May a regulatory incentive increase WTP for cars with a fuel efficiency label? Estimating regulatory costs through a split-sample DCE in New Delhi, India

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Abstract

The Indian government is considering the adoption of fuel efficiency labels for cars. By means of a Discrete Choice Experiment (DCE), this paper assesses New Delhi's car buyers' preferences for such a label. Random parameters specifications yield a willingness to pay (WTP) of 4.93 thousand US dollars for a car with the best efficiency label. As a novelty, and by means of a split-sample approach, we test whether this WTP would increase due to an incentive described as a regulation restricting the number of days a car can be driven weekly unless the car is awarded the best efficiency label —New Delhi's residents experienced a similar policy in January and April, 2016. This incentive increases the WTP by 51.5% —from 4.93 to 7.48 thousand US dollars. These extra 2.55 thousand US dollars can be interpreted as regulatory costs and are close to the 2.96 thousand US dollars implicit in estimates reported by Blackman et al. (2018)[11] in the context of the Mexican Hoy No Circula.

Keywords: fuel efficiency labels; regulatory costs; Discrete Choice Experiment; Willingness to Pay; Random Parameters Logit; Split-sample approach; New Delhi.

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1 Introduction

Air pollution and its implications for climate change and human health remain a pressing issue in megacities. For instance, the recent and unprecedented episodes of air pollution in Delhi have received large Media coverage [4]. In November 2017, air pollution levels in Delhi reached nearly 30 times the level that the World Health Organization considers safe. $PM_{2.5}$ climbed to more than 700 $\mu g/m^3$ which is hazardous to breath. These numbers become alarming when we consider the studies documenting that, given a level of air pollution, impacts on health are larger in a city located in a developing country than in a city of a developed country (Arceo-Gomez, 2012 [6]). Saraswat and Bansal (2019) [31] estimate gains in life expectancy in Delhi to be around 10.3 years when the $PM_{2.5}$ levels in Delhi reach WHO standards and around 6.8 years when the national standards are met in the city.

The smog in Delhi, as in other megacities, results from a combination of industrial pollution, smoke from crop burning in nearby farming areas, and vehicle emissions. Thus, increasing the average fuel efficiency of the vehicle fleet arises as a natural alternative to combat air pollution's effects on climate change and human health. Despite the fact that fuel efficient cars are already available in the market, their adoption has been slower than preferred in social terms which remains a puzzle for economists because the private benefits of driving a fuel efficient car tend to be larger than the private costs.

A popular strategy to promote the purchase of fuel efficient cars is the adoption of a labeling system that ranks cars in terms of fuel efficiency. The economic argument behind this policy is that labels help consumers to overcome asymmetries in information —which is thought to be a reason behind the slow adoption of efficient cars. Fuel efficiency labels have been adopted in a number of developed countries. Evidence suggest that car drivers in those countries do assign economic value to efficiency labels. For instance, Alberini (2016) [2] document how the price that Swiss car owners pay for a car displaying the best efficiency label goes above and beyond the premium derived from fuel costs savings —this extra premium

[4] e.g. https://www.nytimes.com/2017/11/08/world/asia/india-air-pollution.html

falls within a 6% to 11% of the car's price, and is interpreted as the value of the energy efficiency label.

Following suit the implementation of energy consumption labels for house appliances by Bureau of Energy Efficiency in 2006 [5], the Indian government is now considering the introduction of fuel efficiency labels for cars [6]. In this context, and by means of a discrete choice experiment (DCE), this paper assesses car buyers' preferences for cars displaying fuel efficiency labels in New Delhi. The respondents are presented to choice tasks that describe three labeled alternatives —the status quo, a *high star* car (best label), and a *moderate star* car (second best label). We use alternative specific labels so that we are able to infer the preferences for the display of the label in itself. The alternatives have been described in terms of five attributes: price, mileage, engine displacement, transmission, and *social network*. With the exception of social network, the other four attributes are standard characteristics of a car. Following Rasouli et al. (2016) [30], we test for the possibility of a peer-pressure effect by measuring social network as the percentage of people in the respondent's social network (family/friends/neighbors/colleagues) that drive the car described in the choice task. Based on our preferred Random Parameters Logit model, we document that car drivers' in our sample declare a willingness to pay (WTP) of 4.93 thousand US dollars for a car that displays the best energy efficiency label, and a WTP of 3.78 thousand US dollars for a car displaying the second best label.

A novelty in this paper is that we test for whether a regulatory incentive may increase the stated WTP for the cars displaying an energy efficiency label. We test this possibility by implementing a split-sample approach. Half of our sample is told that the government is considering a regulation that would restrict the number of days a car can be driven weekly unless the car displays the label reflecting the best fuel efficiency performance —very much resembling the Mexican Hoy No Circula (HNC). New Delhi's residents are familiar with this type of regulation since a similar policy was implemented for a short period in January 2016

[5] https://beeindia.gov.in/content/s-l

[6] http://www.indiaenvironmentportal.org.in/files/file/BEE%20Consultation%20Paper-21Oct2011.pdf

and again in April 2016, to deal with episodes of unprecedented air pollution.

Based on Random Parameter Logit specifications, we document that the regulatory incentive increases the respondents' WTP for cars displaying the best label by 51.5% —from 4.93 US dollars to 7.48 thousand US dollars. To put these WTP estimates in context, keep in mind that, before presented to the DCE, respondents to our survey report the price of a car they intend to purchase in a near future. The average of this reported price is 19.79 thousand US dollars. That is, a efficiency label would increase the WTP for a car by around 25% and up to 38% under the regulatory incentive scenario.

The extra 2.55 thousand US dollars that respondents are willing to pay for a car to avoid the described regulation can be interpreted as regulatory costs. Our estimates are close to the 2.96 thousand US dollars implicit in estimates reported by Blackman et al. (2018)[11] in the context of the Mexican Hoy No Circula.

This paper contributes to the literature documenting the effects from efficiency labels on the preferences for (efficient) cars. This literature includes revealed preference studies (e.g. Galarrage et al., 2014 [17]; Alberini et al., 2016 [2]; Allcott and Knittel, 2019 [5]) and stated preference studies (e.g. Achtnicht, 2012 [1] ; Gaker and Walker, 2013 [16]; Daziano et al., 2017 [15]; Kormos and Sussman, 2018 [22];). In particular, our DCE study is close to Kormos and Sussman (2018) [22], who explore preferences for fuel efficiency in U.S. via a randomized discrete choice experiment, and document that consumers are willing to pay 10.73 thousand US dollars for a car that allows them to save one thousand US dollars a year in fuel costs.

To the best of our knowledge, no previous DCE study has explored the policy-relevant question of what can be expected in terms of demand for (efficient) cars when fuel efficiency labels are adopted simultaneously with the implementation of a regulatory incentive —with the advantage that this approach yields estimates of regulatory costs. This, we believe, is our very specific contribution.

The rest of this document is organized as follows. Section 2 describes the context of our study. Section 3 presents the strands in the literature that are related to this paper. Section

4 provides details on our theoretical and empirical strategies. Section 5 reports our data gathering strategy and descriptive statistics. Section 6 presents the empirical specifications and welfare estimates. Section 7 concludes and discusses policy implications.

2 Context

Energy consumption in India is on the rise. From 2013 to 2017, energy consumption has increased at an average rate of 5.3%. India's share in global energy consumption reached 5.6% in 2017 (BP statistical review of world energy, 2018 [7]). The Energy Information Administration (EIA) has projected that India and China together will account for around half of the global energy demand growth by 2040. This trend is a matter of concern as energy consumption adversely affects environment and increases green house gas (GHG) emissions —which also are on the rise in India, with an increase of 4.6% in 2016 (Olivier et al., 2017 [29]).

New Delhi, the national capital of India and one of the 46 megacities in the world, is a major generator of carbon emissions in the country — with an emission of 37.91 million tones of CO_2 equivalent in 2014 (Sharma and Dikshit, 2016 [32]). Around 32% of these emissions are due to the transport sector. A recent increase in vehicle ownership in New Delhi has contributed to these emissions. To put some context, the total number of registered vehicles in New Delhi is 8.8 Million which is larger than the combined number of registered vehicles in Chennai and Mumbai (7.7 Million) in 2016 (Statistical year book India 2018, Ministry of Statistics and Programme Implementation, Government of India [8]).

In this context, the introduction of fuel economy standards and labels may play a role in reducing fuel consumption, thereby reducing emissions. Policies based on fuel standards and labels have been in place in developed countries since the 1980's[9]. More recently, countries

[7] https://www.bp.com/content/dam/bp/en/corporate/pdf/energy-economics/statistical-review/bp-stats-review-2018-full-report.pdf

[8] http://mospi.nic.in/statistical-year-book-india/2018/189

[9] United States was first to adopt Corporate Average Fuel Economy (CAFE) standards in 1975 and label in 1980

such as China and India have followed suit. India is currently considering the introduction of fuel standards and labels for cars as part of a wider effort to decrease emissions from the transportation sector. In 2015, the Ministry of Power issued average fuel consumption standards based on kilometers per litre (kmpl) for the passenger cars. These norms will be binding for car manufacturers in two phases by 2017 and 2022. The goal is to improve fuel efficiency (mileage) by 10% in the first phase and by 30% in the second phase. With the implementation of these new fuel efficiency norms, CO_2 emissions are projected to go from 142 gram per km in 2010-11 to 113 gram per km in 2022 (Bureau of energy efficiency, BEE).

In addition to the fuel standards, the BEE plans to introduce a labeling system that would provide information by rating all the new cars in terms of fuel efficiency [10]. This label system would classify cars among five categories. The categories would be represented by stars —with one star reflecting the worst fuel efficiency category and five stars reflecting the best fuel efficiency category. A car displaying an efficiency label would provide private benefits to consumers in the form of fuel cost savings and public benefits in the form of reduced GHG emissions per kilometer driven.

3 Related literature

This paper, by means of a discrete choice experiment (DCE), explores whether a regulatory incentive may increase the stated willingness to pay (WTP) for cars displaying a fuel efficiency label. In doing so, this paper intersects the DCE literature studying fuel efficiency labels and the literature inferring the impacts from regulatory incentives.

3.1 Studies on preferences for fuel efficiency

Previous studies have analyzed consumers' preferences for fuel efficiency labels in the car market. For instance, Norhasyima et al. (2013) [28] shows that if fuel labels for cars are

[10] http://www.indiaenvironmentportal.org.in/files/file/BEE%20Consultation%20Paper\protect\discretionary{\char\hyphenchar\font}{}{}21Oct2011.pdf

adopted in Malaysia, there will be positive changes in consumers' purchasing pattern. Coad et al. (2009) [13] shows that providing more information through energy label will encourage intrinsically motivated consumers to buy green cars in Switzerland. Haq and Weiss (2016) [20] evaluate the car labeling scheme in European Union. Their results suggest that a 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) [14] test the effect of motor vehicle label on cognitive processing and consumers' car purchase decision in randomized control trials in ten European countries. They show that labels focusing on running costs or fuel economy are more effective in capturing consumers' attention as compared to emissions information. Allcott (2013) [4] shows that U.S. consumers' correctly estimate or slightly underestimates the difference in fuel costs when comparing vehicles with different fuel economy ratings. However, when comparing vehicles with similar rating, they tend to incorrectly perceive zero differences in fuel costs. Noblet et al. (2006) [27] found that environmental attributes are significant in purchase of eco-labeled conventionally fueled passenger vehicles in Maine. They suggest that future labeling initiatives should provide specific emissions information for eco-labeled vehicles. Eco-labeling along with educational campaigns is more effective than eco-label alone.

Studies such as Achtnicht, 2012 [1]; Gaker and Walker, 2013 [16]; Daziano et al., 2017 [15] analyzed the effect of information about emissions on consumers' WTP for vehicles. By means of a DCE, Achtnicht (2012) [1] shows that consumers who are interested in purchasing high price cars (above 20 thousand euros) are willing to pay 108 euros for an emission reduction in 1 gram of CO_2 per km. Consumers who want to buy low price cars (below 20 thousand euros) are willing to pay Euro 38 for an emission reduction in 1 gram of CO_2 per km in Germany. The consumers' concern for the climate change motivates them to consider CO_2 emissions as an important variable in car purchasing decision. Gaker and Walker (2013) [16] show that 24% of their sample were willing to pay a rate of 2.68 US dollars per pound of reduction in CO_2 emissions, and 76% of their sample were not willing to spend time and money to reduce CO_2 emissions in San Francisco. Daziano et al. (2017) [15] discuss how changing information about CO_2 emissions influences WTP for CO_2 reductions in Philadelphia and Boston. If CO_2 emissions were presented in tons per year, then respondents are willing to pay 277 US dollars to reduce emissions by one ton. However, if CO_2 emissions were provided with societal objective, then respondents are willing to pay a higher amount —371 US dollars. These studies compare how presenting information on CO_2 emissions impacts preferences for fuel efficiency. Leard (2018) [23] presents information in terms of fuel costs in U.S., and shows that there is a strong correlation between WTP and stated attention to fuel costs. The respondents' are willing to pay 45 cents to reduce fuel costs by one dollar. Beatty (2016) [7] shows that information in the label in form of five year fuel cost comparison and fuel economy in miles per gallon yields significantly higher WTP for fuel economy investments. Studies such as Allcott and Knittel, 2019 [5]; Kormos and Sussman, 2018 [22] presented information in terms of miles per gallon. Allcott and Knittel (2019) [5] show that when fuel economy information was not provided, the average WTP is 464 and 1,186 US dollars for 5 and 15 miles per gallon improvements, respectively. However, the information on fuel economy reduced WTP by 92 and 238 US dollars for 5 and 15 miles per gallon improvements. This could be because quantitative information on fuel costs corrected consumers biased beliefs. While Allcott and Knittel (2019) [5] found that when fuel economy information was provided, consumers WTP reduced for more efficient vehicles, Kormos and Sussman (2018) [22] shows that the WTP is significantly higher for consumers who were informed about fuel economy label. Kormos and Sussman (2018) [22] show that in U.S. when consumers are not informed about fuel label/fuel costs, they are willing to spend 690 US dollars for each additional mile per gallon. When consumers were shown fuel economy label, they were willing to pay 1,200 US dollars for each additional mile per gallon.

3.2 Studies on the effects from regulatory incentives

In our study, we are interested in exploring whether people would more likely buy efficient cars if a regulatory incentive is imposed in combination with the labels. Incentives to address emissions from the transport sector can take the form of subsidies, taxes, restrictions and investments (Beaudoin et al., 2018 [8]). Various European countries have adopted reduced tax rates and special car lanes for low emission cars. For instance, exemption from motor vehicle tax up to 2020, discounted income tax for fully electric cars (followed in Netherlands), exemption from fuel consumption tax, monthly vehicle tax and deduction in VAT for zero emissions cars (followed in Austria since 2016), etc.

Previous studies have incorporated incentive treatments to influence consumer preferences towards green products (Coad et al., 2009 [13]; Ziegler, 2012 [35]; Alberini et al., 2018 [3]). Coad et al. (2009) [13] show that financial incentives such as subsidies or fines are effective for extrinsically motivated consumers for the purchase of green cars in Switzerland. Ziegler (2012) [35] show that policy instruments of promotion of research and development, taxes and subsidy could increase social acceptance for alternative vehicles such as electric cars and hybrid cars in Germany. Bjerkan et al. (2016) [10] show that incentives in the form of exemptions from purchase tax are most effective in promoting adoption of battery electric vehicles in Norway. Alberini et al. (2018) [3] analyzed the impact of bonus and retrospective malus policy for cars in Obwalden and prospective malus policy for cars in Geneva and Ticino, Switzerland. The bonus rewards new fuel efficient cars and malus is charged for both new and existing high emitting cars. Using difference-in-difference design, the paper showed that the lifetime of existing high emitters is reduced by 5.4% in Obwalden; extended by 3.5% in Geneva and insignificant effects in Ticino. Haan et al. (2009) [19] incorporates fee rebate system on the labeling scheme in Europe, where highly fuel efficient cars (label A) receive cash incentive and highly inefficient cars (label G) pay additional fees. Using microsimulation approach, the paper shows that fee rebate system results in reduced CO_2 emissions of new car registrations by 3.9% - 4.3%, increase in market share of label A car and drop in market share of label G car. Yan (2018) showed that a 10% increase of total tax incentive results in an increase in average sales share of battery electric vehicles by 3% in Europe.

To the best of our knowledge, no previous study has analyzed consumers' preference for fuel labels when accompanied with a regulatory incentive.

4 Theoretical and empirical approach

The Random Utility Model (RUM) provides theoretical support for the empirical analysis of DCE (McFadden, 1973 [24], 1995 [25]; Train, 2003 [33]). The departure point of the RUM is that, when faced to J mutually exclusive alternatives, individual i chooses the alternative that provides him/her with the most utility. An individual's indirect utility from each alternative is denoted as U_{ij} for $i = 1, 2, ..., I$ and $j = 1, 2, ..., J$. The individual is assumed to know his/her own utility function with certainty. The researcher, however, cannot fully observe each U_{ij}. Thus, from the researcher's point of view and once a linear indirect utility function is assumed, U_{ij} is more appropriately expressed as

$$\begin{aligned} U_{ij} &= V_{ij} + \epsilon_{ij} \\ V_{ij} &= \beta^{'} x_{ij} \end{aligned} \tag{1}$$

where V_{ij} is the component observed by the researcher; x_{ij} is a $(M + 1)X1$ column vector denoting M alternative-specific attributes and the alternative-specific intercept; β is a $(M + 1)X1$ column vector representing the alternative-specific intercept, and the preferences for the alternative-specific attributes; and ϵ_{ij} represents the purely random heterogeneity that the researcher is unable to observe.

If an individual chooses the alternative associated to the highest utility, then the individual i chooses U_i^{max}, where

$$U_i^{max} = max\{U_{i1}, U_{i2}, ..., U_{iJ}\} \tag{2}$$

The WTP for the alternative associated to the highest utility is expressed as the monetary value of the utility derived from U_i^{max}, i.e.

$$WTP_i = \frac{U_i^{max}}{\beta_p} \tag{3}$$

where WTP_i is individual $i's$ WTP; and β_p is the price preference parameter. Under the assumption that indirect utility is linear in attributes, including income, β_p is the negative of the marginal utility from income.

However, under the assumptions embedded in equation (1), a researcher cannot observe U_i^{max} as defined in equation (2). He/she can only make statements in terms of expected utilities which are calculated over the error term ϵ_{ij}, i.e.

$$E(U_i^{max}) = E_\epsilon[max\{V_{i1}, V_{i2}, ..., V_{iJ}\}] \tag{4}$$

Under the assumption that ϵ_{ij} is distributed according to a type I extreme value distribution, the expected maximum utility can be calculated through the logsum formula[11].

$$E(U_i^{max}) = ln\sum_{j=1}^{J} exp(V_{ij})$$

Accordingly, statements in terms of welfare measures can also only been made in expected terms. Given a before (b) and an after (a) situations, where after implies that a change in the available alternatives has occurred, the expected value of the compensation variation (CV) due to the change in individual $i's$ utility is expressed as

[11]Pioneer derivations of the logsum formula were independently developed by Ben-Akiva, 1972 [9] and McFadden, 1973 [24].

$$
\begin{aligned}
E_\epsilon(CV_i) &= \frac{1}{-\beta_p}(E_\epsilon(U_i^{max,a}) - E_\epsilon(U_i^{max,b})) \\
&= \frac{1}{-\beta_p}(ln\sum_{j=1}^{J} exp(V_{ij}^a) - ln\sum_{j=1}^{J} exp(V_{ij}^b))
\end{aligned}
\tag{5}
$$

The marginal willingness to pay (MWTP) can be derive from equation (5) as follows. Assume attribute q changes in a non-marginal fashion across all alternatives -i.e. $q^a = q^b + \Delta q$ is the level of q after Δq has been added to q^b. Introduce in equation (5) the change in q, and, because such a change occurs across all alternatives, factor it [12]. The expected CV can be expressed as follows

$$
E_\epsilon(CV_i[\Delta q]) = -\Delta q \frac{\beta_q}{\beta_p} \tag{6}
$$

where β_q is the marginal utility from q. Equation (6) reduces to the WTP for a marginal change across alternatives when $\Delta q = 1$, i.e. when the change in q is marginal, and

$$
E_\epsilon(MWTP_i) = -\frac{\beta_q}{\beta_p} \tag{7}
$$

Equation (7) can be interpreted as the ratio of the marginal utility from the attribute that changes and the negative of the marginal utility from income.

Empirical estimations of the parameters required in the calculation of the expected MWTP (i.e. $\hat{\beta}_q$ and $\hat{\beta}_p$) can be obtained via a conditional logit econometric specification. The departure point of this empirical model is the same as to establish the theoretical expectations of the welfare measures under discrete choice modelling, i.e. ϵ_{ij} is distributed according to a type I extreme value distribution. Under this assumption, the probability

[12] Further details can be found in Haab and McConnell, 2002 [18].

that individual i chooses alternative j is expressed as follows

$$\begin{aligned} P_{ij} &= Pr[V_{ij} + \epsilon_{ij} > V_{ik} + \epsilon_{ik} \forall k \neq j] \\ &= Pr[\epsilon_{ij} > V_{ik} - V_{ij} + \epsilon_{ik} \forall k \neq j] \\ &= \frac{e^{V_{ij}}}{\sum_{k \in J} e^{V_{ik}}} = \frac{e^{\beta' x_{ij}}}{\sum_{k \in J} e^{\beta' x_{ik}}} \end{aligned} \quad (8)$$

The conditional logit (CL) face two limitations to model empirical discrete choice data (Train, 2003 [33]). First, the CL can represent systematic variation (i.e. taste variation that related to observed characteristics) but not random taste variation (i.e. differences in tastes that cannot be linked to observed characteristics). Second, the estimation of the CL probabilities implies proportional substitution across alternatives -more flexible, more realistic patterns cannot be fitted with a CL model [13].

The random parameter logit (RPL) results from adapting the CL model to incorporate non-systematic heterogeneity in preferences and discard the proportional substitution across alternatives. The RPL turns out to be a highly flexible model that can approximate any random utility model (McFadden and Train, 2000 [26]).

The RPL probabilities are the integrals of standard logit probabilities over a density of parameters. That is, keeping in mind equation (8), a RPL is a model whose choice probabilities can be expressed in the following form

$$P_{ij} = \int \frac{e^{\beta' x_{ij}}}{\sum_{k \in J} e^{\beta' x_{ik}}} f(\beta) d\beta \quad (9)$$

where $f(\beta)$ is a density function. Thus the RPL probability is a weighted average of the logit formula evaluated at different values of β, with the weights given by the density $f(\beta)$.

[13] A third limitation, that is not relevant in the context of this paper, is that correlation over time is not captured by the conditional logit model (Train, 2003 [33]).

In statistical terms, the weighted average of several functions is called a mixed function. Consequently, a RPL is a mixture of the logit function evaluated at different $\beta's$ with $f(\beta)$ as the mixing function.

5 Survey methods and data

5.1 Design of discrete choice experiment

We design a discrete choice experiment (DCE) to study car owners' preferences for cars displaying a fuel efficiency label in New Delhi, India. Respondents were presented to three labeled alternatives — the status quo (unlabeled car), high star car (5 or 4 stars) and moderate star car (3 stars). Respondents were informed that fuel efficiency of high star cars is better than moderate star cars' efficiency. We use alternative specific labels so that we are able to infer the preferences for the display of the label in itself.

The relevant attributes of the DCE were identified via a series of focus groups and through a review of the DCE studies inferring preferences for cars' attributes. Five attributes were chosen: price, mileage (kilometers per liter, kmpl), engine displacement, transmission, and social network. Table 1 describes the attributes and their levels.

Notice that all but social network attributes are standard characteristics of a car. The social network attribute is not a feature of the car *per se*. It is an attribute of the people who use the car. Social network is described as the percentage of people in the respondent's social network (family/friends/neighbors/colleagues) that drive the car, and takes values 20% and 60%. Following Rasouli et al., 2016 [30], this attribute tests for the possibility of a peer-pressure effect. This attribute that reflects social network and it is measured in terms of market share of family/friends/neighbors/colleagues purchasing the car described in the alternative.

The price attribute is described as percentage increases with respect to a reference price — 10%, 20%, 30%, 40% and 50%. At the beginning of our survey, respondents were asked to provide the price at which they intend to purchase a car in the near future. We take this reported price as the reference from which percentage increases occur.

The mileage attribute is expressed as kilometers per liter (kmpl). Notice that this attribute is essentially a measure of fuel efficiency. In a DCE that presents unlabeled alternatives, mileage would naturally arise as the attribute providing information about fuel efficiency —and the WTP associated to it would capture the marginal benefits from a unit of efficiency. In contrast, the DCE in this study has been designed to disentangle the WTP for a car with a efficiency label from the WTP for fuel efficiency itself. To justify this design, let us elaborate. As documented by Alberini et al., 2016 [2], what individuals pay for a car displaying an efficiency label may go above and beyond the premium derived from savings on fuel costs. Arguably, this *total* WTP can be decomposed into two components. One component refers to the WTP for gains in fuel efficiency —which is bounded by the individual's expected savings in fuel costs. The second component is the WTP for *knowing* that the car is fuel efficient —this is the *above and beyond* documented by Alberini et al., 2016 [2].[14]

In general, the reasoning behind a DCE suggests the implementation of a design in which the levels of the efficiency attribute (mileage) and efficiency labels are presented in an orthogonal or orthogonal-enough manner. While this is statistically recommendable, in this application the priority is given to keep the scenarios as realistic as possible. This is why, as explained above, the respondents were told that the efficiency of a high star car was better than moderate cars' efficiency. To keep the levels of the mileage consistent with the previous statement, we device a design that allows for certain orthogonality and is consistent with the description of the efficiency labels. Thus, the mileage attribute takes values 20 kmpl and 24 kmpl for the high star label, and 16 kmpl and 20 kmpl for the moderate star label. In this way, the attributes are not completely collinear because the value 20 kmpl is presented for both types of efficiency labels. The statistical implication is that coefficients of each attribute can be estimated.

[14] The reasons for this extra WTP can be behavioral or not. In a companion paper, we explore this point. In this paper, we focus on exploring the impacts from the regulatory incentive on the stated WTP for a car with an efficiency label.

The attribute engine displacement measures the engine's power and is expressed as the size of the engine in cubic centimetres (cc). This attribute takes three possible values - upto 1000cc, 1000-1500cc and more than 1500cc. The attribute transmission takes two values - automatic or manual. In automatic transmission, gears automatically change depending on car and engine speed. In contrast, in manual transmission, driver changes gears manually using clutch pedal as per the driving needs.

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 car, 16, 20 for moderate star car, 13 for status qup	+
Engine Displacement	Upto 1000cc, 1000-1500cc, More than 1500cc	+
Transmission	Manual, Automatic	
Social Network (Market Share among Family/Friends/ Neighbors/Colleagues)	20%, 60%	+

Construction of Choice Sets

Each possible set of choices shown to the respondents is called a choice set. The goal is to create choice sets in an efficient way, i.e. that present alternatives that maximize the information obtained from the respondent. We used a D-optimal design (Carlsson and Martinsson, 2003 [12]). The D-efficient design is based on the variance covariance matrix $X'X$, where X is the design matrix. D-efficiency is defined as (Kuhfeld, 2010 [21]) -

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

where p is number of parameters to estimate. The aim is to choose X so that D-efficiency is maximized. With a D-efficiency of 93.94, our design contains 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 car and moderate star car) and a status quo alternative (presently available unlabeled car). The respondents were asked to choose one alternative in each choice set. Table 2 shows an instance of the choice sets.

Table 2: Example of choice set from the choice experiment of cars

Car Attributes	**Choice Set**		
	High Star Car (Star 4, 5)	**Moderate Star Car (Star 3)**	**Status quo (Presently Available Car)**
Price	40% of the reference price	10% of the reference price	Status quo 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/Neighbors/ Colleagues	60%	60%	
Your Choice (mark one alternative)			

5.2 Regulatory incentive

A novelty of this study is the testing of whether a regulatory incentive may increase car owner's WTP for cars with a fuel efficiency label. This paper implements a split-sample approach through which half of the sample is said that the government is considering the implementation of an environmental regulation. This regulation is described as a policy that is under consideration by the Indian government, and it would restrict the number of days a car can be driven weekly unless the car displays the label reflecting the best fuel efficiency performance —very much resembling the Mexican Hoy No Circula (HNC). This information was provided to respondents before presenting them to the choice sets.

New Delhi's residents are familiar with this type of regulation since a similar policy was implemented in January 2016 and again in April, 2016. Under the 2016 regulation, cars could circulate depending on the ending number of their license plate. Cars with even numbers could only circulate on even dates, and correspondingly for odd numbers. Under this regulation, $PM_{2.5}$ decreased from 316 $\mu g/m^3$ to 223 $\mu g/m^3$ during the second week of January 2016 (Centre for Science and Environment [15]).

Thus, taking advantage of such familiarity, we incorporate the even-odd scheme in our split-sample strategy. Half of the sample was told that a unlabeled or moderate star cars would have to comply with the even-odd rule, and that only the high star cars would be exempted from this rule. Arguably, this regulation provides incentives to drive cars with the best efficiency label. Thus we expect that respondents presented to this regulation have a higher WTP for high star cars than those who are not presented to such a policy.

5.3 Sampling and data collection

The DCE was conducted during October to November 2017 in two neighborhoods of New Delhi. We use a multi-stage sampling strategy to select our sample. In the first stage, we select two districts from Delhi, South Delhi and East Delhi. Residents of both districts belong to middle income to high middle income class families. In the second stage, South Delhi and East Delhi are stratified in three sub-districts —Kalkaji, Defence Colony, Hauz Khas in South Delhi; and Gandhi Nagar, Preet Vihar, Vivek Vihar in East Delhi. Within each sub-district, 84 respondents were presented to the DCE, yielding a sample size of 504 respondents. Half of the respondent within each sub-district, i.e. 42 respondents, were presented to the regulatory incentive described above. Each respondent was presented to 7 choice sets which yields a total of 3,528 individual choice tasks. Each choice set included 3

[15] http://www.indiaenvironmentportal.org.in/files/file/Air-pollution-and-odd-even-for-SC.pdf

alternatives yielding 10,584 individual observations. Out of these 10,584 observations, 5,292 individual observations belong to the sample presented to the regulatory incentive.

5.4 Comparison of means across samples

Table 3 reports the mean value and standard deviation of the socioeconomic variables characterizing respondents in our two samples. The first column reports descriptive statistics for respondents that were *not informed* about the regulatory incentive. The second column reports descriptive statistics for respondents that were *informed* about the regulatory incentive. The third column reports two-tailed t-test statistics on the null hypothesis that the difference in means is zero.

Given the split-sample approach in this study, it is essential that respondents in both samples are as similar as possible in socioeconomic characteristics. The descriptive statistics reported in the first two columns of table 3 and the corresponding t-test statistic suggest that, on average, respondents in both samples are similar when it comes to respondent's age, percentage of male respondents, marital status of respondent, household size, household annual income, education attainment, and occupation. The only exception is number of cars owned by the household. Respondents in the regulation sample seem to have on average more cars than respondents in the no regulation sample. We would like to highlight that while this difference is statistically significant, the order of magnitude can be considered very small for practical purposes —i.e. a difference of 0.20 (1.50-1.71) cars should not be of too much concern when it comes to judging the similarity of these samples.

We are less concerned with similarity of our samples to New Delhi's or national's averages. This is the case because we purposely have sampled our respondents from middle income class neighborhoods, and expect them to be wealthier and more educated than the average household. For instance, while people with graduate or higher levels of education represent around 82% of our samples, they represent 11% of the national population [16]. Also, the

[16] Own estimates based on enrollment in school and higher education (source: MHRD, NUEPA, 2014-15)

average annual household income at the national level is around 0.61 million of Rupees[17] which is around a third of the average income in our samples.

6 Results

In this section, we report the results from empirical specifications on our respondents' stated choices and the corresponding welfare estimates. As reported in section 5.4, we have gathered variables describing the respondent's socioeconomic characteristics. Also, not reported in this document, we have gathered respondent's energy/fuel efficiency knowledge. We exploit this information in a companion paper that digs further in the factors behind WTP heterogeneity. In this paper, we report specifications whose main goal is to explore the potential impact of a regulatory incentive on average WTP for cars with a efficiency label.

Table 4 reports the coefficients yielded by conditional and random parameters logit specifications on respondents' stated choices. For the random parameters specifications, we assume normally distributed parameters for all but the price attribute which is kept constant. Coefficients in table 4 cannot be interpreted as marginal effects but their signs do provide information on the direction of the impacts on individuals' utility.

The first three columns in table 4 report specifications on the sample that was not informed about the regulation incentive. Preferences of these respondents work as a sort of baseline. The last three columns in table 4 report specifications on the sample that was informed about the regulation incentive. The stated preferences of these respondents are expected to differ from those who did not receive the information about the regulation incentive —in particular, we expect that respondents presented to the regulation incentive report a higher WTP for a high star car in comparison to those who were not presented to the regulation incentive.

Focusing on the sample that was not informed about the regulation incentive, we highlight five features. First, with no exceptions, coefficients' signs are the same across conditional

[17] Own estimates based on information provided by the Central Statistics Office in India.

Table 3: Comparison of means across samples

	No regulation sample (A)	Regulation sample (B)		
Characteristic	Mean (Std. Dev.)	Mean (Std. Dev.)	Two-tailed t test on (A)-(B)	
Age (years)	40.44	40.56	-0.17	
	(12.61)	(14.31)		
Male (1 if male; 0 if female)	0.60	0.54	1.36	
	(0.49)	(0.50)		
Married (1 if married; 0 if unmarried)	0.75	0.72	0.75	
	(0.44)	(0.45)		
Household size (number of members)	4.95	5.16	-0.99	
	(2.26)	(2.48)		
Annual household Income (Million of Rupees)	1.53	1.62	-1.11	
	(0.89)	(0.98)		
Education (proportion)				
High School	0.17	0.15	0.62	
	(0.37)	(0.35)		
Graduate or higher	0.81	0.83	-0.52	
	(0.39)	(0.37)		
Other	0.02	0.02	0.00	
	(0.14)	(0.14)		
Occupation (proportion)				
Professional/Service	0.48	0.44	0.91	
	(0.49)	(0.49)		
Business	0.32	0.30	0.49	
	(0.46)	(0.46)		
Student	0.07	0.11	-1.59	
	(0.25)	(0.31)		
Not Working	0.11	0.15	-1.35	
	(0.31)	(0.35)		
Other	0.02	0.00	2..27	**
	(0.14)	(0.00)		
Cars owned by the household (number)	1.50	1.71	-2.04	**
	(1.14)	(1.17)		
Number of respondents	252	252		

** denotes that null hypothesis is rejected with 95% of confidence.

and random parameters specifications —i.e. positive for all but the price attribute. Second, with exception of the moderate star label attribute, statistical significance remains the same across specifications —a moderate star label is a significant attribute only when estimating a random parameters specification. Third, while point estimates across specifications differ, they remain within the same order of magnitude. Fourth, the statistical significance of most of the standard deviation parameters in the random parameters specification suggest the presence of unobserved heterogeneity that the conditional logit is not fit to handle. Fifth, the random parameters specification yields a substantial improvement in statistical adjustment —as implied by the higher absolute value of the loglikelihood function (-2,602 versus -1,348), and the smaller values of the BIC (5,274 versus 2,826) and AIC (5,221 versus 2,728) which weigh the improvement in the likelihood function versus the increase in estimated parameters implicit in the random parameters specification. With slight differences, the same five features just mentioned apply to specifications on the sample that was informed about the regulation incentive.

The five features highlighted in the previous paragraph for both sets of specifications allow us to conclude that i) all attributes considered in this DCE are relevant for respondents; ii) the directions of the effects from the attributes are robust across specifications; and iii) random parameters specifications represent an improvement in statistical fit over the conditional logit specifications. All together, these conclusions drive us to believe that we can rely on the random parameters specifications to infer welfare measures for both samples.

We also highlight that, when comparing random parameters specifications across no incentive versus incentive samples, most coefficients are practically identical —including the price parameter. One important exception is the parameter associated to the high star label which, together with the identical price parameter, implies that the WTP for a car with the best efficiency label differs across samples. We test this intuition and report results from comparisons in table 5.

Table 5 reports each attribute's marginal WTP as implied by the random parameters logit specifications reported in table 4. The first three columns report numbers for the sample of respondents that were not presented to the regulation incentive. These columns, respectively, refer to the WTP estimates expressed in thousands of Rupees, the WTP estimates expressed in thousands of dollars, and the 95% confidence interval of the numbers in dollars [18]. The next three columns in table 5 report values for the sample of respondents that were presented to the regulation incentive. The last column in table 5 report the p-value on the t test that compares the average WTP across subsamples. Our discussion focuses on amounts in dollars.

Focusing on the WTP estimates for the sample of respondents that were not told about the regulatory incentive, we emphasize that the average marginal WTP for a car with the best efficiency label is estimated at 4.93 thousand US dollars. The corresponding value for a car with the second best label is around 3.80 thousand US dollars. In terms of order of magnitude, these results seem consistent with the economic expectation that an individual would want to pay more for a car with the best efficiency label —the confidence intervals do not allow for the rejection of the null hypothesis though. To put these numbers in context, keep in mind that, before responding the DCE, individuals were asked to report the price of a car they would buy in the near future. The average of this reported prices is Rupees 12,85,496 equivalent to 19.79 thousand US dollars. That is, a efficiency label would increase the WTP for a car by around 25% and upto 38% under regulatory incentive scenario.

The previous numbers refer to the WTP to buy a car that displays a fuel efficiency label but the WTP for efficiency in itself is obtained from the parameters associated to the mileage attribute. An extra kilometer per liter is valued at around 210 US dollars. To judge whether this number is reasonable, it should be compared against the savings in fuel costs over the lifetime of an average car in New Delhi. Thus, assuming a car with fuel efficiency of 21 kmpl that is driven 12,600 kilometers a year [19] for an average of 10 years, and a gasoline price of Rupees 70 per litre, the savings on fuel costs would represent Rupees 19,090 which are equivalent to around 275 US dollars. Thus, respondents' WTP for an extra kilometer per

[18] We use a exchange rate of 1USD = 64.965 INR, as average of the observed value from October-November 2017.

[19] https://timesofindia.indiatimes.com/business/india-business/indian-commuters-travel-35-km/day-says-survey/articleshow/63140954.cms

litre is in line with 10-year fuel costs savings.

With respect to the two structural attributes in our DCE, the estimated marginal WTP for engine's power is around 3.32 thousand US dollars when the engine is bigger than 1,500 cc, and around 1.88 thousand US dollars when the engine is between 1,000 and 1,500 cc. These results also follow the economic intuition that, at least in point estimates, people would want to pay more for more power. Also, a car with automatic transmission is valued at 1.42 thousand US dollar more than a car with manual transmission.

Finally, consistently with results reported by Rasouli et al., 2016 [30], we find that respondents do attach value to the percentage of social network that drives a car similar to theirs. In particular, respondents report an increase in WTP of around 30 US dollars for a car that is driven by 1% of their social network.

With exception of social network and high star label, the WTP for all attributes do not differ across samples. For the case of social network, the WTP among respondents presented to the regulation incentive becomes zero. For the case of the high star label, the WTP is higher among respondents faced to the regulatory incentive —by 51.5%.

We wish to highlight that these results are in line with what we would expect in case the regulatory incentive works. That is, the regulatory incentive should not change the WTP for car attributes but only for the high star label. As a car with moderate star label is not subject to the regulatory incentive, we should not expect an increase in WTP for this label. The difference across samples in the WTP for social network may reflect that respondents shift their attention to the efficiency related attributes when faced to the regulatory incentive.

7 Conclusions and discussion

This study documents that, in the stated preferences space, a regulatory incentive implemented simultaneously with a fuel efficiency label may be expected to increase the demand from New Delhi's residents for cars displaying the best efficiency label. This result is relevant for policy makers aiming to reduce greenhouse gases (GHG) produced by the transportation

Table 4: Econometric specification on respondents' stated choices

	No Regulation Incentive			Regulation Incentive		
Attribute	**Conditional Logit**	**Random Parameters Logit**		**Conditional Logit**	**Random Parameters Logit**	
		Mean	**SD**		**Mean**	**SD**
High Star Label	0.923***	1.987***	-0.04710	1.647***	2.722***	1.562***
	(0.22)	(0.32)	(0.19)	(0.22)	(0.36)	(0.21)
Moderate Star Label	0.1750	1.521***	0.670***	0.2250	1.575***	0.189
	(0.17)	(0.26)	(0.15)	(0.17)	(0.27)	(0.32)
Mileage (kmpl)	0.0338*	0.0853**	0.419***	0.0184	0.0803**	0.388***
	(0.02)	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)
Engine (More than 1500 cc)	0.627***	0.867***	1.471***	0.364***	0.532***	-1.374***
	(0.09)	(0.17)	(0.26)	(0.09)	(0.18)	(0.25)
Engine (1000- 1500 cc)	0.354***	0.450***	0.244	0.282***	0.503***	-0.2090
	(0.09)	(0.12)	(0.23)	(0.09)	(0.13)	(0.24)
Automatic Transmission	0.269***	0.506***	0.801***	0.215***	0.529***	-1.097***
	(0.07)	(0.13)	(0.24)	(2.85)	(0.14)	(0.23)
Network (%)	0.0109***	0.0118***	0.0216***	0.0062***	0.0029	-0.021***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Price (Rupees/1,000)	-0.003***	-0.006***		-0.002***	-0.006***	
	(0.0002)	(0.0004)		(0.0002)	(0.0004)	
Log Likelihood	-2602.6200	-1348.93		-2513.7781	-1287.5906	
AIC	5221.23	2727.854		5043.556	2605.181	
BIC	5273.82	2826.464		5096.148	2703.79	
LR chi2	673.30***	640.96***		850.98***	671.69***	
Respondents	252	252		252	252	
Observations	5,292	5,292		5,292	5,292	

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

Table 5: Marginal Willingness to Pay implied by random parameters logit specifications

	No Regulation Incentive			Regulation Incentive			
Attributes	**MWTP (thousands of Rupees)**	**MWTP (thousands of US dollars) (A)**	**95% CI (thousands of dollars)**	**MWTP (thousands of Rupees)**	**MWTP (thousands of US dollars) (B)**	**95% CI (thousands of dollars)**	**p-value of t-test on (A)-(B)**
High Star Label	320.69*** (47.91)	4.936*** (0.74)	[3.49, 6.38]	486.00*** (59.91)	7.481*** (0.92)	[5.67, 9.29]	0.0156
Moderate Star Label	245.46*** (38.50)	3.778*** (0.59)	[2.62, 4.94]	281.17*** (43.67)	4.328*** (0.67)	[3.02, 5.64]	0.2699
Mileage (kmpl)	13.76*** (5.80)	0.212*** (0.09)	[0.04, 0.39]	14.34*** (6.93)	0.221** (0.11)	[0.01, 0.43]	0.4744
Engine (More than 1500 cc)	139.90*** (27.15)	2.154*** (0.42)	[1.34, 2.97]	94.95*** (31.93)	1.462*** (0.49)	[0.50, 2.42]	0.1414
Engine (1000 - 1500 cc)	72.71*** (20.05)	1.119*** (0.31)	[0.51, 1.72]	89.83*** (23.43)	1.383*** (0.36)	[0.68, 2.09]	0.2891
Automatic Transmission	81.67*** (19.89)	1.257** (0.31)	[0.68, 1.86]	94.40*** (24.22)	1.453*** (0.37)	[0.72, 2.18]	0.3422
Network (%)	1.90*** (0.51)	0.029*** (0.01)	[0.01, 0.05]	0.51 (0.57)	0.008 (0.01)	[-0.01, 0.02]	0.0380

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

sector. This problem is more urgent than ever as recent years have witnessed unprecedented air pollution episodes in megacities around the world —e.g. New Delhi, Beijing, Mexico.

In particular, this study documents that respondents' WTP for a car with the best efficiency label goes from 4.93 thousand US dollars to 7.48 thousand US dollars to avoid being subject to a regulation that is described as restricting the number of days a car can be driven weekly unless the car is awarded the best efficiency label. This description very much resembles the Mexican Hoy No Circula (HNC) and, at the same time, a temporary policy that New Delhi's residents experienced in January and April, 2016.

The extra 2.55 thousand dollars that our respondents are willing to pay in this context is directly comparable to the estimates reported by Blackman et al. (2018) [11]. By means of a contingent valuation protocol, they estimate the regulatory costs from the Mexican HNC, or alternatively, the costs to avoid being subject to the regulation. Once protest zeros are excluded, they estimate an average WTP of 345 US dollars a year per car. This number, once multiplied by the average age of a car in Mexico (i.e. 8.6 years)[20], yields 2.96 thousand US dollars which can be interpreted as the WTP to avoid the regulation over the lifetime of an average car. Our estimate of 2.55 thousand US dollars is in the same order of magnitude than their 2.96 thousand US dollars.

With respect to future research, our random parameters specifications point to the presence of unobserved heterogeneity that deserves to be explored. We have gathered relevant socioeconomic characteristics and respondents' knowledge about fuel/energy efficiency knowledge. A companion paper explores the respondents' characteristics associated to the unobserved heterogeneity in preferences.

[20]See World Bank (2010) [34].

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