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The Impact of Personalised Digital Information on the Efficiency of Vehicle Choices in Developing Countries

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Abstract

Information on operating costs can enable potential buyers to purchase more fuel-efficient vehicles. We test this hypothesis with a randomised controlled trial in a developing country, Nepal, using personalised information provision on a unique web-based platform. We find that receiving information on five-year operating cost savings improved the fuel economy of motorcycles that respondents selected on the platform (stated preference), and the models that they actually purchased (revealed preference), compared to receiving fuel economy information. Furthermore, the treatment was particularly effective with respondents who displayed behavioural anomalies. Our study provides novel evidence on the effectiveness of information provision in low-education settings, where the opportunity cost of collecting information may be high.

JEL Classification: D1, D8; Q4; Q5

Keywords: Fuel economy; Operating costs; Energy labels; Behavioural anomalies; Randomised informational intervention; Nepal

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1 Introduction

Air pollution in large cities in the developing world is one of the most pressing environmental challenges the world faces, with several associated risks to health, productivity, and well-being more generally. While there are several causes for extensive air pollution in urban areas of developing countries, one of the biggest contributors is the transport sector. For instance, in Kathmandu, the capital of Nepal, vehicle emissions are the main source of pollutants such as particulate matters (PM) (Stockholm Environment Institute, 2009). In some low-income settings, the transport sector is also the single largest source of CO_2 emissions: in 2020, its contribution was about 40% in Nepal (Ritchie et al., 2020). Thus, augmenting the efficiency of vehicles in developing countries, especially motorcycles, which are the most commonly used mode of private transport in many urban areas, has the potential to not only address local environmental problems but it can also play a role in mitigating global warming and climate change.

On the demand side, the choice and purchase of a vehicle, which is a durable good, is a complex investment decision. It can be based on several criteria, one of the most important being the lifetime cost, which includes the purchase cost and lifetime operating costs of owning and using a vehicle. However, individuals often fail to take optimal decisions with respect to investing in cost-minimising as well as energy-efficient choices, due to market failures as well as behavioural anomalies (Gillingham and Palmer, 2014; Gerarden et al., 2015). These barriers can prevent them from correctly identifying the cheapest vehicle to own over the long-run and result in them underestimating future fuel cost savings. For example, consumers may be imperfectly informed about the fuel economy of vehicles (imperfect information), or they may pay insufficient attention to it when deciding which vehicle to buy (inattention). Likewise, an inability to compute the operating costs of owning a durable good such as a vehicle (cognitive limitations) as well as myopia and present bias may prevent individuals from realising the cost-savings from purchasing more fuel-efficient vehicles, and make them focus on the upfront costs of the purchase instead. In the economics literature, such factors have been found to hinder the adoption of both more energy-efficient vehicles as well as other durable goods, such as appliances (Allcott and Knittel 2019; Boogen et al. 2022; d'Adda et al. 2022; Filippini et al. 2021b,a).

It is important to note that the vast majority of these studies have been conducted in developed countries, where average levels of income as well as education are high. The economics literature investigating the hurdles towards the adoption of energy-efficient technologies in developing countries is sparse, with the exception of some recent studies (for example, Berkouwer and Dean (2022) on the adoption of energy-efficient cook-stoves and Rom et al. (2023) on solar lamp adoption, both studies with a focus on Kenya). To our knowledge, no study has evaluated the factors influencing the adoption of fuel-efficient vehicles in developing countries, and the role of information provision in particular.

In our study, we have a primary and a secondary goal. The primary objective is to determine whether providing information about the operating costs of motorcycles through a web page, in which consumers can select and compare different models, helps them choose more efficient models [1]. We hypothesise that such information can be particularly effective in developing countries, where individuals often tend to be liquidity-constrained (and thus they may be drawn to the information on savings), and low levels of education imply that calculation of these costs may be onerous. The secondary goal is to analyse if the information about the operating costs is more effective in improving the efficiency of choices for sub-groups of the population who may display behavioural anomalies, such as present bias or weak abilities to calculate lifetime costs, or do investment analysis.

In this paper, we study the role of information provision in encouraging potential motorcycle buyers

[1] In this study, we use the term 'motorcycle' as a catch-all to denote traditional motorcycles, internal combustion engine-based scooters and electric scooters.

in urban Nepal to make more fuel-efficient vehicle choices and address some of the behavioural anomalies described above. For this purpose, we created a unique web-based information platform that provided information on the most sold motorcycle models (more than 100 of them) on the Nepalese market. We then implemented a randomised intervention on the platform in which we provided personalised information (based on respondent-specific driving distance needs) on annual operating cost savings/expenses (Treatment group 1), and on five-year operating cost savings/expenses (Treatment group 2) of each model relative to the average model, in the form of labels. The control group was shown information on the models' fuel economy, also using energy labels. Through this intervention, we analyse the impact of providing information on the fuel economy of motorcycles. As outcome variables, we firstly consider the preferred choices of the respondents on the platform (in a stated preference analysis), and secondly the actual purchases made or intended to be made about four months after they made the hypothetical choice made on the platform (in a revealed preference analysis).

Our main results from the stated preference analysis (N=972) indicate that respondents in Treatment group 2 (who were provided five-year operating cost information) selected motorcycles on the platform that were about 1.4% more efficient than the control group. We do not find significant effects for the provision of annual operating cost information (Treatment group 1) on the fuel economy of choices. Furthermore, the revealed preference analysis confirms that Treatment 2 effectively improves the fuel economy of the motorcycles. Respondents in this group who purchased or declared to be close to the purchase of a motorcycle (N=224) bought or selected models that had a high fuel economy than the models chosen by the Control group. In our baseline specification, we find that respondents in Treatment Group 2 bought (or intended to purchase) motorcycles that were 3.7% more efficient in terms of fuel economy compared to respondents in the control group. This corresponds to an average fuel economy of about 47.69 km/l for Treatment group 2 respondents, compared to 45.72 km/l for the control group. Importantly, this result is also confirmed by considering only respondents who purchased a motorcycle (N=66). In this case, respondents in Treatment Group 2 bought motorcycles that were about 2.3% more efficient than the Control group.

We also observe a significant and positive difference in the level of fuel economy of the motorcycle chosen in reality (revealed choices) compared to the fuel economy of the models selected on the platform (stated choices) for respondents in Treatment group 2, suggesting that they may have taken the information more seriously when it came to the actual purchase of the motorcycle, compared to the hypothetical choice they made on the website. Lastly, and in the same vein, we find that respondents in Treatment group 2 were also less likely to actually purchase a motorcycle compared to Control group respondents, whereas we do not find this effect for Treatment group 1. This also suggests that the five-year operating cost savings/expenditure information may have made the respondents think more seriously about their purchase.

Based on these findings, we infer that respondents in Treatment group 1 may not have been able to project the annual operating cost savings/expenditure information over the lifetime of the motorcycle, due to factors such as myopia, present bias, or limited cognitive skills. The provision of five-year information, on the other hand, is better-equipped to overcome these barriers: in the heterogeneity analysis, we find that the positive effect of five-year operating cost savings/expenditure information on fuel economy choices was apparent for individuals who were impulsive, myopic or who exhibited low levels of cognitive skills. Thus, this treatment was effective in improving the efficiency of choices of individuals with behavioural anomalies. On the other hand, we do not find significant effects of Treatment 1 on their choices, except on those of individuals with low cognitive skills.

As in previous studies, it is not straightforward to disentangle which anomalies our treatments are able to address. While we believe (and show) that our treatments, particularly five-year operating cost savings information, played a role in improving the efficiency of choices of individuals who were myopic, present-biased as well as facing cognitive limitations, we cannot rule out that our treatments may have also addressed other behavioural anomalies.

Our study fits into a relatively rich stream of literature that analyses the barriers towards investment in energy-efficient vehicles. For example, there is empirical evidence to suggest that consumers may not be adequately informed about fuel economy, or on the repercussions of their choices on the environment or on air pollution, and that they often make errors in estimating fuel costs (Teisl et al., 2008; Turrentine and Kurani, 2007). Sallee (2014) proposed in a theoretical framework that it may, in fact, be rational for consumers to be inattentive to fuel costs in purchasing vehicles, given that the computation of these costs is onerous, and requires considerable time and effort. In a previous study, we explored this in the Nepalese context as well using a stated preference methodology, while focusing on the adoption of electric two-wheelers (Filippini et al., 2021b).

A sub-strand of these studies have focused on the role of consumer myopia with respect to operating costs. There is mixed evidence to suggest that consumers, at least in industrialised country settings, are myopic with respect to fuel costs (Busse et al., 2013; Grigolon et al., 2018; Gillingham et al., 2021). There are fewer studies in developing countries (Li et al., 2020), except a study on China by Xiao and Ju (2014) who showed that consumers did not respond to increases in fuel taxes by selecting more efficient vehicles, suggesting that they were more responsive to the purchase costs compared to the fuel costs of a car.

This paper also finds place in the stream of literature that evaluates policy options to address some of the barriers highlighted above towards the adoption of more energy-efficient durables. There are several stated-choice studies that have evaluated the role of information provision in the form of labels in the context of the adoption of energy-efficient durables (such as appliances and vehicles) (Davis and Metcalf, 2016; Newell and Siikamäki, 2014; Long et al., 2021; Dumortier et al., 2015; Codagnone et al., 2016; Brazil et al., 2019). The general take-away from this literature is that the type of information provided can influence choices of individuals; for example, studies related to vehicle adoption show that respondents participating in stated choice experiments are more likely to respond to information on fuel economy or operating costs rather than on fuel consumption or on environmental impacts, i.e., framing effects can be very important.

Revealed preference studies have also evaluated the effects of information provision on the adoption of energy-efficient appliances and light bulbs, again with mixed results (Boogen et al., 2022; d'Adda et al., 2022; Allcott and Taubinsky, 2015; Gao and Tavoni, 2023; Rodemeier and Löschel, 2023). To the best of our knowledge, only one study has focused on the impact of information provision on the actual adoption of vehicles. Allcott and Knittel (2019), showed using both an in-store as well as an online experiment that providing fuel cost savings information did not lead to significant gains in the efficiency of vehicles purchased by a sample of consumers in the US. They argued that while this may imply that imperfect information and inattention did not hinder the fuel economy choices of consumers, the interventions may also have been ineffective for other reasons, such as cognitive limitations, lack of trust, etc.

Allcott and Knittel (2019) is the study that is closest to ours, in terms of the research questions addressed, and also partially in terms of the experimental design. However, our paper differs from theirs on three important dimensions: firstly, we investigate the role of operating cost information provision on vehicles in a developing country where a) average education levels are low, and thus knowledge of fuel economy and fuel cost savings may not be very high, b) a lack of fuel economy labelling implies that many manufacturers do not prioritise providing fuel economy information to buyers, and c) the potential for operating cost savings by choosing more efficient models is high, given the variation in fuel economy even within motorcycle models of the same engine size. We believe that energy labels may have a role to play in settings such as urban Nepal, due to the reasons mentioned above.

Secondly, Allcott and Knittel (2019) provided information to respondents at the point-of-sale in one experiment and in an online experiment, but in both cases, the information provision was one-shot, i.e., respondents did not have the possibility to go back and view the information again. As the authors themselves pointed out, some participants in their study forgot the content of the informational interventions. In comparison, we have developed and utilised a digital tool that enables the respondents to have easy access to the information, and for us to track search behaviour of respondents over time and examine how choices made on websites change over time. This also sheds some light on whether or not there are any learning effects over time.

Lastly, in comparison to Allcott and Knittel (2019), we show that there are distinct effects of providing information on annual operating cost savings/expenses, compared to five-year operating cost information. In their study, Allcott and Knittel (2019) provided both the annual cost savings/expenses of each car model that respondents were interested in, as well as the cost savings over the lifetime (which was the self-reported expected period of ownership). Thus, they are unable to disentangle the relative magnitude of the effects from providing these two pieces of information. We show that these two treatments have different effects, at least in our context. Our explanation for these findings is that respondents may be failing to project the information on annual operating cost savings/expenses over the lifetime of ownership.

Our contributions to this literature are thus threefold: we are the first, to the best of our knowledge, to test the impact of information provision on the efficiency of actual vehicle choices in a developing country setting. This is important, because consumers in developing countries face very different challenges towards the adoption of durable goods such as vehicles than those in industrialised countries (Kremer et al., 2019), especially factors such as present bias, liquidity constraints and myopia. Secondly, we are among the first to investigate the role of operating cost information provision on the choices of individuals exhibiting behavioural anomalies. Third, to the best of our knowledge, our study is one of the first to use both revealed and stated preference approaches to evaluate vehicle choices in developing countries. Lastly, we also shed light on the role of digital comparison tools, such as the web-based platform, in enabling consumers in developing countries with smartphones and internet connectivity to access information, and use them in decision-making.

The policy implications of this study are related to the value of information provision on the operating costs of vehicles in developing countries, and on the role of labels. Many developing countries, including Nepal, do not currently have energy labels for vehicles such as motorcycles, even though many of them are considering implementing this policy measure. Our study suggests the importance of incorporating monetary savings information on energy labels in developing countries, and not just providing fuel economy. Information provision is critical to not only inform buyers about fuel economy and energy savings, but also to nudge producers to improve the efficiency of their product offerings (and, as we show in our results, to also make them think twice about purchasing a vehicle). This study shows that the type of information can also influence the efficiency of vehicle choices, especially in settings where individuals may be less likely to undertake lifetime cost calculations.

Using back-of-the-envelope calculations, we show that providing five-year operating cost savings information on labels in Nepal, as opposed to fuel economy information, could amount to net benefits of roughly USD 1.8 million over five years, considering the reduction in CO_2 emissions, the potential monetary savings to consumers, and the cost of developing the platform. However, this is likely an underestimation, given that the country currently does not have mandatory fuel economy labels for motorcycles, and given that we do not take into account the potentially large benefits from the possible reduction in air pollution.

Fuel economy labels are often accompanied with emission standards, and there are costs to implementing standards in developing countries. While we cannot use the results of this study to discuss about the validity of fuel economy standards in developing countries like Nepal, Allcott and Knittel (2019) argue that in case consumers are systematically biased against buying fuel-efficient vehicles, stringent fuel economy standards (such as the CAFE regulation in the US) may be justified. However, if information interventions can help address some biases (and we infer that they do in our case), standards can also be less strict. Information provision can thus also be seen as a useful policy tool to complement other policy measures.

The organisation of this paper is as follows: in section 2, we present the data, experimental design and methods that we use for the analysis in this paper, section 3 presents the results, and we conclude and discuss policy implications in section 4.

2 Data and Empirical Approach

Our experimental design relies on evaluating the effect of randomised information-based treatments on both the stated as well as revealed motorcycle choice of respondents. We recruited potential buyers of motorcycles in Nepal (individuals who were looking to purchase a motorcycle in the next 3-6 months), and developed and utilised a unique web-based platform to conduct the stated-choice experiment. In the sub-sections below, we discuss the recruitment of respondents, the experimental design and the content of the treatments, the functioning of the web-based platform, as well as the empirical approach adopted in the study. Appendix A contains details on the web platform functionality, as well as the questionnaires used for the surveys in the study.

2.1 Phases of the Study

The study consists of four phases: i) recruitment and randomisation of participants (Phase 0), ii) platform activity and baseline survey (Phase 1), iii) reminders (Phase 2), and iv) the follow-up survey (Phase 3). During phase 1 we organised the stated choice experiment, whereas in phase 3 we collected the information on the motorcycles bought or close to be bought by the respondents (revealed preference outcomes). Table 1 shows a timeline of these phases.

Table 1: Study phases and timeline

Phase	Description	Time Period
Phase 0	Recruitment, randomisation and web-based plattform	February 2023–March 2023
Phase 1	Platform use and baseline survey (stated preference)	April 2023–June 2023
Phase 2	Reminders (for continued platform use)	July 2023–September 2023
Phase 3	Follow-up survey (revealed preference)	October 2023–November 2023

This table provides a timeline of the four phases of the study. The initial planned start of the study was in August 2022 but the fieldwork needed to be delayed due to the Covid-19 situation in Nepal.

Figure 1 provides an overview of the workflow and data collection steps of these phases. For the purpose of conducting this study, we collaborated with a Nepali survey company (Facts Nepal) which was involved in the recruitment of the respondents for the study, as well as in administering the data collection. Figure 2 provides the information on the sample sizes by different phases of the study.

Phase 0- Recruitment phase: Our survey partner sampled for 3300 respondents, primarily living in Kathmandu Valley, who agreed to participate in our study between February and April 2023. Eligible respondents were identified based on whether they were at least of the legal driving age (16 years in Nepal), whether they were likely to be the main users of the motorcycle, whether they had a touch-screen phone (to be able to access the platform for the treatments, as well as complete the surveys) and whether they were looking to purchase a motorcycle in the next 3-6 months. Respondents

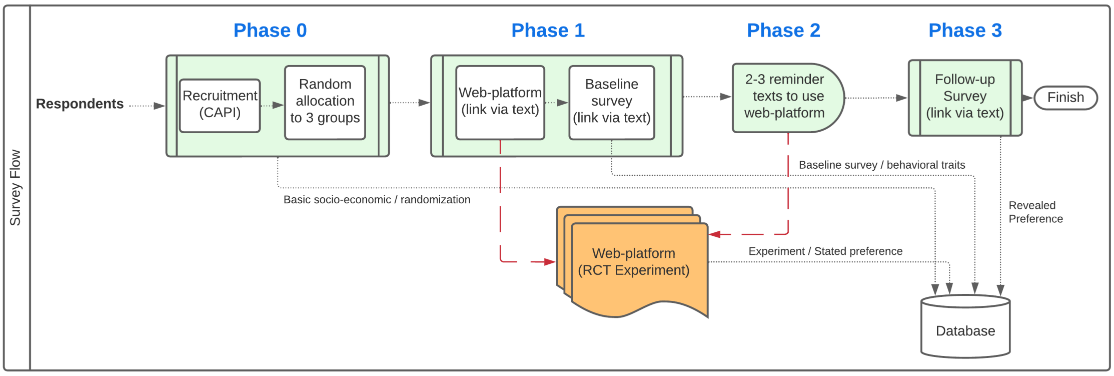


Figure 1: Study workflow and data collection steps

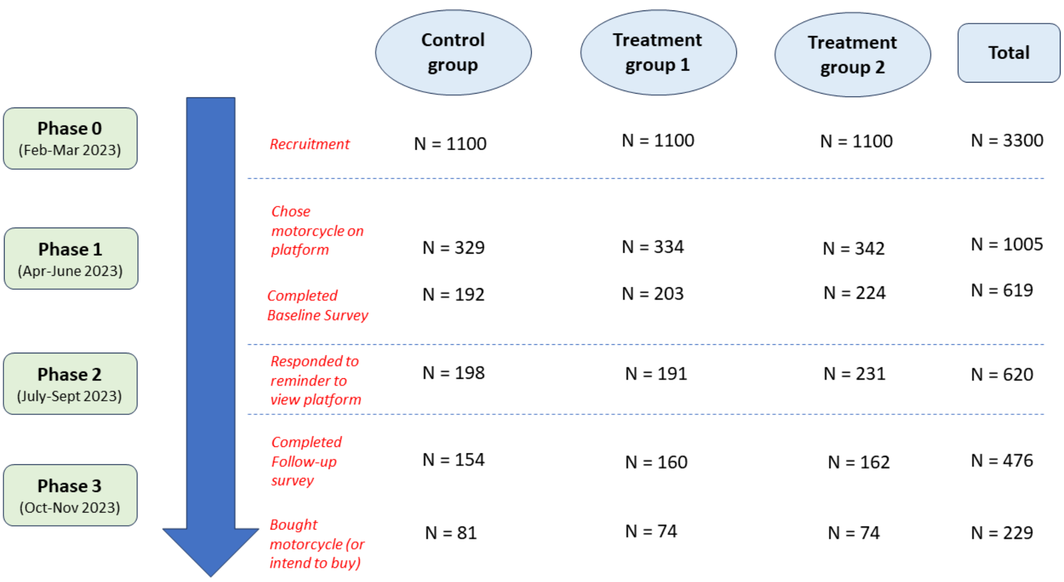


Figure 2: Timeline of Project and Number of Observations

were recruited by study enumerators outside motorcycle shops and garages, universities and offices, and near access points for public transport (such as bus-stops), and the initial information was collected in the form of computer assisted personal interviews (CAPI).

During the recruitment phase, enumerators elicited basic socioeconomic information from the respondents such as their gender, age, occupation, income, their likelihood of purchasing a two-wheeler within the next three months and their educational attainment. This information was used for the re-randomisation and in the allocation of respondents across the three groups. We utilised a re-randomisation process whereby we balanced the three groups on the basis of these variables, and an equal number of respondents were allocated to each of the three groups (the Control group, Treatment group 1 and Treatment group 2), namely 1100 respondents per group. The enumerators also informed the respondents about the goals of the study, the conditions as well as incentives for participation, data privacy and provided the respondents instructions to participate in the study.

Web-based Platform

A unique feature of our study is the creation of a specialised web-based platform where participants in our study could search and compare different motorcycle alternatives available on the Nepalese market. With the help of this platform, we were able to determine the choices of prospective motorcycle buyers (in a stated choice setting). Moreover, we could implement randomised information-based interventions and objectively measure any potential impact on users' comparison activity, as well as on their motorcycle choice.

Users who agreed to participate in our study received a unique link to access the platform. This link comprised the platform address (URL) and two additional identifiers, a unique *user-id*, and the allocated *group-id*. When the user clicked on the link, the platform was able to record their unique user id, and linked it to their platform session activity. On the comparison page, every user had access to the same type of information, **except** the information on the energy labels which varied by treatment group.

Phase 1- Stated choice and baseline survey phase: Once the respondents were allocated across the three groups, our survey partner reached out to the respondents via text message and sent them the website links for the platform, and for accessing and completing the baseline survey. Respondents received individualised website links, depending on their unique user id and the group that they belonged to, and they were informed that they would be incentivized for both browsing through the website, and for clearly indicating which motorcycle they preferred to buy (the stated choice of the respondents).[2] We separated sending the links to access the website and the baseline survey into two steps, to minimise the information provided to the respondents in each text message which would also reduce the risk of attrition and the cognitive load imposed on them. At the end of this phase of the study, we were able to obtain the preferred choices of about 1005 respondents on the website: some of these respondents used the website several times. In these cases, we recorded the last choice of the respondents for our econometric analysis.[3] Thus, phase 1 provides us the stated choice outcomes of the respondents, and we are able to confirm that the three groups are balanced in terms of observable characteristics (we discuss about attrition in further detail in the next section). The detailed baseline survey questionnaire is included in Appendix A.

Choice on the web-based Platform

[2]Respondents were paid with Rs.100 worth of cellular phone data/'top-up' for completing Phase 1 (selecting a motorcycle on the platform, and completing the baseline survey), Rs.50 worth of top-up for using the website during Phase 2 and Rs.50 worth of top-up for completing the follow-up survey. The total incentive amount of Rs. 200 is equivalent to about USD 1.50 woth of mobile top up.

[3]As also mentioned in Section 3.3, control group respondents during Phase 1 used the website a total of 1.61 times, whereas Treatment group 1 respondents used it 1.34 times and Treatment group 2 respondents used it 1.47 times. The median number of times respondents in each of the groups used the website is one.

Users were asked to enter their location (city of residence) as well as how much they expected to drive their motorcycles per day (in kilometres) as a first step on the landing page of the platform. They could then select motorcycle alternatives by make and model to obtain a side-by-side comparison of up to three motorcycles at a time. On selecting models to compare, respondents were presented with energy efficiency information in the form of energy labels; the information provided on these energy labels varies across the three groups and constitutes our informational intervention, which we describe in further detail in the next sub-section. Furthermore, they could also access information on other motorcycle attributes, such as its price, transmission (manual or automatic), fuel type, engine power, dimensions and electrical features, which was included below the energy labels. After viewing the information on the motorcycle models in their choice set, participants were required to indicate the motorcycle model they would like to purchase, by clicking a button below the relevant model: this constitutes their stated choice.[4] Users also had the option to use the platform several times, and modify their previously selected motorcycles, if they wanted.

Information-based Treatments

There are several possible modes of information-based nudges in the context of a web-page. One example is providing information on fuel economy, which can be done either with or without energy labels. Generally, energy labels for vehicles in industrialized countries at least provide information on fuel economy or energy consumption, and in some cases also on operating costs. Few developing countries have introduced energy labels in the transport sector. Due to the fact that some developing countries (such as India) use labels in the transport sector, we decided to design our treatments using energy labels in this study. For this purpose, we adopted the design and format of existing labels for four-wheelers in neighbouring India, as Nepal currently does not have fuel economy labels either for motorcycles, or for cars.[5] While we implemented the treatments in the form of a label, we are not testing the effectiveness of the energy label in this study, as both treatment groups and the control group were shown energy labels, but with different information.

Figure 3 shows English translations of the three different types of labels used in the randomised information-based intervention (the text in the labels was translated to Nepali during the study). Appendix A1 contains screenshots from the platform showing the functionality of the webpage, and demonstrates forms of information provision across the control and treatment groups.

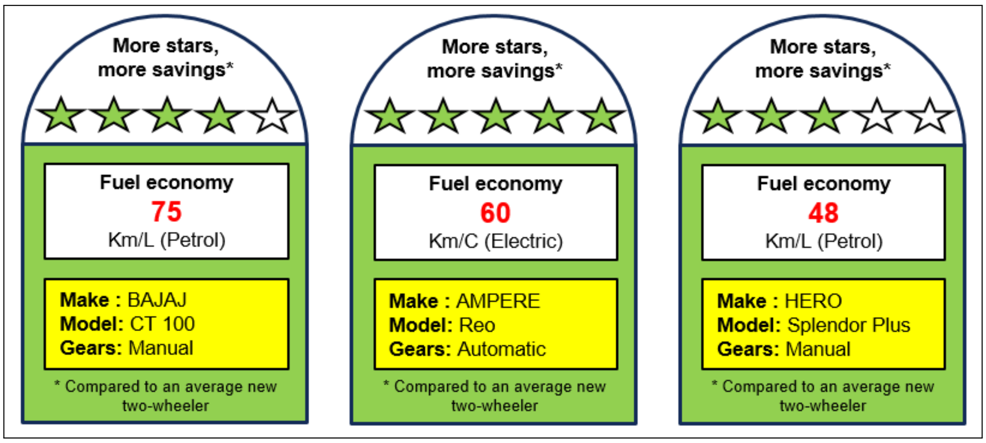
All energy labels, irrespective of the group, had the same colour theme, design, size, as well as font, text colour and text size. The energy labels comprised three pieces of information, two of which were consistently provide across the groups– star ratings[6] found on the top of the label, and the fuel economy of the model (in kilometres per litre, or km/l) mentioned below this in a box with a white background. The piece of information that was different across the three labels was placed at the bottom of the label in a box with a yellow background.

For the **Control group**, the energy label included information on the make, model, and gears (automatic or manual) in this yellow box, along with the fuel economy and the star ratings, as mentioned above.**Treatment group 1** saw, in addition to this information, personalised information on annual operating fuel cost savings/expenditure for the model in question, relative to the average

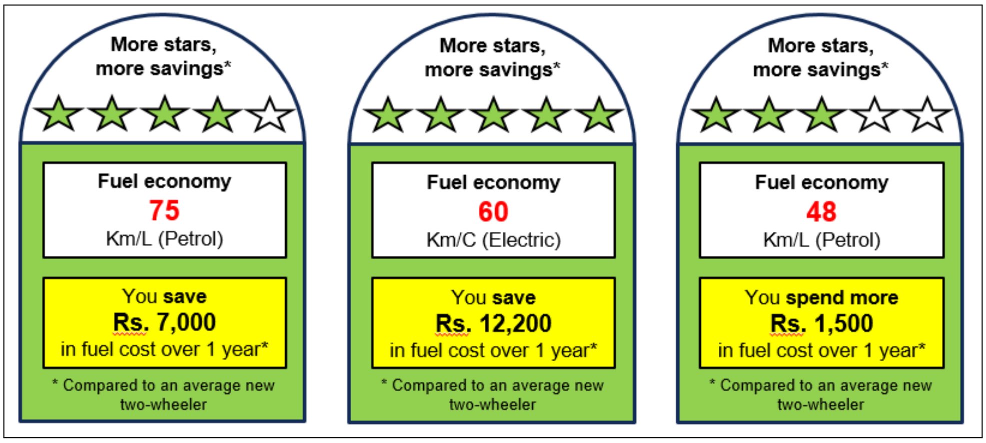
[4]During the entire study, the link to the web platform was shared only with the study participants. Note that participants could not buy a motorcycle via the platform, nor did the platform provide any information on any shops and dealerships. One could only search and compare information across different motorcycle models. The platform (nepal.bikecompare.co) was designed and developed by the research team together with an external IT service provider.

[5]We also tested the acceptability of the format of our labels in a pre-test with about 20-30 university students in Kathmandu before the study began.

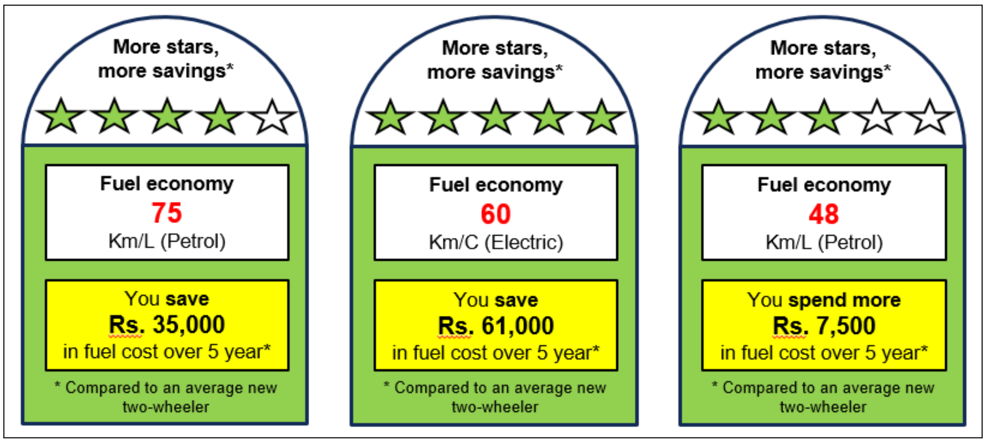
[6]The star ratings are on a scale of 1 to 5 Stars, computed using the running cost *costperkm* (in Rs./Km) according to the following rule: 5 Star = *costperkm* $\epsilon(0, 2.4]$, 4 Star = *costperkm* $\epsilon(2.4, 3]$, 3 Star = *costperkm* $\epsilon(3, 3.5]$, 2 Star = *costperkm* $\epsilon(3.5, 7]$, 1 Star = *costperkm* $\epsilon(7, 100]$



(a) Control group



(b) Treatment group 1



(c) Treatment group 2

Figure 3: The three information-based energy labels used on the web-platform experiment.

new motorcycle. Lastly, for **Treatment group 2**, the label showed personalised information on five-year operating fuel cost savings/expenditure for the model relative to the average new motorcycle. The personalisable element of the operating cost calculations, for both Treatment groups 1 and 2, arises from the distance that respondents reported needing to drive per day. We used this distance to compute the annual operating costs and five-year operating costs as follows:

$$AOC_{i,j} = 365 * distance_i * petrolprice/fueleconomy_j \tag{1}$$

where $AOC_{i,j}$ represents the annual operating costs for individual 'i' from selecting model 'j', $distance_i$ is the daily distance individual 'i's would like to drive, $petrolprice$ is the price per litre of petrol, which was Rs. 181/litre at the beginning of the study in all the cities included in our sample (Nepal Oil Corporation, 2023), and $fueleconomy_j$ denotes the fuel economy (in km/l) for model 'j'. Note that $fueleconomy_j$ is the reported fuel economy of the vehicle provided by the manufacturers, and not information provided by the respondents. The annual cost savings or expenditures of each model were then computed as

$$CS_{i,j} = AOC_{i,j} - (365 * distance_i * petrolprice)/fueleconomy_k \tag{2}$$

where $fueleconomy_k$ refers to the fuel economy of the average motorcycle model 'k' during the study period. Based on data we collected on models sold in Nepal, the mean fuel economy was 52 km/l. Thus, $fueleconomy_k$= 52 in our calculations. $CS_{i,j}$ referred to annual operating cost 'savings' for individual 'i' from model 'j' if $CS_{i,j}$ <0, and it referred to annual operating cost 'expenditures' if $CS_{i,j}$ >0. The energy labels were 'dynamic' in the sense that every time the respondents used the platform and selected new models (or changed their distance needs), the information displayed on the labels was updated accordingly.

Phase 2- Reminder phase: In the next phase of the study, our survey partner reminded all respondents who participated in Phase 1 of the study to access the platform, and use it to help them decide which motorcycle to purchase. We sent about two-three reminders per respondent, and respondents were also incentivised to access the website during this phase.

Phase 3-Follow-up survey phase: In the final phase of the study, our survey partner contacted the sample of 1005 respondents again via text message, and asked them to complete a short follow-up survey, in which we asked them about the motorcycle that they finally purchased, if any. In case they didn't end up purchasing a motorcycle, we ask them about whether they are thinking of purchasing any model, and if yes, which one. In this phase, the survey company was able to establish contact with about 476 respondents in total.[7] This reduction in sample size is typical in similar studies, and we discuss about this in further detail in the next section. After dropping observations for respondents who didn't clearly indicate exactly which motorcycle model they had bought (or wanted to buy), we are left with about 229 valid responses for individuals who either bought a motorcycle, or intended to buy one. The detailed end-line survey questionnaire is included in Appendix A.

Among the 229 respondents, 68 respondents actually purchased a motorcycle, whereas 161 respondents indicated that while they had not already bought a motorcycle, they had decided which motorcycle they wanted to buy. Therefore, the sample of 68 respondents who purchased a motorcycle constitute the main group for the revealed preference analysis. However, we believe that the respondents who declared their intention to be close to a decision can also be used to get suggestive evidence of revealed preferences, because the follow-up survey was conducted at least 4 months after the baseline

[7]Out of these 476, 338 respondents revealed that they either bought a motorcycle, or intended to buy one, however we are able to precisely identify the model purchased (or intended to purchase) for only 229 of these respondents. The rest had neither purchased a motorcycle, nor did they intend to in the next few months.

survey, and it didn't involve using the web platform immediately before expressing their choice. Thus, in a part of our empirical analysis, we will also use this 'enlarged' revealed preference analysis, i.e., the combination of both respondents who actually bought a motorcycle, and those who intended to buy one.

Recall rates were relatively high during the follow-up survey: about 90% of respondents in the control group, 80% in Treatment group 1, and 89% in Treatment group 2 recalled using the platform to compare motorcycle models. This is in contrast to the study by Allcott and Knittel (2019), where recall rates were about 16% for the control group, and 48% for the treatment group. Our platform, as well as the planned implementation of the randomised treatments, was designed to ensure that respondents could view the labels as many times as they wished. We show in the next section that indeed, many respondents used the website several times.

Both the surveys were prepared in English by the research team and translated to Nepali by the survey partner prior to field implementation. In the baseline survey, we collected some additional socioeconomic information on the respondents, including on the motorcycle that they currently owned (if any), and we included some questions to ascertain important behavioural and cognitive traits of the individuals. In the follow-up survey, we elicited information on the motorcycle that the respondents purchased, as well as some information on the their experience with using the web-based platform. We also tested both the baseline survey as well as the follow-up survey in pilot studies before beginning the fieldwork: the pilot was conducted with 69 respondents in Kathmandu Valley between October and December 2022.

2.2 Rationale for Information-Based Treatments

What are the reasons for testing the effects of providing information on annual and five-year operating cost savings/expenditures?

In the baseline survey in Phase 1, we asked a few questions to ascertain the level of energy and fuel-cost related knowledge of the respondents in our study. The first question was a simple lifetime cost calculation, and involved the respondents computing the total lifetime cost of owning a motorcycle, i.e. the sum of its purchase cost and the lifetime operating costs. About 35% of respondents answered this question correctly. Next, we asked a question on the value of money a year from now, and whether it would increase, remain unchanged or decrease. Only about 35% of respondents, again, correctly answered that the value of money is expected to decrease. Lastly, we asked the respondents whether they were aware of the price of petrol per litre in their city in December 2022 (i.e., at the end of the previous year). More respondents were aware of the petrol costs (at about 47%), which can be expected, given that they are either looking to purchase a new motorcycle, or they already owned one (we provide these summary statistics in Table B3 in the Appendix). These responses do not vary systematically between the treatment and control groups in our study.

Thus, our sample comprises individuals whose knowledge on operating costs, and the value of money, is relatively low. This lends some support for the design of our treatments, in particular the information on annual and five-year operating cost savings.

Furthermore, information on operating costs is provided on vehicle energy labels in some countries: a review of fuel economy labels revealed that many countries (developed as well as developing countries) provide operating cost information on energy labels for cars (such as the US, Canada, UK, New Zealand, as well as many European countries). Only one country so far has developed fuel economy labels for motorcycles and two-wheelers, namely Vietnam (which includes information on fuel consumption). The US is the only country that currently provides information on five-year operating cost savings/expenses: to the best of knowledge, none of the developing countries provided this information on fuel economy labels for cars (as of 2022).

Nepal currently does not have mandatory fuel economy labelling requirements for cars or motorcycles, which implies considerable search costs for fuel economy information (for example, in brochures, websites. etc.). Since 2012, it has implemented emission standards for cars (the Nepal Vehicular Mass Emission Standard 2069, which is equivalent to the Euro III norms), and despite discussions to increase the stringency of standards and switch to updated Euro VI norms, the switch has not happened yet (Onlinekhabar, 2022). Taxes include one-time taxes such as an excise duty on the imports of motorcycles, a value-added tax, a registration tax that depends on the engine size of the vehicle, as well as an annual road tax, which also depends on the engine size of the motorcycle (with larger motorcycles being charged more per year) (AutoCell, 2023). Electric motorcycle owners are also required to pay one-time as well as annual taxes, however they benefit from paying a lower customs duty compared to petrol motorcycle owners (Niu, 2023), although policies to promote the adoption of electric motorcycles have varied considerably over time.

Operating cost savings/expenditure information can be pivotal to include on fuel economy labels for potential buyers in developing countries such as Nepal. First of all, evidence suggests that information on annual operating costs (without focusing on savings/expenditure relative to the average model) can help those consumers who place more value on fuel costs rather than on fuel consumption (Camilleri and Larrick, 2014). Five-year operating cost information can be even more effective, given the larger scale of the values (Camilleri and Larrick, 2014). These are both likely to be relevant arguments in developing countries such as Nepal as well, given generally low income levels, as well as credit/liquidity constraints. Furthermore, five-year operating cost spending/savings compared to the average vehicle can also enable loss-averse individuals to choose more efficient vehicles (Greene, 2019; Bull, 2012).

In developing countries in general, individuals face several economic risks without often having adequate social insurance, and they often tend to be liquidity-constrained (Kremer et al., 2019). For these reasons, upfront costs (or purchase costs of durables such as motorcycles) may be more prominent to them when deciding which model to purchase. Providing information on annual (or five-year) operating cost spending/savings can thus improve the efficiency of vehicle choices in this setting, for the following reasons:

1. The trade-off between price and future operating costs, on controlling for engine size, is positive, i.e., more fuel-efficient motorcycles cost more, conditioning on the engine size and on the make-model.
2. If potential buyers tend to by myopic or present-biased (or they simply don't know how to calculate future operating costs), they may over-estimate the price of the motorcycle, and end up under-estimating its operating costs.
3. Providing them information on these costs can thus enable such individuals to make more efficient choices (by selecting motorcycles that have a higher fuel economy), by increasing its salience.

2.3 Summary Statistics

In Table 2, we present the overall summary statistics on the main socioeconomic variables, and test for covariate balance across the groups, for the enlarged revealed preference sample. The descriptive statistics for the stated choice data sample are in Table B1 in the Appendix. For the binary and continuous variables in Table 2, we report the mean values, and for the categorical variables, we provide the share of the respondents that belonged to each category. The reported statistics are based on a sample size of N = 229; while we have data on 229 respondents in the enlarged revealed preference sample, we are missing information on income for five of them.

We find that about 30-40% of respondents in our sample were female, and the average age of the respondents was about 23-24 years. On average, most respondents across groups have completed high school, and we find that the majority of them are students (between 50-60% across the three groups). We find that the respondents belonging to the three groups are fairly similar to one another on important socioeconomic dimensions based on the p-values corresponding to the tests of the null hypothesis that the means of variables are different for two groups at a time (reported in columns (10)-(12) of Table 2), with the exception of the occupational category variable, the means of which are significantly different between the Control group and for Treatment group 2 (p-value = 0.005). The p-values corresponding to the F-test for joint orthogonality of all covariates are reported at the bottom of the Table, and suggest that we cannot reject the null hypothesis that the covariates are jointly orthogonal to the treatment indicator, considering any two groups at a time. This overall insignificance may also be the outcome of low sample size: for this reason, we also confirm the balance of covariates in terms of observables for the stated choice sample (Table B1), both in terms of testing for the difference in means of the individual variables, as well as in terms of the joint F-test testing for orthogonality of all variables to the treatment indicator. Lastly, we are also able to confirm the balance of covariates if we restrict the sample to those individuals who actually purchased a motorcycle (N=68): Table B2 presents this evidence.

Thus, the three groups largely appear to be similar in terms of the mean values of the socioeconomic covariates, however we still control for these variables in our main estimations (given the difference in means of the occupational category variable across groups).

In our baseline survey in Phase 1, we also collected information on some behavioural traits that help us identify the impact of our treatments on heterogeneous groups of respondents. For example, we collected information on whether respondents were "impulsive" (a measure of present bias), and whether they were "patient". We asked survey questions that have already been used in previous studies, such as Gathergood and Weber (2017), to elicit this information. While some papers have used incentivized lab experiments involving agents making choices over different bundles of money to measure these traits, in our field experiment setting, these survey questions were more practical to implement. Furthermore, these measures have been shown to be strongly correlated with those obtained using lab-based experiments (Vischer et al., 2013; Burks et al., 2012). In particular, we asked the following two questions:

- To elicit present bias/impulsiveness, we asked respondents to agree on a 5-point Likert scale (varying from 'agree strongly' to 'disagree strongly') with the following statement: "I am impulsive, and tend to buy things even when I can't really afford them". We then create a binary indicator of impulsiveness equalling one if the respondent answered 'tend to agree' or 'agree strongly', and zero otherwise.
- As a measure of patience, we asked respondents "Are you generally an impatient person, or someone who always shows great patience?" Respondents could answer on an 11-point scale, varying from 0 being 'very impatient' to 10 being 'very patient'. Again, we created a binary indicator of patience equalling one if the respondent answered 6 or above to this question, and zero otherwise.

As argued by Gathergood and Weber (2017), the second question above enables disentangling the effect of present bias from high discount rates or impatience.

Lastly, as a measure of possible cognitive limitations, we also asked respondents several questions to assess their energy-related financial literacy. In previous studies, we have elicited this information by asking a series of questions to measure energy-related knowledge, financial literacy, as well as computational skills, three components of this measure (Adhikari et al., 2023; Filippini et al., 2021b). In this study, we asked four questions to elicit respondents' knowledge of vehicle operating costs, as well as their knowledge of the value of money (the correct answers are highlighted in bold):

1. Suppose you buy a bike for Rs 3,00,000. Your annual cost of petrol is Rs. 20,000. You expect to use the bike for 10 years (lifetime of the bike). What would be the total cost over the lifetime of the bike? Assume that average cost of fuel, fuel economy, distance driven per year, expected lifetime of the bike remains the same, and assume that the value of Rs 1 today is the same as Rs 1 tomorrow. [Options: Rs. 4,50,000 / **Rs. 5,00,000** / Rs. 6,00,000 / Rs. 7,50,000 / I do not know]

2. Imagine that you have Rs. 100 today. What would be the value of this money to you, one year from now, if you do not invest it anywhere? [Options: More than today / The same / **Less than today** / I do not know]

3. What was the price of petrol per litre in your city at the end of last year (Dec. 2022)? [Options: Rs.90-120 / Rs.120-Rs.150 / **More than Rs.150** / I do not know]

4. What is the average fuel economy (in km/L) of a motorcycle having an engine size of 125 cc? [Options: Less than 30/30-44 / **45-64**/ Above 65/ I do not know]

We summed the number of correct responses to these four questions to create an index that captures the energy-related financial literacy of the respondents. If respondents answered 2 or more questions correctly, they were categorised as being 'high-literacy' individuals, and vice-versa. The summary statistics for the individual questions are provided in Table B3 in the Appendix. We see that out of the four measures, the highest share of correct answers were for the knowledge of petrol price in both revealed and stated preference samples, with about 46% of respondents answering this question correctly.

We find that the means of these three binary measures, namely impulsiveness, patience as well as having a high literacy score, are also similar across groups in our revealed preference sample in Table 2 (as well as in the stated preference sample in Table B1): about 75% of respondents are patient according to our definition, whereas about 46% of them are impulsive in nature. The p-values suggest that these variable means are similar across groups.

2.4 Attrition Patterns and Potential Threats to Identification

In this sub-section, we discuss potential threats to identification in our study, as well as shed light on the patterns of attrition. For our results to be valid, we need to firstly ensure that attrition rates do not vary systematically between the treatment and control groups. While we recruited 3300 respondents in total in Phase 0 (along with their basic socioeconomic information), the first main phase of the study was Phase 1, in which we asked them to indicate their stated preference on the platform. The attrition rates were relatively high both in moving from Phase 0 to Phase 1, and from Phase 1 to Phase 3. In moving from Phase 0 to Phase 1, we find no evidence of differential attrition across the three groups. We find that out of the initial set of 1100 respondents in the control group, about 29.8% made a selection in the stated choice experiment. We find similar rates for Treatment groups 1 and 2, at about 30.45% and 31.09%.[8] Furthermore, given that respondents were not required to make any choices in Phase 0, we do not think that this attrition is likely to pose any significant threats to the validity of our results.

[8]The p-values on using a two-sided T-test for a pair-wise comparison of retention rates are 0.745 (Control group and Treatment group 1), 0.517 (Control group and Treatment group 2) and 0.747 (Treatment groups 2 and 3).

Table 2: Summary Statistics and Covariate Balance: Revealed Preference Sample

Sample	Overall			Control			Treatment 1			Treatment 2			P-values		
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Control vs. T1	Control vs. T2	T1 vs. T2
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Female	0.380	0.486	229	0.370	0.486	81	0.432	0.499	74	0.338	0.476	74	0.434	0.675	0.240
Age	24.41	5.18	229	24.90	5.78	81	23.61	4.16	74	24.69	5.38	74	0.115	0.814	0.173
Income													0.802	0.362	0.241
Currently not earning	37.50		84	40.74		33	39.73		29	31.43		22			
Below 25,000	31.70		71	29.63		24	32.88		24	32.86		23			
25,0000-50,000	28.57		64	25.93		21	26.03		19	34.29		24			
50,000-100,000	2.23		5	3.70		3	1.37		1	1.43		1			
Educational attainment													0.597	0.556	0.304
Secondary school (Grades 6-8)	2.18		5				1.35		1	5.41		4			
Higher secondary school (Grades 11-12)	34.5		79	37.04		30	31.08		23	35.14		26			
Bachelors degree	51.97		119	53.09		43	55.41		41	47.30		35			
Masters degree or higher	11.35		26	9.88		8	12.16		9	12.16		9			
Occupation													0.231	0.005	0.125
Currently unemployed	2.18		5				1.35		1	5.41		4			
Business	8.73		20	4.94		4	9.46		7	12.16		9			
Public sector	2.18		5	1.23		1	4.05		3	1.35		1			
Homemaker	1.31		3							4.05		3			
Private sector	14.41		33	14.81		12	12.16		9	16.22		12			
Self-employed	14.85		34	19.75		16	12.16		9	12.164		9			
Student	56.33		129	59.26		48	60.81		45	48.65		36			
Patient	0.750	0.434	180	0.807	0.398	57	0.724	0.451	58	0.723	0.451	65	0.299	0.281	0.99
Impulsive	0.461	0.500	180	0.544	0.503	57	0.414	0.497	58	0.431	0.499	65	0.166	0.216	0.851
High literacy	0.5	0.501	180	0.509	0.504	57	0.534	0.503	58	0.461	0.502	65	0.785	0.606	0.423
F-test of joint significance													1.29	0.84	0.85
P-value													0.257	0.567	0.558

Notes: This table reports the summary statistics of the main covariates both for the overall sample, and by group, for the sample used in the revealed preference analysis. Columns (13) to (15) indicate the p-values testing for differences in mean values across groups.

In moving from Phase 1 to Phase 3, there is again no differential attrition between the control group and the two treatment groups, even if attrition rates are high: the likelihood of respondents who completed the stated preference exercise on the platform staying in the sample till Phase 3, and completing the follow-up survey, was 46.8% in the control group, 47.6% in Treatment group 1 and 46.8% in Treatment group 2.[9] Thus, we do not think that differential attrition was a concern in moving from Phase 1 to Phase 3. Note that in Phase 2, respondents were not required to complete a survey or make a choice on the website, this phase served to only remind them to view the energy labels before deciding which vehicle they wanted to buy (in Phase 3).

In Table B4 in the Appendix, we present some regression-based evidence to support these results. In columns (1) and (2), we show that treatment assignment did not have an effect on the likelihood of respondents participating in the follow-up survey (as argued in the previous paragraph), on excluding or including socioeconomic covariates respectively. Secondly, in column (3), we show that among respondents in Treatment groups 1 and 2, there was largely no selection based on observables into completing the follow-up survey (except for high-income respondents, those earning more than Rs.50,000 per month, who were less likely to participate in the follow-up survey, compared to those who currently did not have a job). Note that studies with a similar experimental design to ours also find relatively high attrition rates: Allcott and Knittel (2019), for example, found a retention rate of 22% between baseline and follow-up stages, compared to our retention rate of between 47 and 48% depending on the group, between phases 1 and 3.

To identify other possible threats to identification, we also provided evidence in the previous section that the three groups of respondents in our study were not significantly different from one another in terms of socioeconomic characteristics, or in terms of behavioural traits. Another factor in favour of the internal validity of our results is that participation rates did not vary significantly across groups: out of the 329 respondents who selected a motorcycle in the control group, about 192 completed most of the baseline survey (about 58%). This conversion rate was about 61% in Treatment group 1, and about 65% in Treatment group 2. While the difference between the control group and Treatment group 2 in terms of the share of participants in the stated preference experiment who also completed the baseline survey is significant at the 10% level (using a two-sided T-test), the completion rates are not significantly different between the control group and Treatment group 1 (p-value of 0.476), as well as between Treatment groups 1 and 2 (p-value of 0.303).

Lastly, a risk with identification, in our case, might be that the three groups are fundamentally different in terms of their preferences for vehicles, i.e., there may be self-selection in vehicle choices, based on the distribution of preferences for vehicle attributes into the groups. In Table B5, we compare the respondents across groups in both our revealed preference as well as stated preference samples based on how important three vehicle attributes were to them, namely engine power and performance, the purchase price and operating costs, and the brand. We created three dummy variables, equal to one if the respondents answered that each of these these three vehicle characteristics were very important to them (and zero if they answered that they were only important, or not important). We find that the respondents in the three groups are similar in terms of their preferences for these three traits. This can be inferred from pairwise comparisons across all three groups (the p-values testing the null hypothesis that the means are significantly different are presented in columns (4) to (6)), and for both samples of analysis. Thus, there is no self-selection of respondents on the basis of preferences for vehicle attributes across groups.

[9]Once again, the differences are not significant: p-values on using two-sided T-tests for the pair-wise comparisons of retention rates are 0.84 (Control group and Treatment group 1), 0.99 (Control group and Treatment group 2) and 0.83 (Treatment groups 1 and 2).

2.5 Methodology

As discussed in the Introduction, one novelty of our paper is that we adopt both stated and revealed preference approaches. In this sub-section, we present the econometric models used within these approaches. For the revealed preference analysis, our main dependent variable of interest is the log of the fuel economy of the motorcycle actually purchased by respondents in the follow-up survey. For the reasons mentioned earlier, we also consider the motorcycles that respondents intended to buy as a revealed preference outcome as well in some specifications. Therefore, we will use an enlarged revealed preference sample for a part of the analysis. In the stated preference analysis, we use two dependent variables: firstly, the log of the fuel economy of the motorcycle chosen by the respondents, and secondly a dummy variable indicating whether the respondent made the best choice in his/her choice set, i.e., whether they selected the motorcycle that had the highest fuel economy among the models in their choice set.

Given the randomised nature of the interventions, we use the ordinary least squares (OLS) methodology to evaluate the impact of our information treatments on these dependent variables. The main model that we estimate in the revealed preference analysis is as shown:

$$F_i = \alpha_i + \beta T_{i,j} + \delta X_i + \epsilon_i, \tag{3}$$

where F_i is a continuous variable and denotes the log of fuel economy of the model selected by respondent 'i', $T_{i,j}$ is a categorical indicator for whether respondent i was treated by Treatment 'j' (j = 1, 2), or belonged to the control group (j = 0), X_i denotes the set of respondent-specific baseline covariates (such as age, gender, income, education and occupation), the engine-size category as well as the number of times the respondent used the website, α_i denotes the intercept and ϵ_i denotes the residual. This model is estimated using standard errors clustered at the city-level. We are interested in estimating the intention-to-treat parameter, namely β. We estimate the same model using the two dependent variables described above for the stated choice analysis.

We also investigate heterogeneous effects of the treatments on different sub-groups of the population, by estimating the following model:

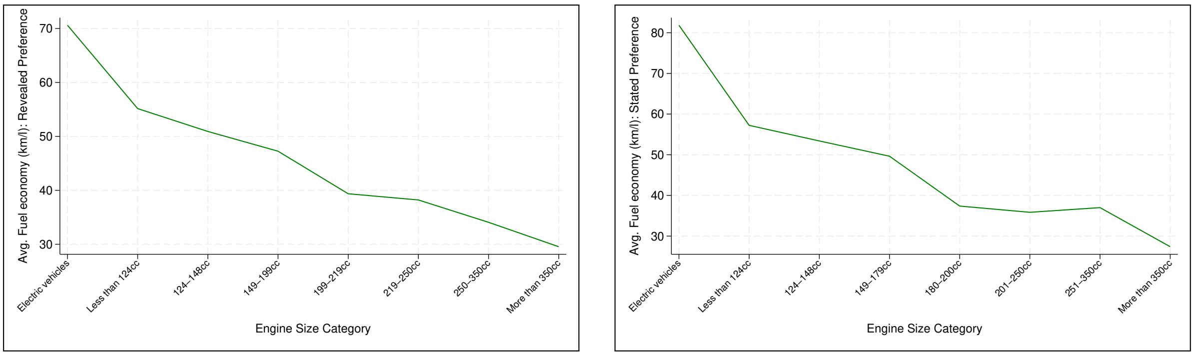
$$F_i = \alpha_i + \beta T_{i,j} + \gamma H_i + \lambda H_i * T_{i,j} + \delta X_i + \epsilon_i, \tag{4}$$

where H_i now denotes a variable over which heterogeneous effects are calculated. The rest of the notation remains unchanged from expression (3). We are interested in estimating the parameter vector λ, and thus evaluating whether the coefficients on the interaction terms differ from that on the main effect, given by β, i.e. whether there are heterogeneous effects over different subgroups of the population, compared to respondents in the control group. In particular, we evaluate heterogeneous effects over our main behavioural variables (impulsive, patient, and high literacy), gender, whether the respondent already owned a motorcycle, and whether they were looking to purchase a motorcycle with a low probability (lower than 50%).

3 Results

3.1 Main Results

In this section, we present the main results of our experiment. Firstly, we present some descriptive statistics on the motorcycles purchased by respondents in both the revealed preference as well as in the stated preference analysis. In Figure 4, we present the the average fuel economy by engine size of the choices of motorcycles of respondents in the enlarged revealed preference (panel (a)) and in the stated preference analysis (panel (b)). In both the revealed preference as well as in the stated preference samples (N=224 and 972, respectively), the majority purchased motorcycles in the 124-148 cc as well as in the 149-199 cc categories; incidentally, most of the models sold in the Nepalese market belong to these two engine size categories. About 63 respondents indicated that they would prefer electric motorcycles in the stated preference sample, but only 5 respondents actually purchased electric motorcycles. In general, we see a declining trend in the fuel economy with larger engine sizes in both these figures.



(a) Revealed Preference **(b)** Stated Preference

Figure 4: Fuel Economy and Engine Size of Selected Motorcycles

Out of the 224 respondents who indicated that they either bought a motorcycle during the period, or intended to buy one in the next few months, 66 respondents (about 30%) purchased a motorcycle, whereas 158 indicated that they had already decided which motorcycle to buy, but just hadn't bought it yet. 4 respondents suggested that they had already bought or intend to buy a second-hand motorcycle. Since we are not sure whether they actually bought a second-hand model, or if they plan on doing so, we include these four respondents' choices with those of the respondents who intended to buy a motorcycle, for a total sample of 158 respondents. The brand and model names of the motorcycles are listed in Table B6 in the Appendix.

In Table B7, we present the summary statistics on the average fuel economy in the stated choice sample. We find that the mean fuel economy of motorcycle models selected on the platform was about 48.11 km/l for the overall sample, with very similar values for the Control group (4877 km/l) and Treatment group 2 (48.72 km/l). On the other hand, respondents in Treatment group 1 selected slightly less efficient motorcycle models (with an average fuel economy of about 46.83 km/l). Likewise, Table B8 provides summary statistics suggesting that respondents in Treatment group 2 on average also purchased more efficient motorcycles (in terms of the mean fuel economy, in km/l) compared to both other groups, both in column (1) which includes actual purchases and purchase intentions, and in column (4) in which we present the results for the actual purchases. Figure A1 in the Appendix presents histograms of the engine size choices by group in the revealed preference sample, which also helps confirm this finding: we find that the share of respondents who selected relatively 'smaller' motorcycles (smaller than 148 cc) was slightly higher in Treatment group 2, compared to the other two groups.

Next, we present the regression-based results evaluating the impact of these treatments. We first evaluate the impact of the treatments on the stated preference on the web-based platform, i.e., on the model that they indicated they preferred to buy on the platform during Phase 1. Then, we present the results of the treatments on the revealed motorcycle choices of respondents. As described in the previous section, in the stated preference analysis, our first outcome variable is the log of the fuel economy of the motorcycle that respondents stated they preferred on the website, and the second is the likelihood of respondents having made the "best choice" in terms of selecting the motorcycle having the highest fuel economy among the models in their choice set.[10]

The results of the stated preference analysis are presented in Table 3, whereas the results of the revealed preference models are in Table 4. In Table 3, columns (1) and (2) include the log of the fuel economy of the selected motorcycle as a dependent variable, whereas in columns (3) and (4) we evaluate the impact of the treatments on whether the respondents made the best choice (in terms of fuel economy) among the models in their choice sets. Columns (1) and (3) of Table 3 present the estimation results excluding socioeconomic covariates, whereas in columns (2) and (4) we include basic controls (such as for gender, age, income and education categories, as well as occupation). The control group means are reported at the bottom of the table.

Table 3: Impact of Information Treatments: Stated Preference

Dependent variable	Log of fuel economy (in km/l) of selected motorcycle		Selected motorcycle with highest fuel economy	
Sample	Without covariates	Inc. covariates	Without covariates	Inc. covariates
Column	(1)	(2)	(3)	(4)
Treatment 1	-0.006	-0.001	-0.026	-0.017
	(0.005)	(0.003)	(0.027)	(0.023)
Treatment 2	0.012*	0.014**	0.029**	0.033**
	(0.003)	(0.001)	(0.005)	(0.005)
Control group mean	48.77	48.7	0.44	0.44
Observations	1005	972	1005	972

Notes: This table reports the marginal effects from the estimation of the stated choice models. All models are estimated using OLS. In all models, we control for the engine size category of the selected motorcycle, and for the number of times the respondent used the platform. In columns (2) and (4), additional covariates include gender, age, as well as income, educational attainment, and occupational category. In all columns, marginal effects are reported at the mean values of other explanatory variables. The difference in number of observations in columns (1) and (2) (and (3) and (4), and (5) and (6), and (7) and (8)) is due to non-responses for the income variable. The control group mean reported at the bottom of the table mentions the mean fuel economy (in km/l) for the control group in columns (1) and (2), and the proportion of control group respondents who selected the most efficient motorcycle in columns (3) and (4). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

The findings indicate that respondents in Treatment group 2 selected motorcycles which were relatively more efficient than respondents in the control group, during their activity on the web-based platform in Phase 1. The effect size varies from about 1.2% in column (1) to 1.4% in column (2). The average fuel economy of the motorcycles selected by the control group was about 48.7 km/l in column (2); respondents in Treatment group 2 thus selected motorcycles having an average fuel economy of 50.1 km/l. On the other hand, we do not observe significant differences between respondents in Treatment group 1 and the control group, across columns.

In column (3), results suggest that respondents in Treatment group 2 were about 2.9 percentage points more likely to have selected the most efficient motorcycle among the models in their choice set, compared to the average respondent in the control group. This effect size is about 3.3 percentage points in column (4). Given that about 44% of respondents in the control group made the most efficient choice among the models that they shortlisted, this corresponds to an approximately 47% rate of 'success' in Treatment group 2. While this effect is small, it is consistent and significant at the 5% level.

These stated preference results suggest that respondents, particularly in Treatment group 2, made more efficient choices on the platform, compared to the control group. In Table 4, we evaluate the impact of our treatments on the actual motorcycles that respondents bought, or the one that they intend to purchase. We consider the enlarged revealed preference sample of respondents in columns

[10] Another way to think about the 'best choice' would be in terms of the total cost of ownership. We also find that respondents in Treatment group 2 selected motorcycles that had lower total cost of ownership, compared to the control group, whereas we do not find significant effects of Treatment 1. These results are provided in Table B15.

(1) and (2). In columns (3) and (4), we present the results for our main sub-sample for the revealed preference analysis, the actual buyers of motorcycles, whereas in columns (5) and (6), we focus on the other sub-group of the enlarged revealed preference sample, comprising individuals who hadn't bought yet, but knew which model they intended to buy.

From column (1), we learn that respondents in Treatment group 1 did not purchase more efficient motorcycles compared to the average respondent in the control group: the coefficient is highly insignificant (p-value of 0.7), and negative. On the other hand, respondents in Treatment group 2 selected motorcycles that were about 4.2% more efficient than the control group respondents: this effect is significant at the 5% level (p-value of 0.011). Given that the mean fuel economy of the motorcycles selected by control group participants was about 45.72 km/l, this corresponds to an average fuel economy in Treatment group 2 of about 49.92 km/l.

Table 4: Impact of Information Treatments: Revealed Preference

Dependent variable	Log of fuel economy (in km/l) of selected motorcycle					
Sample	Bought or intend to buy		Bought		Intend to buy	
Specification	Without covariates	Inc. covariates	Without covariates	Inc. covariates	Without covariates	Inc. covariates
Column	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.005	0.009	-0.106*	-0.091*	0.020*	0.032***
	(0.011)	(0.010)	(0.030)	(0.030)	(0.005)	(0.002)
Treatment 2	0.042**	0.037***	0.037***	0.023*	0.061**	0.064***
	(0.005)	(0.002)	(0.0002)	(0.007)	(0.012)	(0.001)
Control group mean	45.72	45.72	50.04	50.04	44	44
Observations	229	224	68	66	161	158

Notes: This table reports the marginal effects from the estimation of the revealed preference models. All models are estimated using OLS. In all models, we control for the engine size category of the purchased motorcycle, and for the number of times the respondent used the platform. In columns (2), (4)and (6) additional covariates include gender, age, as well as income, educational attainment, and occupational category. In all columns, marginal effects are reported at the mean values of other explanatory variables. The difference in number of observations in columns (1) and (2) (and in columns (3) and (4), and in (5) and (6)) is due to non-responses for the income variable. The control group mean reported at the bottom of the table mentions the mean fuel economy (in km/l) for the control group in columns (1) to (6). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

In column (1), we control for the engine size category of the selected motorcycles, as well as for the number of times the respondents used the platform. Next, the results of column (2) suggest that the positive effect of Treatment 2 on the efficiency of motorcycle purchases persists on controlling for socioeconomic covariates: we find that the treatment increased the efficiency of motorcycle choices by about 3.7% compared to the control group purchases, an effect that is significant at the 1% level. This corresponds to an average fuel economy of about 49.42 km/l for respondents in Treatment group 2. On the other hand, in line with the findings from column (1), Treatment group 1 respondents did not purchase significantly more efficient motorcycles, compared to the control group.

In columns (3) and (4), we restrict the sample to individuals who bought a motorcycle, i.e. N = 68.[11] We estimate these main models controlling for the engine size category as well as for the number of times the respondent used the website in column (3), and additional socioeconomic controls in column (4). Once again, we find that respondents in Treatment group 2 bought motorcycles that were more efficient compared to the control group: the effect size is about 3.7% in column (3), and reduces to 2.3% in column (4). We find significant and negative effects for Treatment 1 in both specifications, compared to the control group.[12] Lastly, we are able to confirm the nature of these findings for those who intended to buy a motorcycle, in columns (5) and (6) as well, with an average effect size of about 6.6% in column (6) for Treatment 2. Interestingly, we find that respondents in

[11]The sample size drops to 66 in column (4) due to missing income data for two respondents.

[12]Given the small sample size for these estimations, we also compute the average fuel economy by group: the mean fuel economy was 50.04 km/l for the control group, 45.5 km/l for Treatment group 1, and 52.87 km/l for Treatment group 2, as reported in column (4) of Table B8. Thus the fuel economy for Treatment group 2 is marginally higher than that for the control group; the means are not statistically different, except on considering Treatment groups 1 an 2 (at the 10% level). The median values of fuel economy echo this trend, at 48 km/l for the control group, 45 km/l for Treatment group 1, and 55 km/l for Treatment group 2, but these are also not statistically different from one another.

Treatment group 1 also intended to buy motorcycles that were more efficient than the control group. This suggests differences between respondents in Treatment group 1 in the actual purchase decisions, and in their intention-to-buy estimates.

Our revealed preference results indicate that respondents in Treatment group 1 in our sample may not be projecting the annual cost savings into the future (due to myopia, present bias, cognitive limitations, or other reasons), whereas the five-year information is more effective in improving the fuel economy of the choices, likely because the extent of the savings are more perceptive to respondents, and because the magnitude of the savings/expenditures displayed are larger. This may arise, for instance, if respondents in Treatment group 1 perceived the displayed savings as being lower than what he/she expected, without using this information in context of the entire lifetime of a motorcycle.

Given that all our participants in the revealed preference group also participated in the stated choice experiment, we can evaluate the presence of a hypothetical bias, as well as the impact of our treatments on this bias. In Panel A of Table 5, we present the average values of the magnitude of the hypothetical bias, namely the difference in fuel economy between the revealed and stated choices, for the group of respondents who actually bought a motorcycle. At the overall level, we find that respondents purchased a motorcycle that was about 2.14 km/l more efficient than the choice that they made on the web-platform. This tells us that with respect to the purchase decision, respondents may have considered fuel economy more seriously; furthermore, respondents in Treatment group 2 selected motorcycles that were about 4.53 km/l more efficient in reality, compared to their stated choices. The difference is marginal for respondents in the control group, on the other hand (at 0.04 km/l).

Panel B of Table 5 presents the regression results of the impact of the our treatments on the difference between the revealed and stated fuel economy choices, for the sub-sample that purchased a motorcycle. In the results of both columns of Panel B, we provide evidence that the difference between the revealed and stated preferences is higher for respondents in Treatment group 2, compared to the control group. We learn that respondents in Treatment group 2 actually bought motorcycles that were about 5 km/l more efficient than what they selected on the platform, compared to the control group. Given that the control group mean is also positive (albeit, of small magnitude), this suggests that Treatment group 2 respondents purchased more efficient motorcycles in reality than the choices they made on the platform. Thus, seeing information on five-year operating cost savings (or expenditures) may be inducing individuals to take operating costs (and thus, fuel economy) more seriously when actually purchasing vehicles. Yet again, we do not find significant effects of Treatment 1 on the magnitude of this hypothetical bias.

Next, we explore the effects of the treatments across different subgroups of respondents in our revealed preference sample, i.e., we conduct a heterogeneity analysis. These results are presented in Table 6. These findings help us to understand which individuals responded more intensively to the information treatments, and to determine whether they were effective for subgroups of the population that displayed some form of behavioural anomalies.

In Table 6, we present the results of the heterogeneity analysis on the enlarged revealed preference data. Unfortunately due to small sample size of the respondents who bought a motorcycle (N=68), we use this enlarged sample for this analysis. Thus, these results should be interpreted as suggestive evidence of sub-group effects of our treatments. The reference group in these estimations is the control group. In column (1), we present the results of the treatment effects for impulsive individuals. We find that Treatment 1 did not have a significant effect on impulsive (or present-biased) individuals, whereas exposure to Treatment 2 positively influenced the fuel economy of the motorcycles bought by impulsive respondents who purchased motorcycles that were about 10.4% more efficient, compared to the respondents in the control group. Likewise, in column (2), heterogeneity is evaluated over the attribute of impatience: we find that respondents who were impatient and in Treatment group 2

Table 5: Impact of Information Treatments: Intention-Action Gap

Panel A: Magnitude of Hypothetical Bias (Revealed fuel econ.-stated fuel econ. (in km/l))				
Sample			Bought a Motorcycle	
Sub-Sample	Overall	Control	Treatment 1	Treatment 2
Hypothetical bias	2.14	0.04	1.84	4.53

Panel B: Regression Results		
Dependent variable	Revealed fuel econ.-stated fuel econ. (in km/l)	
Sample	Bought a Motorcycle	
Specification	Without covariates	Inc. covariates
Column	(1)	(2)
Treatment 1	0.031	0.642
	(1.161)	(0.857)
Treatment 2	5.391***	5.096***
	(0.153)	(0.145)
Control group mean	0.04	0.04
Observations	67	65

Notes: This table reports the magnitude of the hypothetical bias (the difference in fuel economy between the revealed and stated choices), and the marginal effects from the estimation of the impact of the treatments on the hypothetical bias. Panel A presents the magnitude of the bias at the overall level, and by subgroup, whereas Panel B presents the regression results. Both models in Panel B are estimated using OLS. In both models, we control for the engine size category of the purchased motorcycle, and for the number of times the respondent used the platform, whereas in column (2), we include additional covariates such as gender, age, as well as income, educational attainment, and occupational category. In all columns, marginal effects are reported at the mean values of other explanatory variables. The difference in number of observations in columns (1) and (2) is due to non-responses for the income variable. The control group mean reported at the bottom of the table mentions the mean difference in fuel economy (in km/l) between the revealed and stated choices for the control group in columns (1) and (2). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

selected motorcycles that were about 13.4% more efficient than the average control group respondent. Interestingly, again, respondents in Treatment group 1 who were impatient did not end up choosing motorcycles that were more efficient than the control group. Thus, providing annual operating cost savings/expenditure information did not influence the choices of impatient individuals, whereas this information provided over a five year horizon may have induced impatient individuals to make more efficient choices. These results reinforce our previous findings from Table 3, namely that information on annual operating costs may be ineffective on individuals who are present-biased and/or myopic, and suggests a possible reasoning for Treatment 1 having been ineffective at the overall level.[13]

In column (3), we learn that the effects of both treatments were significant on individuals who did not have a high energy-related financial literacy score, or individuals who exhibited cognitive limitations. Exposure to Treatment 1 for respondents with a low score resulted in them purchasing motorcycles that were about 9.5% more efficient than respondents in the control group. Likewise, Treatment group 2 respondents with a low literacy score purchased (or intended to purchase) motorcycles that were about 9.6% more efficient than the control group respondents. Thus, both treatments were effective on individuals who displayed cognitive limitations, measured in terms of their energy-related financial literacy score, even though the effect of Treatment 2 is of a higher significance level than of Treatment 1.

In general, Treatment 2 had a positive effect on the fuel economy of motorcycles purchased by female respondents (6.8% more efficient), as indicated in column (4), whereas female Treatment group 1 respondents did not choose significantly more efficient motorcycles compared to the control group. With the results of column (5) of Table 6, we test whether our treatments were relatively more effective for individuals who stated that they wanted to buy a motorcycle with a low probability (lower than 50%) during Phase 1. If we were to treat this probability as another measure of the seriousness with which respondents were looking to purchase a motorcycle, a hypothesis could be that more serious individuals may be more likely to respond to the operating cost savings information by choosing more efficient motorcycles. On the other hand, individuals who were relatively less sure of purchasing a motorcycle may be swayed by information on operating cost savings, particularly if these are large or if they are positively 'surprised' by it. We find that both the treatments were effective in nudging those individuals who were less likely to purchase a motorcycle to buy more efficient ones: respondents in Treatment group 1 purchased motorcycles that were 6% more efficient than those purchased by the control group, whereas this effect was about 10.5% for respondents in Treatment group 2. Therefore, we can infer that respondents who were not sure of whether they wanted to purchase a motorcycle may have been more influenced by the operating cost information.

Lastly, previous experience with motorcycle ownership may also prime individuals to think about operating costs more seriously. On the other hand, if previous owners experienced that reported fuel economy (or operating costs) differed from actual values, they may also disregard this information (as was also argued by Sallee (2014)). In column (6), we find that respondents in both groups bought more efficient motorcycles, compared to the control group, if they also already owned one: the effect size is about 10.8% for Treatment 1, and about 7.8% for Treatment 2. Thus, learning effects (or general awareness of operating costs and fuel economy) associated with previous motorcycle ownership

[13] Present bias among households in developing countries can be conceived in terms of time inconsistency or impatience, as well as liquidity constraints (Kremer et al., 2019). Our measure of impulsiveness is better equipped to measure present bias in terms of the former definition, rather than the latter. While we do not have any direct measures of liquidity constraints in our survey, we asked respondents in Phase 1 whether they were planning to apply for a loan to buy their motorcycle. If we use this measure as a proxy for being liquidity-constrained, we find similar results to those of column (1) of Table 6, namely that liquidity-constrained individuals in Treatment group 2 purchased more efficient motorcycles than the Control group respondents. However, the effect size is much smaller, at about 1.5%, and it is significant at the 10% level. In line with the results of column (1), we do not find a significant effect of Treatment 1 on this group. Thus, we believe that the results are more likely to be driven by time-inconsistency, rather than liquidity constraints.

dominate in this case.

In Table B9 in the Appendix, we present the heterogeneity analysis results for the difference between the fuel economy of the motorcycle actually purchased by respondents, and the one that they stated they would buy on the platform. The direction of these results are broadly similar to the findings from the enlarged revealed preference analysis in Table 6: in general, exposure to the information treatments, particularly Treatment 2, was more likely to increase the gap between the actual and stated choices for respondents with behavioural anomalies, namely those who were impulsive, impatient, and exhibited cognitive limitations. This implies that for individuals who displayed myopia or cognitive limitations, the information provided in Treatment 2 may have helped them make relatively more efficient purchases, compared to what they stated they would buy on the platform. Interestingly, we also find evidence that exposure to the annual operating cost savings/expenditure information in Treatment 1 enabled individuals who were impulsive, myopic or had low literacy scores to purchase relatively more efficient motorcycles compared to what they stated they would purchase.

The remaining findings of Table B9 are largely in line with the revealed preference results of Table 6, except that we find that respondents who were looking to purchase a motorcycle with a low probability in Treatment group 1 did not make significantly different choices in a revealed preference setting compared to their stated choices, on comparison with the control group. However, we still find differences in the revealed and stated choices in terms of fuel economy for individuals in Treatment group 2 who suggested that they would like to purchase a motorcycle with a low probability. This finding supports the notion that presenting five-year operating cost information even to those individuals who were relatively less likely to purchase a motorcycle may incentivize them to think about efficiency in their purchase decisions.

Table 6: Heterogeneous Impact of Information Treatments: Revealed Preference

Dependent variable	Log of fuel economy (in km/l) of selected motorcycle					
Column	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneous treatment	Impulsive	Impatient	Low literacy	Female	Low prob. of purchase	Already owned motorcycle
Treatment 1	0.080	0.068	0.095*	0.021	0.060***	0.108***
	(0.029)	(0.041)	(0.030)	(0.039)	(0.006)	(0.001)
Treatment 2	0.104***	0.134***	0.096***	0.068***	0.105***	0.078***
	(0.004)	(0.009)	(0.002)	(0.001)	(0.005)	(0.001)
Control group mean	44.02	44.02	44.02	44.02	44.02	44.02
Observations	175	175	175	175	175	175

Notes: This table reports the heterogeneous marginal effects from the OLS estimation of the revealed preference model of column (2), Table 4 using interaction terms to elicit treatment effects for specific types of respondents, indicated by the column header. The dependent variable is the fuel economy of the revealed motorcycle choice (in km/l). The model includes covariates for the engine size category, number of times the respondent used the platform, gender, age, income, educational attainment, and occupation. In addition, we control for a measure of risk aversion. In all columns, marginal effects are reported at the mean values of other explanatory variables. The control group mean reported at the bottom of the table mentions the mean fuel economy (in km/l) for the control group in columns (1) to (6). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city level, and reported in parentheses. The coefficient on the constant has not been reported.

3.2 Impact of Treatments on the Decision to Buy a Motorcycle

In Table B10, we estimate the impact of the treatments on the decision to buy a motorcycle, using the data on the sample of respondents who participated in Phase 3. We find that respondents in Treatment group 2 were *less* likely to purchase a new motorcycle: according to the results of column (2), Treatment group 2 respondents were 2.1 percentage points less likely to buy a new motorcycle, whereas the effect is insignificantly different from zero for Treatment group 1 (although the coefficient is still negative).

This is an interesting result, and suggests that five-year operating cost information may not have only induced more efficient purchases, but it may have also compelled respondents to think twice about their purchase. One possible reason for this finding may be that respondents in Treatment group 2 were dissuaded from purchasing their preferred models, after seeing the information on operating costs on the energy labels (especially on seeing the relative operating cost expenses from buying possibly inefficient models). Another reason may be that the information they received in the treatments encouraged them to hold off on purchasing a motorcycle, either till they had spent more time evaluating which one to buy, or researched a bit deeper. In the follow-up survey, we asked respondents for the reasons why they held off on their purchase if they did; across groups, the main reason respondents stated was that they were still looking, or needed more time to decide. However, the share of respondents providing this reason was comparatively higher in Treatment groups 1 and 2, compared to the control group (25%, 33.96% and 32.56%, respectively).

3.3 Role of Information

The main results of the paper highlight the role of providing operating cost information, particularly that computed over a period five years, in improving the efficiency of vehicle choices of individuals. In this section, we shed light on the mechanisms through which information could influence these choices.

What types of behavioural anomalies and market failures could our treatments address? We showed in the previous section that the provision of operating cost information may have been particularly effective in improving the efficiency of choices of individuals who were myopic, impulsive, or had cognitive limitations, i.e., types of behavioural anomalies that have been shown to contribute to the energy efficiency gap in the literature. While the lack of salience of information has also been shown to be an important barrier hindering energy efficient technology adoption, we believe that in our case, this is less likely to be relevant given that the labels were seen prior to the purchase of the motorcycle, and not at the point-of-sale. Furthermore, all three groups saw energy labels (and information on fuel economy) in our study, which also mitigates the risk of imperfect information driving the purchases of inefficient motorcycles in our setting.

Another question that arises with respect to the use of information is whether there were differences across groups in how they used the information, for example, in the number of times they used the platform. On average, Control group respondents in our stated choice sample used the website a total of 1.61 times, whereas this mean is 1.34 for respondents in Treatment group 1, and 1.47 in Treatment group 2 (the median number of times the platform is used is one, across groups). The pairwise t-tests suggest that these means are only statistically different considering the Control group and Treatment group 1 at the 1% level. Thus, on average, at least for Treatment group 2 respondents, we do not find evidence that they used the website more than Control group respondents.

Do respondents who use the website more frequently somehow make different choices? In the results presented in Table 3, we considered the last choice that respondents made on the website, i.e., their stated preference on the last instance that they both used the website and indicated which motorcycle they would like to choose. Table B11 in the Appendix presents these stated choice results of the paper (those of column (2) of Table 3) separately for respondents who only made a single choice (column (1)) and those who made more than one choice (column (2)). We find a significant and positive effect of Treatment 2 on the fuel economy of the motorcycle selected in column (2), whereas we do not find significant effects in column (1). Thus, respondents in Treatment group 2 who we know used the website more than once selected more efficient motorcycles compared to the Control group respondents, whereas the effect is weaker for respondents who only made a single choice on the website. This indicates that respondents who used the website more than once may have learnt from this information, and used it to make more efficient selections in their last choice.

Another measure that may be helpful in understanding how seriously respondents took the information provided on the labels is the amount of time spent in making the selection on the platform. In particular, we can consider the amount of time (in seconds) passed between when the respondents clicked on the button "Compare these models" and when they click on "I prefer this model", i.e., the amount of time they spent going through the energy labels and deciding which motorcycle to opt for. In columns (3) and (4), we test the impact of the treatments on the amount of time spent. We provide evidence that respondents in Treatment group 1 spent relatively less time than the average respondent in the control group in selecting which motorcycle to purchase, whereas respondents in Treatment group 2 spent more time than the average control group respondent in making their choice. Treatment group 2 respondents spent about 1-2 seconds more in making their choice, whereas Treatment group 1 respondents on average spent about 4-5 seconds less than the respondents in the control group.[14] This indicates that Treatment group 2 respondents may have taken the time to consider the information provided on the labels relatively more carefully in making their choices, whereas Treatment group 1 respondents may not have considered it as seriously, perhaps due to the smaller magnitudes of the savings/expenditures displayed.

Lastly, we can also exploit the activity of the respondents on the web-based platform during phase 2, i.e., during the notification/reminder phase, to better understand how they used information. This information is presented in Table B12. We find that out of the 1005 respondents who completed phase 1, the share of respondents who also used the website during the reminder phase was 59% in the Control group, 55% in Treatment group 1, and 66% in Treatment group 2, with the difference being significant between Treatment group 2 and the Control group at the 10% level. While respondents were not required to make a choice on the platform during phase 2, we find that some of them did: this share was also highest for Treatment group 2 (at 61%). On average, respondents who made choices in phase 2 made more than one choice, across groups. However, there are no significant differences in the mean fuel economy over all the choices made by respondents during this phase, across groups.

3.4 Impact of Information on Savings and Expenditures

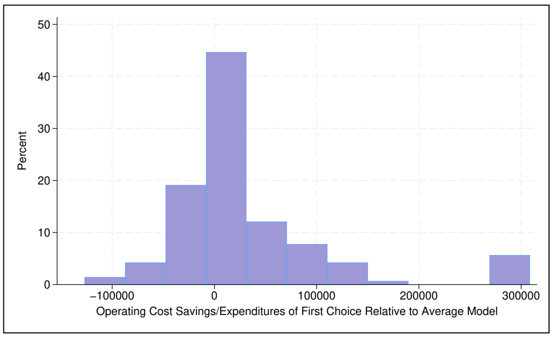
Do consumers respond differently to being shown information on operating cost *savings*, i.e. operating costs being lower than that of the average motorcycle model, compared to being shown information on operating cost *expenditures*? In this section, we investigate firstly whether consumers on average selected motorcycles for comparison that were more or less efficient than the average model, given their personal driving needs, and secondly whether seeing information on operating cost expenditures led to different choices compared to individuals who only saw information on operating cost savings.

In Figure 5, we present three histograms showing the distributions of operating cost savings (or expenses) relative to the average model on the first, second and third models viewed by respondents in the revealed preference sample on the platform. Negative values of the variable represent more efficient choices, whereas positive values indicate choices that were less efficient than the average model. We find the distribution of operating cost savings first viewed by respondents on the platform to be positively skewed, i.e., many respondents viewed inefficient motorcycles. This pattern persists over the second and third choices as well, even though the proportion of respondents who compared relatively efficient motorcycles was higher on the second choice.

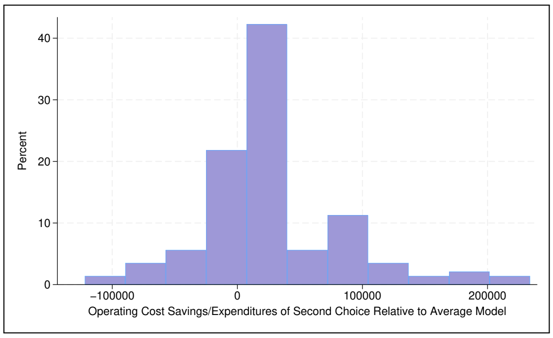
The median value of operating cost expenditures that was displayed on the energy label for respondents in Treatment groups 1 and 2 was Rs. 20602.39 on the first choice (USD 154), Rs. 15556.91 on the second choice (USD 116), and Rs. 18540.35 on the third choice (USD 138). This means that generally, the respondents' choices for comparison on the platform fared *worse* in terms of operating

[14]The mean time taken is about 45 seconds for the control group, 41 seconds for Treatment group 1 and 46 seconds for Treatment group 2.

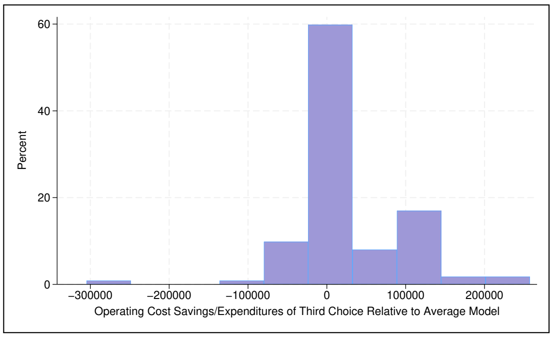
costs compared to the model with the average fuel economy, i.e., on average, respondents in our sample selected relatively inefficient motorcycles to compare on the platform, and were thus shown information on operating cost expenditures (and not on savings).



(a) First choice



(b) Second choice



(c) Third choice

Figure 5: Relative Operating Cost Savings/Expenditures on Platform: Revealed Preference Sample

In Table B13 in the Appendix, we once again evaluate the impact of the treatments on the revealed preference fuel economy, however we categorise respondents into five different groups; the control group, respondents in treatment group 1 who only saw information on relative cost savings, treatment group 1 respondents who selected at least one model where they saw information on relative expenditures, treatment group 2 respondents who only saw information on relative cost savings, and treatment group 2 respondents who selected at least one model with relative expenditures displayed. We find that respondents in Treatment group 2 who only saw information on relative cost savings purchased relatively more efficient models than the average control group respondents, and this effect was larger (effect size of approximately 20% in column (1) and 18% in column (2)) than the effect on treatment group 2 respondents who saw at least one label with relative cost expenditures displayed. Thus, individuals who selected more efficient models to compare on the web platform also bought more efficient models relative to the control group, whereas this effect is still positive, yet somewhat weaker for individuals who included one or more inefficient models in their choice set.

3.5 Robustness Checks

In this section, we present some robustness checks on our main revealed preference findings of Table 4. Table B14 in the appendix presents these results. In column (1), we estimate the main model (column (2) of Table 4), while controlling for the log of annual distance the respondents would drive per year in kilometres (based on the information they inputted before using the comparison tool on the platform). This is likely to be a determinant of the type of motorcycle eventually chosen by respondents; respondents who expect to drive longer distances may consider purchasing more efficient vehicles, than those who only drive short distances[15]. We find that the main result is robust to the inclusion of this covariate, with a marginally smaller effect size of 3.2% for Treatment 2, compared to our main estimation (3.7%).

In column (2), we evaluate the effect of the treatments on the log of fuel economy of the selected motorcycle, excluding all covariates (even those for the engine size category, and the number of times the respondents used the platform). Once again, the main result is robust to these exclusions: the effect size is about 4.2%, which is similar to the magnitude of coefficient in column (1) of Table 4. Column (3) then presents the results of using the fuel economy as a dependent variable, without log-transforming it. We find an effect size for Treatment 2 of about 1.69 km/l, which is significant at the 1% level.

In our main results, we think of vehicle efficiency in terms of fuel economy. Another way respondents could purchase more efficient vehicles could be to buy smaller or lighter models. Smaller motorcycle models, in terms of engine size, tend to be more energy-efficient than larger, more powerful models. In column (4), instead of controlling for engine size, we use it as a dependent variable. This is a categorical variable that takes eight values, depending on the engine size of the model.[16] We use an ordered probit model to evaluate the effects of the treatments. While we find insignificant effects for Treatment 1, Treatment group 2 respondents purchased motorcycles that were also smaller than those purchased by the control group. This provides complimentary evidence on our main hypothesis.

3.6 Welfare Impact of Providing Five-Year Operating Cost Information

What was the overall environmental and economic impact of the treatments in our study? In this section, we use back-of-the-envelope calculations to provide an estimate of the benefits of our intervention on climate change mitigation. Of course, a comprehensive economic analysis should also consider other benefits to society, such as air pollution reductions which are very important for the Kathmandu valley region. However, the relation between air pollution (PM_{10} and $PM_{2.5}$ concentrations) and premature mortality is complex and region-specific, and this information is not available in the Nepali case.

In our main results (column (2) of Table 4), we found that individuals in Treatment group 2 selected motorcycles that were, on average, about 3.8% more efficient than the control group respondents, corresponding to an average fuel economy of about 47.46 km/l (as opposed to about 45.72 km/l for the control group). On average, gasoline combustion produces about 2.3 kilograms of CO_2 per litre burnt. The improvement in average fuel economy for Treatment group 2 thus corresponds to a reduction in CO_2 emissions of about 0.0023 kilograms per kilometre per vehicle, compared to the control group. Thus, for each new motorcycle purchased, presenting information on five-year operating cost savings instead of the fuel economy information can lead up to 2.3 grams fewer CO_2 emissions per kilometre driven. In 2021, about 78% of all vehicles registered were motorcycles, which amounted to about 2.53 million motorcycles (Wagle, 2021). If we assume that the reduction of 2.3 gms of CO_2 emissions per km driven would have been valid in 2021 as well, and use this to calculate the total emissions reduction, we find that up to 5819 kilograms (or about 5.8 tonnes) fewer of CO_2 emissions per km driven by all registered motorcycles could be expected by the information treatment.

[15] It is also likely to be endogenous: for example, we do not have information on where respondents live, which may influence both this variable as well as the dependent variable. For this reason, we do not include this variable as a covariate in our main estimations.

[16] 0 for electric models, 1 for engine size between 100 and 120 cc, 2 for 121 to 125 cc, 3 for 126 to 160 cc, 4 for 161 to 200 cc, 5 for 201 to 250 cc, 6 for 251 to 350 cc, and 7 for 351 to 390 cc.

If we assume that all registered motorcycles in 2021 were driven a mean annual distance of about 14,600 kms (which is the mean in our data sample), the information treatment would have resulted in a total reduction of about 84957.4 tonnes of CO_2 emissions per year. We know that the total CO_2 emissions in Nepal in 2020 was about 14.9 million tonnes (Ritchie et al., 2022) from all sectors, and 5.3 million tonnes of these emissions arose from the transport sector (Ritchie et al., 2020); if we assume that emissions were similar in 2021, this would have constituted a reduction of about 1.6% of total emissions in the year 2021, for instance. While this may seem small, we believe that this effect is under-estimated, given that currently, fuel economy labels do not exist, and this information is not mandated to be provided by firms.

This reduction in CO_2 emissions can also be converted to monetary terms, by using estimates for the country-level social cost of carbon provided by Ricke et al. (2018). On using a growth-adjusted discount rate, SSP2/RCP60 projection for future emissions, and a short-run damage function, the social cost of carbon in Nepal is about USD 0.343 per tonne of CO_2. This amounts to monetary savings of about USD 29,140.39 per year in avoided CO_2 from providing five-year operating cost information, as opposed to providing fuel economy information.

We also calculate the potential savings to consumers from the provision of this information. In Table B15 in the Appendix, we report the impact of our treatments on the five-year total cost of ownership, without covariates (column (1) and with covariates (column (2)). We use a simplified definition of total cost of ownership, which we define as the sum of the purchase cost and the five-year operating costs, and we assume a zero rate of interest. Thus, we ignore all other costs (such as maintenance costs, insurance costs, vehicle registration taxes, etc.) We find from column (2) that respondents in Treatment group 2 bought motorcycles with a five-year total cost of ownership which was about Rs. 8802.82 (USD 66) lower than respondents in the control group. Assuming a lifespan of five years for motorcycles, the monetary savings for each consumer from seeing this information, compared to just seeing the fuel economy, is thus about USD 66. In 2020, about 25380 new motorcycles and scooters were sold in Nepal (Statista, 2020). This would amount to total monetary savings for consumers of about USD 1.68 million over five years. Summing the costs of avoided CO_2 computed over a five-year horizon, the total benefits from information would be about USD 1.83 million over 5 years.

The cost of developing the website, and displaying the operating cost information online, is considerably low in comparison. For our study, we spent a total of about USD 8400 over two years for developing the website, and for annual maintenance and domain fees. Using this as a benchmark, the five-year cost of implementing the policy is approximately USD 21,000. Thus, it is clear that the benefits outweigh the costs, with net benefits of about USD 1.8 million over five years. While we have made several simplifying assumptions for this welfare calculation, we are likely severely underestimating the next benefits from the program, for two important reasons. As mentioned earlier, fuel economy labels are not mandatory or enforced at present, which implies our treatment effects may be higher in comparison to no information availability. Secondly, we do not factor in benefits related to air pollution improvements, which may be high in this setting. Furthermore, even with additional costs such as those related to collecting information on the fuel economy of all models, updating models on the platform, as well as those related to marketing and promotion of the website, the costs from implementing this nudge can be expected to be several orders of magnitude smaller than the annual benefits.

4 Conclusion and Policy Implications

Our objective in this paper was to investigate the role that digital information provision may play in improving the efficiency of vehicle choices in a developing country setting. By implementing our randomised interventions on a web-based platform with a sample of individuals looking to purchase a motorcycle in urban areas of Nepal, we find that providing information through a web-page on five-year operating cost savings of different models to respondents increased the efficiency of the vehicles bought by respondents (or the one that they intended to buy), compared to showing them information on fuel economy, whereas we find weaker effects for the provision of information on annual operating cost savings. In our baseline specification, five-year operating cost savings/expenditure information improved the fuel economy of purchased motorcycles by about 3.8% compared to the control group. Furthermore, we find that individuals who exhibited behavioural anomalies (such as myopia, present bias, or cognitive limitations) and belonged to Treatment group 2 also purchased relatively more efficient vehicles compared to the control group. These findings are confirmed on using a stated preference approach. Lastly, we find that exposure to the five-year operating cost savings information also resulted in respondents making more efficient revealed preference choices compared to their stated choice outcomes, relative to the control group, and also resulted in them being less likely to actually buy a motorcycle.

The policy implications of this study relate to the design of information-based energy efficiency policies in developing countries. Given that energy labels have not been implemented for motorcycles in most developing countries (except Vietnam), our study provides some suggestions on how to design these labels. The most important suggestion is to design and implement energy labels for vehicles that not only provide fuel economy information, but also information on lifetime (or five-year) monetary savings, in enabling consumers to make more efficient choices. Furthermore, we are able to demonstrate the effectiveness of our treatments in improving the efficiency of choices of consumers who display behavioural anomalies such as myopia or present-bias that are relevant in developing countries, which has also not been done, to the best of our knowledge. Thus, we are able to provide some evidence on the effectiveness of cheap information-based measures in a low-education, low-income setting, where the opportunity cost of acquiring such information may be high. Our back-of-the-envelope calculations suggest that switching from displaying fuel economy on labels to displaying information on five-year operating cost saving may contribute to monetary gains of about USD 1.8 million over five years; while Nepal currently does not have mandated fuel economy labels for motorcycles, we believe that the large contribution of motorcycles to Nepal's vehicle fleet may imply a potential reduction in CO_2 emissions from the sector over time.

An important point to keep in mind is that energy labels are often accompanied with other policies such as emission standards, implementing which can be relatively costly, especially in developing country settings. While the cost-benefit evaluation of the emission standards is left for future research, given the relatively low cost of implementing digital information policies in developing countries, we argue that fuel economy or energy labels can be effective tools in improving the efficiency of vehicle choices. This has critical repercussions on air quality and health in urban areas of developing countries.

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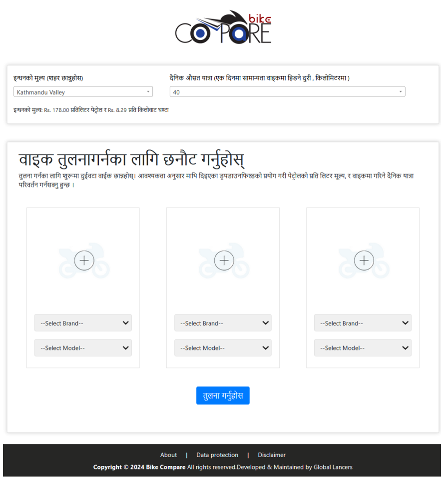
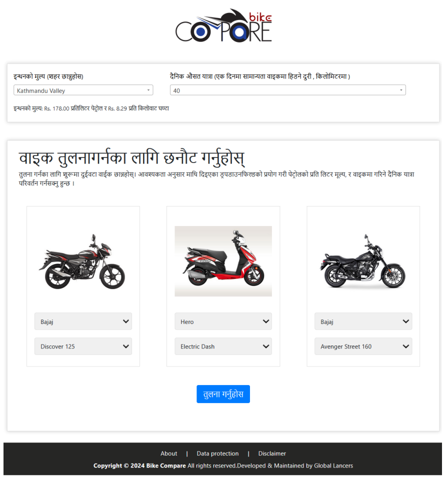
Appendix A: Treatment Screens, Surveys and Figures

A1. Web-platform functionality and information

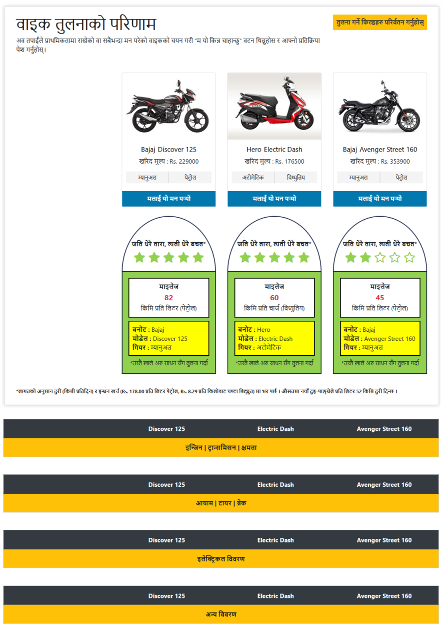
Landing page:



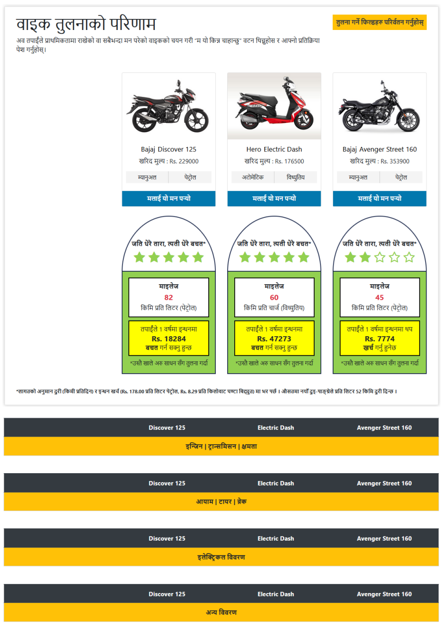
User selects three motorcycles:



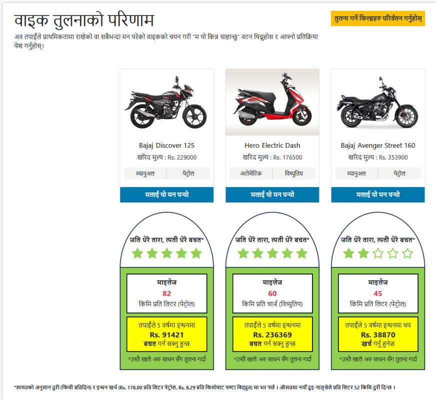
Comparison page for the CONTROL group:



Comparison page for TREATMENT 1 group:



Comparison page for TREATMENT 2 group:



	Discover 125	Electric Dash	Avenger Street 160
	इन्जिन | ट्रान्समिसन | क्षमता		

	Discover 125	Electric Dash	Avenger Street 160
	आयाम | टायर | ब्रेक		

	Discover 125	Electric Dash	Avenger Street 160
	इलेक्ट्रिकल विवरण		

	Discover 125	Electric Dash	Avenger Street 160
	अन्य विवरण		

Notes:

1) The feature categories (accordion bars below the energy labels) are Collapsible – user can click on each of the headers to toggle between showing and hiding (default) underlying content. The content from all headers for the chosen example are shown below:

	Discover 125	Electric Dash	Avenger Street 160
	इन्जिन | ट्रान्समिसन | क्षमता		
इन्धनको प्रकार	Petrol	Electric	Petrol
इन्जिनको प्रकार	4 stroke, Air cooled single cylinder, SOHC, DTS-i	BLDC Hub Motor	Air cooled, 4 stroke, Single Cylinder, SOHC, Fuel Injected
अधिकतम पावर	11 PS @ 7500 rpm	250 W	15 PS @ 8500 rpm
डिस्प्लेसमेन्ट (कति सीसी)	124	NA	160
ट्रान्स्मिसन् (म्यानुअल कि अटोमेटिक)	Manual	Automatic	Manual
गियर बक्स	5	NA	5
अधिकतम स्पिड (किमि/घण्टा)	100	25	NA
ब्याट्री पूर्ण रिचार्ज हुन लाग्ने समय	NA	4-5	NA
आवश्यक युनिट (किलोवाटघण्टा/चार्ज)	NA	1.34	NA
विध्युतिय रेन्ज (किमिसेकेण्ड/चार्ज)	NA	60	NA
लाईसेन्स आवश्यक	✔	✔	✔

	Discover 125	Electric Dash	Avenger Street 160
	आयाम | टायर | ब्रेक		
ट्याङ्कीको क्षमता (लिटर)	8	NA	13
ग्राउण्ड क्लिअरेन्स	165	145	169
तौल (केजी)	125.00	77.00	156.00
पाङ्ग्राको किसिम	Alloy	Alloy	Alloy
अगाडीको ब्रेक	Drum	Drum	Disc
पछाडीको ब्रेक	Drum	Drum	Drum
बस्ने क्षमता (वयस्क)	2	2	2

	Discover 125	Electric Dash	Avenger Street 160
	इलेक्ट्रिकल विवरण		
गति नाप्ने यन्त्र	Digital	Digital	Digital
कुल दुरी नाप्ने यन्त्र	Digital	Digital	Digital
हेडलाईट्	Bulb	LED	Bulb
पछाडीको बत्ती	Bulb	LED	LED
युएसबी तार जोड्ने ठाउँ	✖	✖	✖

A2. Baseline Survey

Baseline Survey (Phase 1)

Filter questions:

1. Are you older than 16 years?
Yes/No

2. Are you looking to purchase a two-wheeler within the next 6 months?
Yes/No

3. With what probability are you looking to purchase a two-wheeler in the next 6 months? Please answer this question as seriously as possible, for the validity of the results of this study.

With high probability (more than 50%)/With some probability (30-50%)/ With low probability (Less than 30%)

Only respondents who answer yes to the filter questions above will be asked the following questions:

User info known from the Facts Nepal survey app:
- Gender
- Age
- City of residence
- Household income
- Occupation (e.g., student / employed)

Main Questionnaire:

Dear Participant,

Thank you for participating in this research study.

Please answer the below questions to the best of your own knowledge and understanding.
Note that the term motorcycle or bike used in the survey below refers to all types of motorized two-wheelers with a petrol or electric engine (scooter / motorbike / electric scooter / moped / etc.).

Socio-economic information:

1. How many members live in your residence?
(Count all people, e.g., parents, children etc. who are living in the same residence as you.)
[Options: 1-2, 3-4, 5-6, 7 or more]

2. Do you have any dependent children?
[Options: Yes, No]

3. What is the highest level of education that you have already completed?
A) Class 8th or below
B) Completed high school (class 12)
C) Completed Graduate degree (BCom, BBA, BSc, Btech, MBBS)
D) Completed Post-graduate degree (MCom, MSc, MBA, Mtech, PhD)
E) Other

4. What was your mathematics grade in your SLC exam (if you did not take the SLC exam, in the SEE exam or the next highest grade you took an exam in)?
   a) A or A+ (Above 80%)
   b) B or B+ (61-80%)
   c) C or C+ (41-60%)
   d) E, D or D + (40% or less)
   e) I do not remember

5. Will you be the main user of the new motorcycle you are looking to purchase?
   A) Yes, I will be the main user
   B) No, someone else will be the main user, e.g., someone else in my household
   C) Two or more persons will be main users
   D) I do not know

6. A) Do you already own a motorized two-wheeler? [Options: Yes/No]

   B) If yes in A), select the make, model name and engine size of your motorcycle below:
   Dropdown (Make/model/engine size]

   C) If yes in A), in which year did you buy the motorcycle?
   [numeric box]

   D) If yes in A), what is the current average fuel economy (in km/L) of your motorcycle?
   [numeric box]

Preferences & Attitudes:

7. Please indicate how important the following attributes of a vehicle are to you when you are deciding which motorcycle to buy (Remember, there is no right or wrong answer. We want to understand how you value different qualities).
   [Options: Very important/important/Not important]
   a) Power and performance
   b) Purchase price and operating costs
   c) Brand

8. Indicate how true the following statement is for you:
   "I tend to buy things impulsively even if I may not be able to afford them."
   [Options: Agree strongly / Tend to agree / Neither agree nor disagree / Tend to disagree / Disagree strongly]

9. Are you generally an impatient person, or someone who always shows great patience?
   Indicate how you see yourself on a scale of 0 (very impatient) to 10 (very patient).
   (Options: 0 - very impatient / 1 / 2 / … / 9 / 10 - very patient)

10. Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Indicate how you see yourself on a scale of 0 (unwilling to take risks) to 10 (fully prepared to take risk).
    (Options: 0 – unwilling to take risk / 1 / 2 / … / 9 / 10 fully prepared to take risk)

Cognitive skills

11. Suppose you buy a bike for Rs 3,00,000. Your annual cost of petrol is Rs. 20,000. You expect to use the bike for 10 years (lifetime of the bike). What would be the total cost over the lifetime of the bike?
    (Assume that average cost of fuel, fuel economy, distance driven per year, expected lifetime of the bike remains the same, and assume that the value of Rs 1 today is the same as Rs 1 tomorrow.)
    [Options: Rs. 4,50,000 / Rs. 5,00,000 / Rs. 6,00,000 / Rs. 7,50,000 / I do not know]

Financial Literacy/Discounting

12. A) Imagine that you have Rs. 100 today. What would be the value of this money to you, one year from now, if you do not invest it anywhere?
    [Options: More than today / The same / Less than today / I do not know]

    B) If you answered "Less than today" in part A), what is the reason for the decline in the value of money?
    [Options: I am uncertain about the future / I could have invested it somewhere or put it to some other use/I do not know]

Knowledge of costs

13. What was the price of petrol per liter in your city at the end of last year (Dec. 2022)?
    [Options: Rs.90-120 / Rs.120-Rs.150 / More than Rs.150 / I do not know]

14. What is the average fuel economy (in km/L) of a motorcycle having an engine size of 125 cc?
    [Options: Less than 30/30-44 / 45-64/ Above 65/ I do not know]

    Note to enumerators: Q15 is only for those respondents who answered "Yes" to Q6 A) (i.e., who already own a bike):

15. A) Were you aware of the fuel economy of the motorcycle when you purchased it?

[Options: Yes / No/ I do not know]

B) If yes, what was its fuel economy?
[numeric box] Km/L

General questions:

16. Are you planning to apply for a financial loan to buy your motorcycle?
    [Options: Yes / No / I do not know yet]

17. Do you, or any of your close family members, suffer from some type of respiratory disorder (e.g., asthma, chronic obstructive pulmonary disorder, bronchitis, wheezing/cough, etc.)?
    [Options: : Yes / No / I do not know]

18. A) What kind of internet plan do you currently have for your mobile device?
    [Options: Pre-paid/ Post-paid/ I do not know]

    B) What is the volume of data use per day that your current internet data package includes (without additional costs or reduction in speed)?
    [Options: : Less than 500 MB / 500 MB-1 GB/I GB-5 GB/ 5 GB- 8GB / More than 8 GB/ I do not know]

19. How good is the internet connectivity (in terms of the amount of time you have access to internet) where you live?
    [Options: : Very good / Good/Okay/Not good/ Very poor / I do not know]

20. Do you have access to free internet at work/in school or college?

    [Options: : Yes, most of the time/ Yes, sometimes/ Not much/Never/ I do not work or use internet for work/study]

21. Which of the following social media websites/apps do you use, if any? Choose whichever (and as many) is relevant.

Options: checkboxes for the following options [Facebook / Twitter /Instagram/ TikTok/ YouTube/ Reddit/ I do not use social media]

22. How many hours would you say you've already spent researching which motorcycle to buy
    [numeric box]

23. How sure are you about which motorcycle you will purchase?
    [Options: : Not at all sure / Not so sure/Fairly sure/Almost certain]

24. How would you generally rate electric motorcycles and e-scooters?
    [Options: Very poor / Poor / Fair / Good / Very Good]

25. What is your opinion on the following policies to encourage the adoption of more electric two-wheeler?
    [Options: Like it/ Do not like it/ Don't care]
    a) Subsidies for the purchase of electric two-wheelers
    b) Electricity subsidies
    c) Environmental standards
    d) Taxes on petrol and diesel

e) Increase in the provision of public charging facilities
f) Preferences for parking
g) Improvements in the power/technical performance of electric two-wheeler

A3. Endline Survey

<u>Endline Survey (Phase 3)</u>

Dear Participant,

You had recently participated in a study titled "Consumer preferences for motorcycles and role of informational nudges". You said you were looking to buy a new motorcycle in the next few months.

Please answer a few short follow-up questions. It will take approximately 2 minutes.

1. Since October 2022, have you already bought a new bike?
   A) Yes (→ Jump to Q4)
   B) No

2. If you have not yet bought a bike, have you already decided which bike you will **most likely** purchase?
   A) Yes (→ Jump to Q4)
   B) No

3. Could you tell us the reason behind why you did not yet decide which bike to you want to buy? *(Multiple answers possible)*
   A) I am **still looking** / need **more time** to explore options
   B) It is **not very urgent** (hence will take time to decide)
   C) **Financial reasons** (e.g., shortage of cash)
   D) Change of plans – **not buying** at the moment
   E) already bought/will buy a **second-hand bike** (→ Jump to Q4)
   F) Bought/interested-in **another type of vehicle** (Car, bicycle, etc.)
   G) Waiting for a **discount season**
   H) Waiting for **launch** of a particular **bike** model
   I) Waiting for **new electric** bike models
   J) Other reasons

From here, jump to Q5.

4. Which bike? Please select from the dropdown:
   [Dropdown with list of all bikes in the Nepali market that we had in the previous survey; include a last option as "Other".]

5. You may recall that you used a website to compare different bike models along different dimensions. Was the web-platform helpful for you to decide on your preferred bike model?
   [**Options**: Yes, definitely / Yes, to some extent / Somewhat / Not at all / I did not use such a website]

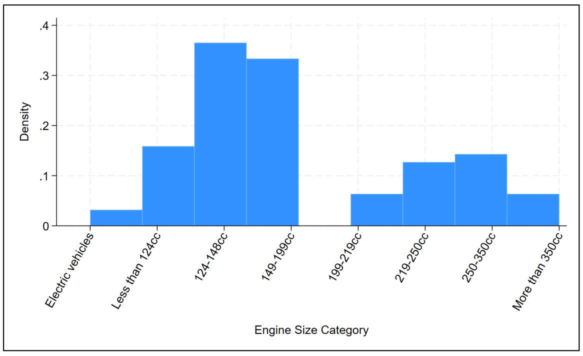
6. Please select which of the following information you remember seeing on the web-platform. *(Multiple answers possible)*
   ☐ Comparison of fuel economies (in km/L) of different bike models
   ☐ Comparison of annual operating cost savings (in Rs.)
   ☐ Comparison of five-year operating cost savings (in Rs.)
   ☐ Technical information on different bike models

- Star ratings of operating cost savings
- None of the above

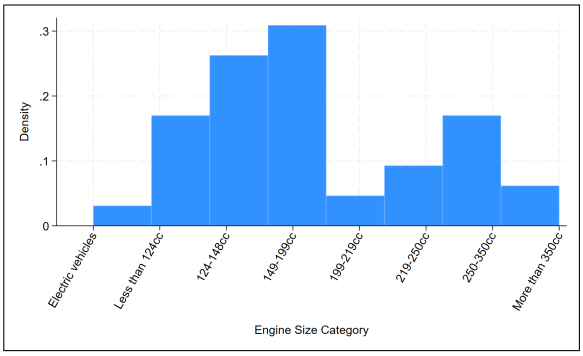
7. Did you again use this website to compare more alternatives before you decided on your preferred bike model?
   [**Options**: Yes, several times / Yes, 1-2 times / No / I do not remember / Not applicable]

End of survey:

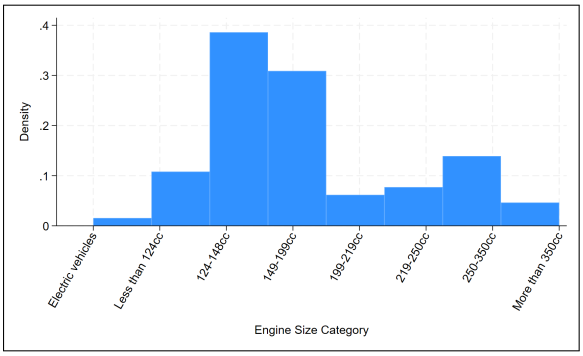
Thank you again for taking part in this research study. Your data will remain strictly confidential and anonymous at all times.



(a) Control group



(b) Treatment group 1



(c) Treatment group 2

Figure A1: Engine Size of Selected Motorcycles By Treatment Group

Table B1: Summary Statistics and Covariate Balance: Stated Preference Sample

Sample		Overall			Control			Treatment 1			Treatment 2			P-values	
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Control vs. T1	Control vs. T2	T1 vs. T2
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Female	0.346	0.476	972	0.335	0.473	332	0.381	0.486	328	0.320	0.467	322	0.225	0.675	0.102
Age	24.823	5.98	972	24.83	6.04	322	24.76	5.74	328	24.88	6.16	322	0.874	0.923	0.798
Income													0.132	1	0.128
Currently not earning	34.98		340	36.96		119	31.71		104	36.34		117			
Below 25,000	32.82		319	32.30		104	33.23		109	32.92		106			
25,0000-50,000	28.29		275	27.02		87	30.49		100	27.33		88			
50,000-100,000	3.60		35	3.42		11	3.96		13	3.42		11			
More than 100,000	0.31		3	0.31		1	0.61		2						
Educational attainment													0.218	0.705	0.116
Primary school (Grades 1-5)	0.72		7	0.62		2	0.30		1	1.24		4			
Secondary school (Grades 6-8)	3.81		37	2.80		9	4.27		14	4.35		14			
Higher secondary school (Grades 11-12)	33.54		326	36.65		118	31.10		102	32.92		106			
Bachelors degree	52.06		506	50.93		164	51.83		170	53.42		172			
Masters degree or higher	9.88		96	9.01		29	12.50		41	8.07		26			
Occupation													0.125	0.202	0.812
Business	8.33		81	6.52		21	9.15		30	9.32		30			
Public sector	1.54		15	1.24		4	1.83		6	1.55		5			
Homemaker	2.78		27	0.62		2	4.27		14	3.42		11			
Private sector	14.61		142	17.39		56	12.20		40	14.29		46			
Self-employed	17.49		170	17.70		57	19.51		64	15.22		49			
Student	55.25		537	56.52		182	53.05		174	56.21		181			
Patient	0.686	0.465	595	0.704	0.458	186	0.658	0.475	199	0.695	0.461	210	0.335	0.845	0.426
Impulsive	0.514	0.500	595	0.548	0.500	186	0.497	0.501	199	0.5	0.501	210	0.319	0.337	0.96
High literacy	0.491	0.500	595	0.511	0.501	186	0.503	0.501	199	0.462	0.500	210	0.872	0.333	0.413
F-test of joint significance													1.45	0.62	1.27
P-value													0.172	0.761	0.258

Notes: This table reports the summary statistics of the main covariates both for the overall sample, and by group, for the sample used in the stated preference analysis. Columns (13) to (15) indicate the p-values testing for differences in mean values across groups.

Table B2: Summary Statistics and Covariate Balance: Sample of Respondents who Actually Bought a Motorcycle

Sample		Overall			Control			Treatment 1			Treatment 2			P-values	
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Control vs. T1	Control vs. T2	T1 vs. T2
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Female	0.31 0.47	68	0.35	0.49	23	0.32	0.48	22	0.26	0.45	23	0.84	0.53	0.68	
Age	25.6	5.56	68	25.7	5.17	23	24.27	3.92	22	26.78	7.03	23	0.31	0.55	0.15
High-income	0.44	0.50	66	0.43	0.51	23	0.38	0.50	21	0.50	0.51	22	0.72	0.67	0.44
High education-level	0.62	0.49	68	0.65	0.49	23	0.64	0.49	22	0.57	0.51	23	0.91	0.56	0.64
Student	0.46	0.50	68	0.48	0.51	23	0.50	0.51	22	0.39	0.50	23	0.89	0.56	0.47
Patient	0.67	0.47		0.83	0.39	12	0.62	0.50	16	0.61	0.50	18	0.24	0.21	0.51
Impulsive	0.57	0.50		0.75	0.45	12	0.44	0.51	16	0.56	0.51	18	0.11	0.30	0.94
High literacy	0.46	0.50		0.42	0.51	12	0.62	0.50	16	0.33	0.49	18	0.29	0.66	0.09
F-test of joint significance													0.64	0.95	0.75
P-value													0.73	0.50	0.65

Notes: This table reports the summary statistics of the main covariates both for the overall sample, and by group, for the sample who actually bought a motorcycle (N= 68 respondents). The information on the income is available for 66 respondents. Columns (13) to (15) indicate the p-values testing for differences in mean values across groups.

Table B3: Summary Statistics for the Literacy Questions: Revealed and Stated Preference Samples

Sample	Revealed		Stated	
Literacy Indicator	Mean	Std. Dev.	Mean	Std. Dev.
Column	(1)	(2)	(3)	(4)
Lifetime cost calculation	0.41	0.49	0.35	0.48
Value of money over time	0.36	0.48	0.34	0.48
Petrol price knowledge	0.46	0.50	0.47	0.50
Fuel economy knowledge	0.29	0.46	0.34	0.48

Notes: This table reports the summary statistics of the four individual literacy questions (described in the Data section) for the overall sample, for both the revealed preference and the stated preference analyses. Mean values denote the proportion of correct answers. The sample size is 224 in columns (1) and (2), and 972 in columns (3) and (4).

Table B4: Attrition Patterns

Dependent variable	Probability of completing follow-up survey		
Column	(1)	(2)	(3)
Sample	Full Sample		Treatment groups 1 and 2
Treatment 1	0.011	0.015	
	(0.019)	(0.022)	
Treatment 2	0.004	-0.001	
	(0.011)	(0.009)	
Female		0.013*	0.018
		(0.004)	(0.043)
Age		0.004**	0.003
		(0.0007)	(0.005)
Income category			
Below 25,000		0.003	0.019
		(0.008)	(0.057)
25000-50000		-0.026***	-0.051
		(0.002)	(0.077)
50000-100000		-0.188***	-0.241**
		(0.008)	(0.122)
More than 100000		-0.197**	-0.517***
		(0.022)	(0.100)
Educational attainment			
Secondary school		0.045	0.243
		(0.171)	(0.220)
Higher secondary school		0.194	0.334
		(0.201)	(0.213)
Bachelor's degree		0.151	0.272
		(0.188)	(0.211)
Masters degree or higher		0.228	0.322
		(0.191)	(0.216)
Occupational category			
Public Sector		0.027	0.111
		(0.138)	(0.158)
Homemaker		-0.020	-0.021
		(0.056)	(0.135)
Private sector		0.017	0.025
		(0.022)	(0.091)
Self-employed		-0.050*	-0.082
		(0.016)	(0.084)
Student		0.058	0.028
		(0.031)	(0.098)
Number of times platform was used		0.004	-0.008
		(0.003)	(0.011)
Observations	1011	977	654

Notes: This table reports the marginal effects from the estimation of the model evaluating treatment effects on the likelihood of participating in the follow-up survey for the overall sample (columns (1) and (2)) and the effects of socioeconomic covariates on the likelihood of finishing the follow-up survey for respondents in Treatment groups 1 and 2 (column (3)). All models are estimated using a linear probability model. In all models, we control for the number of times the respondent used the platform, whereas in columns (2) and (3) we control for the gender, age, education, income and occupational categories of the respondents. Reference categories are 'Currently not earning' for the income category variable, 'Primary school' for the educational attainment variable, and 'Business sector' for the occupational category variable. In all columns, marginal effects are reported at the mean values of other explanatory variables. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

Table B5: Preferences for Vehicle Attributes Across Groups

Sample	Overall			Control			Treatment 1			Treatment 2			P-values		
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Control vs. T1	Control vs. T2	T1 vs. T2
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Revealed Preference Sample															
Engine power and performance: very important	0.72	0.45	175	0.72	0.45	57	0.67	0.48	57	0.77	0.42	61	0.55	0.53	0.21
Purchase price and operating costs: very important	0.59	0.49	175	0.60	0.49	57	0.60	0.49	57	0.57	0.50	61	1	0.80	0.80
Brand: very important	0.39	0.49	175	0.42	0.50	57	0.46	0.50	57	0.31	0.47	61	0.71	0.22	0.11
Stated Preference Sample															
Engine power and performance: very important	0.67	0.47	595	0.66	0.47	186	0.65	0.48	199	0.70	0.46	210	0.79	0.35	0.22
Purchase price and operating costs: very important	0.59	0.49	595	0.56	0.50	186	0.60	0.49	199	0.60	0.49	210	0.38	0.41	0.95
Brand: very important	0.42	0.49	595	0.41	0.49	186	0.43	0.50	199	0.40	0.49	210	0.79	0.85	0.65

Notes: This table reports the summary statistics of vehicle attribute-related preferences for the overall sample, and by group, for the sample used in the revealed preference analysis as well as in the stated preference analysis. Columns (13) to (15) indicate the p-values testing for differences in mean values across groups.

Table B6: Motorcycle Models: Revealed Preference Sample

Brand/Model	Frequency	Share
Aprilia SR 125	1	0.44
Aprilia storm 125	1	0.44
Bajaj Avenger 220	1	0.44
Bajaj Dominar	1	0.44
Bajaj Pulsar 220	2	0.87
Benelli TNT 150i	2	0.87
Benelli TNT 300	7	3.06
Benelli Tnt 15	3	1.31
Hero Splendor Super	1	0.44
Hero Splendor iSmart	1	0.44
Hero Xpulse 200	2	0.87
Hero Xpulse 200T	4	1.75
Hero Xtreme 200S	1	0.44
Hero Pleasure	2	0.87
Honda Activa 125	3	1.31
Honda Aviator	6	2.62
Honda CB Hornet 160R	6	2.62
Honda CB Shine	2	0.87
Honda CB Shine SP	4	1.75
Honda CB Trigger	1	0.44
Honda CB Unicorn 150	1	0.44
Honda Dio	11	4.8
Honda Dio Deluxe	3	1.31
Honda Grazia	2	0.87
Honda XR 150 L	2	0.87
KTM Adventure 250	1	0.44
KTM Duke 125	19	8.3
KTM Duke 200	4	1.75
KTM Duke 250	5	2.18
KTM Duke 390	6	2.62
KTM RC 390	5	2.18
NIU Gova G5	1	0.44
NIU MQi+ Sport	3	1.31
NIU N1s	1	0.44
Royal Enfield Classic 350	21	9.17
Royal Enfield Hunter 350	1	0.44
Suzuki Access 125	2	0.87
Suzuki Gixxer 150	2	0.87
TVS Jupiter	3	1.31
TVS NTORQ 125	10	4.37
TVS NTORQ Disc	2	0.87
TVS NTORQ Race	7	3.06
TVS NTORQ Squad	2	0.87
TVS Radeon	1	0.44
Vespa Sprint 150 s	2	0.87
Vespa SXL 150	2	0.87
Vespa Elegante 125	1	0.44
Vespa Elegante 150	4	1.75
Vespa LX 125	1	0.44
Vespa SXL 125	1	0.44
Vespa VXL 125	2	0.87
Vespa VXL 150	1	0.44
Yamaha Alpha	1	0.44
Yamaha FZ 25	9	3.93
Yamaha FZ V3	6	2.62
Yamaha FZ X	3	1.31
Yamaha FZS V3 X-Connect	1	0.44
Yamaha FZ S v2.0 fi	1	0.44
Yamaha FZ S v3.0 fi	3	1.31
Yamaha FZ v2	2	0.87
Yamaha MT-15	19	8.3
Yamaha RAY ZR	1	0.44
Yamaha YBR	3	1.31
Total	229	100

Notes: This table reports the make and model names of the motorcycle choices of respondents in the revealed preference phase, along with the corresponding frequencies and the share of respondents who purchased each model. These are the models respondents either bought, or intended to purchase.

Table B7: Average Fuel Economy: Stated Preference Sample

Group	Mean fuel economy (km/l)	Median fuel economy (km/l)	Obs.
Column	(1)	(2)	(3)
Control	48.77	45	329
Treatment group 1	46.83	45	334
Treatment group 2	48.72	45	342
Total	48.11	45	1005

Notes: This table reports the average (mean and median) fuel economy by group for the stated preference sample of 1005 respondents in their last choice on the platform.

Table B8: Average Fuel Economy: Revealed Preference Sample

Group	Mean fuel economy (km/l): Bought or intended	Median fuel economy (km/l): Bought or intended	Obs.	Mean fuel economy (km/l): Bought	Median fuel economy (km/l): Bought	Obs.
Column	(1)	(2)	(3)	(4)	(5)	(6)
Control	45.72	45	81	50.04	48	23
Treatment group 1	45.03	45	74	45.5	45	22
Treatment group 2	47.64	45	74	52.87	55	23
Total	46.12	45	229	49.53	48	68

Notes: This table reports the average (mean and median) fuel economy by group for the revealed preference sample of 229 respondents who either bought a motorcycle or intended to purchase one (columns (1)- (3)) and for those respondents who purchased a motorcycle (columns (4) - (6)).

Table B9: Heterogeneous Impact of Information Treatments: Difference in Fuel Economy Between Revealed and Stated Preferences

Dependent variable	Difference in fuel economy (in km/l) of revealed choice and stated choice vehicles					
Column	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneous treatment	Impulsive	Impatient	Low literacy	Female	Low prob. of purchase	Already own motorcycle
Treatment 1	2.565*	2.962**	4.787**	1.868	0.257	5.365**
	(0.0.789)	(0.659)	(1.161)	(0.899)	(1.379)	(1.006)
Treatment 2	2.539**	7.741**	5.488***	3.867***	2.959**	5.488***
	(0.434)	(1.031)	(0.517)	(0.309)	(0.516)	(0.259)
Control group mean	-3.72	-3.72	-3.72	-3.72	-3.72	-3.72
Observations	175	175	175	175	175	175

Notes: This table reports the heterogeneous marginal effects from the OLS estimation of the model of column (6), Table 3 using interaction terms to elicit treatment effects for specific types of respondents, indicated by the column header. The dependent variable is the difference in fuel economy of the revealed and stated motorcycle choices (in km/l). The model includes covariates for the engine size category, number of times the respondent used the platform, gender, age, income, educational attainment, and occupation. In addition, we control for a measure of risk aversion. In all columns, marginal effects are reported at the mean values of other explanatory variables. The control group mean reported at the bottom of the table mentions the mean difference in fuel economy (in km/l) between the revealed and stated choices for the control group in columns (1) to (6). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

Table B10: Impact of Information Treatments: Decision to Purchase a Motorcycle

Dependent variable	Binary variable for whether respondent purchased a motorcycle	
Column	(1)	(2)
Sample	Without covariates	Inc. covariates
Treatment 1	0.013	-0.007
	(0.011)	(0.012)
Treatment 2	-0.008*	-0.021*
	(0.003)	(0.006)
Control group mean	0.23	0.24
Observations	476	460

Notes: This table reports the marginal effects from the estimation of linear probability models to test the impact of the treatments on the decision to actually purchase a motorcycle. Both models are estimated using OLS, and in both, we control for the number of times the respondent used the platform. In column (2), additional covariates include gender, age, as well as income, educational attainment, and occupational category. Marginal effects are reported at the mean values of other explanatory variables.The difference in number of observations in columns (1) and (2) is due to non-responses for the income variable. The control group mean reported at the bottom of the table mentions the mean proportion of respondents who bought a motorcycle in the control group, in columns (1) and (2). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

Table B11: Role of Information: Stated Preference

Dependent variable	Log of fuel economy (in km/l) of selected motorcycle		Time spent in making choice	
Sample	Inc. covariates	Inc. covariates	Without covariates	Inc. covariates
Column	(1)	(2)	(3)	(4)
Treatment 1	0.0001	0.004	-4.465**	-4.759**
	(0.004)	(0.002)	(0.833)	(1.017)
Treatment 2	0.004	0.031**	1.423*	2.010**
	(0.001)	(0.002)	(0.339)	(0.254)
Control group mean	49.07	47.82	44.59	44.72
Observations	703	269	1011	977

Notes: This table reports the marginal effects from the estimation of the main stated choice model (column (2) of Table 3) for respondents who used the platform once (column (1)) to make a choice, or more than once (column (2)), and the impact of the treatments on the time spent in making a selection (columns (3) and (4)). All models are estimated using OLS. In all estimations, we control for the engine size category of the selected motorcycle, and for the number of times the respondent used the platform. In columns (1), (2) and (4), additional covariates include gender, age, as well as income, educational attainment, and occupational category. In all columns, marginal effects are reported at the mean values of other explanatory variables. The difference in number of observations in columns (3) and (4) is due to non-responses for the income variable. The control group mean reported at the bottom of the table mentions the mean stated fuel economy (in km/l) for the control group in columns (1) and (2), and the mean time taken between clicking "Compare" and "I prefer" on the platform for the control group in columns (3) and (4). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

Table B12: Website Activity During Phase 2

Group	Control	Treatment 1	Treatment 2
Respondents who used platform in phase 1	329	334	342
No. of respondents who used platform in phase 2	194	185	342
Share of phase 1 respondents who used platform in phase 2	59%	55%	66%
Share of phase 1 respondents who made a choice in phase 2	55%	52%	61%
Mean no. of choices made in phase 2	1.57	1.61	1.62
Mean fuel economy of choices in phase 2 (in km/l)	49.81	50.07	49.97

Notes: This table reports the summary statistics on the website activity during phase 2 of the study, by treatment group.

Table B13: Impact of Information Treatments: Operating Cost Savings vs. Expenditures

Dependent variable	Log of fuel economy (in km/l) of selected motorcycle	
Column	(1)	(2)
Sample	Without covariates	Inc. covariates
Treatment group 1 who only saw relative savings on labels	-0.015	0.011
	(0.059)	(0.064)
Treatment group 1 who saw at least one label with relative expenditures	-0.002	0.009*
	(0.004)	(0.002)
Treatment group 2 who only saw relative savings on labels	0.182***	0.169***
	(0.002)	(0.003)
Treatment group 2 who saw at least one label with relative expenditures	0.031**	0.025***
	(0.005)	(0.002)
Control group mean	45.72	45.72
Observations	229	224

Notes: This table reports the marginal effects from the estimation of the revealed preference model of column (2), Table 4, interacting the treatment indicators with a dummy variable for whether they saw any relative expenditure information on the labels. Both models are estimated using OLS, and in both estimations, we control for the engine size category of the purchased motorcycle, and for the number of times the respondent used the platform. In column (2), additional covariates include gender, age, as well as income, educational attainment, and occupational category. In both columns, marginal effects are reported at the mean values of other explanatory variables.The difference in number of observations in columns (1) and (2) is due to non-responses for the income variable. The control group mean reported at the bottom of the table mentions the mean fuel economy (in km/l) for the control group in columns (1) and (2). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

Table B14: Robustness Checks

Dependent variable	Log of fuel economy (in km/l) of selected motorcycle		Fuel economy (in km/l) of selected motorcycle	Engine size category of selected motorcycle
Column	(1)	(2)	(3)	(4)
Treatment 1	0.006	-0.013	0.319	0.021
	(0.011)	(0.006)	(0.505)	(0.048)
Treatment 2	0.032***	0.042**	1.693***	-0.139***
	(0.003)	(0.005)	(0.087)	(0.029)
Control group mean	45.72	45.72	45.72	3.17
Observations	224	229	224	226

Notes: This table reports the marginal effects from the estimation of the robustness checks for the main revealed preference results. In column (1), we control for the distance the respondent expects to drive, column (2) does not include any covariates, in column (3) we use the fuel economy as a dependent variable without applying the log transformation, and in column (4) we use the engine size category as the dependent variable. The models in columns (1)-(3) are estimated using OLS, whereas in column (4) we use an ordered probit model. In columns (1) and (3), we control for the engine size category of the purchased motorcycle, and in columns (1), (3) and (4), for the the number of times the respondent used the platform. In columns (1), (3) and (4), additional covariates include gender, age, as well as income, educational attainment, and occupational category. In all columns, marginal effects are reported at the mean values of other explanatory variables. The control group mean reported at the bottom of the table mentions the mean fuel economy (in km/l) for the control group in columns (1) to (3), and the mean engine size category in column (4). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

Table B15: Impact of Information Treatments: Total Lifetime Costs

Dependent variable	Log of fuel economy (in km/l) of selected motorcycle	
Column	(1)	(2)
Sample	Without covariates	Inc. covariates
Treatment 1	-4043.07	-5486.60
	(5943.36)	(5391.95)
Treatment 2	-15395.32*	-8802.82**
	(5200.88)	(0.005)
Control group mean	685016	685016
Observations	229	224

Notes: This table reports the marginal effects from the estimation of the impact of the treatments on the total lifetime cost of the motorcycle (defined as the sum of purchase cost and the five year operating cost, assuming zero rate of interest). Both models are estimated using OLS, and in both, we control for the engine size category, and for the number of times the respondent used the platform. In column (2), additional covariates include gender, age, as well as income, educational attainment, and occupational category. Marginal effects are reported at the mean values of other explanatory variables. The difference in number of observations in columns (1) and (2) is due to non-responses for the income variable. The control group mean reported at the bottom of the table mentions the mean total lifetime costs (in Rs., defined as the sum of the purchase cost and undiscounted five-year operating costs) for the control group in columns (1) and (2). *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the city-of-residence level, and reported in parentheses. The coefficient on the constant has not been reported.

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