative vehicles. Dimitropoulos et al. (2016) discussed incentive in the form of tax advantages on purchasing electric cars. The paper showed that the policy of tax advantages with purchase of electric car in Netherlands lead to welfare loss and it outweighs the forgone tax revenues. Bjerkan et al. (2016) show that incentives in the form of exemptions from purchase tax, VAT are most effective in promoting adoption of battery electric vehicles in Norway. Galarraga et al. (2016) examined designing of incentive scheme to promote adoption of energy efficient appliances - dishwasher, refrigerators and washing machines in Spain. The optimal incentive schemes designed is the combination of taxes and subsidies to minimise deadweight loss.

Our study has adds value, as it is one of the first experimental study on labels for cars, with exception of Codagnone et al. (2016). There are no experiments carried out for labeled products in India. Moreover, only limited number of studies has incorporated the effect of behavioural motives including social network and regulatory incentive on consumer preferences for green products. Consumers' may believe that good becomes more useful when connected to a network. We contribute to the literature by analyzing consumers' willingness to pay for star labeled cars and how this willingness to pay is affected by behavioural motives and regulatory incentive in India.

3 Survey Methods and Data

3.1 Design of Discrete Choice Experiment

BEE has proposed to introduce fuel efficiency standards and star label for cars, similar to power saving electrical appliances. With the implementation of new fuel efficiency norms, CO_2 emissions are projected to reduce from 142 gm per km in 2010-11 to 113 gm per km in 2022 (BEE). Annual fuel requirement for cars is expected to exceed 25 Mn ton of oil equivalent due to increase in annual car sales in India by 2020 (BEE Consultation Paper, 2011). In addition, BEE star label will indicate fuel efficiency of the car. Since these labels have not yet been introduced for cars in India, real market based data is not available. We design a discrete choice experiment to study consumer preferences for fuel efficiency star labels in India.

In choice experiment, in each choice tasks respondents were presented with three alternatives, viz., High star labeled car (star 4, 5), Moderate star labeled car (star 3) and presently available unlabeled car. Respondents choose an alternative among various alternatives presented to them. They were informed that high star labeled cars are more fuel efficient. We use alternative specific labels so that we are able to infer the preferences for the label. To select relevant attributes, a series of focused group studies were conducted. Based on focused group studies and existing literature, the vehicle attributes included in choice experiment were price of the car, mileage (kilometre per litres (kmpl)), engine displacement and transmission. We are also interested in studying influence of social network effect in purchase decision of cars. For the purpose we include an attribute that reflects social network effect, viz., market share of the family/friends/neighbours/colleagues. We tried to ensure that respondents understand and could meaningfully relate to various attributes included in the choice set.

In the beginning of the survey, respondents were asked to provide the price at which he/she intends to purchase a car in near future, among the currently available cars. We treat this price of the car as a reference price. The levels of the attribute price were taken as 10%, 20%, 30%, 40% and 50% higher than the reference price[6]. The attribute - mileage is expressed in distance travelled per unit of fuel consumed (kilometre per litre, kmpl). High star label car is more fuel efficient, i.e., has higher mileage (kmpl) compared to the other cars. There are two mileage levels for high star label car - 20, 24 kmpl and two mileage levels for moderate star label car - 16, 20 kmpl. Based on the mileage of currently available cars in Delhi, we inform the respondents that on an average presently available car (unlabeled) have mileage of 13 kmpl. The attribute - engine displacement measures size of the engine internally in cubic centimetres has three levels - upto 1000cc, 1000-1500cc and more than 1500cc. The attribute - transmission has two levels - automatic or manual. In automatic transmission, gears automatically change depending on vehicle and engine speed. In contrast, in manual transmission, driver changes gears manually using manual clutch pedal as per the driving needs. In our experiment we include an attribute that reflects social network effect and it is measured in terms of market share of family/friends/neighbours/colleagues purchasing the car described in the alternative. The levels of this attribute are 20% and 60%[7]. Table 1 summarizes the list of choice set attributes with their levels (refer appendix).

The choice experiment was accompanied by a survey that had questions on socio-economic characteristics such as age, gender, education, income etc., car ownership and decisions on purchasing car. In addition, there were a set of questions to gauge respondents' intrinsic motivation, environmental knowledge, extrinsic motivation (social network) and social interaction. The respondents' intrinsic motivation and social network is measured by statements

[6]For air conditioner, high star label air conditioner has seen as increase in price, ranging from 20 - 40%, as compared to low star air conditioner.

[7]Following Cameron and Trivedi (2005) pp 502-03, engine displacement, transmission and social network for the status quo alternative (unlabeled car) is normalized to 0

on a Likert scale of 1 to 5, where 1 reflects strongly disagree and 5 reflects strongly agree (refer Table 2 in appendix). We introduce social network ways. One we introduce social network effect as an attribute in choice experiment and other in the questionnaire also we try to measure social network using likert statements. We term the one they report in questionnaire as reported social network and the attribute in the choice experiment will be termed as social network.

We capture respondents' knowledge by including questions on environmental awareness. Though the literature incorporates network effects, but it does not deal with mechanisms through which network effect gets transmitted. We feel that social interaction is one mechanism through which these networks gets transmitted. Therefore, we develop a set of questions to gauge individuals' interactions with their peer group. We include questions such as how many times respondent meets his relatives/friends/colleagues (outside work place) during a month, invites relatives/friends/colleagues to their home (or visit their home). For peer group to have an effect on individual choices, not only how many times do they meet, but also how much they trust each other is relevant in decision making. The strength of the network depends on the level of trust they have in their peer group. We introduce an innovative way to measure trust. It is captured through questions on how often respondents lend household items or money to their relatives/friends/neighbours/colleagues or leaving house/car keys or children with friends/neighbours .

Regulatory Incentive

Another novelty of the study is to analyze whether regulatory incentive acts as a nudge for consumers choice towards fuel efficient star labeled cars. We use a specific regulation that was implemented for a short period of time in Delhi, in January 2016 and again in April 2016, so that respondents can relative to the incentive treatment. Under the scheme implemented in 2015, cars with even numbered registered plates were permitted to ply on the even dates and cars with odd numbered registered plates were permitted to ply on the odd dates. We incorporate the above scheme in our experiment by giving a treatment in terms of regulatory incentive to half of the sample. We inform half of the sample that if they purchased high star label car they will be exempt from the regulation, i.e., it will be permitted to ply on both odd as well as even dates. However, if they purchase moderate star label or presently available car then cars with odd numbered registered plates will be permitted to ply on the odd dates and cars with even numbered registered plates will be permitted to ply on the even dates. This information was provided to the respondents before giving the choice sets.

Construction of Choice Sets

Each possible set of choices shown to the respondents is called a choice set. The main concern is to create choice sets in an efficient way, i.e., levels of various attributes are combined to get alternatives, which are further divided into various choice sets (Alpizar et al., 2001). Based on literature, we constructed choice sets using D-optimal design (Carlsson and Martinsson, 2003). The D-optimal designs maximize D-efficiency. The D-efficient design used in the study is based on the variance covariance matrix $X'X$, where X is the design matrix. D-efficiency is defined as (Warren Kuhfeld, 2005) -

$$D - Efficiency = 100X \frac{1}{N_D |(X'X)^{-1}|^{1/p}}$$

where p is number of parameters to estimate. The aim is to choose X, to maximize D-efficiency. We get D-Efficiency of 93.94. This design generated 21 unique choice sets, which are assigned to three blocks of 7 choice set each. Respondents are randomly assigned to any of the three blocks. Each respondent was shown all the choice sets belonging to one of the block. Each choice set has two alternatives (high star labeled car and moderate star labeled car) and a status quo alternative (presently available unlabeled car). The respondents were asked to choose one alternative in each choice set. Table 3 shows one sample choice set for cars used in the study (refer appendix).

3.2 Sampling and Data Collection

The choice experiment and the accompanying survey were conducted during October to November 2017 in two neighbourhoods of Delhi. Delhi, the national capital of India, is one of the largest emitter of carbon emissions in the country. The transport sector is one of the major contributors towards carbon emissions accounting for 66% of the total carbon emissions in Delhi. The other sources of carbon emissions in Delhi are energy use in buildings and industry/electricity (32%) and agriculture/forestry (2%) (Sovacool and Brown, 2010). An alarming increase in vehicle ownership has contributed to these emissions. With in India, the maximum number of vehicles are in Delhi (8.8 Mn), which is larger than the combined number of vehicles in Kolkata and Mumbai (6.6 Mn) in 2016 (Times of India). With increasing economic prosperity of people of Delhi, it is likely that more vehicles will be added leading to increase in air pollution.

We use multi-stage sampling to select our survey sample. In the first stage, we select two districts from Delhi, South Delhi and East Delhi. The former is relatively more affluent as compared to the later. Both districts can be considered inhabited by middle income to high middle income class families. In the second stage, we stratify blocks (sub-districts) within these districts. Both South Delhi and East Delhi are further divided into three sub-districts. These are Kalkaji, Defence Colony, Hauz Khas in South Delhi and Gandhi Nagar, Preet Vihar, Vivek Vihar in East Delhi. In each sub-district, we randomly interview 84 respondents, which give a total sample size of 504 respondents. Half of the respondent from each sub-district, i.e., 42 respondents per sub-district were given the treatment in terms of regulatory incentive. Each of 504 respondents was asked to complete 7 choice sets, giving a total of 3528 individual choice tasks. Each choice set included 3 alternatives, giving possible 10584 individual observations. Out of these 10584 observations, 5292 individual observations belong to the treatment group (respondents are provided with regulatory incentive).

The summary statistics of the sample is reported in Table 4 (refer appendix). The socio-economic variables included in our study are age, gender, marital status, household size, annual family income, education and occupation. The respondents' age ranges from 18 to

79, with an average age of 41 years. 57% of the respondent were males, 73% were married and average household size is 5. In the study sample, only 15% of the respondents had annual family income of less than Rs. 0.5 Mn, which we classify as low income households. Our study sample has educated class with 47% of the respondents were graduate and 34% of the respondents were post graduate. 46% of the respondents were in professional/service, 31% in business and 13% were not employed. The majority of the respondents own a car, i.e., 439 out of the sample of 504 respondents; with mean number of cars owned by the household is 1.6. Among those respondents who do not own a car currently, about 85% are planning to buy a new car in near future. While comparing summary statistics of South Delhi with that of East Delhi, our sample showed that South Delhi has higher mean annual family income (Rs. 1.8 Mn) compared to East Delhi (Rs. 1.4 Mn). We also report summary statistics of control group (where respondents are not provided information on any incentive) versus treatment group (respondents are given incentive information). The socio-economic characteristics are similar across control and treatment group, so that we can reasonably presume that division into control and treatment group is random. The two sample t test shows that socio-economic characteristics such as age, gender, income, number of cars owned by households and plan to buy a new car have insignificant difference across control and treatment group.

4 Econometric Model and Interpretation of Willingness to pay

Stated preference approach such as discrete choice experiment used in our study is based on the Lancaster's theory of value (1966) and Marschak random utility theory (1959). These theories assume that decision maker aims at maximization of the utility. The utility derived by individual n from choosing alternative j is U_{nj} for $n = 1, 2, ..., N$ and $j = 1, 2, ..., J$. The decision maker chooses an alternative in a choice situation that gives him maximum utility, i.e., $U_{nj} > U_{ni}\ \forall\ j \neq i$ (Train, 2003). The utility derived by individual n from choosing alternative j is given by

$$\begin{aligned} U_{nj} &= V_{nj} + \epsilon_{nj} \\ &= \beta' X_{nj} + \epsilon_{nj}, \forall j = 1, 2, ..., J \end{aligned} \tag{1}$$

where V_{nj} is the deterministic component of the utility. The deterministic component is assumed to be linear in parameters, i.e., $V_{nj} = \beta' X_{nj}$, where X_{nj} is the observed variables associated with alternative j for individual n, β is the vector measuring the weight assigned on these observed variables. ϵ_{nj} is the independently and identically distributed random error term. The well-known models used to analyze discrete choice experiment are conditional logit, random parameter logit and latent class logit model. The conditional logit model is unable to capture random taste variations and it assumes independence of irrelevant alternatives. Therefore, model can be modified to incorporate heterogeneity in tastes across individuals and allow for correlation in unobserved factors over time (McFadden and Train, 2000), i.e., random parameter logit model. The random parameter logit choice probability that individual n chooses an alternative j is specified as

$$P_{nj} = \int_{\beta} \frac{exp(\beta' X_{nj})}{\sum_{i=1}^{J} exp(\beta' X_{ni})} f(\beta) d\beta \tag{2}$$

where $f(\beta_j|\beta, \sum \beta)$ is the density function and $[\beta, \sum \beta]$ are the distribution parameters (mean and covariance matrix) to be estimated. We capture heterogeneity using normal density function. All the coefficients except price are allowed to vary. The model is estimated using maximum likelihood estimation by maximizing log likelihood function with respect to β and $\sum \beta$. If β takes a finite set of distinct values, say G possible classes, then random parameter logit model becomes latent class logit model with G classes.

The latent class logit model observes individual heterogeneity by characterizing individuals into various preference classes. This approach assumes that sample of the individuals drawn from the population consists of a finite number of classes, say G classes, and each individual in the sample belongs to one of these classes (Cameron and Trivedi, 2005). The maximum likelihood method is used to estimate class-specific utilities for each attribute and each individual assigned the probability of belonging to each class. The main advantage of using latent class approach over random parameter logit is that latent class model does not require any assumption about distribution of parameters. In case of random parameter logit model, parameters are normally distributed.

Assume that sample of individuals drawn from population consists of G number of latent classes, where individuals within each class have homogenous utility functions and utility function can differ across classes. The utility function is defined by equation (1), where $V_{nj} = \beta_g^{'} X_{nj}$ is the deterministic component of the utility function; $\beta_g^{'}$ is the class specific vector measuring the weight assigned on these observed variables. The latent class model consists of two separate probabilistic models - the choice model and the class membership model. The first part - the choice model explains individuals' choice among various alternatives available in different choice scenarios. The latent class logit choice probability that individual n chooses an alternative j belonging to class g is (Shen and Saijo, 2009)

$$P_{nj|g} = \frac{exp(\beta_g^{'} X_{nj})}{\sum_{i=1}^{J} exp(\beta_g^{'} X_{ni})}, \forall g = 1, 2, ..., G \tag{3}$$

The second part - the class membership model allocates each individual to the G classes, based on their socio-economic characteristics and behavioural motivation variables. The probability that individual n belongs to class g is

$$P_{ng} = \frac{exp(\alpha_g^{'} Z_n)}{\sum_{g=1}^{G} exp(\alpha_g^{'} Z_n)} \tag{4}$$

where α is the parameter vector of class g and Z_n denotes the observable individual specific characteristics such as age, income, etc. Combining the choice model equation (3) and the class membership equation (4), the unconditional probability of individual n choosing an alternative j is

$$P_{nj} = \sum_{g=1}^{G} P_{nj|g} P_{ng} = \sum_{g=1}^{G} \{ \frac{exp(\beta_g' X_{nj})}{\sum_{i=1}^{J} exp(\beta_g' X_{ni})} X \frac{exp(\alpha_g' Z_n)}{\sum_{g=1}^{G} exp(\alpha_g' Z_n)} \} \tag{5}$$

The parameters β_g and α_g are simultaneously estimated by the maximum likelihood method. The number of classes has to be specified a priori. There are various criteria for deciding the optimal number of classes such as Akaike information criterion, 1973 and Schwarz Bayesian information criterion, 1978, defined as

$$\begin{aligned} AIC &= -2lnL_g + 2K_g \\ BIC &= -2lnL_g + K_g lnN \end{aligned} \tag{6}$$

where lnL_g denotes the maximised log-likelihood of the model with g classes; K_g is the number of parameters estimated in the model with g classes and N is the sample size. The model with smaller values of AIC and BIC are considered better.

5 Empirical Results

In this section, we discuss the results of random parameter logit model followed by latent class logit model used in analyzing consumers' willingness to pay for star labeled cars. In latent class logit model, we determine the number of classes and characterize each class based on socio-economic variables and behavioural motivation (intrinsic motivation, environmental knowledge, social network and social interaction). For the above models, the results are reported for control group (respondents not provided with information on regulatory incentive) and treatment group (respondents provided with additional regulatory incentive).

5.1 Random Parameter Logit

The estimated parameters of conditional logit and random parameter logit are reported in Table 11 and 13 for control and treatment group, respectively. Column 2 and column 3 of these tables gives the estimation results of conditional and random parameter logit model of 252 households for both models, respectively. The results state mean values for the marginal utility parameters assuming normal distribution. In random parameter logit model, all the utility parameter attributes (except price) are treated as random. The star label is included as an alternative specific dummy. The alternative specific dummy captures the impact of star label itself, regardless of other attributes. We include high star label, moderate star label, price, mileage, engine (1000 - 1500cc, more than 1500cc), transmission (automatic) and social network effect for the estimation. The random parameter logit model showed that star label (high and moderate star) coefficient is positive and highly significant in both control and treatment group, suggesting that respondents prefer cars with star label. Consumers have stronger preference for high star labeled car compared to moderate star labeled car. The attribute parameters - price, mileage, engine displacement (1000-1500cc, more than 1500cc) and transmission are in line with theoretical expectations and have a significant impact at 1% on the choices in both models. The variable price is taken as ten thousand of rupees. As expected, price has a negative coefficient which is highly significant in all models. Respondents are sensitive to price changes and are likely to buy high star labeled car, lower is its price. As engine displacement increases, the probability of choosing a car increases and utility levels increase (shown by positive and significant coefficient of engine displacement). Engine displacement is an important attribute in the control group but remains a weak factor in the presence of regulatory incentive. Consumers have preferences for automatic transmission (positive and highly significant) under both models. The social network effect coefficient is positive and highly significant for control group and insignificant for treatment group.

5.2 Latent Class Logit

Determining the number of classes

The optimal number of classes is decided based on AIC and BIC criteria discussed in section 4. We determine AIC and BIC till 6 latent classes under control and treatment group (refer Table 6). AIC criteria suggest 6 classes and BIC criteria suggest 4 classes for control group. There is not much difference in BIC value for 3 and 4 classes under control group. AIC criteria suggest 4 classes and BIC criteria suggest 3 classes for treatment group. We decided to use three class model based on BIC criteria. With four or more classes, the estimated parameters start to deteriorate, give large standard error and becomes insignificant. Therefore, we have selected 3-class model as the most appropriate model for estimating latent class logit model in both control and treatment group.

Characterizing the class members

The latent class model identifies heterogeneity in consumer preferences. The three classes are classified based on respondents' socio-economic characteristics and behavioural motives. The socio-economic characteristics included are age, gender, income, education and the behavioural motives include intrinsic motivation, environmental knowledge, social network and social interaction. We have included questions in our questionnaire to quantify behavioural motives of respondents. The variable intrinsic motivation has three statements where respondents can answer on a likert scale of 1, strongly disagree to 5, strongly agree (refer table 2 in appendix). We sum each respondents' response for the three statements and assign a dummy variable that takes value 1 if the sum is greater than equal to the median value. Through a similar process we create dummy for reported social network. For environmental knowledge we generate a dummy following the similar procedure as above, but instead of likert scale the correct answer gets value 1. For social interaction the value given are 1 to

3 for responses in questions, respectively (refer table 5 in appendix). Following Filippini et al. (2017) approach, we use the parameter estimates obtained by latent class to calculate individual posterior probabilities of belonging to each class. We use these probabilities to assign each individual to the class he/she belongs with highest probability.

Table 7 and 9 reports summary statistics (mean and standard error) of each class under control and treatment group, respectively. Table 8 and 10 reports significant comparisons of means of the explanatory variables across classes for control and treatment group, respectively. Based on summary statistics and comparisons of means of the explanatory variables across classes, class 1 of the sample is classified as old age (above 50 years), high income (above Rs. 1.5 Mn under control group, above Rs. 2.5 Mn under treatment group), educated males (graduates and post graduates) with high intrinsic motivation, high environmental knowledge, average to high reported social network and high social interaction. Class 1 is most guided by the behavioural motives and are concerned for the environment. This class acts as trend setters, therefore, we name this class as "Social Leaders". Class 2 of the sample is classified as middle age (31 - 50 years), middle income (less than Rs. 0.5 Mn, Rs. 0.5 - Rs. 1.5 Mn for control group, less than Rs. 0.5 Mn, Rs. 1.5 - Rs. 2.5 Mn for treatment group), educated males and females (graduates and post graduates) with average intrinsic motivation, average environmental knowledge, average to high reported social network and average social interaction. Class 2 are generally under the social pressure to follow their leaders, therefore, we name this class as "Social Pressure Group". The remaining respondents were classified in Class 3. Class 3 of the sample is classified as young age (18 - 30 years), low income (less than Rs. 0.5 Mn, Rs. 0.5 - Rs. 1.5 Mn for control group, Rs. 0.5 - Rs. 1.5 Mn for treatment group), high school and females with low intrinsic motivation, low environmental knowledge, low reported social network and average social interaction. Class 3 is named as "Non-Followers". This class doesn't follow the leaders or their income mayn't be enough to follow the leaders. The relative size of each class under control group (treatment group) shows that social leaders (class 1) represents 30% (36%) of the sample, social pressure group (class 2) represents 52% (40%) and Non-Followers (class 3) represents

18% (24%).

Estimation Results

In a random parameter logit model all the respondents belong to a single class, where as in latent class logit model respondents are classified into 3 classes. The estimated parameters of latent class logit model of 252 households are reported in Table 11 and 13 for control and treatment groups, respectively. The results show that in both control and treatment groups, choice probability for labeled cars is highest among social leaders (class 1), followed by social pressure group (class 2) and is the least in less environmental friendly non-followers (class 3). Social Leaders have a personal sense of responsibility towards environment (shown by high intrinsic motivation and high environmental knowledge), therefore, information through labels is most effective for this class. Social pressure group tends to base their decisions on other individual choices (say leaders choices), therefore this class also has high preference for labeled cars. However, non-followers are not much impacted by behavioural motives and have less preference for labels compared to other classes. This class is less environmental friendly. The coefficient of price is highly statistically significant in all classes under both groups.

Under control group, coefficient of engine displacement (more than 1500cc) is positive and highly statistically significant for social leaders and social pressure group. Transmission is statistically significant for social leaders and non-followers. Social network effect is insignificant for social leaders, highly statistically significant for social pressure group and weakly statistically significant for non-followers.

Under treatment group, automatic transmission is highly statistically significant for social leaders and engine (1000-1500cc, more than 1500cc) is highly statistically significant for social pressure group. Not surprisingly, social network effect is statistically significant for social pressure group and insignificant for other two classes. This is not surprising because social pressure group tends to follow the leaders.

The likelihood ratio test was carried out to compare conditional, random parameter and latent class logit model. The results indicate that under both groups, latent class logit model is prefered the most (log-likelihood under control group = -1191.0, log-likelihood under treatment group = -1110.29, $p - value < 0.01$), followed by random parameter logit model (log-likelihood under control group = -1348.9, log-likelihood under treatment group = -1287.6, $p - value < 0.01$) and least prefered is conditional logit model (log-likelihood under control group = -2602.6, log-likelihood under treatment group = -2513.8 , $p - value < 0.01$).

5.3 Willingness to Pay: Control versus Treatment Group

The willingness to pay refers to the maximum amount an individual is willing to sacrifice to acquire a good or avoid something undesirable. For our estimation purpose, we allow coefficients related to all attributes to vary (random), except we keep price coefficient as fixed. The willingness to pay for each attribute is the ratio of the non-price attribute's coefficient to the price coefficient (Revelt and Train, 1998). The estimate for willingness to pay for attribute k is obtained as

$$WTP_k = -\frac{\bar{\hat{\beta}}_k}{\bar{\hat{\beta}}_p} \tag{7}$$

where $\bar{\hat{\beta}}_k$ is the estimated mean coefficient of the k^{th} attribute, i.e., non-price attribute and $\bar{\hat{\beta}}_p$ is the estimated mean coefficient of the price attribute. For various models we estimate the willingness to pay for label and attributes. For latent class model, we estimate willingness to pay for each class.

Table 12 reports willingness to pay for conditional, random parameter logit and latent class logit model for control group. The random parameter logit model showed that under control group, respondents' on average are willing to pay around Rs. 0.32 Mn for high star label, Rs. 0.25 Mn for moderate star label, Rs. 0.013 Mn for mileage, Rs. 0.073 Mn for engine displacement of 1000-1500cc, Rs. 0.14 Mn for engine more than 1500cc, Rs. 0.081 Mn for automatic transmission. A 10% increase in the market share of family/friends, etc. results in increase in Rs. 0.019 Mn willingness to pay for cars. Weighted by the class probability, latent class model for control group showed that respondents' on an average are willing to pay Rs. 0.60 Mn for high star label, Rs. 0.50 Mn for moderate star label, Rs. 0.01 Mn for mileage, Rs. 0.05 Mn for engine (1000-1500cc), Rs. 0.16 Mn for engine (more than 1500cc), Rs. 0.07 Mn for automatic transmission and Rs. 0.01 Mn for 10% increase in social network effect (market share of family/friends/neighbours/colleagues). Social leaders are willing to pay on an average Rs. 1.48 Mn and social pressure group are willing to pay on an average Rs. 0.30 Mn for high star label car. The high income and environmental friendly individuals, i.e., social leaders are willing to pay a higher amount for labeled cars as compared to other classes. The non-followers are willing to pay a lower amount for labeled cars, mileage, engine (1000-1500cc, more than 1500cc) and automatic transmission as compared to other classes.

Table 14 reports willingness to pay for conditional, random parameter logit and latent class logit model for treatment group. The random parameter logit model showed that under treatment group respondents' on average are willing to pay around Rs. 0.49 Mn for high star label, Rs. 0.28 Mn for moderate star label, Rs. 0.014 Mn for mileage, Rs. 0.09 Mn for engine displacement of 1000-1500cc, Rs. 0.095 Mn for engine more than 1500cc and Rs. 0.094 Mn for automatic transmission. The latent class model showed willingness to pay across classes. Weighted by the class probability, latent class logit model for treatment group showed that respondents' on average are willing to pay Rs. 0.98 Mn for high star label, Rs. 0.60 Mn for moderate star label, Rs. 0.07 Mn for engine (1000-1500cc), Rs. 0.10 Mn for engine (more than 1500cc), Rs. 0.13 Mn for automatic transmission. The willingness to pay for mileage and social network is insignificant under treatment group. Social leaders are willing to pay on average Rs. 2.24 Mn, Rs. 0.39 Mn by social pressure group, Rs. 0.074 Mn by non-followers for high star label car. The social leaders (old-age, males, high income, graduates, post graduates and high behavioural motivations) are willing to pay higher for labeled cars and automatic transmission as compared to other classes. The social pressure group (middle age, middle income, graduates, postgraduates, average behavioural motivation) gave more importance to engine displacement (1000-1500cc, more than 1500cc) and social network effect compared to other classes. This group is willing to pay Rs. 0.05 Mn for engine 1000-1500cc, Rs. 0.12 Mn for engine more than 1500cc and Rs. 0.001 for 10% increase in social network. Non-followers (young age, low income, high school and low behavioural motivations) are willing to pay Rs. 0.07 Mn for high star label and Rs. 0.06 Mn for moderate star label. Under both groups, price has the highest impact for non-followers, i.e., budget constraint matters the most for these respondents.

Comparison of Attributes and Willingness to Pay under Control and Treatment Group across Classes

The results show that both non-incentivised and incentivized individuals have stronger preference for high star label cars in comparison to unlabeled cars, except for non-followers (class 3) for non-incentivised individuals. For each class, incentivized individuals have higher preference for high and moderate star label car over non-incentivized individuals. The effect of the incentive is not only that people tend to prefer high label cars but also that they will react less to changes in prices due to this inherent preference to high label cars, i.e., larger changes in prices are need in order for individuals to choose moderate label or unlabeled cars.

Amongst the classes, social leaders have the highest willingness to pay for labeled cars under both control and treatment group. Further, social leaders reacts less to changes in prices as compared to the non-followers. For the other attributes treatment has varying effect on willingness to pay. Social leaders have stronger preference for engine (more than 1500cc), automatic transmission under treatment group as compared to control group. However, social pressure group have stronger preference for engine (1000 - 1500cc, more than 1500cc) under treatment group as compared to control group. The non-followers gave importance to automatic transmission and social network effect under control group as compared to treatment group. For all the classes, the social network effect is important in the control group as compared to the treatment group. However, in both groups, amongst all classes social pressure group has highest valuation for what their family and friends are buying.

We compare respondents' valuation across control and treatment group using willingness to pay estimates. Using two-sample t test we show that respondents weighted willingness to pay is higher for labeled car (high and moderate star) under treatment group as compared to control group, significant at 1% (for random parameter and latent class logit model). We also compare respondents' willingness to pay for each class across control and treatment group using two sample t test. The results show that social leaders, social pressure group and non-followers are willing to pay a higher amount for high star label under treatment group as compared to control group, significant at 1%. Thus, incentive nudges respondents' preferences towards highly efficient labeled cars. We find that willingness to pay for fuel efficient cars increases with information on label and it increases even further under incentive treatment.

Comparing fuel efficiency label and the mileage, we find that the coefficient for label as well as mileage for both groups are statistically significant under random parameter logit model. However, under latent class logit model respondents for all the classes under treatment group only care about the label and not the mileage. This could be because the regulatory incentive associated with the label is more important to them than the mileage. However, in the control group mileage is only significant for social leaders. Since the social pressure group tends to follow leaders in terms of whether they have bought a labeled car or not, a label is important for them. However, the non-followers do not consider either label or mileage of the car in their purchase decisions. We find that all the attributes play a role in respondents purchase decisions. However, in terms of magnitude willingness to pay is higher for high star label and moderate star label. Our finding is that social network effect is important in decision on purchasing cars and is in line with what respondents have stated in likert statements on social network. Further, social network effect is comparatively more important under control group as compared to treatment group.

6 Discussion

The results suggest that on average, respondents' are willing to pay higher amount for labeled cars under both control and treatment group. This result is in line with previous studies discussing energy efficient label for appliances. Shen and Saijo (2009) in their analysis showed that consumers are willing to pay higher for labeled refrigerator and air-conditioner in China. Ward et al. (2011) showed higher willingness to pay for Energy Star label for refrigerator in U.S. In contrast, Zainudin et al. (2014) talked about negative correlation between energy label and consumers' purchasing behaviour in Malaysia. These studies have shown consumer preference for labeled appliances and in our study we focus on labeled cars.

We also investigated whether premium that consumers' are willing to pay for labeled cars is influenced by socio-economic characteristics, behavioural motivation and some regulatory incentive. We find that old age, high income, educated males are more concerned about the environment and are willing to pay higher for labeled cars. This result is in contrast with study by Khan et al. (2016), which showed that high income households had lower preference for alternative environmental friendly vehicles (such as hybrid electric or plug-in electric vehicles) and wanted to continue with their non-environmental friendly gasoline vehicles in Canada. However, Ziegler (2012) showed that being young, male and environmentally aware increases the probability of buying hydrogen or electric cars in Germany. The above studies are for electric cars, however, we compare consumer preferences for labeled cars in India. In addition, we report consumer preferences by socio-economic variables for all attributes - price, engine displacement, transmission and social network.

With respect to inclusion of behavioural motive variables, we observe that respondents with high behavioural motives (high intrinsic motivation/environmental knowledge/social interaction and average reported social network) have higher willingness to pay for labeled cars. Previous studies (Hidrue, 2011; Ziegler, 2012) have shown that consumers' who have more concern for the environment are willing to pay more for environmental friendly products such as electric cars or labeled appliances. In our study, we go in depth by analysing various components of behavioural motivation. Coad et al. (2009) in line with our study analysed the impact of information policy for intrinsically motivated consumers and incentives for extrinsically motivated consumers. The paper showed that both these policies are beneficial in encouraging adoption of cleaner technologies in Switzerland. However, this paper doesn't examine factors such as consumers' knowledge for environmental issues, social network and social interaction. Also, Coad et al. (2009) used dynamic model of adoption of environmental innovation, where as we analyse using discrete choice experiment. In addition, in order to deepen our understanding on behavioural motivation we include social network effect as an attribute in choice experiment. We find that social network effect is important in influencing consumer preference for labeled cars. Consumers want to be in social conformity with what other individuals are buying. This result is different from Rasouli and Timmermans (2016), which showed that network effect plays a minor role in influencing consumer preferences towards electric cars.

The important contribution of our study is analysing the role of policy instrument of regulatory incentive in increasing consumers' acceptance for labeled cars. Few studies such as Bjerkan et al. (2016); Ziegler (2012); Dimitropoulos et al. (2016) have examined the role of incentives for adoption of electric vehicles. Bjerkan et al. (2016) showed that incentive in the form of exemption from VAT or purchase tax is useful in promoting electric vehicles in Norway. Ziegler (2012) showed that the policy instrument of taxation or subsidy, promotion of research and development is useful in increasing acceptance for alternative fuel vehicles. In contrast to previous papers, in our study we have incorporated incentive in the form of odd-even rule for highly efficient labeled cars. Our study shows that the regulatory incentive along with fuel labels is effective in shifting consumer preferences towards highly efficient labeled cars.

7 Conclusion

The study aims to analyze consumers' willingness to pay for fuel efficient labeled cars in India. The novelty of the study is to examine the impact of behavioural motives and regulatory incentive in nudging consumer preferences for labeled cars. The regulatory incentive is incorporated in the form of lenient environmental regulation with the purchase of highly efficient labeled cars. For the purpose, we designed a discrete choice experiment in two districts of Delhi. We used random parameter logit and latent class logit model for the estimation.

The most important result we find from our study is that regulatory incentive has a positive effect in nudging consumer preferences towards labeled cars. The incentivized individuals have significant higher preference for high and moderate star label cars over non-incentivized individuals. In context with behavioural motivation, the study shows that consumers' who have high intrinsic motivation/environmental knowledge/social interaction and average reported social network are willing to pay higher for fuel efficient labeled cars. In addition, we show that social network effect is important in respondents' decision to purchase cars. Among the classes, social network effect is statistically significant for social pressure group and insignificant for other two classes.

The policy implication of the study is that policy maker can complement information policy, i.e., label for cars along with regulatory incentive to nudge consumer preferences towards highly fuel efficient labeled cars, thereby meeting the objective of reduced emissions. For future research, the same experiment could be applied to analyze consumer preferences for electric cars.

It is very challenging to capture social network effect. We tried to capture it in two ways, one by introducing market share of family/friends/neighbours/colleagues as an attribute in choice experiment and other by including questions pertaining to how much consumers gets influenced by choice of other members in their network. Future research can explore other ways to capture social network effect. Further, in future the same experiment could be applied to analyse consumer preferences for electric cars. Future studies could empirically analyse impact of other policy instruments such as reduced tax or registration fees, special car lanes for labeled cars, etc. to promote adoption of fuel efficient products.

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Appendix

Table 1: Choice Sets Attributes and Levels

Attributes	**Levels**	**Hypothesized Sign**
Price	10%, 20%, 30%, 40%, 50% higher than your reference price	-
Mileage (kilometre per litre, kmpl)	20, 24 for high star label, 16, 20 for moderate star label, 13 for presently available car	+
Engine Displacement	Upto 1000cc, 1000-1500cc, More than 1500cc	+
Transmission	Manual, Automatic	
Social Network (Market Share among Family/Friends/ Neighbours/Colleagues)	20%, 60%	+

Table 2: Behavioural Motives Statements: Intrinsic Motivation and Social Network

Likert Statements (1 is strongly disagree and 5 is strongly agree)
A. Intrinsic Motivation: Warm Glow
I feel personally obliged to save energy While purchasing household items such as air-conditioner, I take into account how my use will affect the environment I am willing to purchase energy efficient/ star label electrical appliances even if they are more expensive
B. Extrinsic Motivation: Social Network
I consider recommendations from family/friends/neighbours, while making decisions to purchase cars, household appliances etc. I consider recommendations from colleagues, while making decisions to purchase cars, household appliances etc.

Table 3: Example of choice set from the choice experiment of cars

Car Attributes	**Choice Set**		
	High Star Labeled Car (Star 4, 5)	**Moderate Star Labeled Car (Star 3)**	**Presently Available Car**
Price	40% of the reference price	10% of the reference price	Conventional presently available car which has mileage of 13kmpl
Mileage (kilometres per litre, kmpl)	20	16	
Engine Displacement	Upto 1000cc	1000 - 1500cc	
Transmission	Automatic	Manual	
Market Share among Family/Friends/Neighbours/ Colleagues	60%	60%	
Your Choice (mark any one alternative)			

Table 4: Summary Statistics of the households in the sample

Household Characteristics	**Pooled Sample**	**South Delhi**	**East Delhi**	**Control Group**	**Treatment Group**	**Delhi**	**India**
Age	40.55	41.05	40.05	40.44	40.65	37.40*	38.93*
Gender (proportion)							
Male	57.14%	57.94%	56.35%	59.92%	54.37%	53.58%	51.54%
Female	42.86%	42.06%	43.65%	40.08%	45.63%	46.42%	48.46%
Marital Status (proportion)							
Married	73.21%	73.81%	72.62%	74.60%	71.83%	72.13%**	74.66%**
Unmarried	26.79%	26.19%	27.38%	25.40%	28.17%	27.87%**	25.34%**
Family Type							
Nuclear Family	65.08%	67.46%	62.70%	65.48%	64.68%	77.96%	79.03%
Joint Family	34.92%	32.54%	37.30%	34.52%	35.32%	22.04%	20.97%
Household size (number of members)	5.05	4.91	5.2	4.95	5.16	4.9	4.8
Mean Household Annual Family Income (Rupees)	1578400	1806600	1350200	1531800	1625000		
Less than 0.5 Mn	14.68%	9.92%	19.44%	14.28%	15.08%		
0.5 to 1.5 Mn	39.09%	32.14%	46.04%	40.48%	37.70%		
1.5 to 2.5 Mn	23.61%	27.78%	19.44%	26.59%	20.63%		
More than 2.5 Mn	22.62%	30.16%	15.08%	18.65%	26.59%		
Education (proportion)							
High School	16.27%	15.08%	17.46%	17.46%	15.08%		88.35%***
Graduate	47.42%	47.22%	47.62%	50%	44.84%		9.25%
Post Graduate or higher	34.33%	34.92%	33.73%	30.56%	38.10%		1.48%
Others	1.98%	2.78%	1.19%	1.98%	1.98%		0.91%

. . . continued

Household Characteristics	**Pooled Sample**	**South Delhi**	**East Delhi**	**Control Group**	**Treatment Group**	**Delhi**	**India**
Occupation							
Professional/Service	45.83%	48.41%	43.25%	48.41%	43.25%		
Business	31.35%	31.75%	30.95%	32.54%	30.16%		
Student	8.73%	8.33%	9.13%	6.35%	11.11%		
Not Working	12. 90%	11.11%	14.68%	10.32%	15.48%		
Other	1.19%	0.40%	1.99%	2.38%	0%		
Mean number of cars owned by households	1.61	1.76	1.45	1.5	1.71		
Mean number of households owning diesel car	0.27	0.29	0.24	0.27	0.26		
Mean number of household members having driving license	2.65	2.7	2.6	2.52	2.78		
Whether respondents knows the mileage of current car							
Yes	62.50%	61.11%	63.89%	63.10%	61.90%		
No	37.50%	38.89%	36.11%	36.90%	38.10%		
Mean mileage of current car (kmpl)	14.97	15.04	14.91	15.1	14.85		
Average Commuting distance (km)	21.59	21.12	22.06	21.36	21.82		
Plan to buy a new car							
Yes	53.37%	54.37%	52.38%	55.56%	51.19%		
No	46.63%	45.63%	47.62%	44.44%	48.81%		
Reason to buy a new car							
Replacement of old car	49.82%	54.01%	45.45%	50%	49.62%		
Additional Car	27.88%	30.66%	25.00%	24.29%	31.78%		
First Car Purchase	19.33%	13.87%	25.00%	22.86%	15.50%		
Other	2.97%	1.46%	4.55%	2.86%	3.10%		
Households owning 3 star and above appliances							
Yes	78.57%	79.76%	77.38%	78.57%	78.57%		
No	21.43%	20.24%	22.62%	21.43%	21.43%		
Number of observations	504	252	252	252	252		

Source for Delhi and India Statistics: Census of India, 2011; *Mean age for Delhi and India is reported for 18 years and above ; ** Percentage of marital status for Delhi and India is reported for age 18 years & above; ***The figures are based on enrollment in school and higher education (Source: MHRD, NUEPA, 2014-15)

Table 5: Social Interactions

Social Interactions (Pooled Data)	
How many times respondent meets his relatives/friends during a month 17.06% (0-1 time) 40.67% (2-3 times) 42.26% (more than 3 times)	How many times respondent meets his colleagues outside work place during a month 42.66% (0-1 time) 35.52% (2-3 times) 21.83% (more than 3 times)
How often respondent invites his relatives/friends to his home (or visit their home) 12.7% (once a year or less) 51.19% (2 - 6 times a year) 36.11% (more than 6 times a year)	How often respondent invites his colleagues to his home (or visit their home) 46.23% (once a year or less) 41.87% (2 - 6 times a year) 11.90% (more than 6 times a year)
How often respondent lend household items to his friends/neighbours 23.81% (never) 48.61% (seldom) 27.58% (often)	How often respondent lend money to his relatives/friends/colleagues 26.98% (never) 44.25% (seldom) 28.77% (often)
How often do respondent leave house/car keys or children with his friends/neighbours 51.59% (never) 29.17% (seldom) 19.25% (often)	

Table 6: Information criterion for different number of latent class

Classes	**Akaike information criterion (AIC)**	**Bayesian information criterion (BIC)**	**Akaike information criterion (AIC)**	**Bayesian information criterion (BIC)**
	Control Group		**Treatment Group**	
2	2821.01	2926.88	2571.04	2680.46
3	2486.08	2669.62	2323.32	2513.91
4	2407.47	2668.65	2294.71	2566.48
5	2394.09	2732.91	-	-
6	2343.64	2760.11	-	-

Table 7: Summary Statistics by Class: Control Group

Variables	Social Leaders (Class 1) (n = 1603)		Social Pressure (Class 2) (n = 2725)		Non-Followers (Class 3) (n = 963)	
	Mean (or Proportion)	**Std Error**	**Mean (or Proportion)**	**Std Error**	**Mean (or Proportion)**	**Std Error**
	Socio-Economic Variables					
Age						
18 - 30 years	0.311	0.012	0.205	0.008	0.348	0.015
31 - 50 years	0.419	0.013	0.636	0.009	0.391	0.016
Above 50years	0.270	0.011	0.159	0.007	0.261	0.014
Gender (Male)	0.743	0.011	0.561	0.009	0.478	0.016
Income						
Less than 0.5 Mn	0.068	0.006	0.098	0.006	0.391	0.016
0.5 - 1.5 Mn	0.311	0.012	0.439	0.009	0.457	0.016
1.5 - 2.5 Mn	0.311	0.012	0.280	0.009	0.152	0.012
More than 2.5 Mn	0.311	0.012	0.182	0.007	0.000	
Education						
High School	0.054	0.006	0.144	0.007	0.457	0.016
Graduate	0.622	0.012	0.462	0.009	0.413	0.016
Post Graduate	0.297	0.012	0.379	0.009	0.109	0.010
Others	0.027	0.004	0.015	0.002	0.022	0.005
	Environmental Variables					
High Intrinsic Motivation	0.689	0.012	0.492	0.009	0.370	0.016
High Environment Knowledge	0.757	0.011	0.576	0.009	0.435	0.016
	Social Variables					
High Social Network	0.689	0.012	0.659	0.009	0.565	0.016
High Social Interaction	0.635	0.012	0.409	0.009	0.587	0.016

Note: The summary statistics is based on individual posterior probabilities of belonging to a particular class. These probabilities are assigned to each individual to the class he belongs with highest probability.

Table 8: Comparison of Means of Explanatory Variables across Classes for Control Group

Variable	**Mean Difference**	**Standard Error**	**95% Confidence Interval**		**Mean Difference**	**Standard Error**	**95% Confidence Interval**	
	Age (18-30yrs)				**Age (31-50yrs)**			
Pressure vs Leaders	-0.1063	0.0138	-0.1333	-0.0792	0.2174	0.0154	0.1872	0.2476
Non-Followers vs Leaders	0.0370	0.0178	0.0020	0.0720				
Non-Followers vs Pressure	0.1433	0.0163	0.1114	0.1752	-0.2451	0.0182	-0.2807	-0.2095
	Age (Above 50years)				**Gender**			
Pressure vs Leaders	-0.1112	0.0128	-0.1363	-0.0861	-0.1826	0.0152	-0.2125	-0.1528
Non-Followers vs Leaders					-0.2650	0.0197	-0.3036	-0.2264
Non-Followers vs Pressure	0.1018	0.0151	0.0722	0.1314	-0.0823	0.0179	-0.1175	-0.0472
	Income (Less than 0.5 Mn)				**Income (0.5 - 1.5 Mn)**			
Pressure vs Leaders	0.0309	0.0104	0.0104	0.0514	0.1286	0.0154	0.0983	0.1589
Non-Followers vs Leaders	0.3237	0.0135	0.2973	0.3502	0.1457	0.0200	0.1066	0.1848
Non-Followers vs Pressure	0.2928	0.0123	0.2687	0.3170				
	Income (1.5 - 2.5 Mn)				**Income (More than 2.5 Mn)**			
Pressure vs Leaders	-0.0305	-0.0033	0.0139	-0.0577	-0.1290	0.0119	-0.1523	-0.1057
Non-Followers vs Leaders	-0.1586	-0.1234	0.0180	-0.1939	-0.3108	0.0154	-0.3410	-0.2807
Non-Followers vs Pressure	-0.1281	0.0164	-0.1602	-0.0960	-0.1818	0.0140	-0.2093	-0.1543
	Education (High School)				**Education (Graduate)**			
Pressure vs Leaders	0.0899	0.0112	0.0679	0.1118	-0.1595	0.0156	-0.1902	-0.1288
Non-Followers vs Leaders	0.4025	0.0145	0.3741	0.4309	-0.2086	0.0202	-0.2482	-0.1689
Non-Followers vs Pressure	0.3126	0.0132	0.2867	0.3385	-0.0491	0.0184	-0.0852	-0.0129
	Education (Post Graduate)				**Education (Others)**			
Pressure vs Leaders	0.0815	0.0143	0.0535	0.1094	-0.0119	0.0044	-0.0205	-0.0032
Non-Followers vs Leaders	-0.1886	0.0184	-0.2247	-0.1525				
Non-Followers vs Pressure	-0.2701	0.0168	-0.3030	-0.2371				
	Intrinsic Motivation				**Environmental Knowledge**			
Pressure vs Leaders	-0.1968	0.0154	-0.2270	-0.1666	-0.1810	0.0151	-0.2106	-0.1514
Non-Followers vs Leaders	-0.3196	0.0199	-0.3587	-0.2806	-0.3220	0.0195	-0.3602	-0.2837
Non-Followers vs Pressure	-0.1229	0.0182	-0.1585	-0.0872	-0.1410	0.0178	-0.1759	-0.1061
	Social Network				**Social Interaction**			
Pressure vs Leaders	-0.0301	0.0151	-0.0596	-0.0006	-0.2260	0.0155	-0.2564	-0.1957
Non-Followers vs Leaders	-0.1240	0.0195	-0.1621	-0.0858	-0.0482	0.0200	-0.0875	-0.0089
Non-Followers vs Pressure	-0.0939	0.0177	-0.1287	-0.0591	0.1779	0.0183	0.1421	0.2137

Note: We report difference in means only for statistical significant comparisons.

Table 9: Summary Statistics by Class: Treatment Group

Variables	**Social Leaders (Class 1) (n = 1905)**		**Social Pressure (Class 2) (n = 2127)**		**Non-Followers (Class 3)(n= 1259)**	
	Mean (or Proportion)	**Std Error**	**Mean (or Proportion)**	**Std Error**	**Mean (or Proportion)**	**Std Error**
	Socio-Economic Variables					
Age						
18 - 30 years	0.267	0.101	0.297	0.009	0.377	0.013
31 - 50 years	0.400	0.112	0.514	0.011	0.475	0.014
Above 50years	0.333	0.011	0.188	0.008	0.147	0.010
Gender (Male)	0.600	0.112	0.554	0.011	0.442	0.013
Income						
Less than 0.5 Mn	0.089	0.007	0.198	0.009	0.164	0.010
0.5 - 1.5 Mn	0.311	0.011	0.386	0.011	0.459	0.014
1.5 - 2.5 Mn	0.178	0.009	0.228	0.009	0.213	0.011
More than 2.5 Mn	0.422	0.011	0.188	0.008	0.164	0.010
Education						
High School	0.100	0.007	0.158	0.008	0.213	0.011
Graduate	0.422	0.011	0.485	0.011	0.426	0.014
Post Graduate	0.444	0.011	0.356	0.010	0.328	0.013
Others	0.033	0.004	0.000		0.033	0.005
	Environmental Variables					
High Intrinsic Motivation	0.611	0.112	0.535	0.011	0.393	0.014
High Environment Knowledge	0.611	0.011	0.624	0.011	0.574	0.014
	Social Variables					
High Social Network	0.656	0.011	0.734	0.010	0.607	0.014
High Social Interaction	0.567	0.011	0.495	0.011	0.443	0.014

Note: The summary statistics is based on individual posterior probabilities of belonging to a particular class. These probabilities are assigned to each individual to the class he belongs with highest probability.

Table 10: Comparison of Means of Explanatory Variables across Classes for Treatment Group

Variable	Mean Difference	Standard Error	95% Confidence Interval		Mean Difference	Standard Error	95% Confidence Interval	
	Age (18-30yrs)				**Age (31-50yrs)**			
Pressure vs Leaders	0.0304	0.0145	0.0019	0.0588	0.1149	0.0157	0.0841	0.1456
Non-Followers vs Leaders	0.1104	0.0166	0.0778	0.1429	0.0754	0.0180	0.0402	0.1106
Non-Followers vs Pressure	0.0800	0.0162	0.0482	0.1118	-0.0394	0.0176	-0.0739	-0.0050
	Age (Above 50years)				**Gender**			
Pressure vs Leaders	-0.1452	0.0131	-0.1709	-0.1196	-0.0455	0.0156	-0.0762	-0.0149
Non-Followers vs Leaders	-0.1858	0.0150	-0.2151	-0.1564	-0.1574	0.0179	-0.1925	-0.1223
Non-Followers vs Pressure	-0.0406	0.0146	-0.0693	-0.0119	-0.1118	0.0175	-0.1461	-0.0775
	Income (Less than 0.5 Mn)				**Income (0.5 - 1.5 Mn)**			
Pressure vs Leaders	0.1091	0.0112	0.0871	0.1311	0.0750	0.0152	0.0452	0.1049
Non-Followers vs Leaders	0.0750	0.0128	0.0499	0.1002	0.1479	0.0174	0.1137	0.1821
Non-Followers vs Pressure	-0.0341	0.0126	-0.0587	-0.0095	0.0729	0.0170	0.0395	0.1063
	Income (1.5 - 2.5 Mn)				**Income (More than 2.5 Mn)**			
Pressure vs Leaders	0.0499	0.0128	0.0249	0.0750	-0.2341	0.0135	-0.2605	-0.2077
Non-Followers vs Leaders	0.0353	0.0146	0.0067	0.0640	-0.2583	0.0154	-0.2885	-0.2281
	Education (High School)				**Education (Graduate)**			
Pressure vs Leaders	0.0584	0.0112	0.0364	0.0804	0.0629	0.0157	0.0321	0.0937
Non-Followers vs Leaders	0.1131	0.0129	0.0879	0.1383				
Non-Followers vs Pressure	0.0547	0.0126	0.0301	0.0793	-0.0589	0.0176	-0.0934	-0.0245
	Education (Post Graduate)				**Education (Others)**			
Pressure vs Leaders	-0.0880	0.0153	-0.1180	-0.0580	-0.0333	0.0044	-0.0419	-0.0247
Non-Followers vs Leaders	-0.1166	0.0175	-0.1509	-0.0823				
Non-Followers vs Pressure	-0.0286	0.0171	-0.0621	0.0050	0.0328	0.0049	0.0232	0.0424
	Intrinsic Motivation				**Environmental Knowledge**			
Pressure vs Leaders	-0.0765	0.0156	-0.1070	-0.0459				
Non-Followers vs Leaders	-0.2177	0.0178	-0.2526	-0.1827	-0.0373	0.0177	-0.0720	-0.0027
Non-Followers vs Pressure	-0.1412	0.0174	-0.1754	-0.1071	-0.0500	0.0173	-0.0839	-0.0161
	Social Network				**Social Interaction**			
Pressure vs Leaders	0.0771	0.0147	0.0482	0.1060	-0.0716	0.0157	-0.1025	-0.0408
Non-Followers vs Leaders	-0.0490	0.0169	-0.0821	-0.0159	-0.1240	0.0180	-0.1594	-0.0887
Non-Followers vs Pressure	-0.1261	0.0165	-0.1584	-0.0938	-0.0524	0.0176	-0.0870	-0.0179

Note: We report difference in means only for statistical significant comparisons.

Table 11: Estimation results for car choices in Control Group

Attribute	**Conditional Logit**	**Random Parameter Logit**		**Latent Class Logit**		
		Mean	**SD**	**Social Leaders (Class 1)**	**Social Pressure (Class 2)**	**Non-Followers (Class 3)**
High Star	0.923***	1.987***	-0.04710	3.788***	2.740***	-0.0092600
Label	(4.30)	(6.24)	(-0.25)	(4.93)	(6.23)	(-0.01)
Moderate	0.1750	1.521***	0.670***	3.107***	2.283***	0.0814
Star Label	(1.04)	(5.82)	(4.44)	(3.48)	(6.38)	(-0.11)
Price	-0.00290***	-0.00619***		-0.0026***	-0.0091***	-0.0244***
	(-15.77)	(-15.43)		(-7.13)	(-11.13)	(-6.64)
Mileage	0.0338*	0.0853**	0.419***	0.0965**	0.0497	0.0167
	(1.83)	(2.34)	(11.12)	(2.31)	(1.50)	(0.20)
Engine (1000	0.354***	0.450***	0.244	0.217	0.343**	0.5210
- 1500cc)	(4.12)	(3.67)	(1.10)	(0.94)	(2.06)	(1.33)
Engine	0.627***	0.867***	1.471***	1.032***	0.604***	0.0135
(More than 1500cc)	(6.61)	(5.04)	(5.56)	(4.41)	(3.43)	(0.03)
Transmission	0.269***	0.506***	0.801***	0.441**	0.224	0.773**
(Automatic)	(3.64)	(4.03)	(3.35)	(2.39)	(1.62)	(2.21)
Social Net-	0.0109***	0.0118***	0.0216***	0.00451	0.0123***	0.0157*
work	(5.88)	(3.76)	(6.03)	(1.05)	(3.48)	(1.90)
Share of each class				0.303	0.515	0.182
Log Likelihood	-2602.6200	-1348.93		-1191.03		
LR chi2	673.30***	640.96***				
N	5292	5292		1603	2725	963

Note: t statistics are reported in parenthesis; *, ** and *** denote that the parameters are significant at 10%, 5% and 1% level respectively.

Table 12: Willingness to Pay Estimates for Control Group

	Conditional Logit	**Random Parameter Logit**			**Latent Class Logit**			
			Confidence Interval		**Mean WTP (in Rs'000)**			
Variables	**Mean WTP (in Rs'000)**	**Mean WTP (in Rs'000)**	**Lower**	**Upper**	**Social Leaders (1)**	**Social Pressure (2)**	**Non-Followers (3)**	**Weighted WTP**
High Star Label	318.19***	320.69***	226.76	414.62	1483.08***	302.29***	-0.38	604.98
Moderate Star Label	60.41	245.46***	170.01	320.91	1216.47***	251.83***	3.34	498.89
Mileage	11.66*	13.76***	2.40	25.13	37.77**	5.48	0.68	14.39
Engine (1000 - 1500cc)	121.83***	72.71***	33.42	112.00	84.89	37.82**	21.38	49.09
Engine (More than 1500cc)	216.14***	139.90***	86.68	193.11	404.12***	66.63***	0.56	156.86
Transmission (Automatic)	92.63***	81.67***	42.68	120.66	172.57**	24.72	31.75**	70.80
Social Network	3.77***	1.90***	0.90	2.90	1.77	1.35***	0.64*	1.35

Note: t statistics are reported in parenthesis; *, ** and *** denote that the parameters are significant at 10%, 5% and 1% level respectively.

Table 13: Estimation results for car choices in Treatment Group

Attribute	**Conditional Logit**	**Random Parameter Logit**		**Latent Class Logit**		
		Mean	**SD**	**Social Leaders (Class 1)**	**Social Pressure (Class 2)**	**Non-Followers (Class 3)**
High Star Label	1.647***	2.722***	1.562***	4.961***	3.561***	1.583**
	(7.56)	(7.50)	(7.44)	(6.72)	(6.98)	(2.17)
Moderate Star Label	0.2250	1.575***	0.189	2.740***	3.192***	1.264**
	(1.32)	(5.58)	(0.60)	(4.3)	(8.20)	(2.20)
Price	-0.00239***	-0.00560***		-0.0022***	-0.0092***	-0.0215***
	(-14.61)	(-13.64)		(-7.21)	(-12.87)	(-10.14)
Mileage	0.0184	0.0803**	0.388***	0.0210	0.0177	0.0969
	(0.97)	(2.03)	(11.23)	(0.39)	(0.43)	(1.42)
Engine (1000 - 1500cc)	0.282***	0.503***	-0.20900	0.262	0.510**	0.3730
	(3.23)	(3.86)	(-0.87)	(0.92)	(2.47)	(1.21)
Engine (More than 1500cc)	0.364***	0.532***	-1.374***	0.333	1.090***	-0.343
	(3.76)	(2.95)	(-5.61)	(1.15)	(5.49)	(-0.91)
Transmission (Automatic)	0.215***	0.529***	-1.097***	0.769***	0.00882	0.2080
	(2.85)	(3.78)	(-4.70)	(3.33)	(0.05)	(0.81)
Social Network	0.00618***	0.00287	-0.021***	-0.002520	0.00877**	0.000471
	(3.25)	(0.91)	(-4.87)	(-0.51)	(2.24)	(0.07)
Share of each class				0.36	0.402	0.238
Log Likelihood	-2513.7781	-1287.5906		-1110.2946		
LR chi2	850.98***	671.69***				
N	5292	5292		1905	2127	1259

Note: t statistics are reported in parenthesis; *, ** and *** denote that the parameters are significant at 10%, 5% and 1% level respectively.

Table 14: Willingness to Pay Estimates for Treatment Group

	Conditional Logit	**Random Parameter Logit**			**Latent Class Logit**			
			Confidence Interval		**Mean WTP (in Rs'000)**			
Variables	**Mean WTP (in Rs'000)**	**Mean WTP (in Rs'000)**	**Lower**	**Upper**	**Social Leaders (1)**	**Social Pressure (2)**	**Non-Followers (3)**	**Weighted WTP**
High Star Label	687.94***	486.00***	368.58	603.42	2235.66***	386.67***	73.80**	977.84
Moderate Star Label	93.87	281.17***	195.59	366.76	1234.99***	346.55***	58.94**	597.94
Mileage	7.68	14.34***	0.75	27.93	9.48	1.92	4.52	5.26
Engine (1000 - 1500cc)	117.73***	89.83***	43.89	135.76	118.17	55.4**	17.40	68.95
Engine (More than 1500cc)	152.17***	94.95***	32.38	157.52	150.22	118.3***	-15.98	97.83
Transmission (Automatic)	89.97***	94.40***	46.93	141.87	346.68***	0.96	9.72	127.50
Social Network	2.58***	0.5100	-0.60	1.62	-1.14	0.95**	0.02	-0.02

Note: t statistics are reported in parenthesis; *, ** and *** denote that the parameters are significant at 10%, 5% and 1% level respectively.