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# Behavioral Anomalies and Fuel Efficiency: Evidence from Motorcycles in Nepal

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**Abstract**

Air pollution is a grave problem in urban areas of developing countries, with the transport sector being one of the largest contributors to emissions. A possibility to reduce carbon dioxide emissions would be for individuals to switch to more fuel-efficient vehicles. However, a gamut of behavioral anomalies and market failures have been known to inhibit individuals from investing in fuel-efficiency (due to the well-known 'energy-efficiency gap'). In this study, we use novel data from Kathmandu, Nepal to understand the socio-economic and psychological determinants of three behavioral anomalies, namely present bias, loss aversion, risk aversion, as well as time preferences. In a second step, we evaluate the effect of these anomalies on the energy-efficiency gap in the choice of motorcycles of individuals. We find that present-biased individuals are less likely to invest in fuel-efficient motorcycles, and thus more likely to buy motorcycles having relatively high total lifetime costs. We also find that other factors such as income, as well as having applied for loans, play an important role in determining these choices. Our results suggest that behavioral anomalies may indeed pose as a hindrance to individuals making cost-minimizing (and also environmentally sound) investment decisions.

**JEL Classification:** D1, D8; Q4; Q5

**Keywords:** Behavioral anomalies; Present bias; Fuel efficiency; Energy-efficiency gap; Motorcycles; Nepal

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

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# 1 Introduction

Air pollution is the cause for almost seven million deaths globally every year according to the World Health Organization, out which 4.2 million deaths can be attributed to outdoor air pollution (World Health Organization, 2016). While the negative health implications of excessive levels of air pollution are widespread, urban areas in low and middle-income countries (LMICs) bear the brunt: according to statistics from the WHO Urban Air Quality Database, 98% of cities in LMICs with more than 100,000 inhabitants do not meet WHO air quality guidelines (this share is 56% in high-income countries) (World Health Organization, 2016). These alarming statistics, combined with the fact that these countries are often ill-equipped to deal with the economic costs of air pollution, necessitates identifying the sectors having high local and global negative externalities, as well as understanding the reasons.

Kathmandu, Nepal is an example of one such city, where air pollution poses a grave threat to public health: the Environmental Performance Index (EPI) of Nepal's air quality ranked 176th out of 180 countries (Wendling et al., 2018), while an individual living in Kathmandu can expect to gain up to 4.7 years of life if concentrations of $PM_{2.5}$ are reduced to the WHO guidelines (Energy Policy Institute at the University of Chicago, 2019). One of the primary sources of air pollution in Kathmandu is the transport sector. Inefficient transport contributes to approximately 63% of all $PM_{10}$ emissions in the Kathmandu valley, for example (Schwela, 2009).

Improving the efficiency, reliability as well as quality of public transport remains an important objective in many cities in developing countries. However, given the large share of two-wheelers in the vehicle fleet in Kathmandu (including motorcycles, internal combustion engine (ICE)-based scooters and electric scooters, which accounted for about 80% of vehicle sales in 2016-17 (Facts Research and Analytics, 2018)), improving the efficiency of private transport is pivotal in reducing greenhouse gas emissions, as well as air pollution, from private transport.

As of 2010, about 25% of two-wheelers in Kathmandu still used pre-Euro standard engine technologies (Shrestha et al., 2013). In 2010, they consumed the largest share of petrol (about 25%) compared to other vehicle types in the Kathmandu valley (Bajracharya and Bhattarai, 2016). Moreover, the two-wheeler fleet in Kathmandu was also the largest contributor to other greenhouse gas emissions, such as those of VOC, CO and $CH_4$ (Shrestha et al., 2013). These statistics suggest the possibility that two-wheelers operating in Kathmandu are likely to be inefficient. Hereafter, we will use the term 'motorcycle' in order to refer to both the traditional motorcycles, as well as ICE-based scooters (but not electric scooters, which are not the focus of this study).

For instance, we find that there is significant variation in the fuel efficiency (measured in terms of kilometres per litre of petrol, or km/l) of motorcycles within a given engine size (measured in cubic centimetres, or 'cc') in Nepal, which is reflected in our data.[1] These differences in fuel economy can lead to substantial differences not just in emissions, but also in terms of annual fuel costs, depending on usage.[2] Moreover, fuel-efficient motorcycles in

[1] In our data, motorcycles of engine size 125 cc have a fuel economy starting from 45 km/l (the Mahindra Rodeo 2016 model), ranging up to 78 km/l (the Yamaha Saluto 2016 model) and those of engine size 150cc have fuel economy ranging from 37 km/l (the Hartford VR 2018 model) to 72 km/l (the Bajaj Discover 2004 model).

[2] Using the examples we provide in the previous footnote, for a person who drives 40 kms per day on average,

Nepal are not necessarily much more expensive than fuel-inefficient ones. Therefore, investing in fuel-efficiency can not only address the negative externalities due to pollution, but it can also provide significant private gains (in terms of fuel cost savings). Given that total lifetime costs (defined as the sum of purchase price and discounted operating costs over the lifespan of a vehicle) are likely to vary across different motorcycle models depending on their price and fuel efficiency, as well as on personal use, it is therefore plausible that not all individuals would be making the most optimal choices in terms of minimizing total lifetime costs.[3]

This finding resonates with a large literature on the energy-efficiency gap, which has shown that individuals fail to make optimal decisions in many situations when the benefits and costs of owning energy-consuming durables (such as motorcycles, or appliances) are unevenly distributed over time (Hausman, 1979; Jaffe and Stavins, 1994; Train, 1985). More energy-efficient durables, for example, generally have lower operating costs and thus may be less expensive to own over the long-run (even from a private perspective, without accounting for any underlying environmental or health benefits).

Reasons for the energy-efficiency gap in the literature have been ascribed to market failures as well as behavioral anomalies, that prevent individuals form realizing the gains from investing in energy-efficient technologies (Gillingham and Palmer, 2014).

The set of market failures that have been found to impede decisions to invest in energy-efficient technologies include asymmetric or imperfect information, principal-agent problems, unpriced externalities, as well as credit or liquidity constraints. Mullainathan and Thaler (2000) broadly categorize behavioral anomalies based on agents either displaying "bounded rationality", such as cognitive/skills limitations, framing problems, loss aversion, risk aversion and limited attention; or displaying "bounded willpower", such as myopia or present bias.

In this paper, we focus our attention on a set of behavioral anomalies, namely present bias, loss aversion and risk aversion. In particular, we are interested in assessing the impact that present bias may have on the types of motorcycles that individuals have purchased, based on their fuel economy. Given that the purchase of a vehicle is a large investment, and given that we are conducting our analysis in a low-income context, we hypothesize that time and risk preferences may contribute towards undermining the adoption of fuel-efficient motorcycles.

Present bias implies that individuals exhibit a high discount rate in the short run but a relatively low discount rate in the long run. Theoretically, this behavior has been modeled using a (quasi) hyperbolic time discounting function (Frederick et al. 2002; Laibson 2011). Individuals who are myopic place less weight on the future, possibly due to the uncertain utility that they would derive from future consumption (Strotz, 1955). This present bias may cause temporizing

opting for the less fuel efficient model would translate into needing an extra 137 litres of petrol annually (for 125 cc) or 192 litres annually (in the 150 cc category), to drive the same distance. In monetary terms, this could translate to savings in the range of Rs. 15'000 (USD 129.04) to Rs. 20'000 (USD 172.06) per year when using the most fuel efficient motorcycle of the same engine size (assuming an exchange rate of Nepal Rs. 10,000 $\approx$ USD 86.03, as of 29th March 2021). These calculations are based on motorcycle fuel economy specifications provided by the manufacturers, and the average fuel price in Nepal is assumed to be Rs. 110 per litre (as on January 26, 2021). The on-road fuel efficiency naturally also depends on road, traffic and weather conditions, as well as driving style and several other practical factors which are assumed to be the same for the purpose of this comparison.

[3]Other types of costs such as maintenance, financing, insurance and depreciation may also depend on the intensity of use, the purchase price as well as the lifespan of the motorcycle. For the purposes of the analysis in this paper, we only consider total lifetime costs in terms of operating (fuel) costs.

behavior on the part of individuals, especially when the costs are immediate. Present bias observed in situations where consumers have to incur a higher upfront cost for the purchase of an efficient technology has been found to play a role in exacerbating the energy-efficiency gap (Bradford et al., 2017; Cohen et al., 2017; Fuerst and Singh, 2018; Harding and Hsiaw, 2014). Thus, present-biased individuals may find it difficult to factor in future energy cost savings in a manner consistent with a rational agent economic model of discounting. Moreover, the considerable upfront effort required for estimating these savings can create a reluctance to exert this effort among present-biased individuals. This symbiosis between between present bias and effort was investigated by Augenblick et al. (2015), who found that even when there may be limited evidence of present bias over monetary payments, there may be significant present bias and thus dynamic inconsistency in choices over effort. In our context, this implies that present-biased individuals may tend to inflate the upfront effort required to do a lifetime cost calculation, and undervalue the future benefits of doing this calculation.

In a developing country setting, the possible role of present bias in determining investment decisions deserves even more attention from researchers. Individuals in developing countries are often exposed to risk, have limited social security options, and also have a reduced scope for borrowing in order to undertake investments. As present-biased individuals are likely to have high marginal propensities to consume, and thus have difficulties saving and maintaining liquid assets, it is likely to create additional liquidity constraints. This renders it difficult for these individuals to undertake investments, without additional provisions of credit (Kremer et al., 2019). Thus, while credit or liquidity constraints are a form of market failure that may prevent individuals from making investments in energy efficiency in themselves (particularly in cases when energy-efficient durables are more expensive), present bias in itself can introduce an additional source of liquidity constraints.

Our objective in this paper is twofold, a) to evaluate the determinants of behavioral anomalies that have previously been found to be relevant in explaining the energy-efficiency gap using survey data from Kathmandu, and b) to assess the impact of the presence of these anomalies on the energy-efficiency gap in the adoption of fuel-efficient motorcycles. We utilize novel data on existing petrol-driven motorcycle owners in Kathmandu for this purpose and construct a measure of the energy-efficiency gap, using which we intend to capture possibly inefficient choices made by individuals.

In order to address our first research question, we estimate a set of discrete-choice models to discern the socio-economic variables that may play a role in determining the behavioral anomalies. Our methodology in the second part of the analysis, where we are evaluating the role of these anomalies on a measure of the energy-efficiency gap, involves estimating linear models, sample-selection models as well as instrumental variable models employing a control function approach in order to correct for possible endogeneity of the present bias indicator.

We find that income is a strong determinant of time preferences, as well as risk and loss aversion in our sample, with relatively higher-earning individuals being less likely to be loss averse, more likely to be risk-averse, and more likely to have high discount rates. In addition, having a university education implies having lower discount rates, and being less risk-averse. Individuals who stated that they themselves, or a family member suffered from a respiratory disorder were more likely to be present-biased, and more likely to have high discount rates. We also find that certain psychological factors affected the occurrence of these anomalies; for instance, individuals who stated that they lived according to religious principles were more

likely to be loss-averse as well as risk-averse, as were those who stated that they held on to their family traditions. On the other hand, individuals who stated that they were likely to buy the latest technological innovation (even if they didn't need it) were more likely to be present-biased, as well as loss and risk-averse.

In the second part of our analysis, we find that present-biased individuals are more likely to have made relatively inefficient choices with respect to the fuel economy of the motorcycle that they purchased. They are more likely to have bought motorcycles with relatively larger total lifetime costs than the total lifetime cost that is achievable with buying the most fuel-efficient model of the same engine size. We do not find this effect for either loss or risk aversion. Moreover, while we find that individuals who applied for a loan to purchase their motorcycle were more likely to buy relatively fuel-inefficient vehicles, we also learn that individuals having higher levels of income have invested in relatively inefficient motorcycles (controlling for vehicle specifications such as engine size and brand). This effect is also echoed in respondents who own more than one motorcycle, i.e. they are also more likely to have made relatively fuel inefficient purchases for the vehicle that they use most frequently. Lastly, individuals whose families use the motorcycle regularly are more likely to have bought relatively fuel-inefficient motorcycles. We find that these results are confirmed across different specifications and assumptions.

These findings suggest that present bias is likely to be important in determining the fuel economy choices for motorcycles in Kathmandu; individuals who are present-biased or myopic are less likely to have realized the expected future cost savings from investing in fuel-efficiency. While it is difficult for us to pinpoint the exact channel through which present bias determines choices given our data, we hypothesize that these effects may either be driven by consumers undervaluing future fuel cost savings, or by the fact that present-biased individuals may find it onerous to compute total lifetime costs. Being cognizant of the total lifetime costs requires effort, not just in doing the computation, but also requires knowing how long one wants to own the motorcycle, the fuel efficiency of the motorcycle, the relevant discount rate to use, etc.

The finding on the effects of higher income suggests to us that it is not necessarily poorer individuals who purchase fuel-inefficient vehicles in this context. At the same time, our finding about individuals who applied for a loan making less efficient choices seems to suggest that being liquidity or credit-constrained may also lead to buying vehicles having relatively high total lifetime costs when fuel-efficient motorcycles are more expensive. While we do not have information in our data on whether these individuals were granted a loan or not, this finding suggests that they may also have chosen not to exert effort do lifetime cost calculations, or that they may have prioritized other attributes over fuel economy in choosing their motorcycles.

Our contribution to the literature is that to the best of our knowledge, this study is one of the first to evaluate the socio-economic determinants of these behavioral anomalies for Nepal, and one of the first to look at the role of psychological factors in explaining these anomalies in a developing country context. We construct a novel measure to capture the energy-efficiency gap in the purchase of vehicles, and complement this literature by evaluating the role of specific anomalies in determining fuel economy choices in a low-income country context.

Our results have important implications for the design of transport policy instruments in similar contexts: if present bias is likely to hinder the adoption of fuel-efficient vehicles, then it is plausible that information campaigns stressing the long-term benefits of switching to cleaner transport would be unlikely to succeed. On the other hand, the prevalence of present bias

also implies that standards as well as product taxes may be more relevant than fuel taxes in ensuring that individuals purchase more fuel-efficient vehicles. Currently, there are no emission standards for motorcycles in Kathmandu. Another effective policy option could be to relax liquidity constraints for households looking to buy fuel-efficient motorcycles (possibly through subsidies or low-interest loans). Economic incentives such as subsidies may also be useful for people who are loss or risk averse as they would lower the upfront costs of an investment.

The rest of the paper is organized as follows: Section 2 provides a review of the previous literature, Section 3 includes details on our data and the empirical strategies, Section 4 presents the main results, and Section 5 concludes.

# 2 Previous Literature

In this section, we summarize the literature that is relevant to the discussion of this paper. This paper can fit into four strands of the economic literature. The first one focuses on the effects of various market failures and behavioral anomalies in determining the energy-efficiency gap. The second studies the barriers to technology adoption in developing countries, and in particular on the role of present bias, as well as of liquidity constraints. Our study also fits into the (third) strand of literature that evaluates the determinants of various behavioral anomalies. Lastly, we can contribute to a large literature in transport economics, in which some studies have evaluated the determinants of vehicle attribute choices (such as fuel economy).

The energy-efficiency gap has been attributed in the economic literature to market failures and behavioral anomalies that prevent individuals from adopting energy-efficient technologies which can both reduce operating costs, and environmental damage from the use of energy (Gillingham and Palmer 2014; Shogren and Taylor 2008). Examples of market failures include information imperfections and asymmetries (Allcott and Taubinsky 2015; Anderson and Newell 2004), environmental externalities, principal-agent problems and credit constraints or liquidity constraints (Golove and Eto, 1996). Behavioral anomalies, on the other hand, include myopia, loss and risk aversion, cognitive limitations, inattentiveness (or limited attention), as well as reference-dependent preferences (Gerarden et al., 2015).

Myopia has been found to undermine the adoption of energy-efficient technologies, at least in some contexts. For instance, Allcott and Wozny (2014) found that US consumers were indifferent between one dollar in discounted future petrol costs and 76 cents in vehicle purchase price, providing some evidence of discount rates playing a role in the adoption decision for more fuel-efficient cars. Cohen et al. (2017) used data on the refrigerator market in the UK and conclude that consumers exhibited moderate levels of myopia. Harding and Hsiaw (2014) found that present-biased individuals consumed more electricity than consumers who were not present-biased before joining a goal setting program. Interestingly, Bradford et al. (2017) found, using US data, that both discount factors as well as present bias are significantly associated with several kinds of activities in the health, finance and energy domains; for instance, they found that individuals who were not present-biased were much more likely to purchase fuel-efficient vehicles (in a similar strain to what we find in our study), whereas individuals having higher discount factors (and thus lower discount rates) were more likely to install energy-efficient lighting. The main reasoning provided in the paper for non-present-biased individuals to buy fuel-efficient cars is that cars qualify as "big-ticket" items, and it is likely that individuals may

face liquidity constraints when making their purchase, which renders time preferences to be potentially important. On the other hand, Sallee et al. (2016) used data from wholesale used car auctions to conclude that buyers fully valued fuel economy, i.e. that the prices of used cars moved one for one with changes in future discounted petrol costs. Busse et al. (2013) also found very low likelihoods for consumer myopia in the US new and used car markets, with implicit discount rates mostly near zero.

Present bias or myopia has traditionally been measured in terms of time inconsistency with respect to monetary rewards using a multiple price list approach, however it has also been conceptualized in terms of the choice to exert effort. As an example of the latter, Augenblick et al. (2015) show, using an experimental approach, that individuals may exhibit present bias in terms of effort tasks (such as text transcription, or solving puzzles and games), i.e. procrastinate, even if they are not present-biased in terms of monetary rewards. This definition of present bias has been elaborated as well as tested in several other studies, such as Berkouwer and Dean (2019); Carvalho et al. (2016); Dean and Sautmann (2021); Kaur et al. (2015); Lockwood (2020). In this paper, following the approach of other studies focusing on the effect of present bias on the energy-efficiency gap Bradford et al. (2017); Schleich et al. (2019), we measure present bias in terms of time inconsistency in monetary rewards, however we provide some suggestive evidence that individuals categorized as being present-biased by this method, may also be averse to exerting effort in order to undertake lifetime cost calculations.[4]

Loss aversion as well as risk aversion have also been found to be important determinants of the fuel economy choices of vehicles, as well as investment decisions in energy-efficient durables. Greene et al. (2013), for instance, found some evidence to suggest that loss aversion played a role in fuel economy decisions for individuals in the US, due to uncertainty about fuel economy as well as future fuel prices. Schleich et al. (2019) found, using data from a large-scale survey across eight European countries, that more risk-averse individuals, more loss-averse individuals and individuals who exhibited a lower time discount factor were less likely to adopt energy-efficient technologies (such as LED lamps, appliances, or retrofit measures). On the other hand, they found weaker evidence to suggest that present bias played a role in the choices of individuals (their results suggested that present bias affected choice only when they did not account for extreme values). Heutel (2019) also found that loss aversion may be relevant in explaining under-adoption of high-efficiency light bulbs, replacement of air conditioners, and investment in alternative fuel vehicles, using data from the US.

Our focus is on present bias, and the role that it plays on the adoption of durables having high initial costs, such as motorcycles, in a low-income setting. Present bias has been found to be an important deterrent towards many behaviors in developing countries: given that many individuals in these cases exhibit liquidity constraints, as well as high marginal propensities to consume, present bias is likely to make them seem even more impatient compared to richer individuals (Cassidy, 2018). Present bias in turn generates its own liquidity constraints (Angeletos et al., 2001), which implies that often in developing countries, it is difficult for present-biased agents to respond to surprise opportunities for investment without accompanying provisions for credit (Kremer et al., 2019). These liquidity constraints also cause households to decline high-return investments, such as in preventative health, or energy-efficient technologies.

Several studies have evaluated the determinants of behavioral anomalies, especially in the

[4]The empirical analysis in Section 4 provides details.

psychology and behavioral economics literature. For instance, risk aversion has been found to be correlated with the presence of macro as well as micro-level shocks (Sakha, 2019) in Thailand, with gender, age, height, and parental background in Germany (Dohmen et al., 2011), and with household circumstances (such as success with agricultural operations, as well as income and assets) in Ethiopia (Yesuf and Bluffstone, 2009). The degree of loss aversion has been found to be influenced by socio-economic determinants such as age (positively) and education (negatively) by Hjorth and Fosgerau (2011) and Booij and van de Kuilen (2009). Income has also been found to be a determinant in certain contexts, as well as gender with some studies finding that females are more likely to be loss averse than males (Booij and van de Kuilen, 2009). The prevalence of present bias has been found to be higher in individuals with low levels of income in some studies (Can and Erdem, 2013), but not in others (Meier and Sprenger, 2010). In health-related contexts, present bias has also been found to be correlated with physical activity, i.e. individuals who exercised for longer periods were less likely to be present-biased (Hunter et al., 2018). Moreover, present bias has been found to be negatively correlated with age, and positively with education (i.e. more highly educated individuals were more likely to be present-biased), while gender has been found to be an insignificant determinant of present bias by Meier and Sprenger (2010), using data from the US. Thus, while some mixed evidence exists on the role of socio-economic factors in determining these behavioral anomalies, there is scant evidence from low and middle-income countries. We contribute to this literature, by using novel data from Nepal. Moreover, we also explore the role of some specific psychological factors in determining the presence of behavioral anomalies among respondents.

Lastly, this paper also fits into the transport literature on the determinants of fuel economy choices of individuals. Hedonic models, have been used for modeling vehicle model attributes, such as fuel economy and horsepower, as a function of the market price of the vehicle to estimate consumers' implicit willingness-to-pay for each individual feature (Espey and Nair, 2005). Alberini et al. (2019) found that more fuel-efficient variants of a car costed more using sales data on new cars from eight European countries, but that future fuel costs were heavily discounted by individuals, and that people expected very short payback periods on these models. Nayum and Klöckner (2014) found, using Norwegian survey data, that the intention to buy a fuel-efficient car, brand loyalty, number of cars owned and the number of drivers license holders in the household, as well as socio-economic factors such as household size, and income had significant direct effects on choosing a more fuel-efficient car. Using data on Swiss car buyers, Peters et al. (2011) used psychological theories such as the theory of planned behavior (TPB) and the norm activation model (NAM) to examine the determinants of fuel economy. They found that traits such as valence of less power and small size, general attitudes regarding fuel-efficient and small cars and perceived behavioral control were direct predictors of fuel economy choices. Our study intends to complement these studies, by explicitly modeling the energy-efficiency gap in the purchase of motorcycles in Nepal, and evaluating the role of behavioral anomalies in consumers not making the most efficient (or cost-minimizing) choices.

# 3 Data and Methodology

## 3.1 Data

Our study is based on data drawn from a survey of a total of 2,500 respondents in the districts of Kathmandu, Bhaktapur, and Lalitpur, i.e. in the region of Kathmandu valley in Nepal. The field survey was conducted in the form of computer assisted personal interviews (CAPI) over three weeks during the months of October and November in 2019 in collaboration with a local survey partner.

The objective of this survey was to sample eligible individuals (older than 16 years, the legal age for obtaining a drivers license in Nepal) who were looking to purchase a motorcycle in the next few months, or were at least considering it. Thus, survey participants were sampled at places where one might expect a higher share of potential and existing motorcycle owners, such as at universities, near motorcycle dealerships, public and office parking places.

Out of the 2500 respondents sampled in the survey, 839 stated that they already owned a motorcycle. We were able to extract vehicle-related information (such as the brand, model name, engine size as well as on other technical specifications) based on the information that the respondents provided us for 668 respondents. In addition to vehicle specification-related information, we also collect socio-economic data from our respondents, as well as some psychological as well as behavioral information.

Given the large share of motorcycle ownership in the Kathmandu valley, as well as the opportunities that are available to potential buyers to invest in more efficient vehicles, this region was a natural choice of location for this study. At the start of the CAPI-based survey, enumerators informed the respondents about the goals of the study, conditions and incentives for participation, data privacy, and provided simple instructions on completing the questionnaire. The survey was first prepared in English by the research team and translated to Nepali by our survey partner prior to the field implementation. Participation in the survey was incentivized, with 20% of the respondents being eligible for a lottery.

In the first part of our analysis, we are interested in evaluating the socio-economic as well as psychological determinants of some behavioral anomalies. We use the entire data sample for conducting this analysis. In the second part, given that we are interested in the fuel economy choices of individuals (and possible prevalence of the energy-efficiency gap), i.e. we are interested in the intensive margin, we will be using data on the sub-sample of individuals who already own a motorcycle. However, in order to mitigate concerns of sample selection, we also estimate models using a Heckman-based approach in the second part of the analysis (refer to section 3.2 section for details).

Our focus in the second part of this study is on a specific set of behavioral anomalies that we hypothesize may be relevant in determining the energy-efficiency gap with respect to fuel-efficient vehicles in Kathmandu. These are present bias, loss aversion, as well as risk aversion. Present bias can be detected using either the multiple price list (MPL) approach, or choices over effort tasks. In this paper, we choose to test for present bias as well as capture time preferences using the former approach (which has been adopted in other studies in the energy economics literature), however we do not use this for eliciting parameters related to loss

aversion or risk aversion, and instead choose to adopt other methodologies from the literature.[5]

In Figures 1 and 2 in the Appendix, we provide the MPL-based questions that we used to measure present bias as well as time preferences in the survey. These questions are adapted from Schleich et al. (2019). In these price list-based questions, respondents faced a list of choices between two monetary options, A and B, and they were asked to pinpoint their preferred choice among these options. The monetary values were expressed in Nepali Rupees, and the responses were not incentivized, i.e. we did not pay the respondents based on their choices.[6]

Following Schleich et al. (2019), the MPL-based question consisted of two parts, each offering respondents seven choices. In the first part, respondents had to choose between Option A which yielded a monetary gain to be paid in one week, and Option B which specified an amount to be paid in 6 months, information which we use to determine the discount factor $\delta$. In the second part, Option A specified a possible monetary gain to be paid out in six months and one week, while option B denoted the amount that could be paid out in 12 months, which we use together with the first part to determine the present bias indicator $\beta$. The rationale for using this approach is that if a respondent chose Option A more frequently, the more she discounts future gains (i.e. the lower would be her discount factor). Present bias, on the other hand, can be detected by accounting for differences in choices of respondents between the two parts of this question, which would be a sign of a possible inconsistency in time preferences.

One point of difference with the methodology of Schleich et al. (2019) is that in calculating these two parameters, we assume a risk-neutral utility function, where the utility derived from a monetary payment is equal to the value of the payment. Schleich et al. (2019) solve for four preference parameters using four equations, allowing for risk aversion in the utility function, i.e. using a constant relative risk aversion (CRRA) utility function. Our choice to use the risk-neutral utility function largely stems from constraints related to the length of the survey. While we do not compute loss and risk aversion parameters using the MPL approach, we measure these anomalies using alternative approaches used in the literature (as described below), and thus are able to account for these anomalies in our estimations as well.

More details on how the preference parameters (namely the discount factor, as well as the present bias parameter) are calculated are provided in the Appendix.

We measure risk preferences by asking respondents to state how risk-loving they are, on a

[5]We chose the MPL approach, because budgetary restrictions prevented us from doing in-person surveys multiple times, which is required for implementing effort tasks (Augenblick et al., 2015; Berkouwer and Dean, 2019). Budget considerations and other practical constraints also resulted in us prevented us from using the MPL approach to compute parameters for loss and risk aversion. Given the breadth of information that we were seeking to collect with the survey, its duration would have been very long had we adopted the MPL approach to assess these parameters. Prior to the baseline survey, we conducted a pilot test with 104 respondents, where we implemented a MPL approach to assess loss and risk aversion. The median duration of the survey was about 52 minutes, and many respondents expressed frustration at the length of the survey. Based on this feedback, we adapted the questions, as well as reduced the length of the survey. The final questionnaire took about 22 minutes to complete (median duration).

[6]While incentivizing has been found to be important in the energy economics literature for respondents to honestly reveal their true preferences (Schleich et al., 2019), other economic studies have found that having to make hypothetical or unincentivized choices over money provides fairly similar results (Ubfal 2016, Falk et al. 2016). While we did not incentivize the responses due to budget-related constraints, we attempt to address any shortcomings that this may have created in our measures using an instrumental variable approach, as discussed in the next subsection.

scale of zero to ten, where choosing zero denotes someone completely unwilling to take risks, and choosing ten implies that the respondent is very willing to take risks. This method for capturing risk preferences has been adopted in several other studies (such as Ding et al. (2010); Dohmen et al. (2011); Hardeweg et al. (2013)). We convert this categorical variable to a dummy variable for our main analyses, by categorizing all individuals who stated that their score was less than 5 as being 'risk-averse'.[7].

In order to capture possible loss aversion among our respondents, we adopt an approach suggested by Heutel (2019). We asked the respondents to choose between two motorcycles having different fuel economies. In the first part of this question, the respondents were told that they owned a 110 cc motorcycle, with annual fuel costs of Rs. 20,000, and they were offered the possibility to replace this with a 125cc motorcycle which had annual fuel costs of Rs. 30,000, i.e. they were asked whether or not they would like to replace their current vehicle with the larger one. The second part of this question involved assuming the opposite situation, i.e. respondents were told that they owned the bigger motorcycle having higher fuel costs, and they were asked whether they would replace it with the smaller one. Respondents who chose to keep the current motorcycle in both parts of the question (rather than replace it) are categorized as being loss averse.

Summary statistics on these parameters are provided in Table 1, along with those for the other explanatory variables that we use in our analysis. We report these statistics for the entire sample of respondents for whom we have non-missing information on socio-demographic variables (2245 observations) as well as for those respondents who own a motorcycle and for whom we have non-missing information on socio-demographic information as well as vehicle specifications (591 observations). These summary statistics are computed for the sample of respondents who are the main decision-maker with respect to the purchase of durables in their household, and who are the main users of their motorcycles. We also exclude observations in which the engine size of the motorcycle was greater than 500 cc.[8]

From Table 1, we find that the mean value of the present bias parameter $\beta$ is about 0.999 for both the the entire sample, and for the sub-sample that already own a motorcycle, suggesting a very slight present bias averaged over the sample.[9] About 12% of respondents are present-biased in both groups, while 50% of the sample is risk averse (the share is slightly higher among those who own a motorcycle), and about 7% can be categorized as being loss averse according to our measure. The mean annual discount factor for our sample $\delta$ is about 0.87, which is slightly higher than the value 0.851 that Schleich et al. (2019) found for a sample of European countries.

The average age of respondents in our sample is about 29 years for the entire sample, and 30 years for those who own a motorcycle. About 29% of the whole sample is female, whereas this share shrinks to about 15% for existing motorcycle owners (among female respondents in our survey, about 15% already own a motorcycle, whereas the remaining 85% are looking to buy a new motorcycle). About 34% of the respondents in the whole sample have children,

[7]In section 4.3, we estimate some models using alternative definitions of risk aversion, and find that our main results are robust to the choice of specification.

[8]The majority of the motorcycles in Nepal belong to 100-180 cc engine sizes; we consider motorcycles above 350cc to be premium or luxury vehicles, moreover there are only two such observations in our data.

[9]A $\beta$ value equal to one denotes a person who is neither present-biased, nor future-biased, $\beta > 1$ denotes a future-biased individual, whereas $\beta$ <1 denotes a present-biased individual.

## **Table 1:** Summary Statistics of Explanatory Variables

| Sample | Entire sample | | | | Sub-sample owning a motorcycle | | | |
|---|---|---|---|---|---|---|---|---|
| Explanatory variable | Mean | Standard Deviation | Minimum | Maximum | Mean | Standard Deviation | Minimum | Maximum |
| Behavioral anomalies and time preferences | | | | | | | | |
| Present bias indicator | 0.115 | 0.319 | 0 | 1 | 0.118 | 0.323 | 0 | 1 |
| Beta | 0.999 | 0.091 | 0.561 | 1.782 | 0.999 | 0.105 | 0.561 | 1.782 |
| Annual discount factor | 0.867 | 0.185 | 0.259 | 0.955 | 0.872 | 0.173 | 0.259 | 0.955 |
| Whether risk averse | 0.493 | 0.500 | 0 | 1 | 0.535 | 0.499 | 0 | 1 |
| Whether loss averse | 0.070 | 0.256 | 0 | 1 | 0.073 | 0.260 | 0 | 1 |
| Socio-economic variables | | | | | | | | |
| Age of respondent | 28.629 | 7.034 | 17 | 58 | 30.433 | 7.906 | 18 | 58 |
| Whether female | 0.287 | 0.453 | 0 | 1 | 0.147 | 0.355 | 0 | 1 |
| Whether student | 0.229 | 0.420 | 0 | 1 | 0.132 | 0.339 | 0 | 1 |
| Whether have children | 0.335 | 0.472 | 0 | 1 | 0.428 | 0.495 | 0 | 1 |
| Monthly household income (shares) | | | | | | | | |
| Less than Rs. 30,000 | 19.420 | | | | 10.830 | | | |
| Between Rs. 30,000 and 50,000 | 40.940 | | | | 35.700 | | | |
| Between Rs. 50,000 and 75,000 | 25.210 | | | | 35.870 | | | |
| More than Rs. 75,000 | 14.430 | | | | 17.600 | | | |
| Whether have a Bachelor's or Master's degree | 0.502 | 0.500 | 0 | 1 | 0.492 | 0.500 | 0 | 1 |
| Whether member of a club or society | 0.299 | 0.458 | 0 | 1 | 0.347 | 0.476 | 0 | 1 |
| Whether self/family member known to have a respiratory disorder | 0.090 | 0.287 | 0 | 1 | 0.103 | 0.304 | 0 | 1 |
| Whether receive remittances from family members abroad | 0.205 | 0.404 | 0 | 1 | 0.208 | 0.406 | 0 | 1 |
| Whether self/someone known owned a motorcycle during the blockade | 0.699 | 0.459 | 0 | 1 | 0.717 | 0.451 | 0 | 1 |
| Whether correctly solved math question on lifetime costs | 0.211 | 0.408 | 0 | 1 | 0.242 | 0.429 | 0 | 1 |
| Whether own more than one motorcycle | | | | | 0.052 | 0.223 | 0 | 1 |
| Whether applied for loan to purchase motorcycle | | | | | 0.092 | 0.289 | 0 | 1 |
| Whether motorcycle is second-hand | | | | | 0.220 | 0.415 | 0 | 1 |
| Whether family use motorcycle regularly | | | | | 0.457 | 0.499 | 0 | 1 |
| Whether aware of fuel economy when bought motorcycle | | | | | 0.785 | 0.411 | 0 | 1 |
| Whether reimbursed for petrol costs | | | | | 0.234 | 0.423 | 0 | 1 |
| Psychological variables | | | | | | | | |
| Whether live according to religious principles | 0.720 | 0.449 | 0 | 1 | 0.741 | 0.438 | 0 | 1 |
| Whether hold on to family's old traditions | 0.771 | 0.421 | 0 | 1 | 0.799 | 0.401 | 0 | 1 |
| Go out a lot (dinners, parties, other leisure activities etc.) | 0.675 | 0.468 | 0 | 1 | 0.702 | 0.458 | 0 | 1 |
| Likely to buy the latest technological innovation | 0.548 | 0.498 | 0 | 1 | 0.548 | 0.498 | 0 | 1 |
| Enjoy my life to the full | 0.908 | 0.289 | 0 | 1 | 0.942 | 0.233 | 0 | 1 |

*Note:* The table reports the means, standard deviations as well as minimum and maximum values for the main explanatory variables. The relevant sample size is 2245 observations in columns (1) to (4), and 591 observations in columns (5) to (8) for whom we have information on vehicle specifications (except for the "whether applied for loan" variable, for which it is 590 observations due to a missing value). The sample comprises respondents who were the main decision-makers regarding purchase of durables in the household, as well as the main users of their motorcycles. We exclude respondents owning motorcycles with engine size 500 cc and above from our data sample.

whereas this share is higher for the sub-sample owning a motorcycle, at 43%. About 50% of both samples have a university education, whereas the share of respondents who were students during the survey was relatively lower in the group that owns a motorcycle (at 13%, compared to 23% for the entire sample). Most of the respondents belong to households that earn a monthly income between Rs. 30,000 and Rs. 50,000 in the whole sample, whereas a majority belong to the group that earns between Rs.50,000 and Rs.75,000 in the sub-sample owning a motorcycle, i.e. motorcycle owners earn higher incomes in our sample (as expected).

About 21% of respondents in the whole sample as well as the sub-sample receive remittances from family members living abroad, while about 9-10% of the respondents know that either they or their family members have a respiratory disorder in both samples. About 30% of respondents stated that they were a member of some club or group (such as a neighborhood associations, student associations, sports groups, etc.) in the entire sample, with the share being marginally higher at about 35% in the sub-sample. We also asked a simple multiple-choice question in the survey to assess the computational skills of the respondents; having provided them with the purchase price, expected duration of ownership, and annual operating costs, we asked them to compute the total lifetime costs (assuming zero discounting).[10] We find that only about 21% of respondents answered this question correctly in the whole sample. This share was not much higher among those who owned a motorcycle, at about 24%. Lastly, about 70% of respondents in both groups stated that either they, or someone they knew, owned a motorcycle during the blockade of 2015.[11]

Among the sample that owned a motorcycle, we find that about 22% of respondents own a second-hand vehicle. 9% of respondents stated that they had applied for a loan in order to purchase their motorcycle, while about 5% stated that they owned more than one motorcycle. About 46% of respondents stated that other members of their family also used the motorcycle on a regular basis. A relatively high share (about 79%) of respondents stated that they were aware of the fuel economy of the motorcycle back when they bought it, while about 23% of respondents have their petrol costs reimbursed by an employer, or their family (if they are students, for example).

We also collected information on some psychological variables in our data. The five psychological variables in our data were measured as categorical variables, with four possible responses: whether the respective trait applied fully to the respondent, applied somewhat to the respondent, did not apply to them, or did not apply at all to them. In order to obtain clearer distinction between categories of responses, we converted these variables into dummy variables, with the base category including individuals who stated that it did not apply to them, or did not apply at all to them (and the variables taking the value '1' if they stated that it applied either somewhat, or fully, to them). We find that for about 72% of respondents, 'living according to religious principles' was a trait that applied to them, while about 77% stated that they are likely to hold on to their family's old traditions, in the entire sample. About 68% of respondents stated that

[10] The exact question was: Suppose you buy a bike for Rs 300,000. 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. The possible responses were Rs. 450,000, Rs.500,00, Rs.600,000, Rs. 750,000 and "don't know", with Rs.500,000 being the correct answer.

[11] The blockade was an economic crisis that arose due to ethnic tensions, and resulted in shortage of essential supplies such as fuel and medicines in Nepal.

they went out a lot (for e.g., for dinners, parties or other leisure activities), whereas about 91% of the respondents stated that the statement 'enjoy my life to the full' applies at least somewhat to them. Lastly, we also find that about 55% of respondents stated that they are somewhat likely to buy the latest technological innovations, even if they may not necessarily need them.

We provide additional information on the motorcycles owned in Table 5 in the Appendix. This includes information on the engine size, the year of purchase of the motorcycle as well as average fuel economy by engine size and year of purchase. The engine size as well as fuel economy represent the vehicle specifications as advertised by the manufacturers. We find that in general, larger motorcycles (in terms of engine size) are less fuel-efficient, although this is not a monotonic trend. The largest motorcycles in our data sample have a 350 cc engine capacity, whereas the smallest have a 100 cc size. Also, we observe that motorcycles which were bought earlier had higher levels of fuel economy, compared to those that were bought relatively recently. The oldest motorcycles in our sample are about 11 years old.

## 3.2 Methodology

In this subsection, we explain the econometric approach that we adopt in this study. In the first part, we are interested in understanding the role of socio-demographic as well as psychological factors in determining three specific behavioral anomalies, as well as the time preferences for individuals in Kathmandu. Our second objective is then to evaluate the role of these behavioral anomalies in determining the energy-efficiency gap in the purchase decision for motorcycles.

The model that we estimate in the first part takes the following form:

$$A_i = \alpha_0 + \alpha_1 S_i + \alpha_2 P_i + \mu_i \tag{1}$$

In Eq.(1), $A_i$ could represent one of four possible dependent variables; three dummy variables capturing the existence of specific behavioral anomalies (present bias, loss aversion and risk aversion), or the annual discount factor of the $i^{\text{th}}$ respondent. $S_i$ denotes the set of socio-economic explanatory variables, while $P_i$ denotes the set of psychological determinants, and $\mu_i$ denotes the residual.

In order to estimate the models that use the dummy variables denoting presence of behavioral anomalies as dependent variables, we use a probit methodology. For the model with the annual discount factor, given that the variable takes values between 0 and 1, we estimate a fractional response model, where we assume that the functional form of the annual discount factor is a cumulative normal density, i.e. we estimate a fractional probit model. As mentioned in the previous sub-section, these models are estimated for the entire sample of respondents.

In the second part of the paper, we estimate the effects of the three behavioral anomaly indicators at the centre of our analysis as well as that of the discount factor, on the energy-efficiency gap, focusing the analysis on the sub-sample that already own a motorcycle. Of course, as discussed in Section 1, an energy-efficiency gap may exist due to the effects of other behavioral anomalies as well, such as limited attention, as well as cognitive limitations that impede lifetime cost calculation. As an example of the former, individuals may not pay attention to the fuel economy when they purchase their motorcycle (if fuel economy were not

clearly advertised, or if they simply chose to focus their attention on other attributes). In the latter case, consumers may not be able to evaluate the present discounted costs of buying fuel when they make their choice, due to the cognitive load that it necessitates.

Consumers observe various attributes of the product (such as engine power, brand, color, design, etc.), however they may have only a partial understanding of lifetime fuel costs (Sallee, 2014; Turrentine and Kurani, 2007). In order to do a lifetime cost computation, consumers need information on how much they are likely to drive, relevant discount factors, future fuel prices, as well as how long they expect to use the vehicle. This implies that there are considerable cognitive costs (as well as time and information-collection costs) in doing this computation. These costs may thus create, in some consumers, an aversion to exert upfront effort to do the calculation and identify vehicles have low lifetime costs, and this may be, as discussed above, representative of a form of present bias. When such costs are considerable due to present bias, the consumer may put in less effort than their "long-run self" (Lockwood, 2020). As a result, not all individuals would be making the most optimal choices in terms of minimizing total lifetime costs. In order to better distil the effect of possible present bias on the energy-efficiency gap net of the other anomalies that may confound this effect, we control for the possible limited attention paid by respondents to fuel economy, as well as for their computational ability in all our regression results.

We assume in this paper that individuals first decide the engine size of the motorcycle that they would like, and then make their final choice based on other factors (among them, possibly fuel economy), conditional on purchasing a vehicle of their preferred engine size. This sequential decision-making process, where individuals first decide the engine size of vehicle, enables us to quantify the extent of the energy-efficiency gap. Based on the discussion above, some consumers will end up purchasing relatively fuel-inefficient motorcycles in a given engine size category, resulting in an energy-efficiency gap with respect to the most fuel-efficient motorcycle model in that category.

For the estimations in the second part, we need to define the level of the energy-efficiency gap, i.e. our dependent variable. To do this, we first calculate the total lifetime cost of owning the motorcycle for each individual in our sample. The total lifetime cost of a motorcycle for respondent $i$ is denoted as $TC_i$ and is defined as:

$$TC_i = P_i^I + \sum_{t=0}^{T} \frac{1}{(1+r)^t} \frac{P_t^E D_i}{F_i} \tag{2}$$

where $P_i^I$ denotes the purchase price of the motorcycle in Nepali Rupees (Rs.), $P_t^E$ denotes the per litre price of petrol in year $t$ (about Rs. 110 per litre during the time of our survey), $D_i$ denotes the average annual distance driven by respondent $i$ in kilometres, and $F_i$ denotes the fuel economy of the motorcycle. $T$ denotes the lifespan of the motorcycle in years, and $r$ is the discount rate. In calculating the lifetime costs in our main specifications, we assume a lifespan of 10 years for all motorcycles, i.e. $T = 10$ (which represents the $99^{th}$ percentile of the distribution of vehicle age in our data), and that the fuel price and fuel efficiency remains constant over the lifespan.[12] Moreover, we simplify the consideration of costs in this study, by only computing the total lifetime costs in terms of operating (fuel) costs.

[12] In section 4.3, we also estimate some models using a lifespan of five years, and find that our main results are robust to the choice of specification.

Next, for each engine size, we identify the motorcycle having the highest fuel efficiency; we then compute the lifetime costs using the fuel economy as well as purchase price of this model, while still using the actual distance driven by the individual '$D_i$' for the calculation. This measure of total lifetime costs is used as a benchmark against which to compare the actual lifetime costs of the vehicle owned by the respondent, and to compute the energy-efficiency gap. The level of the energy-efficiency gap, and our dependent variable for respondent 'i' $EE_i$, is defined as the log of the ratio of the total lifetime cost of owning the motorcycle $TC_i$, to the total lifetime cost of the most fuel-efficient motorcycle of the same engine size $TC_{min}$, as shown below:

$$EE_i = log(\frac{TC_i}{TC_{min}}) \tag{3}$$

The value of the discount rate $r$ to be considered in Eq.(2) is not always obvious. The discount rate not only captures the time value and opportunity cost of money, but it can also be thought of as the cost of borrowing. In a first variant of the outcome variable, we assume that $T = 10$ and $r = 7\%$, i.e we assume that the discount rate equals the market interest rate.[13] On the other hand, the second variant of the dependent variable sets the discount rate $r$ equal to the average loan rate for motorcycle loans, at about $10\%$.[14] As robustness checks, we also use alternative versions of the discount rate; these results are presented in columns (1) to (3) of Table 7.

Thus, higher values would imply that respondent 'i' made a relatively inefficient choice of motorcycle (since the total lifetime costs of the actual choice would then be higher than the total lifetime costs possible by buying the most fuel-efficient motorcycle). The model that we estimate, using these two variants of our dependent variable, can be expressed as follows:

$$EE_i = \beta_0 + \beta_1 A_i + \beta_2 X_i + \eta_i \tag{4}$$

where $EE_i$ could denote either of the two versions of the dependent variable that we construct to represent the energy-efficiency gap in the choice of motorcycle of respondent $i$, $A_i$ is the set of behavioral anomalies as well as the individual-specific discount factor, $X_i$ denotes a set of socio-economic variables, and $\eta_i$ denotes the residual.

We estimate this model using four methodologies. The first is the ordinary least squares (OLS) approach. The second is a sample-selection model (following Heckman (1976)), where the first stage models the decision of respondents to own a motorcycle. The third and fourth models adopt an instrumental variable control function estimation (following Wooldridge (2010)).

While our focus in the second part of the analysis is on the sub-sample of individuals who already own a motorcycle, we estimate a sample-selection model to mitigate concerns related to sample selection. This model is estimated using the maximum likelihood approach. In the selection equation, we include two variables that may influence the decision to own a motorcycle (without directly affecting the energy efficiency gap): the first is the number of bus stops

[13] The average interest rate from 2010-2019 in Nepal was about $7.2\%$ (Trading Economics, 2020).

[14] Many banks in Nepal offer special loans for motorcycle purchases, independent of auto loans that are valid for car purchases. For instance, Everest Bank introduced a motorcycle loan in 2020, offering an interest rate of 9.98% (Nepal Drives, 2020).

within 500 metres of the centre of the locality where the respondent resides[15], and the second is the number of motorcycle showrooms and shops within 500 metres of the centre of the locality where the respondent lives[16]. These variables intend to capture access to public transport, as well as the ease of finding and purchasing a new motorcycle, that are both likely to affect the decision to buy a motorcycle (but unlikely to directly influence the energy-efficiency gap, in our opinion).

In order to elicit the time preference parameters, namely the discount factor as well as an indicator for present bias, we use the MPL approach that we explained in Section 3.1. However, for the reasons that we discussed, it is possible that these variables are measured with error. This may engender endogeneity in our estimation. In order to address endogeneity due to measurement error, we additionally estimate instrumental variable (IV)-based models as the third and fourth methodological approaches. We treat the present bias indicator to be endogenous in these estimations.[17]

Given that the present bias indicator is a dummy variable, we estimate a control function-based model, following Wooldridge (2010). The use of the control function approach involves estimating a first stage probit model, where the present bias indicator is regressed on an IV as well as on all explanatory variables from the second stage estimation. The reduced-form residuals from this first stage estimation are then used as an instrument in a two-stage least squares estimation, with the relevant energy-efficiency gap measure as a dependent variable. The second-stage coefficients from this model serve as the final estimates of the control function approach.

In the first control function-based estimation in this paper, we use self-reported information on whether the respondents have experienced and suffered major damages such as death, injury or damage to property from natural disasters (including earthquakes, flooding and droughts) as an IV. In the second model, we continue to use this subjective measure as an IV, and additionally include a more objective IV measure capturing the intensity of the 2015 Nepal earthquake in the locality where the respondent lives. The earthquake intensity is measured in terms of the Modified Mercalli Intensity (or MMI) scale.

Natural disasters have been found to be important determinants of behavioral anomalies in the economic literature. Individuals who have experienced natural disasters such as floods and earthquakes have been found to be more likely to be present-biased, and discount the future more (Cassar et al., 2017; Sawada et al., 2015) to be more loss averse (Shupp et al., 2017) and also likely to be more risk averse (Cameron and Shah, 2015), however other studies also find that natural disasters could have the opposite effect (for instance, Shupp et al. (2017) find that after a tornado struck Oklahoma City in 2013, survey participants who lost a friend or neighbor were less risk averse.) Based on this evidence, exposure to natural disasters is likely

[15]The centre of each locality was identified by the centroid of the polygon corresponding to that locality using Google Earth or Google Maps.

[16]The showrooms refer to shops that sell new, as well as used motorcycles. These may be single-brand or multi-brand outlets, and may also include service and repair centres. The centre of each locality was identified by the centroid of the polygon corresponding to that locality using Google Earth or Google Maps.

[17]Given that the annual discount factor was also derived using the MPL approach, it is likely that this variable is also measured with error. This implies that we could treat both variables as endogenous. However, it is not straightforward to estimate, as well as to interpret the results of, control function-based IV models with more than one endogenous variable. Moreover, our focus in this study is on the effect of present bias on the energy-efficiency gap. Thus, we choose to treat only this variable as endogenous in our estimations.

to influence each of the behavioral anomaly variables (including present bias) as well as the time preferences. Thus, by controlling for the discount factor and loss as well as risk aversion in our second stage estimation, we strengthen the argument for the exclusion restriction to be satisfied. Moreover, we choose to adopt both an individual-specific instrument on whether respondents have been affected by natural disasters (in our third model specification), as well a more objective measure of the intensity of a large-scale disaster where the respondent resides in the fourth specification (along with the subjective measure), so as to capture the effect of natural disasters on present bias in a more balanced and comprehensive manner.

As controls, we include several respondent-specific socio-economic variables such as income, education, gender, age, whether the respondent has children, etc. In addition, we include controls related to the motorcycle, as well as the respondent's use of it (such as whether it was second-hand, whether the respondent owns more than one motorcycle, whether the respondent needed to apply for a loan to purchase their motorcycle, and whether the family of the respondent also used the vehicle regularly). Moreover we also include controls for the engine size, the brand of the motorcycle, and the age of the motorcycle, along with the distance of the centre of the locality where the respondent lives from the city centre. We cluster standard errors by locality in all regressions.

# 4 Results

In this section, we present the main results of the analysis. Table 2 includes the estimations of the socio-demographic as well as psychological determinants of the three behavioral anomalies that we consider in our study (present bias, loss aversion, as well as risk aversion) along with those of the annual discount factor. In Table 3, we then estimate the effect of each of these biases as well as time preferences on the energy-efficiency gap, using the two variants of the dependent variable that we defined in the previous section.

## 4.1 Results on the determinants of behavioral anomalies

Columns (1), (2), (3) and (4) of Table 2 present the results of the coefficients of estimating the models on the determinants of present bias, the annual discount factor, loss aversion, and risk aversion, respectively for the entire sample of respondents. The respective marginal effects are presented in Table 6 in the appendix. The results of columns (1), (3) and (4) are estimated using a probit model, whereas the model of column (2) is estimated using a fractional response methodology. The reference category for the explanatory variable on monthly household income is individuals whose household income is less than Rs. 30,000, or 257 USD per month, whereas for the 'university' variable, it is individuals whose highest level of educational attainment is either high school or below or those having a professional/vocational education. The reference categories for the five psychological variables in these models are whether the respondent answered that the respective trait either did not apply to them, or did not apply at all to them.

In column (1) of Table 2, we find that respondents who stated that they receive remittances from family members are more likely to be present-biased. While receiving remittances may relieve liquidity constraints at least partially, it does not obviate the fact that such respondents

**Table 2:** Determinants of Behavioral Anomalies and Time Preferences

| Dependent variable<br>Model | Present biased<br>Probit | Annual discount factor<br>Fractional response | Loss averse<br>Probit | Risk averse<br>Probit |
|---|---|---|---|---|
| | Socio-demographic variables | | | |
| Monthly household income | | | | |
| Between Rs. 30,000 and 50,000 | 0.108 | -0.062 | -0.292*** | 0.410*** |
| | (0.127) | (0.057) | (0.106) | (0.101) |
| Between Rs. 50,000 and 75,000 | 0.167 | -0.028 | -0.282* | 0.425*** |
| | (0.165) | (0.068) | (0.161) | (0.167) |
| More than Rs. 75,000 | -0.115 | -0.217*** | -0.282** | 0.580*** |
| | (0.125) | (0.072) | (0.148) | (0.151) |
| Whether have a university degree (Bachelor's or Master's) | -0.011 | 0.130*** | 0.005 | -0.292*** |
| | (0.105) | (0.036) | (0.116) | (0.057) |
| Whether have children | 0.109 | 0.066 | -0.095 | -0.005 |
| | (0.109) | (0.056) | (0.127) | (0.100) |
| Whether student | -0.102 | 0.133*** | 0.009 | 0.008 |
| | (0.113) | (0.056) | (0.109) | (0.078) |
| Age | 0.009 | 0.001 | 0.012 | -0.002 |
| | (0.006) | (0.003) | (0.008) | (0.005) |
| Whether female | -0.058 | -0.036 | 0.047 | 0.047 |
| | (0.084) | (0.040) | (0.114) | (0.076) |
| Whether receive remittances | 0.182** | 0.074* | -0.166 | -0.150** |
| | (0.085) | (0.042) | (0.156) | (0.080) |
| Whether have a respiratory disorder (self or close family) | 0.386*** | -0.182*** | 0.051 | -0.014 |
| | (0.134) | (0.070) | (0.147) | (0.111) |
| Whether member of a club or society | 0.322*** | 0.121*** | -0.271*** | -0.012 |
| | (0.115) | (0.047) | (0.115) | (0.111) |
| Whether self/someone known owned a vehicle during blockade | -0.226*** | -0.210*** | -0.137 | 0.042 |
| | (0.086) | (0.056) | (0.119) | (0.079) |
| Log of distance of locality from the city centre | -0.008 | -0.007*** | 0.028 | 0.017** |
| | (0.006) | (0.003) | (0.018) | (0.008) |
| | Psychological variables | | | |
| Live according to religious principles | 0.159 | 0.028 | 0.391*** | 0.542*** |
| | (0.108) | (0.042) | (0.117) | (0.077) |
| Hold on to my family's traditions | 0.186** | -0.127*** | 0.519*** | 0.153** |
| | (0.099) | (0.052) | (0.147) | (0.079) |
| Go out a lot (e.g. dinners, parties, other leisure activities etc.) | 0.002 | 0.086 | -0.041 | -0.336*** |
| | (0.110) | (0.056) | (0.139) | (0.106) |
| Enjoy my life to the full | 0.140 | -0.208*** | 0.244 | 0.357** |
| | (0.143) | (0.072) | (0.169) | (0.165) |
| Likely to buy the latest technological innovation | 0.215** | 0.027 | 0.367*** | 0.311*** |
| | (0.110) | (0.048) | (0.111) | (0.096) |
| Observations | 2245 | 2245 | 2245 | 2245 |

*Note:* The table reports the coefficients as well as standard errors in parentheses for the main explanatory variables. The sample includes both current motorcycle owners as well as respondents who don't currently own a motorcycle, and comprises respondents who were the main decision-makers regarding purchase of durables in the household, as well as the main users of their motorcycles. We exclude respondents owning motorcycles with engine size 500 cc and above from our data sample. All models include dummies for districts. Standard errors are clustered at the locality level. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient on constant is not reported.

may have been more cash-strapped to begin with, and that implies that credit or liquidity constraints might effectively play a role in determining present bias as well. Interestingly, we find that individuals who have a respiratory disorder, or know someone in their household who does, are also more likely to be present-biased, as are those individuals who are members of certain clubs or groups. We do not find any significant differences across gender, age, income or education, in determining present bias in our sample.

As far as the role of the psychological variables is concerned, we find that for individuals who stated that holding on to their family's traditions was important to them were more likely to be present-biased, than those who said that it did not apply to them. Intuitively, buying the latest innovation/gadget, even if it was not needed, was also positively associated with being present-biased in our sample.

In the model of column (2), we estimate the determinants of the annual discount factors of individuals in our sample. We find that individuals having high levels of income are more likely to have relatively low discount factors (and thus high discount rates) compared to lower-income individuals (the indicator for household monthly income being higher than Rs.75,000 or 642 USD is significant at the 1% level). This is an interesting finding, as it suggests that richer individuals are more likely to discount the future more than relatively poorer individuals. Intuitively, we find that respondents having a university education are likely to have higher discount factors (and thus lower discount rates) than individuals who are only educated up to high school or below or those that have a professional education. This result is also valid for individuals who are currently students; students are more likely to have lower discount rates that non-students. The presence of respiratory disorders is negatively associated to the discount factor, i.e. individuals who know that they or their family members suffer from a respiratory disorder are likely to have high discount rates. With respect to the psychological variables, we find that individuals for whom holding on to family traditions is important are likely to have lower discount factors/higher discount rates, as do those individuals who stated that they enjoyed their life to the full.

In column (3), we report the results on the determinants of loss aversion among respondents in our sample. In line with intuition, individuals having higher levels of income are less likely to be loss averse, as the coefficients on the income category variables suggest. We find that individuals who were members of clubs or groups are also less likely to be loss averse, suggesting a possible role for more social ties in mitigating loss aversion. Among the psychological variables, we find some interesting correlations as well: for instance, individuals who state that they live by religious principles, hold on to their family's traditions, or like to buy the latest innovations (even if they don't need them) are more likely to be loss averse, than individuals for whom these qualities are not important (these coefficients are significant at the 1% level). These findings hint at the possible role of family traditions and culture in determining these biases.

Lastly, in column (4), we provide the results of the model estimating the determinants of risk aversion among respondents. We find that higher income has a significant and positive effect on risk aversion; each of the three dummy variables have a positive coefficient, and are significant at the 1% level. Furthermore, individuals who have a university education are less likely to be risk averse, compared to individuals who have lower levels of education. Receiving remittances also mitigates risk aversion partially; individuals who receive remittances are less likely to be risk averse than those who don't. Among the psychological variables, we find that each of the explanatory variables has a significant effect on risk aversion in our sample, and for

most of these variables, if the statement applies, individuals are more likely to be risk-averse, i.e. the coefficients are positive. The exception is the variable for going out a lot; individuals who stated that they went out a lot were less likely to be risk-averse than those who stated that going out a lot was not something they did, or was not applicable to them.

## 4.2 Results on the energy-efficiency gap

In Table 3, we present the results of estimations evaluating the effect of these anomalies on the energy-efficiency gap. As mentioned in the previous section, we use two dependent variables for this analysis. These are the log of the total lifetime cost of the owned motorcycle to that of the most efficient motorcycle of the same engine size, computed assuming a discount rate equal to the market interest rate of 7%, and assuming a discount rate equal to 10%. We estimate four models using each dependent variable; an OLS model, a Heckman-based approach to account for sample selection, an IV based model using the Wooldridge (2010) control function approach with a single instrument, and the Wooldridge model using two instruments. We use self-reported information on having been affected by natural disasters as an instrumental variable for the present bias indicator in columns (3) and (7), whereas in columns (4) and (8), we supplement this measure with a more objective measure, the MMI scale measure of the intensity of the 2015 earthquake for the locality where the respondent lives. A point to note about the IV-based control function estimation results in columns (3), (4), (7) and (8) of Table 3 is that the first-stage F-statistics are reasonably strong across estimations. Moreover, the coefficients are also of a similar order of magnitude across estimations.

Our main results suggest that present-biased consumers were associated with having a relatively higher ratio of total lifetime costs, compared to what they could purchase given the engine size of the vehicle, and given the distance that they drove on their motorcycle. We observe that the present bias indicator has a positive coefficient across all models, the OLS results of columns (1) and (5), in the Heckman results of columns (2) and (6) when we correct for sample selection, as well as in the IV-based results of columns (3), (4), (7) and (8) where we attempt to address for possible endogeneity of the present bias variable due to possible measurement error. It is reassuring for us to note that the coefficients on the present bias indicator are similar in columns (1) and (2), as well as in (5) and (6); these results suggest that sample selection may not be a significant concern in our estimations. This is further confirmed by the results of the Wald test for the independence of equations; in both columns (2) and (6), the null hypothesis that the selection equation and the main outcome equation are independent cannot be rejected even at the 10% level.

One might conjecture that the results of the effect of present bias on the energy-efficiency gap may be driven by whether or not individuals paid attention to fuel economy when they bought their motorcycles, i.e. it may be the outcome of limited attention. Indeed, we find that about 71% of present-biased individuals in the regression sample of columns (3), (4), (7) and (8) of Table 3 were aware of the fuel economy of their motorcycle when they bought it, compared to 80% of non-present-biased individuals (and this difference is significant at the 5% level, using a one-sided T-test and at the 10% level using a two-sided T-test). In order to mitigate this as a possible channel, we control for whether or not the respondent was aware of the fuel economy of the motorcycle when they purchased it. While this variable is insignificant across all specifications, it allows us to control at least partially for possible the effects of limited

**Table 3:** Energy-efficiency gap estimations

| Dependent variable | Log of ratio of total lifetime cost (7% discount rate) | | | | Log of ratio of total lifetime cost (10% discount rate) | | | |
|---|---|---|---|---|---|---|---|---|
| Methodology | OLS | Heckman | Wooldridge (2010): one IV | Wooldridge (2010): two IVs | OLS | Heckman | Wooldridge (2010): one IV | Wooldridge (2010): two IVs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present bias indicator | 0.021* | 0.023** | 0.070** | 0.066* | 0.021* | 0.022** | 0.071** | 0.066* |
| | (0.012) | (0.012) | (0.036) | (0.037) | (0.012) | (0.012) | (0.040) | (0.037) |
| Annual discount factor | 0.026 | 0.023 | 0.017 | 0.018 | 0.025 | 0.023 | 0.017 | 0.018 |
| | (0.024) | (0.024) | (0.025) | (0.025) | (0.024) | (0.023) | (0.025) | (0.025) |
| Whether risk averse | -0.0004 | -0.001 | -0.006 | -0.006 | -0.0005 | -0.001 | -0.006 | -0.006 |
| | (0.007) | (0.007) | (0.009) | (0.009) | (0.007) | (0.007) | (0.009) | (0.009) |
| Whether loss averse | -0.001 | -0.001 | -0.005 | -0.005 | -0.001 | -0.001 | -0.005 | -0.005 |
| | (0.016) | (0.016) | (0.016) | (0.017) | (0.016) | (0.016) | (0.016) | (0.017) |
| Age of respondent | -0.0004 | -0.0004 | -0.0005 | -0.0005 | -0.0004 | -0.0005 | -0.0005 | -0.0005 |
| | (0.0009) | (0.0009) | (0.001) | (0.0008) | (0.001) | (0.001) | (0.0009) | (0.0008) |
| Whether have children | -0.007 | -0.008 | -0.009 | -0.009 | -0.006 | -0.008 | -0.009 | -0.009 |
| | (0.012) | (0.011) | (0.012) | (0.012) | (0.012) | (0.011) | (0.012) | (0.012) |
| Monthly household income | | | | | | | | |
| Between Rs. 30,000 and 50,000 | 0.019** | 0.016 | 0.023*** | 0.022*** | 0.018** | 0.015 | 0.022*** | 0.022** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Between Rs. 50,000 and 75,000 | 0.038*** | 0.030*** | 0.043*** | 0.042*** | 0.038*** | 0.030*** | 0.043*** | 0.042*** |
| | (0.012) | (0.013) | (0.013) | (0.013) | (0.012) | (0.013) | (0.013) | (0.013) |
| More than Rs. 75,000 | 0.042*** | 0.035*** | 0.049*** | 0.048*** | 0.041*** | 0.034*** | 0.049*** | 0.048*** |
| | (0.012) | (0.012) | (0.013) | (0.013) | (0.011) | (0.012) | (0.013) | (0.013) |
| Whether student | -0.003 | -0.0004 | -0.001 | -0.002 | -0.004 | -0.001 | -0.002 | -0.002 |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.014) | (0.015) | (0.015) |
| Whether female | -0.005 | 0.002 | -0.002 | -0.002 | -0.006 | 0.002 | -0.002 | -0.003 |
| | (0.009) | (0.011) | (0.009) | (0.009) | (0.009) | (0.011) | (0.009) | (0.009) |
| Whether have a university degree | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 |
| | (0.008) | (0.008) | (0.009) | (0.009) | (0.008) | (0.008) | (0.009) | (0.009) |
| Whether receives remittances | 0.005 | 0.006 | 0.002 | 0.003 | 0.005 | 0.006 | 0.002 | 0.002 |
| | (0.010) | (0.009) | (0.010) | (0.010) | (0.010) | (0.009) | (0.010) | (0.009) |
| Whether member of a club or society | -0.011 | -0.011 | -0.014*** | -0.014*** | -0.011 | -0.011 | -0.014*** | -0.014*** |
| | (0.007) | (0.007) | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.006) |
| Whether self/family member known to have a respiratory disorder | -0.014 | -0.015 | -0.017 | -0.017 | -0.014 | -0.014 | -0.016 | -0.016 |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Whether aware of fuel economy when bought motorcycle | 0.002 | 0.002 | 0.005 | 0.004 | 0.002 | 0.002 | 0.004 | 0.004 |
| | (0.011) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Whether correctly solved math question on lifetime costs | -0.006 | -0.006 | -0.009 | -0.009 | -0.006 | -0.006 | -0.009 | -0.009 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Whether reimbursed for petrol costs | -0.002 | -0.002 | -0.006 | -0.006 | -0.002 | -0.002 | -0.006 | -0.006 |
| | (0.012) | (0.012) | (0.013) | (0.013) | (0.012) | (0.012) | (0.013) | (0.013) |
| Whether family uses motorcycle regularly | 0.017*** | 0.017*** | 0.020*** | 0.020*** | 0.017*** | 0.017*** | 0.020*** | 0.020*** |
| | (0.007) | (0.006) | (0.007) | (0.007) | (0.007) | (0.006) | (0.007) | (0.007) |
| Whether applied for loan to purchase motorcycle | 0.032** | 0.032*** | 0.037*** | 0.036*** | 0.032*** | 0.032*** | 0.037*** | 0.037*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| Whether motorcycle is second-hand | 0.014 | 0.014 | 0.013 | 0.013 | 0.013 | 0.013 | 0.012 | 0.012 |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Whether self/someone known owned a vehicle during blockade | 0.004 | 0.002 | 0.008 | 0.007 | 0.004 | 0.002 | 0.008 | 0.008 |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) |
| Whether own more than one motorcycle | 0.048*** | 0.048*** | 0.049*** | 0.049*** | 0.047*** | 0.047*** | 0.048*** | 0.048*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.013) | (0.014) | (0.014) |
| Observations | 579 | 2244 | 559 | 559 | 579 | 2244 | 559 | 559 |
| Wald test for independence of equations | | 1.26 | | | | 1.31 | | |
| P-value | | 0.261 | | | | 0.2523 | | |
| Cragg-Donald F-statistic | | | 62.386 | 62.838 | | | 62.386 | 62.838 |

*Note:* The table reports the coefficients as well as standard errors (in parentheses) for the main explanatory variables. The sample comprises respondents for whom vehicle specification data was available i.e., who own a motorcycle, and who were the main decision-makers regarding purchase of durables in the household, as well as the main users of their motorcycles in columns (1), (3), (4), (5), (7) and (8). In columns (2) and (6), we also include respondents who don't currently own a motorcycle. We exclude respondents owning motorcycles with engine size 500 cc and above from our data sample. All models include controls for district, as well as for brand, distance to the city centre, engine size and age of the motorcycle. Standard errors are clustered at the locality level. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient on constant is not reported.

attention, and thus helps isolate the effect of present bias on the energy-efficiency gap.

Similarly, in order to control for cognitive limitations that inhibit individuals from using computational skills to calculate lifetime costs, we include a regressor measuring whether the individual correctly answered a math question on the computation of lifetime costs. We find that this variable is also insignificant across models in determining the energy-efficiency gap. Moreover, we find that about 24% of non-present-biased individuals answered this question correctly, whereas 35% of present-biased respondents got it right (the difference is significant 1% level using a one-sided T-test, and at the 5% level using a two-sided T-test). This suggests to us that cognitive limitations may not play a significant role in driving the effect of present bias on the energy-efficiency gap.

Present-biased individuals may be choosing relatively inefficient motorcycles, either because they are undervaluing fuel economy and future cost savings, or because they may find it onerous to do the lifetime cost calculation, and computing lifetime costs requires exerting upfront effort. We already observed that present-biased individuals in our sample were less likely to be aware of fuel economy when they bought their motorcycles. Furthermore, they were more likely to state that they did not know what was to happen to future petrol prices than non-present-biased individuals.[18] In a similar vein, we find that about 65% of present-biased individuals stated that they did not know how long they planned to own their motorcycle (with respect to the purchase of the new motorcycle), as opposed to 58% of non-present-biased individuals (although the p-value of 0.13 with a one-sided test implies that the difference is only marginally significant). Moreover, we also find that about 32% of present-biased respondents stated that they were reimbursed for their petrol costs, as opposed to 22% of non-present-biased individuals (the difference being significant at the 5% level using a one-sided T-test and at the 10% level using a two-sided T-test). This correlational evidence further points to the fact that present-biased individuals may be further disincentivised from doing lifetime cost calculations. While we do not measure present bias in terms of effort in our study, this suggestive evidence points to the fact that present-biased (measured in the form of monetary rewards) individuals may also tend to be averse to computing lifetime costs. Therefore, we can speculate that our measure of present bias in terms of monetary payments approximates the level of present bias in terms of effort.

It may also be the case that present-biased individuals prioritize other aspects of the motorcycle more than its fuel economy. For example, we find that 64% of present-biased individuals, in a question in the survey on the importance of different attributes in forming their decision (for the new vehicle that they wanted to purchase), stated that the popularity of the motorcycle model among family and friends was very important to them, compared to 54% of non-present-biased individuals (and the difference is significant at the 5% level using a one-sided T-test, while it is insignificant using a two-sided T-test). It is possible that these individuals chose to overlook differences in fuel economy when they purchased their motorcycles.

On the other hand, we observe that none of the other behavioral anomalies are significant in determining the ratio of lifetime costs, across model specifications (in this sense, our findings are similar to Bradford et al. (2017), who also found a role for present bias in determining fuel-efficiency choices, but not for time preferences). Another finding that is consistent across

[18] About 4.3% of present-biased individuals stated that they did not know how petrol prices would develop in the future, as opposed to 1.6% of non-present-biased respondents. This difference is significant at the 5% level using a one-sided T-test.

models in Table 3 is that income plays an important role in determining the ratio of total lifetime costs, with individuals having higher levels of income being associated with relatively higher total lifetime costs, compared to individuals who have low levels of income. Thus, richer individuals are likely to purchase more fuel-inefficient motorcycles compared to individuals who have lower levels of income. We observe this, having controlled for engine size as well as other motorcycle-related specifications in our model (such as brand, and age of the motorcycle). In addition, we find that respondents who stated that other members of their family also used the motorcycle on a regular basis were more likely to make relatively inefficient choices, and choose motorcycles that have higher total lifetime costs than the most efficient one, given the engine size. This result is also confirmed across model specifications.

Membership in clubs or groups is likely to result in relatively efficient motorcycle choices, as we find from the results of the IV-based estimations of columns (3), (4), (7) and (8). The negative coefficient suggests that some form of social ties and contacts may be associated with individuals preferring to adopt more efficient motorcycles. Interestingly, we also find across estimations that owning more than one motorcycle is correlated with individuals making relatively less efficient choices on the motorcycle that we asked them about in the survey (the motorcycle that they use most frequently), and this variable is significant at the 1% level across models.

Lastly, we also identify individuals who stated that they applied for a loan in order to purchase their motorcycles as having made relatively inefficient choices. We do not have information on whether they were actually granted a loan to buy the motorcycle, and while it is difficult to identify the underlying reason for this correlation without further information, this finding suggests that liquidity and credit may play a role in determining the efficiency of motorcycle choices as well (perhaps because these individuals, much like present-biased individuals, are likely to have focused on other attributes, and not on the fuel economy). In a question in our survey on the importance of different attributes in forming their decision f the new vehicle that they wanted to purchase, about 62% of respondents who had applied for a loan for their existing motorcycle stated that fuel economy was very important to them; this proportion was 84% for those who didn't apply for a loan (and this difference is significant at the 1% level using either one-sided or two-sided T-tests). By not paying attention to fuel economy, individuals who applied for loans may have ended up buying motorcycles having higher total lifetime costs.

However, it may also be the case that these individuals found it difficult to do the calculation of total lifetime costs, or that they didn't really care to do it; for example, we find that among those who applied for a loan, about 40% of respondents were able to use information on fuel economy to compute total fuel costs (in a hypothetical computational question), whereas 58% of people who didn't apply for a loan were able to solve this question (this difference is significant at the 1% level, using either a one-side or a two-sided T-test).

Thus, while we are able to find some suggestive support for our main results, the identification of exact channels of influence requires more detailed data.

The selection equation and first-stage estimation results corresponding to the Heckman and IV models in columns (2)-(4) and (6)-(8) of Table 3 are presented in Table 4. Column (1) presents the Heckman selection equation results corresponding to the models in columns (2) and (6) of Table 3, whereas columns (2) and (3) include the probit estimation results for the

IV-control function approach using one instrument (which corresponds to the first-stage of the models in columns (3) and (7) of Table 3), and the probit results for the control function estimation using two instruments (relevant for columns (4) and (8) of Table 3) respectively.

In column (1) of Table 4, we find that individuals who have children are more likely to own a motorcycle than those who did not; moreover, rather intuitively, income is another important determinant of the decision of households to purchase a motorcycle, with higher levels of income associated with higher likelihoods of owning a motorcycle. We find that both students as well as female respondents are less likely to already own a motorcycle, compared to non-students or male respondents. In this model, we use two external instruments to account for selection; the first is the number of bus stops within 500 metres of the centre of the locality where the respondent resides. The second is the number of motorcycle shops and showrooms within 500 metres of the locality centre. We find that these variable coefficients have a positive sign in this specification, even though they are insignificant.

From the probit results in column (2), we learn that individuals who stated that they had been affected by natural disasters were more likely to be present-biased than those who had not been affected, as expected. This variable serves as our instrumental variable. In addition, we find that individuals having higher discount factors (or lower discount rates) are more likely to be present-biased. This finding has been observed in previous studies; for instance, Schleich et al. (2019) find in their data from a sample of European countries that the average correlation coefficient between the annual discount factor and the 'beta' parameter that determines present bias (with lower values of beta representing present bias) is negative. Moreover, we find that individuals who are risk-averse or loss averse are also more likely to be present-biased. On the other hand, individuals who were aware of the fuel economy of the motorcycle when they purchased it were less likely to be present-biased. Having children is also a trait that is positively associated with being present-biased, among individuals who own a motorcycle, whereas higher levels of income are negatively associated with present bias. Lastly, we find that individuals who applied for a loan to purchase the vehicle were less likely to be present-biased; while we do not know whether these individuals were granted a loan or not, this result hints that liquidity constraints as a factor for present bias may be less relevant for our sample. The results of column (3) are similar, except that we introduce another instrumental variable, namely the intensity of the 2015 earthquake in the locality where the respondent lives. We find that while this variable has a positive coefficient (suggesting that individuals who lived in localities that were worse affected by the earthquake were more likely to be present-biased), it is insignificant in the model.

## 4.3 Robustness checks

Table 7 in the appendix includes the results of robustness checks. In this table, we only report the results that test for the robustness of the model specifications in columns (4) and (8) of Table 3, i.e. the models estimated using the IV control function approach and two instruments. We choose these to be our baseline model results, as we address endogeneity concerns in these specifications, and we use both a subjective as well as an objective measure of the impact of natural disasters as instrumental variables. The results reported in this table are all also confirmed if we use the model specification with one instrumental variable (as in columns (3) and (7) of Table 3), these results can be provided on request.

## **Table 4:** First-stage estimation results

| Dependent variable<br>Model<br>Column | Probability of being selected<br>Heckman (MLE)<br>(1) | Present bias indicator<br>Probit (control function with 1 IV)<br>(2) | Present bias indicator<br>Probit (control function with 2 IVs)<br>(3) |
|---|---|---|---|
| Present bias indicator | -0.132 | | |
| | (0.124) | | |
| Annual discount factor | 0.248 | 1.412** | 1.444** |
| | (0.190) | (0.704) | (0.692) |
| Whether risk averse | 0.086 | 0.621*** | 0.646*** |
| | (0.080) | (0.197) | (0.198) |
| Whether loss averse | -0.007 | 0.597** | 0.601** |
| | (0.129) | (0.285) | (0.278) |
| Age of respondent | 0.006 | 0.005 | 0.006 |
| | (0.005) | (0.010) | (0.010) |
| Whether have children | 0.146* | 0.341* | 0.324 |
| | (0.085) | (0.209) | (0.211) |
| Monthly household income | | | |
| Between Rs. 30,000 and 50,000 | 0.260** | -0.644*** | -0.669*** |
| | (0.116) | (0.249) | (0.256) |
| Between Rs. 50,000 and 75,000 | 0.774*** | -0.530*** | -0.540*** |
| | (0.101) | (0.231) | (0.233) |
| More than Rs. 75,000 | 0.620*** | -1.012*** | -1.046*** |
| | (0.127) | (0.276) | (0.279) |
| Whether student | -0.260*** | -0.119 | -0.096 |
| | (0.080) | (0.285) | (0.289) |
| Whether female | -0.663*** | -0.522** | -0.506** |
| | (0.079) | (0.253) | (0.256) |
| Whether have a university degree | 0.008 | 0.088 | 0.088 |
| | (0.067) | (0.196) | (0.197) |
| Whether receives remittances | -0.116 | 0.231 | 0.227 |
| | (0.079) | (0.187) | (0.189) |
| Whether member of a club or society | 0.055 | 0.152 | 0.156 |
| | (0.102) | (0.178) | (0.178) |
| Whether self/family member known to have a respiratory disorder | 0.046 | 0.162 | 0.158 |
| | (0.093) | (0.281) | (0.283) |
| Whether aware of fuel economy when bought motorcycle | | -0.322** | -0.310** |
| | | (0.142) | (0.147) |
| Whether correctly solved math question on lifetime costs | | 0.262** | 0.260** |
| | | (0.140) | (0.138) |
| Whether reimbursed for petrol costs | | 0.342 | 0.325 |
| | | (0.213) | (0.217) |
| Whether family uses motorcycle regularly | | -0.280* | -0.287* |
| | | (0.172) | (0.170) |
| Whether applied for loan to purchase motorcycle | | -0.730*** | -0.727*** |
| | | (0.278) | (0.276) |
| Whether motorcycle is second-hand | | 0.244 | 0.225 |
| | | (0.185) | (0.181) |
| Whether own more than one motorcycle | | 0.060 | 0.086 |
| | | (0.358) | (0.354) |
| Whether self/someone known owned a vehicle during blockade | 0.158** | -0.444*** | -0.460*** |
| | (0.067) | (0.174) | (0.175) |
| Number of bus stops within 500 metres | 0.009 | | |
| | (0.034) | | |
| Number of motorcycle shops within 500 metres | 0.022 | | |
| | (0.020) | | |
| Whether affected by natural disasters and experienced severe damage | | 0.741*** | 0.723*** |
| | | (0.163) | (0.169) |
| Intensity of 2015 earthquake (MMI) | | | 0.464 |
| | | | (0.376) |
| Observations | 2244 | 570 | 570 |

*Note:* The table reports the coefficients as well as standard errors in parentheses for the main explanatory variables. The sample in column (1) includes both current motorcycle owners as well as respondents who don't currently own a motorcycle, and comprises respondents who were the main decision-makers regarding purchase of durables in the household, as well as the main users of their motorcycles. In columns (2) and (3), it only includes current motorcycle owners. We exclude respondents owning motorcycles with engine size 500 cc and above from our data sample. All models include controls for districts and distance from the city centre, whereas the models in columns (2) and (3) also include controls for brand, engine size and age of the motorcycle. Standard errors are clustered at the locality level. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient on constant is not reported.

In columns (1) to (3), we check the sensitivity of our main results to the choice of discount rate. In column (1), we present the second-stage estimation results of the IV-control function estimation in which the dependent variable is calculated assuming a discount rate of 3%, whereas in columns (2) and (3), it is calculated assuming rates of 5% and 9% respectively. We find that our main result on the effect of present bias on the energy-efficiency gap holds across models, on using varying discount rates.

In columns (4) to (7), we present the second-stage estimation results using alternative definitions of the risk aversion variable. As described in the Data section, for our main specifications, we converted the categorical variable capturing risk aversion and taking values from 0 to 10 into a dummy variable based on the median cutoff of 5. In columns (4) and (6), we use the $25^{th}$ percentile as a cut-off to create the dummy variable, whereas in columns (5) and (7), we use the $75^{th}$ percentile. Columns (4) and (5) are estimated using the ratio of lifetime costs computed using a discount rate of 7% as the dependent variable, whereas the models in columns (6) and (7) are estimated using a 10% discount rate. Across model specifications, we find that our main result on the positive effect of present bias on the ratio of total lifetime costs is confirmed. Moreover, we find that in the results of columns (5) and (7), the risk aversion dummy is significant at the 10% level, with a negative sign, suggesting that individuals who are risk averse are less likely to make inefficient motorcycle choices.

Lastly, in columns (8) and (9), we present the results estimated using a life time of 5 years to compute the total lifetime costs, instead of 10 years, as was used in the main specifications of Table 3, with a discount rate of 7% being used to calculate the lifetime cost ratio in column (8), and 10% used in column (9). Our main result on the positive effect of present bias is again valid for both model specifications, suggesting that varying the hypothetical duration of ownership of the motorcycle does not significantly hamper the magnitude of the effect of present bias on the energy-efficiency gap.

# 5 Conclusion

Our study aims to shed light on the role of present bias, loss aversion, risk aversion as well as time preferences in determining the energy-efficiency gap associated with the choice of a durable in a low-income context, as well as on what factors determine the existence of these biases. Present bias has been found to be an important roadblock towards individuals in low-income countries undertaking investments in privately beneficial technologies and behaviors (such as in the adoption of preventative health measures). In this paper, we sought to investigate whether present bias may also impede purchases of fuel-efficient motorcycles in Kathmandu, Nepal.

We find that income is a strong determinant of time preferences, as well as risk and loss aversion in our sample. In addition, education, health status, as well as membership in groups or clubs also determined the occurrence of different anomalies. We find that certain psychological factors played a salient role in determining the existence these anomalies in Kathmandu. In subsequent analyses, we find that present-biased individuals are less likely to have bought more fuel-efficient motorcycles, and more likely to have purchased motorcycles having relatively higher total lifetime costs. This result is robust across several specifications. Moreover, we do not find a role of other biases (such as loss or risk aversion), but we do find that individuals who applied for loans to purchase a motorcycle were more likely to buy relatively inefficient

models, as were individuals who had higher levels of income or those who owned more than one motorcycle.

While our data does not allow us to sufficiently disentangle the channels for these observed effects, we hypothesize, and provide suggestive evidence, that present-biased individuals are likely to undervalue future energy cost savings, and find it burdensome to compute total lifetime costs given the substantial effort that it often warrants. Present bias can manifest itself as a preference for immediate rewards over later ones, but it can also imply that individuals find it onerous to undertake tasks in the present (such as computing total lifetime costs). In our study, we measure present bias in terms of monetary rewards, however we highlight some reasons as to why present-biased individuals may be more reluctant to calculate total lifetime costs (and this may result in purchasing relatively inefficient motorcycles). A more detailed exploration of the role of present bias in effort in hindering lifetime cost calculations (and thus possibly contributing to the energy-efficiency gap) makes a fruitful topic for future research.

Our results have important policy implications, given that standards as well as product taxes may be more relevant than fuel taxes in ensuring that present-biased individuals purchase more fuel-efficient vehicles. Moreover, liquidity constraints, that are also closely linked to present bias in this context, may need to be addressed as well in order to enable individuals to invest in fuel-efficient transport. This is particularly important in low and middle-income settings such as Nepal, where strong negative externalities from air pollution are a cause for concern, and other policy instruments such as standards and labels are yet to be implemented.

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# Appendix

9. a) Suppose you have to make a hypothetical choice. Which of the following would you prefer?

   A) Receive Rs 1000 in 6 months
   B) Receive an amount between Rs 550 and Rs 980 in one week.

   b) If 9B is selected,
   You said you would prefer to receive an amount between Rs 550 and Rs 980 in one week. Please choose one of the options below that you would further prefer.

   A) Rs. 980 in one week. Below this amount I would rather receive Rs 1000 in 6 months.
   B) Rs. 940 in one week. Below this amount I would rather receive Rs 1000 in 6 months.
   C) Rs. 900 in one week. Below this amount I would rather receive Rs 1000 in 6 months.
   D) Rs. 860 in one week. Below this amount I would rather receive Rs 1000 in 6 months.
   E) Rs. 800 in one week. Below this amount I would rather receive Rs 1000 in 6 months.
   F) Rs. 700 in one week. Below this amount I would rather receive Rs 1000 in 6 months.
   G) Rs. 550 in one week. Below this amount I would rather receive Rs 1000 in 6 months.

**Figure 1:** Present Bias and Time Preferences: First MPL-based Question

10. a) Suppose you have to make another hypothetical choice. Which of the following would you prefer?

    A) Receive an amount between Rs 550 and Rs 980 in 6 months and one week
    B) Receive Rs 1000 in 12 months.

    b) If 10A is selected,
    You said you would prefer to receive an amount between Rs 550 and Rs 980 in 6 months and one week. Please choose one of the options below that you would further prefer.

    A) Rs. 980 in 6 months and one week. Below this amount I would rather receive Rs 1000 in 12 months.
    B) Rs. 940 in one week and one week. Below this amount I would rather receive Rs 1000 in 12 months.
    C) Rs. 900 in one week and one week. Below this amount I would rather receive Rs 1000 in 12 months.
    D) Rs. 860 in one week and one week. Below this amount I would rather receive Rs 1000 in 12 months.
    E) Rs. 800 in one week and one week. Below this amount I would rather receive Rs 1000 in 12 months.
    F) Rs. 700 in one week and one week. Below this amount I would rather receive Rs 1000 in 12 months.
    G) Rs. 550 in one week and one week. Below this amount I would rather receive Rs 1000 in 12 months.

**Figure 2:** Present Bias and Time Preferences: Second MPL-based Question

# Calculating the Time Preference Parameters

We calculated two preference parameters individually for each respondent using the questions presented in Figures 1 and 2, the discount factor as well as the present bias 'beta' parameter which is then used to construct the indicator variable.

In order to compute these values, we identified the "switch-points" for each respondent, which is the point at which he/she stated that they would prefer option B to option A, in each of the MPLs. Following the methodology adopted in Schleich et al. (2019), we assume that individuals are indifferent at the mean values of the lines between which they switched: for instance, if the respondent chose option B) first and then again option B) in response to the question presented in Figure 1 above, he or she is assumed to be indifferent between receiving Rs. 1'000 in 6 months and Rs. 940 in one week. Respondents who never switched, i.e. always chose A, were assumed to be indifferent between receiving option A and the first option in the second price list, and vice-versa for those respondents who immediately switched.

These two switch points were then used to compute the 6-month discount factor $\delta$, as well as the present bias $\beta$ parameter, using the following equations:

$$u^*(x_{A1.1}) = \delta u^*(x_{B1.1}) \tag{5}$$

$$u^*(x_{A1.2}) = \delta\beta u^*(x_{B1.2}) \tag{6}$$

where A1.1 and B1.1 are the monetary amounts to which the respondent is indifferent in the first question, and A1.2 and B1.2 are the monetary amounts to which the respondent is indifferent in the second question.

In computing these parameters, we assume that respondents have monotonous preferences (and thus at most one switch-point in both the MPLs), and we assume that the utility function is linear in the monetary amount, i.e. we assume a risk-neutral utility function. The value of $\delta$ derived by solving equation 5 above is raised to the power of 52/23 in order to compute the annual discount factor.

The parameter $beta$ is used to identify individuals who are present-biased. A $\beta$ value equal to one denotes a person who is neither present-biased, nor future-biased, $\beta > 1$ denotes a future-biased individual, whereas $\beta <$1 denotes a present-biased individual.

**Table 5:** Summary Statistics of Vehicle Specifications

| Engine Size (in cc) | Observations | Average fuel economy (km/l) |
|---|---|---|
| 100 | 25 | 70.32 |
| 110 | 132 | 53.83 |
| 125 | 181 | 65.60 |
| 150 | 139 | 59.40 |
| 160 | 49 | 56.08 |
| 180 | 10 | 47 |
| 190 | 4 | 35 |
| 200 | 30 | 35 |
| 220 | 4 | 39.5 |
| 250 | 4 | 43 |
| 350 | 13 | 43.15 |
| **Year of purchase of motorcycle** | **Observations** | **Average fuel economy (km/l)** |
| 2008 | 5 | 65.6 |
| 2009 | 8 | 60.125 |
| 2010 | 3 | 56 |
| 2011 | 18 | 64.22 |
| 2012 | 26 | 61.23 |
| 2013 | 53 | 58.70 |
| 2014 | 53 | 61.98 |
| 2015 | 72 | 59.13 |
| 2016 | 116 | 58.04 |
| 2017 | 129 | 55.57 |
| 2018 | 97 | 56.13 |
| 2019 | 11 | 51.55 |

*Note:* The table reports the average values of fuel economy (measured in km/l) by engine size and by year of purchase of two-wheeler. The relevant sample size is 591 observations. The sample comprises respondents for whom vehicle specification data was available, and who were the main decision-makers regarding purchase of durables in the household, as well as the main users of their motorcycles. We exclude respondents owning motorcycles with engine size 500 cc and above from our data sample.

**Table 6:** Determinants of Behavioral Anomalies and Time Preferences: Marginal Effects

| Dependent variable<br>Model | Present biased<br>Probit | Annual discount factor<br>Fractional response | Loss averse<br>Probit | Risk averse<br>Probit |
|---|---|---|---|---|
| | Socio-demographic variables | | | |
| Monthly household income | | | | |
| Between Rs. 30,000 and 50,000 | 0.018 | -0.013 | -0.031*** | 0.163*** |
| | (0.022) | (0.012) | (0.011) | (0.040) |
| Between Rs. 50,000 and 75,000 | 0.028 | -0.006 | -0.030* | 0.169*** |
| | (0.028) | (0.014) | (0.017) | (0.066) |
| More than Rs. 75,000 | -0.019 | -0.045*** | -0.030** | 0.231*** |
| | (0.021) | (0.015) | (0.015) | (0.060) |
| Whether have a university degree (Bachelor's or Master's) | -0.002 | 0.027*** | 0.0006 | -0.116*** |
| | (0.018) | (0.008) | (0.012) | (0.023) |
| Whether have children | 0.018 | 0.014 | -0.010 | -0.002 |
| | (0.019) | (0.012) | (0.013) | (0.040) |
| Whether student | -0.017 | 0.028*** | 0.001 | 0.003 |
| | (0.019) | (0.012) | (0.012) | (0.031) |
| Age | 0.001 | 0.0003 | 0.001 | -0.001 |
| | (0.001) | (0.0006) | (0.001) | (0.002) |
| Whether female | -0.010 | -0.008 | 0.005 | 0.019 |
| | (0.014) | (0.008) | (0.012) | (0.030) |
| Whether receive remittances | 0.031** | 0.015* | -0.018 | -0.060** |
| | (0.015) | (0.009) | (0.016) | (0.032) |
| Whether have a respiratory disorder (self or close family) | 0.065*** | -0.038*** | 0.005 | -0.005 |
| | (0.023) | (0.015) | (0.016) | (0.044) |
| Whether member of a club or society | 0.055*** | 0.025*** | -0.029** | -0.005 |
| | (0.019) | (0.010) | (0.013) | (0.044) |
| Whether self/someone known owned a vehicle during blockade | -0.038*** | -0.044*** | -0.015 | 0.017 |
| | (0.015) | (0.013) | (0.013) | (0.032) |
| Log of distance of locality from the city centre | -0.001 | -0.001*** | 0.003 | 0.007** |
| | (0.001) | (0.0006) | (0.002) | (0.003) |
| | Psychological variables | | | |
| Live according to religious principles | 0.027 | 0.006 | 0.042*** | 0.216*** |
| | (0.019) | (0.009) | (0.012) | (0.031) |
| Hold on to my family's traditions | 0.031** | -0.027*** | 0.055*** | 0.061** |
| | (0.017) | (0.011) | (0.015) | (0.031) |
| Go out a lot (e.g. dinners, parties, other leisure activities etc.) | 0.0003 | 0.018 | -0.004 | -0.134*** |
| | (0.019) | (0.012) | (0.015) | (0.042) |
| Enjoy my life to the full | 0.024 | -0.044*** | 0.026 | 0.142** |
| | (0.024) | (0.015) | (0.019) | (0.066) |
| Likely to buy the latest technological innovation | 0.036** | 0.006 | 0.039*** | 0.124*** |
| | (0.018) | (0.010) | (0.013) | (0.038) |
| Observations | 2245 | 2245 | 2245 | 2245 |

*Note:* The table reports the marginal effects represented in terms of change in the dependent variable, for a unit change in each explanatory variable, computed at the means of the explanatory variables. The sample includes both current motorcycle owners as well as respondents who don't currently own a motorcycle, and comprises respondents who were the main decision-makers regarding purchase of durables in the household, as well as the main users of their motorcycles. We exclude respondents owning motorcycles with engine size 500 cc and above from our data sample. All models include dummies for districts. Standard errors are clustered at the locality level. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient on constant is not reported.

# **Table 7:** Robustness checks

| Dependent variable | Log of ratio of lifetime costs with varying discount rates | | | Log of ratio of lifetime costs with 7% discount rate | | Log of ratio of lifetime costs with 10% discount rate | | Log of ratio of lifetime costs with 7% discount rate | Log of ratio of lifetime costs with 10% discount rate |
|---|---|---|---|---|---|---|---|---|---|
| Specification | 3% | 5% | 9% | Risk aversion $25^{th}$ percentile | Risk aversion $75^{th}$ percentile | Risk aversion $25^{th}$ percentile | Risk aversion $75^{th}$ percentile | Life of motorcycle of 5 years | Life of motorcycle of 5 years |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Present bias indicator | 0.065* | 0.065* | 0.066* | 0.066** | 0.067** | 0.066** | 0.067** | 0.068** | 0.068** |
| | (0.038) | (0.038) | (0.037) | (0.035) | (0.037) | (0.035) | (0.036) | (0.037) | (0.037) |
| Annual discount factor | 0.019 | 0.019 | 0.018 | 0.013 | 0.017 | 0.012 | 0.016 | 0.015 | 0.015 |
| | (0.026) | (0.025) | (0.025) | (0.024) | (0.026) | (0.024) | (0.025) | (0.023) | (0.023) |
| Whether risk averse | -0.005 | -0.005 | -0.006 | 0.010 | -0.025* | 0.010 | -0.024* | -0.006 | -0.006 |
| | (0.009) | (0.009) | (0.009) | (0.011) | (0.014) | (0.011) | (0.014) | (0.009) | (0.009) |
| Whether loss averse | -0.005 | -0.005 | -0.005 | -0.007 | -0.006 | -0.007 | -0.006 | -0.005 | -0.005 |
| | (0.017) | (0.017) | (0.017) | (0.016) | (0.017) | (0.016) | (0.017) | (0.017) | (0.017) |
| Age of respondent | -0.0005 | -0.0005 | -0.0005 | -0.0005 | -0.0004 | -0.0005 | -0.0004 | -0.0006 | -0.0006 |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0009) | (0.0008) | (0.0009) | (0.0008) | (0.0008) |
| Whether have children | -0.009 | -0.009 | -0.009 | -0.008 | -0.010 | -0.008 | -0.010 | -0.008 | -0.008 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Monthly household income | | | | | | | | | |
| Between Rs. 30,000 and 50,000 | 0.023*** | 0.023** | 0.022** | 0.021** | 0.027*** | 0.020** | 0.027*** | 0.020*** | 0.020** |
| | (0.010) | (0.010) | (0.010) | (0.009) | (0.011) | (0.009) | (0.010) | (0.010) | (0.010) |
| Between Rs. 50,000 and 75,000 | 0.043*** | 0.042*** | 0.042*** | 0.040*** | 0.049*** | 0.040*** | 0.048*** | 0.041*** | 0.041*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.015) | (0.013) | (0.014) | (0.012) | (0.012) |
| More than Rs. 75,000 | 0.049*** | 0.048*** | 0.048*** | 0.047*** | 0.054*** | 0.047*** | 0.054*** | 0.047*** | 0.046*** |
| | (0.014) | (0.013) | (0.014) | (0.013) | (0.015) | (0.013) | (0.014) | (0.013) | (0.013) |
| Whether student | -0.001 | -0.001 | -0.002 | -0.003 | -0.003 | -0.003 | -0.003 | -0.004 | -0.004 |
| | (0.012) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Whether female | -0.002 | -0.002 | -0.003 | -0.003 | -0.0001 | -0.003 | -0.0007 | -0.004 | -0.004 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.010) | (0.009) | (0.010) | (0.008) | (0.008) |
| Whether have a university degree | -0.004 | -0.004 | -0.004 | -0.003 | -0.003 | -0.003 | -0.003 | -0.004 | -0.004 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.008) | (0.008) |
| Whether receives remittances | 0.003 | 0.003 | 0.002 | 0.004 | 0.002 | 0.004 | 0.002 | 0.002 | 0.002 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.009) | (0.009) |
| Whether member of a club or society | -0.014*** | -0.014*** | -0.014*** | -0.014*** | -0.014** | -0.014*** | -0.014** | -0.013** | -0.013** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Whether self/family member known to have a respiratory disorder | -0.018 | -0.017 | -0.016 | -0.015 | -0.015 | -0.014 | -0.014 | -0.014 | -0.014 |
| | (0.012) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Whether aware of fuel economy when bought motorcycle | 0.005 | 0.005 | 0.004 | 0.007 | 0.005 | 0.006 | 0.005 | 0.003 | 0.003 |
| | (0.010) | (0.010) | (0.010) | (0.011) | (0.010) | (0.011) | (0.010) | (0.009) | (0.009) |
| Whether correctly solved math question on lifetime costs | -0.009 | -0.009 | -0.009 | -0.009 | -0.007 | -0.009 | -0.007 | -0.008 | -0.008 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.009) | (0.010) | (0.009) | (0.009) | (0.009) |
| Whether reimbursed for petrol costs | -0.006 | -0.006 | -0.006 | -0.006 | -0.003 | -0.006 | -0.003 | -0.004 | -0.004 |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) |
| Whether family uses motorcycle regularly | 0.020*** | 0.020*** | 0.020*** | 0.019*** | 0.017*** | 0.019*** | 0.017*** | 0.020*** | 0.020*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Whether applied for loan to purchase motorcycle | 0.036*** | 0.036*** | 0.036*** | 0.034*** | 0.037*** | 0.034*** | 0.038*** | 0.037*** | 0.037*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.013) |
| Whether motorcycle is second-hand | 0.014 | 0.013 | 0.012 | 0.013 | 0.015 | 0.012 | 0.015 | 0.010 | 0.010 |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Whether self/someone known owned a vehicle during blockade | 0.007 | 0.007 | 0.008 | 0.006 | 0.010 | 0.007 | 0.010 | 0.008 | 0.008 |
| | (0.007) | (0.007) | (0.006) | (0.006) | (0.007) | (0.006) | (0.007) | (0.006) | (0.006) |
| Whether own more than one motorcycle | 0.051*** | 0.050*** | 0.048*** | 0.049*** | 0.051*** | 0.047*** | 0.050*** | 0.043*** | 0.043*** |
| | (0.014) | (0.014) | (0.014) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Observations | 559 | 559 | 559 | 559 | 559 | 559 | 559 | 559 | 559 |
| Cragg Donald F-statistic | 62.838 | 62.838 | 62.838 | 55.049 | 59.444 | 55.049 | 59.444 | 62.838 | 62.838 |

*Note:* The table reports the coefficients as well as standard errors (in parentheses) for the main explanatory variables in the second-stage estimation results of the control function estimation using two instrumental variables. The sample comprises respondents for whom vehicle specification data was available i.e., who own a motorcycle, and who were the main decision-makers regarding purchase of durables in the household, as well as the main users of their motorcycles. We exclude respondents owning motorcycles with engine size 500 cc and above from our data sample. All models include controls for district, as well as for brand, distance to the city centre, engine size and age of the motorcycle. Standard errors are clustered at the locality level. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient on constant is not reported.

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