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Herd behavior in the choice of motorcycles: Evidence from Nepal

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Abstract

This article sheds light on a scarcely explored area of research related to herd behavior in urban settings of developing economies, where the use of motorized two-wheelers has been increasing rapidly. Using primary survey-based data from Nepal, we examine whether potential motorcycle buyers in the Kathmandu valley exhibit herd behavior or price-conscious behavior when making a hypothetical choice decision and then evaluate the determinants of the observed behavior. Using factor analysis, the paper identifies distinct homogeneous groups of respondents based on their preferences towards motorcycle attributes and on their psychological traits and attitudes. Not only do we find a prevalence of herding in the choice of motorcycles, the results also find strong suggestive evidence that, in addition to gender and income, several latent factors related to preferences and psychological traits might play a crucial role in determining the herd behavior. We discuss policy implications in the context of consumer behavior and environmental policy in the backdrop of rapid vehicle demand and dangerous air pollution levels.

JEL Classification: D12, D83, D91, Q58

Keywords: herd behavior; determinants; motorcycle choice; psychological factors; bounded rationality; Nepal

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1 Introduction

Herd behavior has been known to be a mainstay of the human decision-making process. When individuals decide to follow group behavior, rather than take decisions based on private information, herding is said to occur (Banerjee, 1992; Bikhchandani et al., 1992). Individuals may herd in order to benefit from payoff externalities, they may herd due to reputational concerns, or herd behavior may also manifest as individuals acquire information about the actions of other agents in the presence of uncertainty (the so-called "wisdom of the crowds") (Merli and Roger, 2013).

Researchers have observed herd behavior across different domains, notably in finance and investment –for instance, stock market bubbles have been attributed to herding by investors (Spyrou, 2013; Bikhchandani and Sharma, 2001; Merli and Roger, 2013), in technology adoption decisions, and in consumption decisions (Chen, 2008; Cheung et al., 2014; Duan et al., 2008). Consumption and adoption decisions, in particular, are quite plausibly swayed by the actions of others, and this is often exploited by firms as well as marketing companies. For example, "popularity cues" such as metrics on social media sites, stickers, as well as claims by vendors are possible means of facilitating herd behavior. These popularity cues have been found to play a role in influencing decision-making, particularly in the presence of strong social norms or uncertainty (Muchnik et al., 2013; Shen et al., 2016; Chen, 2008; Lee et al., 2015).

While ample empirical evidence exists documenting herd behavior, as well as its determinants, there is a dearth of literature on the behavioral or psychological traits that may determine herd behavior (Baddeley, 2010). A more interdisciplinary and eclectic approach to herd behavior suggests that emotions (such as fear, hope, anxiety and greed), willingness to take risks, as well as other behavioral constructs (such as cognitive ability, ambiguity aversion and the availability heuristic) are important determinants of herding tendencies in economic and financial contexts (Baddeley, 2010). Through this study, we seek to make a contribution to this line of enquiry that examines the role of psychological and behavioral determinants of herding.

In this study, we aim to shed some light on herd behavior and its determinants in the context of the purchase of durable goods. The study draws on primary data collected through a survey of potential motorcycle[1] buyers in the Kathmandu valley, Nepal, in which we ask respondents to choose among hypothetical motorcycle models in an experimental framework.

We capture the tendency to herd with the help of two survey questions. In each question, respondents make a choice between two otherwise similar hypothetical motorcycle models that have different star ratings and prices; a cheaper model with a lower star rating, and a more expensive model with a higher star rating. Respondents must choose their preferred motorcycle, i.e. we adopt a stated-preference approach. We then categorize consumers as being either "price-conscious" —those who tend to choose the cheaper model, despite its lower star rating; or "popularity-conscious" —those who tend to exhibit herd behavior and follow the information conveyed by the popularity cue (the star rating). Thus, we exploit a popularity-price trade-off to examine herd behavior and its determinants in this context.

Of course, the purchase decision for durables such as motorcycles is also likely to be intertwined

[1] In Nepal and other neighbouring regions, a motorcycle or a motorized two-wheeler is often referred to just as a 'bike'. In our study too, we use the term 'motorcycle' and 'bike' interchangeably. The term bike used in this research should not be confused with a pedal-based cycle or a bicycle.

with several other factors such as preferences for technical attributes of the motorcycle, its price, operating costs, as well as design-related features, as has been extensively documented in the transport literature (McFadden (1974) first modelled the role of attributes in determining choice of mode of transportation). For instance, consumers who assign a lot of importance to fuel economy of the motorcycle or its operating costs may also be price-conscious, and may pay less attention to star ratings. On the other hand, consumers who highly value attributes such as design, popularity of the model and engine power may be more likely to be influenced by visual cues such as star ratings. Our paper also seeks to identify different categories of consumers, based on their personal valuation for several bike-related attributes, and to distinguish how these groups of consumers differ in terms of their propensity to herd.

Our objectives in this study are thus twofold: 1) to identify distinct latent groups of consumers, based on psychological traits and attitudes as well as preferences for vehicle attributes, and 2) to evaluate the determinants of herd behavior as well as of price-constrained behavior in the hypothetical decision to buy motorcycles. In our analysis, we focus on psychological traits such as adherence to religion and family traditions, whether the respondent has an outgoing nature, their propensity to buy the latest technological innovations, and whether they enjoy life. We also account for behavioral variables, such as loss aversion, present bias and risk and time preferences in some models. With respect to bike-related attributes, we consider a rich set of characteristics that are likely to be relevant to motorcycle buyers (such as engine power, price, fuel economy, design, etc.).

We aim to test the following hypotheses: 1) respondents who are price-constrained, or value attributes of a motorcycle such as its fuel economy and operating costs, or other non-price attributes such as its environmental impact and safety, are likely to exhibit distinct behavior than those who value attributes such as design, engine power, brand, etc.; 2) respondents who value attributes such as fuel economy and operating costs, or are price-constrained, are more likely to exhibit price-conscious behavior, whereas respondents who value more visible attributes such as design, appearance and engine power are more likely to exhibit herd behavior; 3) respondents who are more grounded in tradition, i.e. more likely to be religious and value family customs and traditions are more likely to represent a relatively homogeneous group, whereas respondents who enjoy going out a lot, and derive satisfaction from buying the latest innovations and technologies are likely to represent another homogeneous group; and 4) respondents who are more likely to be traditional are less likely to herd in their decisions, whereas respondents who are more consumerist in their approach are more likely to herd.

Methodologically, we adopt factor analysis to obtain latent groups of consumers, based on both their preferences for bike-related attributes, as well as some psychological traits and attitudes. We then estimate simple discrete choice models to analyze the role of these factors, as well as of socio-economic information, in determining herd behavior.

We are able to categorize respondents into four latent groups based on preferences for bike-related attributes, and three latent groups based on psychological traits and attitudes. We find that respondents belonging to the first group - for whom non-salient/less visible attributes such as environmental impact, resale value and safety are more important - are more likely to exhibit price-conscious behavior, whereas individuals in the second group - for whom salient/visible characteristics of the motorcycle such as its design and appearance, brand, popularity and engine power are important - are more likely to exhibit herd behavior. Individuals in the third group who stated that the purchase price of the motorcycle is a constraint for them, are also less likely to exhibit herding, and rather intuitively, more likely to be price-conscious. Lastly, the fourth group comprises individuals who have actively searched for information on the fuel economy and operating costs for the new motorcycle that they want to buy. This group resembles proactive consumers who search for fuel costs, and they are also less likely to exhibit herding in their choice of motorcycle.

With respect to the three groups related to psychological traits and attitudes, we find that in the first group, individuals who state that they are more likely to abide by religious principles or hold on to their family's traditions are more likely to be price-constrained, i.e. less likely to exhibit herding. We do not obtain significant results for the second group, namely individuals who go out a lot for leisure activities, or are likely to buy the latest technological innovations even if they may not need them. On the other hand, respondents in the third group who stated that they enjoyed their life to the full and who were more likely to buy the latest gadget (such as an IPhone) today than wait for a slightly improved version next year, are more likely to exhibit herding in their choices. We neither obtain any significance for the behavioral anomaly variables, namely loss aversion or the present bias 'beta' parameter, nor we find the time or risk parameters significant in our main estimations.

In addition to these findings, our results regarding the socio-economic variables suggest that female respondents, as well as relatively richer respondents are less likely to exhibit herding in the choice of motorcycles (compared to male respondents and relatively poorer respondents, respectively). On the other hand, respondents whose highest level of educational attainment is a Bachelor's degree are more likely to exhibit herd behavior (compared to those with the highest level of educational attainment being a high school diploma or below).

Herd behavior is highly relevant and important to study in developing countries for multiple reasons; first and foremost, in the absence of perfect information, which is plausible in low and middle-income country (LMIC) settings, consumers might be relying on signals from other buyers to ascertain unknown product quality, and thus be more likely to exhibit herd behavior. On the other hand, tighter budget restrictions among credit-constrained households may imply that consumers may be reluctant to blindly follow the choices of others. Our study contributes to understanding the role of both socio-economic as well as psychological factors in herd behavior (or conversely, in the propensity to not herd), and provides novel insights on the drivers of herding in adoption decisions in countries such as Nepal. For instance, we are able to account for factors that may be particularly relevant to the context, such as whether households receive any remittances from family members working abroad, household size, as well as levels of their willingness to take risks.

A study of herd behavior in developing countries is likely to be even more important to better understand the adoption of durables such as motorcycles. Firstly, unlike consumption goods, the purchase of motorcycles is likely to engender tighter budget constraints. Moreover, the market for vehicles is often plagued by imperfect information. Lastly, given that there are often several factors that determine the adoption of vehicles, it becomes difficult to disentangle the possible role that social influence (or herding) might play in decision-making. We are able to shed some light in this direction, by focusing our analysis on the role of star ratings as well as price in determining the adoption of otherwise similar motorcycles.

Our contribution to the literature on herd behavior is two-fold: firstly, we identify some behavioral and psychological determinants of herding among consumers looking to buy a durable such as a motorcycle. To the best of our knowledge, our study is one of the first to undertake this evaluation, especially in a low-income context. Secondly, we are able to delineate consumers on the basis of their preferences for various attributes of motorcycles, and evaluate the role that these preferences could play in determining herd behavior. We are not aware of other similar studies that have evaluated the effect of preferences for attributes on vehicle choice. To this end, the policy implications of our study are related to the identification of heterogeneous groups of consumers. This is particularly relevant in the context of environmental policy; for example, in cities of developing countries where air pollution levels can be dangerously elevated, it is invaluable for policy-makers to know how consumers can be expected to react to different policies. Our study provides some initial insights into the factors driving consumer behavior.

The rest of the paper is arranged as follows: Section 2 provides a review of the literature on herd behavior, Section 3 describes the data as well as adopted methodology in detail, Section 4 present the main results of the paper, whereas Section 5 concludes and provides some policy implications. We include additional data description and results in the Appendix.

2 Previous Literature

Herd behavior falls within the realm of social influence, whereby agents rely on information gathered from others when making choices. Foster and Rosenzweig (1995) differentiate between herding and social learning by arguing that in the latter, some exchange of information is required between agents, whereas herding can be more passive.

Several important papers on herd behavior in economics are based on the premise that others' actions provide information on what one's action could be. This idea largely borrows on the principle of Bayesian updating, and how individuals can revise probabilistic judgements using information about others actions; this generates what are known as information cascades or herding, as was articulated by Banerjee (1992) and Bikhchandani et al. (1992). Previous studies have also termed this type of imitative behavior, when individuals tend to flock to the same decision based on information derived from the decision of others, an 'upward cascade´ (Dholakia et al., 2002). Bikhchandani et al. (1992) highlighted that individuals may ignore their own private information, and choose to rely on the history of others actions (when it comes to durable goods purchase, for example) because it provides them a signal on the private information of other individuals.

This behavior could be perceived as being both rational, as well as irrational, depending on the context and circumstances. For instance, Akerlof and Kranton (2000) place herding in the realm of imitative behavior; when individuals cave to pressure from within a social group to which they belong, they can end up mimicking behavior of others in the group. Mimicry or imitation is, within the confines of this world, rational, as social factors and reputation play an important role in guiding behavior.[2] This contrasts to behavior observed when agents blindly follow others, which is likely to be non-information based. For instance, Simonsohn and Ariely (2008) observe that buyers of DVDs on Ebay were more likely to choose auctions in which were more existing bids, even if this did not provide more information to them. In turn, they

[2]Rational herding has also been extensively studied in the context of financial markets; Spyrou (2013) provides a detailed summary.

show that this bias incentivizes sellers to adopt suboptimal strategies, for instance charging low starting prices in the auctions.

Studies exhibiting herd behavior can also find a place within a broader literature on social norms. Melnyk et al. (2019) provide a comprehensive summary of the literature on the role of social norms in influencing consumption decisions of individuals, while making a distinction between descriptive norms (what most others do) and injunctive norms (what most others approve of). Providing a meta-analysis of the literature, they conclude that descriptive norms are likely to directly influence behavior (such as actual purchase decisions), while injunctive norms are more strongly correlated with intentions (such as what we attempt to capture in our study, with the hypothetical choice of a motorcycle).

A large literature in finance has studied the role of herding in financial markets, as well as in investment and lending decisions, with mixed results on the prevalence of herd behavior (Bikhchandani and Sharma (2001) and Spyrou (2013)) provide an overview of the literature, particularly with respect to investment behavior). Some papers have adopted an experimental approach to investigate whether herd behavior exists (Cipriani and Guarino 2005, Drehmann et al. 2005), others have used a structural approach to understand the prevalence of herding as well as to estimate the inefficiencies that it causes (Cipriani and Guarino, 2014). Khanna and Mathews (2011) provide theoretical insights to suggest that herding may increase the quality of investment decisions, and lead to improved aggregate information in financial markets, which is also in line with many studies summarized in Devenow and Welch (1996). On the other hand, Cipriani and Guarino (2014) find, using transaction-level data on trading in a stock, that the informational asymmetries generated in the presence of herding could amount to about 4% of the asset's expected value.

Our study examines herd behavior in the hypothetical choice of a durable good, namely motorcycles, and therefore fits into a strand of the literature that discusses herding in consumption decisions. Many of these studies have explored the role of online ratings as well as product evaluations. For instance, Chen (2008) finds, using data from an experimental study done in an online bookstore, that individuals use product evaluations and choices of others as signals in order to make their own purchase decisions. In particular, this study focuses on the role of star ratings and sales volumes in influencing these decisions, and finds that consumers value opinions of other consumers more than the recommendations of experts. This is in line with further evidence that suggests that consumers tend to rely on the information provided by the choices of others when faced with a lot of information (Bonabeau, 2004). In a slightly different context, namely the consumption of news online, Muchnik et al. (2013) use the setting of a randomized controlled trial on a social news aggregation website to evaluate the extent of herd behavior, and find that positive manipulations on comments (by giving a 'thumbs-up', for example) increased the ratings of the comments by 25%, and that this effect persisted over five months. Shen et al. (2016) find that consumer perception of the similarity of online review contributors, in terms of social backgrounds and attitudes, plays an important role in determining herding: a consumer who perceives greater homophily among contributors is more likely to disregard his or her private information, and imitate others.

While most papers identify a positive effect for ratings as well as recommendations, some studies offer mixed evidence as well. Duan et al. (2008), for example, find that while online software buyers' choices were deeply influenced by the download rankings as well as popularity information of products, online user ratings had no impact on the decision to buy popular products whereas they had an effect on the purchase of less popular products. Lee et al. (2015) find that social influence also had an effect on online movie ratings, with previous ratings by friends of individuals always inducing herd behavior. On the other hand, ratings by strangers both encouraged herding and discouraged it, depending on the popularity of the movie. Cheung et al. (2014) find, using revealed preference data on the purchase of beauty products online, that consumers having a higher level of expertise in a particular brand are less likely to be influenced by the opinions or actions of others. However, they also find that the more involved consumers are in an online social community, the more likely it is for them to be influenced by peer consumers' opinions and actions.

Herd behavior has been studied in other contexts as well, such as in innovative activity by firms (Melissas, 2005), in the application for kidney transplants in the US (Zhang, 2010), in lending in the microloan market in the US (Zhang and Liu, 2012), in seed choices by cotton farmers in Andhra Pradesh in India and in the launch of new products by firms (Liu and Schiraldi, 2011).

Economic decisions, in a large majority of these studies, are assumed to rely on cognitive processes that use information available to form expectations. This line of reasoning has thus far largely ignored the role of sociological, or emotional/ other psychological factors in determining herd behavior. From a behavioral or psychological point of view, there is also a large literature that finds that cognitive limitations, nudges, as well as framing effects may lead to herd behavior, and to individuals following possibly "irrational" decisions of a group (Tversky and Kahneman, 1974). Previous studies on social learning have also suggested that individuals may prefer simple heuristics in order to learn about uncertain situations, rather than expending personal effort (Katona, 1975).

Baddeley (2010) argues that economists have ignored psychological and sociological factors in explaining herd behavior, which has resulted in a simplistic but insufficient categorization of herd behavior as being either rational or irrational. Most of the previous studies have categorized agents whose behavior is consistent with a model of Bayesian updating as being rational. However, this has resulted in using narrow behavioral assumptions that largely overlook the complexities of sociological, emotional and psychological factors that may influence these decisions (Loewenstein, 2000). For example, there is some evidence suggesting that individuals of lower cognitive ability are more likely to be risk averse (Dohmen et al., 2010), and if herding is a response to risk, then cognitive factors may play a role in determining tendencies of agents to follow the decisions of others.

Some experimental evidence exists on the role between behavioral traits such as risk aversion and herd behavior (Baddeley et al., 2007). Luetje (2009) finds, in a study involving German asset managers, that risk-averse as well as loss-averse managers are more likely to exhibit herding (by stating that they took steps to be evaluated as being as good as their peer group, instead of being better than them). On the other hand, Corrazini and Greiner (2007) find, in an experimental study, that framing possible outcomes in terms of losses instead of gains has no significant effect on herd behavior. To the best of our knowledge, studies have not looked at the role of discount rates or present bias on herding. In our study, we incorporate controls for loss aversion, present bias, as well as risk and time preferences in our main estimations. While we do not find strong evidence on their role in determining herd behavior, our methodology benefits from accounting for confounding factors that may contribute to herding.

In our main estimations, we additionally control for the energy-related knowledge as well as the financial literacy of individuals. Previous studies have found that these measures of cognitive skills as well as of awareness may explain the adoption of energy-efficient durables (such as appliances, as well as vehicles) in both developed country settings (Blasch et al., 2019, 2021) as well as in LMIC settings including Nepal (Filippini et al., 2020). While the focus of our study is not solely on the adoption of fuel-efficient motorcycles, controlling for these factors may be important in case respondents may be using price-related information to draw inferences on fuel economy as well as on the environmental impact of the motorcycles.

Other studies have sought to shed light on some of the other psychological underpinnings of social influence: for instance, Göckeritz et al. (2010) find that if people don't think too much about an issue or message, they are less likely to reason extensively before taking a decision, and more likely to make choices in an unconscious way. Such individuals are more likely to respond to social cues from the behavior of others (i.e., descriptive norms) and thus exhibit energy conservation behavior. Other papers have found that consumers have a tendency to follow the crowd to avoid judgement or feelings of guilt (Berkowitz, 1972). However, this remains a relatively nascent direction to pursue in the economics literature, that has so far been understudied.

A few studies have considered the role of attributes of products in determining herd behavior: for example, Langley et al. (2012) undertake a comparative analysis of the role of both product characteristics and consumer characteristics in determining social contagion in the adoption of telecom and financial products. They find that product characteristics dominate consumer characteristics. In particular, product fecundity (when users stimulate others to take the first steps with the product themselves) as well as product longevity (the continued use of a product) are important determinants of social contagion in adoption. Ding and Li (2019) find evidence of 'rational herding' using data from a Chinese literature website; they find that herding in the consumption as well as purchase of digital books is partially accounted for by product characteristics such as new book status, the frequency of entering top-clicked lists, author reputation, etc. Through this paper, we aim to contribute to this particular strand of literature, by using factor analysis to classify individuals on the basis of their preferences for motorcycles and then evaluating the herding outcomes for each group. Thus, we use rich and diverse information on preferences that consumers have for various aspects of motorcycles to identify classes of consumers who are more likely to herd.

3 Data and Methodology

In this section, we first present the survey and the dataset used in this study. Thereafter, we present the empirical methodology that we use to analyze the herd behavior.

3.1 Data

The dataset used for the empirical analysis is based on a field survey conducted in 2019 in the Kathmandu valley. The survey was administered with the help of a local survey partner using a computer assisted personal interview (CAPI) framework. The target respondents were adult Nepalese respondents who were looking to buy a new motorcycle (they may or may not already own a motorcycle). The survey was prepared based on existing literature such as Blasch et al. (2019); Allcott and Knittel (2019); Filippini et al. (2021) related to measurement of energy-related literacy, attitudes, and social norms with the primary objective of shedding light on social and behavioral factors behind preferences and purchase decisions of motorcycles in a LMIC context. This is important as motorcycles (typically petrol-based) are often the largest share of vehicle fleet in several densely populated urban regions in LMICs.

The survey comprised several short modules in order to collect information of participants related to basic mobility needs; preferences and requirements underlying their purchase decision of a new motorcycles and, if applicable, of an already owned motorcycle; the level of fuel-economy related literacy, financial literacy, and awareness on environmental and health related impacts of mobility; attitudes, norms, and values; and socio-economic characteristics of respondents.[3]

For this study, data on 324 respondents is relevant.[4] These respondents were randomly selected and presented an additional short module towards the beginning of the survey which consisted of questions designed to capture herd behavior.

3.1.1 Measuring herd behavior

We captured the tendency to herd with the help of two stated preference survey questions. Respondents were asked in these questions to consider two motorcycle models belonging to the same brand. They were shown a figure with two models, "Model A" and "Model B", with information on fuel type, engine size, star ratings on a popular website, and price in Nepali Rupees (Rs.).[5] Among these characteristics, while the fuel type and engine size were kept the same, the star ratings and price were different.

In the first question, the difference in price was small, Rs. 240,000 for Model A versus Rs. 245,000 for Model B, whereas the star ratings were assigned as three stars (Model A) versus five stars (Model B). The respondents were then asked which of the two motorcycles they would prefer.

In the subsequent question, respondents were again shown two motorcycle models and asked to mention their preferred model. The only change this time was the price of Model B, which now was Rs. 265,000. That is, there was a higher price difference between the two models. Figure 1 shows the two questions asked in that particular sequence.

We are interested to exploit how respondents answer the two questions to not only identify herd behavior (i.e. forming preferences based primarily on peer star ratings) but also to identify price sensitive behavior. We think this to be particularly relevant in a low and middle-income setting. While the price difference of Rs. 5,000 in the first question may be small, we argue the price difference of Rs. 25,000 in the second question to be non-marginal given that the

[3]Readers can find further details of the survey and a copy of the questionnaire in the online appendix (open access) of Filippini et al. (2021).

[4]Overall, 2500 respondents participated in the entire survey of which 324 respondents were randomly selected to take part in the module with herd behavior questions, and the remaining 2176 respondents were randomly selected to participate in a stated preference experiment with randomized information based treatments (Filippini et al., 2021).

[5]1 USD = Rs. 102.62, as per the average exchange rate in 2015. The current exchange rate is 1 USD = Rs. 120.28, as on Dec 01, 2021.

Consider two models of bikes belonging to the same brand (which is one of the market leaders of bikes in Nepal)

	Model A	Model B
Fuel type	Petrol	Petrol
Engine	110 cc, 4-stroke	110 cc, 4-stroke
Star ratings on a popular website (amongst 1200 buyers)	★★★☆☆	★★★★★
Price	Rs. 240,000	Rs. 245,000

Which bike would you prefer?

- A
- B
- Hard to say / Don't know
- None, based on the information provided

(a) Question 1

Now, consider these variants of the models shown to you in the previous question, belonging to the same brand (which is one of the market leaders of bikes in Nepal)

	Model A	Model B
Fuel type	Petrol	Petrol
Engine	110 cc, 4-stroke	110 cc, 4-stroke
Star ratings on a popular website (amongst 1200 buyers)	★★★☆☆	★★★★★
Price	Rs. 240,000	Rs. 265,000

Which bike would you prefer?

- A
- B
- Hard to say / Don't know
- None, based on the information provided

(b) Question 2

Figure 1: Survey questions used to measure herd behavior.

average monthly household income in urban areas of Nepal in 2015 was Rs. 32,336 (CEIC and Nepal Rastra Bank, 2015).[6] Nevertheless, our empirical specifications control for the income.

Among all 324 respondents in our sample, we drop those who chose 'Hard to say/ Don't know' or 'None, based on the information provided' in any of the two questions. We are left with 310 observations - these respondents opted for either Model A, or Model B, in the two questions. Next, we group these respondents into one of the following categories:

- **Price-conscious consumers** refers to the category of respondents who exhibit price sensitive behavior. One can identify two answer combinations under this group. The first are those who opted for Model A in both the questions, i.e. these respondents (95 out of 310, or 30.65%) may have stronger price constraints and they simply preferred the least priced motorcycles. The second combination includes those individuals who preferred Model B in the first question but switched to Model A in the second (17 out of 310, or 5.48%). Hence these respondents preferred a higher star rating, and a slightly more expensive alternative in the first question. But they were conscious of the price which factored into their decision in the second question, and they switched to Model A when the price difference was much higher.
- **Consumers exhibiting herd behavior** are those respondents who exhibited herd behavior. These are respondents who preferred Model B in both the questions (196 out of 310, or 63.23%). These respondents were likely to put more weight on a higher peer star ratings in spite of the noticeably higher price difference in the second question.[7]

Theoretically, there is also one other possible group of respondents – those who preferred Model A in first question and switched to Model B in the second question. The reasoning behind such a choice is not straight-forward. It can be argued that may be these respondents chose randomly, as they may have preferred Model B already in the first question (higher star ratings but lower price difference than in second question). It could be the case that these respondents valued star ratings only when they intend to buy more costly items. For the purpose of our analysis, we do not consider these respondents (2 respondents out of 310, or 0.65%). From the remaining 308 respondents, we also excluded 22 observations because of missing household income information (robustness check discussed in Section 4.1). Our final sample thus consists of 286 respondents.

Having described our dependent variable, we proceed to describing the explanatory variables in the subsections below.

3.1.2 Basic set of socio-economic variables

We collected some basic demographic and socio-economic information about respondents and their household. At the respondent level, we have information on gender, age, and the level of

[6] Using the average exchange rate in 2015, these amounts in USD are: Rs. 5,000 = 48.7 USD; Rs. 25,000 = 243.6 USD; and Rs.32,336 = 315.1 USD.

[7] Some readers may look at this group as a more price insensitive group than one exhibiting herd behavior. However, given the fact that the star ratings in our experiment provide important visual cues that may be difficult to completely ignore, and that our experiment was conducted in a low income setting, we argue that herd behavior is more likely at play. Our empirical estimations control for household income and we obtain negative coefficients for higher income groups, which does not support the notion of price insensitivity.

education. We also account for a few additional variables in our empirical analysis that could potentially affect the herd behavior, such as whether the respondent is a student, whether they are members of a club or association, and whether they already own a motorcycle.

At the household level our dataset has information on the household size, monthly household income, and whether the household receives regular remittances from family members working outside Nepal. In the context of Nepal, the remittance aspect is important to consider when looking at spending ability of resident households – according to The World Bank (2020), personal remittances received in Nepal, have typically accounted for about 25% of the country's GDP since 2013.[8]

3.1.3 Financial literacy and energy-related knowledge

As mentioned in Section 2, accounting for financial literacy as well as energy-related knowledge of respondents has been found to be relevant in identification and adoption of energy-efficient durables (Blasch et al., 2021; Filippini et al., 2020). These measures of cognitive skills and awareness could affect how respondents perceive the price-related information and star ratings in our task, which in turn may influence whether or not they exhibit herd behavior.

We captured information on financial literacy and energy-related knowledge of our respondents with the help of several 'quiz-style' questions within our survey similar to Filippini et al. (2020). Table 1 presents the summary statistics of the correct responses to these underlying questions. The detailed survey questions have been reported in Table 9 in the Appendix.

We sum up the number of correct responses to a set of three standard questions related to compound interest, inflation, and diversification of risks to create a 'financial literacy index' (Lusardi and Mitchell, 2014). We find that a high share of respondents correctly answered the questions on compound interest (88.5%) and inflation (74.1%), but not on diversification of risk (27.6%). On average respondents answered two out of three questions correctly (mean value of the financial literacy index is 1.9).

Another set of five questions were used to create an 'energy knowledge index'. Herein, the first four questions comprised general statements related to motorized transport, air pollution, and electricity generation in Nepal. The respondents had to indicate if these statements were true or false. Another question asked if respondents knew the price of one unit of electricity in Nepal. We find that respondents, on average, answered about three out of five questions correctly (mean value of the energy knowledge index is 3.12).[9]

[8] Table 4 presents an overview of these variables in our final dataset whereas Table 9 in the Appendix reports how these variables are constructed from the respective survey questions.

[9] It is worth mentioning that our study incentivized the respondents to correctly answer all the quiz-style questions. The respondents were informed that if they answered more of these questions correctly, they would have a higher chance of wining the prize draw at the end of the study. We believe this had an impact. For example, we can observe that our sample performed noticeably better on the financial literacy aspect than has been previously found in other studies, e.g., Filippini et al. (2020) report a mean score of 0.63 on a somewhat similar financial literacy measure from a different region of Nepal.

Table 1: Financial literacy and energy knowledge

	Mean	Std. Dev.	Min.	Max.
Compound interest calculation	0.885	0.32	0	1
Inflation	0.741	0.439	0	1
Diversification of risk	0.276	0.448	0	1
Financial literacy index (0-3)	1.902	0.709	0	3
(T/F) Motorized transport, air pollution and health damages	0.864	0.344	0	1
(T/F) Registration tax on petrol versus electric bikes in Kathmandu	0.752	0.433	0	1
(T/F) Motorized transport and global warming	0.406	0.492	0	1
(T/F) Share of electricity produced in Nepal from hydropower	0.409	0.493	0	1
Price of one unit of electricity in Kathmandu	0.692	0.462	0	1
Energy knowledge index (0-5)	3.122	1.051	0	5

Notes: Table reports the summary statistics on individual questions used to construct a financial literacy index and an energy knowledge index for 286 observations in our final sample. All individual questions are dichotomous with 1 implying a correct response. T/F represents True or False type questions. Statements 1 and 2 were true whereas statements 3 and 4 were false.

3.1.4 Preferences for bike-related attributes

The level of importance individuals assign to specific bike-related attributes, such as the price, performance, design, fuel-economy etc. could be helpful to understand the heterogeneous nature of their preferences. Given the low-income setting, the price and operating costs of using the bike and the general attitude of respondents towards these measures are also equally relevant.

We asked respondents to rate ten bike-related attributes in terms of their importance in determining their purchase decision. Furthermore, we also asked three other questions in order to specifically capture whether or not they were proactive in searching for additional information related to operating costs, and whether they were price- constrained. More specifically, these questions asked i) whether they have been computing and comparing total costs for the new bike that they are considering to purchase in the next months, ii) whether they have been searching for information on fuel-economy, and iii) whether purchase price of a new bike was a constraint to them.[10] Table 2 presents an overview of these thirteen variables.

We find that participants generally find all attributes to be between somewhat important to very important. Among all the listed attributes, engine power (mean score of 2.797) followed by fuel-economy (mean score of 2.741) appear to be most important, whereas environmental friendliness of the bike has the lowest mean score (2.346). Around 59% respondents declare they were computing and comparing totals costs, 73% claimed to have searched for information on fuel economy, and almost 75% respondents declare that they face purchase price constraints.

As many of these variables are expected to be correlated, we run exploratory factor analysis in Section 3.2.1 to identify a reduced set of underlying latent factors which we then use as controls in our empirical estimations.

[10]These questions may seem closely related to the question on importance of few bike-related attributes, but we asked these additional questions because a) we found that the information on fuel-economy of motorcycles was not easily available or displayed at dealerships in Kathmandu, and b) we wanted to directly capture price constrained consumers given our LMIC setting.

Table 2: Bike-related attributes

	Mean	Std. Dev.	Type
Importance of factors in determining purchase decision			
Engine power	2.797	0.452	1–3 scale
Popularity of the model (among your circle of friends and family)	2.409	0.602	1–3 scale
Design and appearance	2.507	0.608	1–3 scale
Brand	2.605	0.587	1–3 scale
Resale value	2.392	0.638	1–3 scale
Fuel economy (km/litre)	2.741	0.499	1–3 scale
Purchase price	2.619	0.603	1–3 scale
Expense for fuel per year and over the lifetime (operating costs over the lifetime)	2.465	0.607	1–3 scale
Vehicle safety	2.5	0.642	1–3 scale
Environmentally-friendly	2.346	0.672	1–3 scale
Are you computing and comparing total cost (sum of the purchase price and fuel cost over expected lifetime of the vehicle) when making the decision to buy one?	0.591	0.493	Binary
Have you been searching for information on fuel economy?	0.731	0.444	Binary
Is price of the vehicle a constraint for you in deciding which bike to buy?	0.748	0.435	Binary

Notes: Table reports the summary statistics on individual questions related to preferences for bike-related attributes for 286 observations in our final sample. The 1–3 scales were labelled as Not important (1) / Somewhat important (2) / Very important (3). The binary variables were encoded as 1 = Yes, 0 = otherwise (i.e. No, or Don't know).

3.1.5 Psychological traits and attitudes

We also collected information on psychological traits related to values, norms and attitudes based upon respondent's personal opinion on their conduct of life. We asked respondents six questions that focus on traits such as adherence to religion and family traditions, whether they have an outgoing nature, their propensity to buy the latest technological innovations, and whether they enjoy life to the full. Table 3 presents description and summary statistics of these six variables.

Table 3: Psychological traits and attitudes

	Mean	Std. Dev.	Type
Personal opinion on what applies to your conduct of life			
I live according to religious principles	2.885	0.78	1–4 scale
I hold on to my family's old traditions	2.979	0.854	1–4 scale
I enjoy my life to the full	3.388	0.649	1–4 scale
I go out a lot (e.g., dinners, parties and other leisure activities)	2.685	0.776	1–4 scale
I am likely to buy the latest technological innovation (IPhone, electronics etc.) even if I may not necessarily need it	2.668	0.861	1–4 scale
Would you rather buy the latest version of IPhone today, or wait until next year for a slightly improved version of the same model?	0.182	0.386	Binary

Notes: Table reports the summary statistics on individual psychological traits and attitudes questions for 286 observations in our final sample. The 1–4 scales were labelled as Does not apply at all (1) / Does not apply (2) / Applies somewhat (3) / Applies fully (4). The last question was encoded as 1 = Buy latest IPhone today, 0 = otherwise (i.e. Wait till next year for a slightly improved version, or Don't know).

While respondents in general seem to adhere to traditions and religious principles (each with a mean score of around 3), most respondents say that they enjoy life to the full (highest mean score of 3.388). The variables related to going out a lot and likely to buy latest technological innovations each have a mean score of around 2.7, whereas 18.2% respondents appear to have a high propensity to buy the latest IPhone today.

Based on underlying latent factors on these psychological and attitudinal traits, we expect that it may be possible to identify some homogeneous groups of consumers that are relevant given our outcome of interest - whether or not to herd. For example, respondents who are more likely to be religious, value family customs and traditions may represent a relatively homogeneous group that may exhibit a certain behavior towards whether or not to herd. On the other hand, respondents who enjoy going out a lot, and derive satisfaction from buying the latest innovations and technologies may represent another homogeneous group, one that may be more likely to herd. Therefore, we conduct another exploratory factor analysis for these variables (Section 3.2.1) to try to identify underlying latent factors representing distinct homogeneous groups that could be interesting to study as possible determinants of herding in our empirical estimations.

3.1.6 Behavioral anomalies

Finally, we also account for a few other measures of some behavioral anomalies that may be relevant in the context of determining herd behavior. These include variables capturing loss aversion, present bias as well as risk and time preferences of respondents. Below we briefly summarize these variables, details on how these parameters are computed from their respective survey questions can be found in Table 9 (for the willingness to take risks and loss aversion variable) and in the Appendix (for the measure of present bias, as well as time preference parameter).

Loss aversion is represented by a dichotomous variable that is equal to one if the respondent is loss averse, and zero otherwise. We borrow the methodology adopted in (Heutel, 2019) to generate this variable (exact definition provided in the Appendix). The first part of the question asks respondents to assume that they own a smaller, more fuel-efficient bike; they are then asked to indicate whether they would replace this choice with a larger, less fuel-efficient bike. In the second part of the question, the respondents are asked to assume the reverse, i.e. that they own the larger bike, and then they are asked whether they would replace it with a smaller, more fuel-efficient bike. Respondents are categorized as being loss averse if they choose to keep their current bike in both scenarios. In our sample, we notice that about 9% respondents are loss averse, using this definition.

Present bias, or the phenomenon of exhibiting a high discount rate in the short-run and a relatively low discount rate in the long-run, is captured by a 'beta' parameter that is measured using the multiple price list-based approach, as is common in the literature (Schleich et al., 2019) (refer to the appendix for more details on this approach)– beta values less than one imply that the respondent is present biased; beta higher than one implies that the respondent is future biased; and beta equal to one implies neither present biased nor future biased. For our sample, the beta parameter ranges from 0.625 to 1.78 with a mean value approximately equal to one. In addition, the multiple-price list approach is also useful for us to capture time preferences of individuals; we measure time preferences by a variable that represents the annualised discount factor of the respondents. For our sample, the annualised discount factor varies from 0.259 to 0.955 with a mean value of 0.864. This implies, that on average, the annual discount rate for our sample is about 15.74% [(1/0.864-1)*100]. This is marginally lower than the discount rate for a cross-country European sample (17.5%) that was used in the study by Schleich et al. (2019) to compute preference parameters, which suggests that the average individual in Kathmandu may discount the future less than the average European individual.

Lastly, we control for the risk preferences by grouping individuals into three categories – Low, Medium and High willingness-to-take risk (hereafter, WTT Risk). Respondents self-reported their general willingness to take risks on a scale of zero (completely unwilling) to ten (very willing). From this, we re-coded a score between 0–2 as Low WTT Risk (28.3% respondents), 3–7 as Medium WTT Risk (40.2% respondents), and 8-10 as High WTT Risk (31.5% respondents).

3.1.7 Descriptive statistics

Table 4 reports the overall summary statistics of for 286 complete observations in our sample for the variables described above. Table 9 in the Appendix summarizes how these variables were constructed from their respective survey questions.

Table 4: Overview of the dataset

Variable	Mean	Std. Dev.	Min.	Max.
Exhibits herd behavior	0.626	0.485	0	1
Female	0.217	0.413	0	1
Age (years)	28.899	7.152	18	55
Household size	5.098	1.645	2	13
Monthly household income (Rs.)				
Less than Rs. 30,000	0.252	0.435	0	1
Rs. 30,000-50,000	0.385	0.487	0	1
Rs. 50,000-75,000	0.224	0.418	0	1
More than Rs. 75,000	0.14	0.347	0	1
Education level				
High school or below	0.476	0.500	0	1
Professional education	0.031	0.175	0	1
Bachelors	0.385	0.487	0	1
Masters	0.108	0.311	0	1
Student	0.157	0.365	0	1
Household receives regular remittances	0.171	0.377	0	1
Member of a club or association	0.269	0.444	0	1
Owns a bike	0.409	0.493	0	1
Financial literacy index (0-3)	1.902	0.709	0	3
Energy knowledge index (0-5)	3.122	1.051	0	5
Loss averse	0.087	0.283	0	1
Willingness to take risks				
WTT Risk = Low	0.283	0.451	0	1
WTT Risk = Medium	0.402	0.491	0	1
WTT Risk = High	0.315	0.465	0	1
Present bias (beta)	0.999	0.066	.625	1.78
Annualised discount factor	0.864	0.191	.259	.955

Notes: Table reports the overall summary statistics (mean, standard deviation, minimum and maximum) for 286 observations in our final sample.

About 22% of the respondents in the sample are female. The respondent age ranges from 18 to 55 years with a mean value of about 29 years. About 16% of the respondents were students at the time of the survey. The household incomes from the least (Less than Rs. 30,000) to the highest (More than Rs. 75,000) income categories are distributed as 25%, 38.5%, 22.4%

and 14%. In terms of education, while 47.6% of respondents have attained the highest level equivalent to high school or below, 38.5% respondents have a bachelors levels education and about 10.8% have a masters level education. The latter shares of respondents with tertiary education are noticeably higher than the known national average of Nepal.[11]

Table 5: Comparison of means across the herding and price-conscious groups

	Price-conscious group		*Herd behavior group*			
Variable	Mean	Std. Dev.	Mean	Std. Dev.	diff. in means	T-test
Female	0.299	(0.460)	0.168	(0.375)	0.131	(2.63)***
Age (years)	28.93	(7.423)	28.88	(7.006)	0.0426	(0.05)
Household size	5.140	(1.925)	5.073	(1.457)	0.0676	(0.34)
Monthly household income (Rs.)						
Less than Rs. 30,000	0.196	(0.399)	0.285	(0.453)	-0.0887	(-1.67)*
Rs. 30,000-50,000	0.346	(0.478)	0.408	(0.493)	-0.0620	(-1.04)
Rs. 50,000-75,000	0.252	(0.436)	0.207	(0.406)	0.0456	(0.89)
More than Rs. 75,000	0.206	(0.406)	0.101	(0.302)	0.105	(2.50)**
Education level						
High school or below	0.514	(0.502)	0.453	(0.499)	0.0615	(1.01)
Professional education	0.0374	(0.191)	0.0279	(0.165)	0.00945	(0.44)
Bachelors	0.299	(0.460)	0.436	(0.497)	-0.137	(-2.31)**
Masters	0.150	(0.358)	0.0838	(0.278)	0.0657	(1.73)*
Student	0.140	(0.349)	0.168	(0.375)	-0.0274	(-0.61)
Household receives regular remittances	0.168	(0.376)	0.173	(0.379)	-0.00496	(-0.11)
Member of a club or association	0.299	(0.460)	0.251	(0.435)	0.0477	(0.88)
Owns a bike	0.439	(0.499)	0.391	(0.489)	0.0482	(0.80)
Financial literacy index (0-3)	1.953	(0.678)	1.872	(0.727)	0.0818	(0.94)
Energy knowledge index (0-5)	3.290	(1.099)	3.022	(1.011)	0.267	(2.09)**
Loss averse	0.112	(0.317)	0.0726	(0.260)	0.0395	(1.14)
Willingness to take risks						
WTT Risk = Low	0.271	(0.447)	0.291	(0.455)	-0.0195	(-0.35)
WTT Risk = Medium	0.505	(0.502)	0.341	(0.475)	0.164	(2.76)***
WTT Risk = High	0.224	(0.419)	0.369	(0.484)	-0.144	(-2.57)**
Present bias (beta)	0.993	(0.0508)	1.003	(0.0736)	-0.0104	(-1.29)
Annualised discount factor	0.854	(0.215)	0.869	(0.176)	-0.0154	(-0.66)

Notes: Table reports the variable means and standard deviations (in parentheses) across the price-conscious group and the group exhibiting herd behavior, the difference in the means, and the *t*-statistics for testing difference in the means between the groups. The sample consists of 286 observations of which 179 respondents are part of the herding group and the remaining 107 are in the price-conscious group. *,** and *** respectively denote significance at 10%, 5% and 1% levels.

Table 5 reports the means and t-test statistics across the two consumer groups based on our outcome variable related to herd behavior. While several variables show insignificant differences in means shares across the herding and price-conscious groups, we notice significant differences across gender, and some categories of income and education. The energy knowledge index and WTT risk measures are also significantly different for both groups of respondents. As we will later show in the empirical results, some of these explanatory variables are important determinants of herding and price-conscious behavior.

[11] According to UNESCO Institute for Statistics (2021), the Gross enrollment ratio for tertiary education was 17.1% in 2013 whereas the Gross graduation ratio in tertiary education was 9.95% in 2013.

3.2 Methodology

3.2.1 Factor analysis

We ran two sets of exploratory factor analysis in order to identify and use a reduced set of potentially more meaningful underlying (latent) factors instead of several correlated variables. The first exploratory factor analysis focused on the set of 13 variables related to preference of motorcycle attributes and attitudes towards new motorcycle purchase (Section 3.1.4). The second factor analysis focused on the 6 variables related to psychological traits and attitudes (Section 3.1.5). In both cases, we exploit correlations between the variables so as to find a limited number of underlying latent factors which we later use as explanatory variables in our empirical analysis.

For both factor analysis, we use the principal component factors approach where the number of latent factors are selected based on two criteria a) eigenvalues greater than one, and b) together the factors explain at least 50% of the cumulative variation. Note that our underlying latent factors may also be correlated given the original set of variables. Hence, in order to obtain a simple structure of these factors, we used oblique promax rotation which typically assigns higher loading values to few variables. This is useful to achieve better interpretability of the resulting factors and is particularly helpful given that we have several underlying variables. Nevertheless, we also performed robustness checks by using the more typical orthogonal varimax rotation of factor loadings and found the results to be consistent.[12]

For the first set of variables related to bike-related attributes, the Cronbach's alpha is 0.7852 which appears to indicate scale reliability. We obtained a KMO (Kaiser-Meyer-Olkin) score of 0.7876 which also seems to warrant a factor analysis. The factor analysis results in four principal component factors (unrotated) that together explained about 61% of variance cumulatively (29.8% explained by first factor, 12.4% by second, 10.8% by the third, and 8.1% by the fourth).

Table 6: Factor analysis on preferences of respondents concerning bike-related attributes

	Factor 1	Factor 2	Factor 3	Factor 4
Engine power		0.55	0.48	
Popularity of the model	0.29	0.62	-0.22	
Design and appearance		0.87		
Brand		0.77		
Resale value	0.66			
Fuel economy (km/litre)		0.52	0.38	
Purchase price	0.59		0.33	
Expense for fuel per year and over the lifetime	0.78			
Vehicle safety	0.64			-0.21
Environmentally-friendly	0.83		-0.27	
Are you computing and comparing total cost?				0.85
Have you been searching for information on fuel economy?				0.80
Is price a constraint?		-0.28	0.75	

Rotated component matrix (promax rotations) for principal component factors with four factors. Factor loadings with absolute value less than 0.2 not reported.

Table 6 reports the factor analysis results with the rotated factor loadings for better interpretation. Looking at these values across all the manifest variables, we interpret and assign the following

[12] Calculated in Stata 13.1 using the `factor` command. Orthogonal varimax rotations is achieved with `rotate, varimax` and Oblique promax rotations with `rotate, promax`.

labels to these latent factors:

Factor 1 resembles **Importance of non-salient attributes** (Environment, Operating Cost, Resale, Safety).
Factor 2 resembles **Importance of salient attributes** (Design and Appearance, Brand, Popularity, Power).
Factor 3 resembles being **Price-constrained**.
Factor 4 resembles propensity of being **Proactive in searching for additional information** related to operating costs.

For the second set of variables related to psychological traits and attitudes, we obtain a relatively weaker level of Cronbach's alpha (0.3470) and the KMO measure (0.4929). The factor analysis results in three principal component factors (unrotated) that together explained about 67.5% of variance cumulatively (28.7% explained by first factor, 20.4% by second, and 19% by the third).

Table 7: Factor analysis on psychological and attitudinal aspects

	Factor 1	Factor 2	Factor 3
I live according to religious principles	0.88		
I hold on to my family's old traditions	0.89		
I enjoy my life to the full	0.35		0.46
I go out a lot (e.g., dinners, parties and other leisure activities)		0.81	-0.27
I am likely to buy the latest technological innovation (IPhone, electronics etc.) even if I may not necessarily need it		0.74	0.32
Would you rather buy the latest version of IPhone today, or wait until next year for a slightly improved version of the same model?			0.84

Rotated component matrix (promax rotations) for principal component factors with four factors. Factor loadings with absolute value less than 0.2 are not reported.

Table 7 reports the factor analysis results for psychological traits and attitudes. We interpret the values and assign the following labels to the three latent factors:

Factor 1 resembles **Adherence to religious principles and traditions**
Factor 2 resembles **Consumerist attitude**, e.g., in going out a lot and spending, likely to buy latest technological innovation even if not a necessity
Factor 3 resembles inclination to **Buy latest iPhone today and to enjoy life**

One notable limitation, also indicated by the low Cronbach's alpha and KMO measure, is that the factor analysis strategy may not be the best approach with the second set of variables for psychological traits and attitudes. This is due to relatively weaker level of correlations among the six manifest variables (except perhaps religion and tradition). The weak correlation is also the reason that three latent factors were needed for just six manifest variables, as opposed to the first set of factor analysis on motorcycle attributes. Nevertheless, the underlying latent factors are very distinct and provide more intuitive explanations in this context. Hence we decided to keep this in our main empirical estimations. We discuss robustness checks to these results in Section 4.1.

3.2.2 Empirical estimation

The preceding sections have presented our dataset and provided details on a rich set of potential explanatory variables extending across many themes. We also used a factor analysis strategy to identify several underlying latent factors related to two broad themes – a) preferences of respondents concerning bike-related attributes, importance of fuel efficiency and lifetime costs of owning a motorcycle, and price related constraints faced by the respondents; and b) psychological traits and attitudes based upon respondents' personal opinion on their conduct of life.

Next, we are interested in examining the determinants of the herd behavior. Our outcome variable is a dichotomous variable – it is equal to one for respondents exhibiting herd behavior, and is zero otherwise (for those displaying a price-conscious behavior), and we have several explanatory variables. Given this framework, our empirical approach relies on first estimating a binary logit model and then calculating the marginal effects of each covariate. The logit model takes the following stylized form:

$$\text{logit}(P(Y=1)) = \sum_{k=0}^{K} \beta_k \, x_k \tag{1}$$

Here, Y is the binary outcome variable for herd behavior, x represents the (K) explanatory variables in the model, and β represents the model coefficients to be estimated.[13]

4 Results

In this section, we report and discuss the main findings obtained from our empirical analysis. We estimate four different logit model specifications starting from a base specification, model (1) of Table 8, that includes some basic socio-economic variables and a few other standard variables that are useful in capturing the effect of context-specific drivers of purchase behavior. Model (2) includes control variables for financial literacy and energy knowledge, and includes some of our variables of interest, namely four underlying factor variables on bike-related attributes. Model (3) additionally includes the three factor variables related to the respondents' personal opinion on their conduct of life. Lastly, model (4) includes some controls for behavioral anomalies that, as argued earlier, are of relevance and hence could be interesting to include. Recall that the binary outcome variable is equal to one for a respondent who exhibits herd behavior, and is zero otherwise. For the purpose of interpreting the effect sizes, we primarily utilize the marginal effects reported in Table 8 (corresponding logit coefficients are reported in Table 10 in the Appendix).

We find that the coefficient estimates are comparable for most of socio-demographic variables considered in terms of signs and magnitudes across specifications. For example, we find from the results of model (4) of Table 8 that females are 18.9% less likely to exhibit herding than male respondents, while the variables for age and household size have no significant impact.

[13] It is worth recalling that the estimated coefficients in a logit model are interpreted as the log of the odds ratio of exhibiting herd behavior (compared to the reference level). This is sometimes useful for quick interpretation of binary and categorical variables.

Income and the probability of herding seem to have a negative association, i.e. respondents having higher levels of income seem to have a lower propensity to herd. One interpretation of this result may be that individuals from relatively well-off families may be better informed about the market and different motorcycle alternatives in general, and thus may be less likely to rely on information provided by other buyers. Another interpretation could be that given their plausibly relaxed budget constraints, relatively richer respondents are more likely to have preferences for relatively larger motorcycles, and thus be less likely to be influenced by herding in the purchase of a 110 cc bike. Both these factors may explain somewhat counter-intuitive behavior of richer individuals acting as price-conscious buyers.

In terms of education, individuals who have completed a bachelors degree exhibit a greater likelihood to herd compared to those who have completed high school or below although this finding is not significant across all models. We do not observe an identical pattern for individuals with other levels of educational attainment, such as a Masters degree (except in the model (2) in which individuals having a Masters degree seem to have a lower propensity to herd). A priori, we do not have grounds to explain why individuals with a Bachelor's degree would be more likely to herd than those having a high school diploma or below. One reason for this finding may be the fact that respondents with a Bachelor's degree may plausibly have more of an online presence, and thus be more familiar with online product reviews and ratings (which perhaps less educated respondents may not be as well acquainted with). However, in the absence of further data, it is difficult for us to confirm this reasoning.

Furthermore, we do not find a significant association between the receipt of remittances and herding. This may be partly due to the fact that remittances do not constitute a significant proportion of total income of urban residents in Kathmandu (as compared to rural households). However, despite being insignificant, we note that the coefficient has a positive sign, which is consistent with the fact that remittances have been primarily utilized by Nepalese households to relax liquidity constraints (Central Bureau of Statistics, 2011; Acharya and Leon-Gonzalez, 2014). This may explain why households receiving remittances may be (slightly) more likely to exhibit herd behavior.

These results also point to the possibility that non-socio-economic factors such as product attributes, as well as the psychological and behavioral attributes of buyers, may play a prominent role in determining herd behavior by individuals in this context. As already discussed in Section 2, cognitive biases may have an effect on herding. Two indicators of cognitive abilities viz., financial literacy and the energy knowledge index, which we control for in models (2) to (4), are negatively associated with the herd behavior, while only the coefficient on the energy knowledge index is significant. This finding on the energy knowledge index can be understood in terms of the ability of these buyers to understand not only the financial but also the environmental and health implications of their choices. For instance, motorcycles that are more expensive generally also tend to have poor fuel economy, controlling for engine size. More environmentally-tuned buyers may be more likely to be aware of this fact, and may thus choose to not herd towards the more expensive alternative. As reported in the models in Table 8, the marginal effect of an increase in the energy knowledge index by 1 unit is associated with a decline in the probability to herd by 5.1 to 5.4 percentage points (given that the index is measured on a 0 to 5 scale). Financial literacy, on the other hand, seems to have a weaker effect in determining herd behavior.

The main results of our study pertain to the role of factor variables with respect to bike-related

Table 8: Marginal effects

	Model (1)	Model (2)	Model (3)	Model (4)
Female	-0.184***	-0.209***	-0.186***	-0.189***
	(0.066)	(0.063)	(0.062)	(0.063)
Age (years)	0.002	0.001	0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Household size	0.013	0.020	0.031*	0.027
	(0.018)	(0.017)	(0.017)	(0.017)
Rs. 30000-50000	-0.098	-0.048	-0.070	-0.078
	(0.066)	(0.065)	(0.063)	(0.064)
Rs. 50000-75000	-0.181**	-0.147*	-0.163**	-0.148*
	(0.082)	(0.082)	(0.079)	(0.080)
More than Rs. 75000	-0.363***	-0.425***	-0.424***	-0.400***
	(0.102)	(0.094)	(0.094)	(0.100)
Professional education	0.043	0.027	-0.009	-0.002
	(0.164)	(0.158)	(0.161)	(0.158)
Bachelors	0.163***	0.131**	0.095	0.109*
	(0.059)	(0.057)	(0.059)	(0.062)
Masters	-0.105	-0.161*	-0.114	-0.099
	(0.097)	(0.094)	(0.093)	(0.094)
Student	0.042	0.072	0.097	0.130
	(0.085)	(0.080)	(0.079)	(0.081)
Household receives regular remittances	0.127	0.093	0.085	0.084
	(0.080)	(0.075)	(0.074)	(0.075)
Member of a club or association	-0.036	-0.024	-0.049	-0.066
	(0.064)	(0.061)	(0.061)	(0.061)
Owns a bike	-0.048	0.012	0.022	0.017
	(0.060)	(0.059)	(0.057)	(0.057)
Financial literacy index (0-3)		-0.027	-0.035	-0.028
		(0.039)	(0.038)	(0.038)
Energy knowledge index (0-5)		-0.054**	-0.051**	-0.053**
		(0.027)	(0.026)	(0.026)
Non-salient attributes important		-0.081***	-0.065**	-0.053*
(Environment, Operating Cost, Resale, Safety)		(0.029)	(0.029)	(0.030)
Salient attributes important (Design		0.085***	0.086***	0.097***
and Appearance, Brand, Popularity, Power)		(0.030)	(0.030)	(0.032)
Has price constraints		-0.095***	-0.092***	-0.094***
		(0.031)	(0.032)	(0.032)
Proactive towards fuel economy and		-0.065**	-0.077***	-0.072***
lifetime costs		(0.028)	(0.028)	(0.027)
Religious principles, holds on to			-0.096***	-0.085***
family's traditions			(0.028)	(0.029)
Out-going, likely to buy latest tech			-0.001	-0.003
innovations			(0.029)	(0.029)
Would rather buy latest iphone today,			0.070***	0.066**
enjoys life			(0.025)	(0.027)
Loss averse				-0.093
				(0.084)
WTT Risk = Medium				-0.068
				(0.069)
WTT Risk = High				0.032
				(0.075)
Present bias (beta)				0.728
				(0.547)
Annualised discount factor				-0.099
				(0.166)

Average marginal effects (AME) following logit model estimations. The binary outcome variable is equal to one for a respondent who exhibits herd behavior, and is zero otherwise. The reference levels for categorical variables are: 'Less than Rs. 30,000' (income); 'High school or below' (education); and 'WTT Risk = Low' (WTT Risk, or Willingness-to-take risk). *,** and *** respectively denote significance at 10%, 5% and 1% levels.

attributes, and with respect to psychological traits and attitudes, that we hypothesize could determine herd behavior. So far as the attributes of motorcycles are concerned, it is clear from the estimates in Table 8 that three sets of potential buyers i.e., those who report that non-salient attributes are important, those who are price-constrained and those who are proactive towards fuel economy, operating costs and lifetime costs are less likely to exhibit herd behavior, while the opposite is true for the customers for whom salient attributes are important i.e., those considering design, brand, popularity, and power as important factors in basing their decision. This result is consistent across models (2) to (4). Our results generally seem to suggest that individuals who are more conscious of the purchase price of a motorcycle, its operating costs, as well as its less visible features such as resale value and environmentally-friendly nature will have a weaker tendency to follow the purchase decisions of other buyers, in line with our intuition. Interestingly, this group also includes individuals who give importance to the environmental impact of their vehicle. Our results seem to point to the fact that environmentally-conscious buyers might be aware of the fact that more expensive motorcycles are likely to be less fuel-efficient, and thus might choose to be more price-conscious. This result is also somewhat confirmed by the finding that individuals who are more likely to be proactive towards the operating costs of the motorcycle (its fuel economy and its lifetime costs) are also less likely to herd. On the other hand, characteristics such as design, popularity of the motorcycle and engine power are more likely to be associated with herding: individuals who value these traits are more likely to give importance to the opinions of other buyers. Based on the magnitude of the marginal effects in Table 8, the likelihood of herding of potential buyers who value non-salient attributes varies from 5.3 to 8.1 percentage points across various specifications, while the magnitude of the marginal effect varies from (negative) 6.5 percentage points to 7.7 percentage points for those who value fuel economy and lifetime costs. The likelihood of herding by price-constrained individuals varies from 9.2 to 9.5 percentage points lower as compared to individuals who are not price-constrained, whereas this varies from 8.5 to 9.7 percentage points lower for respondents valuing salient attributes more than other respondents.

In models (3) and (4), we introduce the factor variables related to the psychological traits and attitudes. Our estimates show that individuals who value religious principles and family traditions have a lower likelihood of herding, while those who state that they enjoy their life and would like to buy the latest iPhone today (rather than wait till next year for a slightly improved version of the same model) have a higher likelihood to herd. The former finding suggests that religion and family traditions seem to go hand-in-hand with being more price-conscious, rather than following trends. This is relevant in the case of low-income settings where religious beliefs may occupy an important place in the lives of many individuals, and thus economic decisions may in some cases be guided by such beliefs. In the case of the latter finding, a desire to own the latest innovations and gadgets such as iPhones not only reflect status symbols in low-income societies such as in Nepal, but are also representative of prevailing trends, which is very likely to be correlated with the tendency to herd. Lastly, we find that the variable denoting whether an individual is outgoing, or likes to buy the latest innovations, is insignificant.

In the regression results of model (4), we add variables related to behavioral anomalies such as loss aversion, their willingness to take risks, present bias, and time preferences (measured by the discount factor) in order to understand whether they influence herd behavior as well and if they do, the extent of this influence. We find that while the signs of most of these coefficients are largely in line with our expectations, they are not significant. A loss averse individual is less likely to exhibit herding, i.e. more likely to be price-conscious than an individual who is not loss averse, which is intuitive. At the same time, we find that individuals who have a high willingness to take risks are more likely to herd, compared to individuals who are more risk-averse, i.e., less likely to take risks. These findings are consistent with most of the literature investigating the effects of risk or loss aversion on herd behavior (Baddeley et al., 2007; Luetje, 2009). As already mentioned in Section 2, we also include controls for the annual discount factor, as well as the 'beta' parameter, to capture the effects of time preferences and time-inconsistent behavior. The positive sign of the coefficient on the beta parameter, although insignificant, indicates that the likelihood of herding is higher for individuals who are more likely to be future-biased, and individuals who are present-biased are less likely to herd (values of beta less than 1 are associated with present-biased individuals, while values of beta higher than 1 are associated with future-biased individuals). In other words, individuals who are future-biased tend to follow the choices of other individuals more closely, compared to individuals who are present-biased. One possible explanation for this finding is the fact that present bias, in a developing country context, is closely associated to the notion of being liquidity or credit-constrained (Kremer et al., 2019). Present bias generates liquidity constraints, which means that such individuals are more likely to be price-conscious, rather than exhibiting herding. Present bias is going to make it difficult for them to make a higher upfront payment. On the other hand, our finding on the sign of the coefficient on the annualised discount factor variable suggests that higher discount factors, i.e. lower discount rates, are associated with a higher likelihood of being price-conscious. This suggests that individuals having higher discount rates, i.e., those individuals who discount the future more heavily, are also more likely to herd. Even though the coefficients on these variables are insignificant, we feel that these results are intuitive, and add an additional dimension to the literature on the psychological and behavioral determinants of herd behavior.

Thus, to summarize our main findings in light of the hypotheses that we wanted to test (mentioned in Section 1), we find that 1) respondents who value motorcycle attributes such as engine power, design and brand are a distinct group from those who value fuel economy and operating costs, 2) the first group described in the previous point is more likely to exhibit herding, whereas the second group is more likely to exhibit price-conscious behavior, 3) respondents who value tradition and religion comprise a relatively distinct group from those who may enjoy a more consumerist way of life, and 4) the former are more likely to be price-conscious, whereas the latter are more likely to exhibit herd behavior (among the two groups mentioned in point 3) above).

4.1 Robustness checks

Our main models control for basic socio-demographic characteristics as well as several rich context-specific variables. Overall the results report robust estimates across different model specifications, both in sign and magnitude. We summarize below main findings from additional robustness checks that we performed to account for some data/survey related aspects and some methodological aspects.

The final sample size consisted of 286 respondents as household income was missing for 22 out of 308 respondents. We performed robustness checks by re-estimating our empirical models using all 308 observations. In one check, we encoded the missing household income as a separate category. In another check, we dropped the income variable from the set of explanatory variables as income is also somewhat correlated with other variables in our model, such as variables on foreign remittances, education, age and household size. Compared to the reported results, the marginal effects in these checks are typically within ±4 percentage points for important socio-economics variables such as gender and education, and within ±1 percentage points for other significant variables.[14]

Similarly, we also checked for the quality of survey responses taking into account the total time respondents spent on the survey. For our final sample of 286 respondents, the median time spent on the entire survey was about 25 minutes. We re-estimated all models by dropping i) the fastest 5% respondents, and ii) the fastest 10% respondents —the results remained robust.

We discussed some limitations with the use of exploratory factor analysis in Section 3.2.1, particularly with the second set of variables on psychological traits and attitudes. As robustness checks, we re-estimated our models using other specifications – one without using factor analysis on the second set of variables (models (3) and (4)), and another specification without using any factor analysis at all (models (2), (3), and (4)). In these estimations the underlying set of variables were directly included as controls in the model specifications. The results obtained are also generally similar to our main findings and marginal effects values on existing variables are typically within ±1 percentage points. With respect to psychological traits and attitudes, previous notable observations concerning the role of adherence to religious principles and enjoying life to the full are found to persist. For bike-related attributes too, we observe significant estimates on variables related to price constraints, proactively searching for fuel-economy and environmental-friendliness which is in line with the results discussed using the factor analysis approach. These additional sets of results are reported in Table 11 in the Appendix.

Finally, in investigations concerning a binary outcome measure, empirical researchers sometimes prefer to fit a linear probability model, or LPM, and directly report the estimated coefficients as average marginal effects. LPM generally tends to produce estimates close to the average marginal effects obtained from a two-step approach using a non-linear model like a logit. There are however some exceptions. Nevertheless, for completion we have reported the LPM results for all our main models in Table 12 in the Appendix. The findings are analogous to our main results in Table 8.

5 Conclusions

This study analyzes the determinants of herd behavior exhibited by potential buyers of motorcycles in a low-income economy, where majority use these for intra-city transportation. We are primarily interested to understand how buyer's characteristics and their preferences influence their hypothetical decision to buy durable goods such as motorcycles and thereby exhibit either a herding or a price-conscious behavior. Our focus is on the bike-related attributes and psychological traits and attitudes of the buyers. We also controlled for the socio-demographic context of the buyers, their cognitive abilities/aptitude as well as their behavioral attributes in our empirical model; the latter is included to capture the effects that risk and time preferences would have on herd behavior. More importantly, we distinguished between price-constrained

[14] Results are available upon request.

buyers from the buyers who consider non-price factors, such as design, brand, power, popularity, and power, important in making choices relating to motorcycles. We used factor analysis to include major factor variables in the empirical models; the first set of (four) factor variables are related to preference towards bike-related attributes, and their attitudes towards new motorcycle purchases, while the second set of (three) factor variables are related to psychological traits and attitudes.

We find that vehicle attributes and psychological traits of buyers, the major variables of interest in the current study, are important factors determining the likelihood of herding. Intuitively, those considering "non-salient attributes" (such as environment, operating cost, resale, and safety) important, and those who are proactive in searching for additional information relating to operating costs, are more likely to be price-conscious. This notion (of price-consciousness) is also confirmed by the negative sign of coefficient on whether respondents consider themselves to be price-constrained buyers. Conversely and as expected, buyers considering "salient attributes" (such as design, appearance, brand, popularity and power) important are less price-conscious. In other words, these buyers are more likely to herd. Psychological attributes explained by one's attachment towards religion and traditions have negative association with herding while the association is positive for average buyers who state that they enjoy life and those who are inclined to buy the latest iPhone today. Furthermore, the results also suggest that socio-demographic variables such as gender and income are also important determinants of herd behavior. Of the two variables relating to cognitive abilities included in the models (2-4), the findings hints that energy-related knowledge is of some importance. Finally, the findings reject the notion of the importance of behavioral attributes such as risk and time preferences of the consumers although signs of the coefficients on these variables are intuitive, and we believe that these variable remain important in explaining the stated choice of high-value durables in low-income countries like Nepal.

This study has important policy implications for densely-populated urban areas in LMICs, where the use of motorized two-wheelers have been increasing rapidly and air pollution due to inefficient transport are stark. This study signals the prevalence of herding in Kathmandu valley (according to our data, 62.6% of the eligible respondents exhibited herd behavior). The herding phenomenon may also be true for powerful bikes, instead of the more efficient 110 cc alternative considered in the experiment, that requires serious policy attention for its financial, environmental and health implications. This may be particularly relevant, given our finding on higher herding likelihoods for respondents who value design and power of the motorcycles. Nevertheless, the categorization of consumers, based on both preferences as well as psychological traits and attitudes, can also be valuable information in targeting policies to expedite the adoption of more fuel-efficient (or electric) motorcycles, while also isolating factors that may cause consumers to herd towards the adoption of relatively inefficient alternatives. For example, based on our findings, consumers who are more likely to adopt the latest innovations as well enjoy their life to the full, or those that place importance on attributes such as design, brand and power of the motorcycle, are more likely to follow the herd; once a sufficient mass start to adopt electric motorcycles, these consumers may need only minor policy pushes to follow the trend. On the other hand, price-sensitive consumers, or those who are more likely to be traditional, may need additional policy efforts to adopt electric vehicles.

Having said that, price-sensitive consumers are also less likely to gravitate towards fuel-inefficient vehicles in the case of petrol-powered motorcycles, given that these are likely to be more powerful and thus more expensive, all else equal. Thus, policy-makers may need to target specific policies towards those consumers who are more likely to herd in the adoption of inefficient motorcycles (such as young consumers looking to buy powerful motorcycles, or those that are more likely to follow fads in the purchase of new technologies). Our study also has important implications for firms and manufacturers looking to identify factors that cause consumers to gravitate towards specific vehicle models, especially in a low-income context. Information on the role of socio-economic factors (such as gender and levels of income), as well as of the psychological and preference-based factors can help firms to understand the proclivity of different consumer groups to herd towards particular model choices, and to identify different market segments. Also, the positive effect of remittances on herding, as discussed earlier, may hint the prevalence of 'some' herding. This is indeed a very important piece of policy evidence hinting that remittances, in fact, may also be used to meet the long-term physical and human capital investment needs of households in remittance-dependent countries like Nepal (Yang, 2008; Raut and Tanaka, 2018).

There are, of course, some limitations to this study: firstly, we employ a stated-choice approach, rather than looking at herding with respect to actual motorcycle choices, i.e. we do not consider revealed preferences. Secondly, we adopt a "static" approach to identify herding: some of the previous studies were conducted on online platforms, where information is updated in real-time as individuals browse the contents (Chen, 2008; Duan et al., 2008; Muchnik et al., 2013; Cheung et al., 2014). In our experiment, all respondents are shown the same information on star ratings of the motorcycles. Furthermore, we have a relatively small sample size of about 300 respondents. While we provide suggestive evidence on the effects of bike-related attributes and psychological traits on herding decisions, these are to be interpreted as associations, rather than causal evidence.

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Appendix

Table 9: Explanatory variables and related survey questions

Variable	Type	Related survey question
Female	Binary	Your gender? (=1 if Female)
Age (years)	Continuous	Your age?
Household size	Continuous	Total number of people in the household?
Monthly household income (Rs.)	Categorical	What is your total monthly household income? (Less than Rs.15,000 / Between Rs.15,000-30,000 / Between Rs.30,000-50,000 / Between Rs.50,000-75,000 / More than Rs.75,000 / (No answer/Don't know))
Education level	Categorical	What is the highest education level that you have attained? (High school or below / Professional education / Bachelors / Masters)
Student	Binary	What is your occupational status? (Employed full-time / Employed part-time / Own business / Unemployed (looking for work) / **Student** / Retired / Full time housewife or househusband / Other)
Household receives regular remittances	Binary	Does your household receive regular remittances from family members living abroad? (**Yes** / No / Don't know)
Member of a club or association	Binary	Do you belong to any types of clubs or associations? (**Yes** / No)
Owns a bike	Binary	Do you currently own a bike? (**Currently own** / Do not own)
Financial literacy index (0-3)	Continuous	Constructed by adding up number of correct responses to three questions: (Q1) Let's say you have Rs. 1,000 in a fixed deposit in a saving or credit cooperative/association account which earns 10% interest per year. How much money would you have in the account and after 2 years? (Rs. 1,100 / Rs. 1,110 / Rs. 1,200 / Rs. 1,210 / Don't know); (Q2) Imagine that the interest rate on your savings or credit cooperative/association account was 8% per year and inflation was 5% per year. After 1 year, how much would you be able to buy with the money in this account? (More than today / Exactly the same / Less than today / Don't know); (Q3) True or false: buying shares in a single company's stock provides safer returns than buying shares of several companies. (True / False / Don't know)
Energy knowledge index (0-5)	Continuous	Constructed by adding up number of correct responses to five questions: (Q1) Motorized transport significantly contributes to air pollution and causes health damages. (True/False/Don't know) (Q2) In Kathmandu, the registration tax on an electric bike is lower than a petrol-based bike. (True/False/Don't know) (Q3) Motorized transport and mobility contributes very little to global warming. (True/False/Don't know) (Q4) About 50% of total electricity produced in Nepal is from hydropower. (True/False/Don't know) (Q5) What is the price of one unit of electricity (namely, one KwH) in Kathmandu?
Loss averse	Binary	Imagine that you own a 110 cc bike with annual fuel costs of Rs. 20,000. You are offered the possibility to replace this with a 125 cc bike with annual fuel costs of Rs.30,000. Would you like to replace it? (Replace, not replace) Now, imagine that you own a 125 cc bike with annual fuel costs of Rs. 30,000 and that you are offered the possibility to replace it with a 110 cc bike with annual fuel costs of Rs. 20,000. Would you like to replace it? (Replace, not replace) Individuals who answer 'no' in both cases are categorized as being loss-averse.
Willingness to take risks	Categorical	Are you a person who is generally willing to take risks, or do you try to avoid taking risks? Choose between zero and 10. Zero means completely unwilling to take risks, 10 means you are very willing to take risks. (Categories: 0-2 as Low; 3-7 as Medium; and 8-10 as High)
Present bias (beta)	Continuous	Multiple price list-based as described in the appendix
Annualised discount factor	Continuous	Multiple price list-based as described in the appendix

Calculating the Time Preference Parameters

We calculated two preference parameters individually for each respondent using the questions presented in Figures 2 and 3, 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 2, 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 δ, as well as the present bias β parameter, using the following equations:

$$u^*(x_{A1.1}) = \delta u^*(x_{B1.1}) \tag{2}$$

$$u^*(x_{A1.2}) = \delta\beta u^*(x_{B1.2}) \tag{3}$$

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 δ derived by solving equation 2 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 β value equal to one denotes a person who is neither present-biased, nor future-biased, $\beta > 1$ denotes a future-biased individual, whereas β <1 denotes a present-biased individual.

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 2: 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 3: Present Bias and Time Preferences: Second MPL-based Question

Table 10: Logit model estimation results

	Model (1)	Model (2)	Model (3)	Model (4)
Female	-0.874***	-1.116***	-1.061***	-1.103***
	(0.328)	(0.361)	(0.374)	(0.387)
Age (years)	0.009	0.007	0.019	0.025
	(0.020)	(0.022)	(0.024)	(0.024)
Household size	0.061	0.108	0.176*	0.156
	(0.085)	(0.094)	(0.100)	(0.102)
Rs. 30000-50000	-0.509	-0.280	-0.431	-0.486
	(0.353)	(0.384)	(0.398)	(0.406)
Rs. 50000-75000	-0.891**	-0.804*	-0.959**	-0.887*
	(0.412)	(0.457)	(0.478)	(0.490)
More than Rs. 75000	-1.692***	-2.253***	-2.413***	-2.301***
	(0.520)	(0.601)	(0.643)	(0.667)
Professional education	0.193	0.140	-0.047	-0.012
	(0.754)	(0.818)	(0.878)	(0.882)
Bachelors	0.794***	0.712**	0.543	0.639*
	(0.299)	(0.324)	(0.340)	(0.371)
Masters	-0.462	-0.801*	-0.607	-0.540
	(0.426)	(0.479)	(0.494)	(0.513)
Student	0.200	0.386	0.552	0.759
	(0.406)	(0.428)	(0.456)	(0.481)
Household receives regular remittances	0.601	0.499	0.484	0.493
	(0.386)	(0.406)	(0.426)	(0.444)
Member of a club or association	-0.171	-0.127	-0.280	-0.385
	(0.303)	(0.329)	(0.348)	(0.359)
Owns a bike	-0.226	0.065	0.126	0.097
	(0.285)	(0.315)	(0.324)	(0.331)
Financial literacy index (0-3)		-0.147	-0.197	-0.162
		(0.211)	(0.221)	(0.225)
Energy knowledge index (0-5)		-0.290**	-0.293*	-0.309**
		(0.146)	(0.150)	(0.156)
Non-salient attributes important		-0.433***	-0.374**	-0.311*
(Environment, Operating Cost, Resale, Safety)		(0.164)	(0.173)	(0.178)
Salient attributes important (Design		0.453***	0.490***	0.567***
and Appearance, Brand, Popularity, Power)		(0.170)	(0.179)	(0.199)
Has price constraints		-0.506***	-0.526***	-0.550***
		(0.177)	(0.190)	(0.199)
Proactive towards fuel economy and		-0.349**	-0.440***	-0.418**
lifetime costs		(0.153)	(0.164)	(0.167)
Religious principles, holds on to			-0.551***	-0.494***
family's traditions			(0.173)	(0.177)
Out-going, likely to buy latest tech			-0.004	-0.017
innovations			(0.165)	(0.172)
Would rather buy latest iphone today,			0.399***	0.388**
enjoys life			(0.152)	(0.161)
Loss averse				-0.546
				(0.496)
WTT Risk = Medium				-0.383
				(0.392)
WTT Risk = High				0.190
				(0.444)
Present bias (beta)				4.255
				(3.233)
Annualised discount factor				-0.576
				(0.975)

Logit model estimation results. The binary outcome variable is equal to one for a respondent who exhibits herd behavior, and is zero otherwise. The coefficients represent log of the odds ratio of exhibiting herd behavior. The reference levels for categorical variables are: 'Less than Rs. 30,000' (income); 'High school or below' (education); and 'WTT Risk = Low' (WTT Risk, or Willingness-to-take risk). *,** and *** respectively denote significance at 10%, 5% and 1% levels.

Table 11: Robustness check without latent factors: Marginal effects

	No psychological latent factors		*No latent factors*		
	Model (3)	Model (4)	Model (2)	Model (3)	Model (4)
Female	-0.179***	-0.183***	-0.215***	-0.184***	-0.184***
	(0.062)	(0.062)	(0.061)	(0.061)	(0.061)
Age (years)	0.004	0.005	0.000	0.002	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Household size	0.031*	0.027	0.023	0.030*	0.027
	(0.017)	(0.017)	(0.016)	(0.016)	(0.017)
Rs. 30000-50000	-0.074	-0.083	-0.016	-0.044	-0.050
	(0.063)	(0.064)	(0.065)	(0.064)	(0.064)
Rs. 50000-75000	-0.151*	-0.135*	-0.082	-0.095	-0.083
	(0.079)	(0.080)	(0.081)	(0.080)	(0.081)
More than Rs. 75000	-0.416***	-0.396***	-0.362***	-0.368***	-0.362***
	(0.096)	(0.100)	(0.097)	(0.098)	(0.100)
Professional education	-0.048	-0.047	0.028	-0.026	-0.023
	(0.170)	(0.167)	(0.166)	(0.171)	(0.165)
Bachelors	0.102*	0.120**	0.133**	0.115**	0.124**
	(0.058)	(0.061)	(0.055)	(0.056)	(0.060)
Masters	-0.142	-0.131	-0.189**	-0.183**	-0.196**
	(0.093)	(0.094)	(0.087)	(0.085)	(0.086)
Student	0.085	0.116	0.106	0.129	0.134
	(0.080)	(0.082)	(0.080)	(0.081)	(0.082)
Household receives regular remittances	0.098	0.099	0.116	0.110	0.100
	(0.073)	(0.074)	(0.071)	(0.070)	(0.071)
Member of a club or association	-0.045	-0.062	-0.054	-0.060	-0.070
	(0.061)	(0.061)	(0.059)	(0.058)	(0.058)
Owns a bike	0.016	0.008	0.025	0.018	0.008
	(0.057)	(0.056)	(0.057)	(0.057)	(0.057)
Financial literacy index (0-3)	-0.031	-0.023	-0.025	-0.029	-0.022
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Energy knowledge index (0-5)	-0.054**	-0.056**	-0.058**	-0.053**	-0.060**
	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)
Non-salient attributes important	-0.051*	-0.039			
(Environment, Operating Cost, Resale, Safety)	(0.031)	(0.031)			
Salient attributes important (Design and	0.082***	0.095***			
Appearance, Brand, Popularity, Power)	(0.031)	(0.033)			
Has price constraints	-0.100***	-0.104***			
	(0.031)	(0.032)			
Proactive towards fuel economy and	-0.072**	-0.067**			
lifetime costs	(0.028)	(0.028)			
I live according to religious principles	-0.118***	-0.114***		-0.118***	-0.119***
	(0.043)	(0.044)		(0.042)	(0.043)
I enjoy my life to the full	0.079*	0.088**		0.070*	0.080*
	(0.043)	(0.043)		(0.041)	(0.042)
Loss averse		-0.098			-0.021
		(0.084)			(0.086)
WTT Risk = Medium		-0.060			0.014
		(0.068)			(0.066)
WTT Risk = High		0.029			0.028
		(0.075)			(0.078)
Present bias (beta)		0.898*			1.187**
		(0.542)			(0.563)
Annualised discount factor		-0.103			-0.039
		(0.165)			(0.154)
Resale value			-0.137***	-0.103**	-0.096*
			(0.050)	(0.050)	(0.050)
Expense for fuel per year and over the			0.188***	0.166***	0.166**
lifetime			(0.060)	(0.062)	(0.065)
Environmentally-friendly			-0.165***	-0.165***	-0.161***
			(0.056)	(0.056)	(0.059)
Have you been searching for information			-0.194***	-0.164**	-0.168**
on fuel economy?			(0.070)	(0.072)	(0.072)
Is price a constraint?			-0.350***	-0.348***	-0.385***
			(0.076)	(0.076)	(0.079)

Individual manifest variables not significant in any model have not been reported for brevity.

Table 12: Linear probability model estimation results

	Model (1)	Model (2)	Model (3)	Model (4)
Female	-0.191***	-0.208***	-0.193***	-0.202***
	(0.072)	(0.070)	(0.070)	(0.070)
Age (years)	0.002	0.002	0.004	0.005
	(0.004)	(0.004)	(0.004)	(0.004)
Household size	0.013	0.016	0.027	0.024
	(0.019)	(0.018)	(0.018)	(0.018)
Rs. 30000-50000	-0.105	-0.044	-0.077	-0.080
	(0.074)	(0.074)	(0.073)	(0.074)
Rs. 50000-75000	-0.189**	-0.140	-0.171*	-0.152*
	(0.088)	(0.089)	(0.089)	(0.090)
More than Rs. 75000	-0.365***	-0.407***	-0.409***	-0.378***
	(0.109)	(0.107)	(0.107)	(0.109)
Professional education	0.038	0.042	0.007	0.016
	(0.168)	(0.168)	(0.165)	(0.165)
Bachelors	0.165***	0.128**	0.095	0.097
	(0.062)	(0.062)	(0.062)	(0.065)
Masters	-0.103	-0.160*	-0.116	-0.110
	(0.095)	(0.092)	(0.091)	(0.093)
Student	0.036	0.058	0.082	0.113
	(0.086)	(0.083)	(0.081)	(0.084)
Household receives regular remittances	0.127	0.104	0.089	0.078
	(0.082)	(0.079)	(0.077)	(0.079)
Member of a club or association	-0.036	-0.023	-0.050	-0.065
	(0.066)	(0.065)	(0.063)	(0.064)
Owns a bike	-0.049	0.011	0.020	0.015
	(0.061)	(0.061)	(0.060)	(0.060)
Financial literacy index (0-3)		-0.025	-0.034	-0.030
		(0.040)	(0.039)	(0.040)
Energy knowledge index (0-5)		-0.052*	-0.057**	-0.057**
		(0.028)	(0.028)	(0.028)
Non-salient attributes important		-0.082***	-0.064**	-0.054*
(Environment, Operating Cost, Resale, Safety)		(0.031)	(0.031)	(0.031)
Salient attributes important (Design and		0.089***	0.088***	0.097***
Appearance, Brand, Popularity, Power)		(0.032)	(0.032)	(0.034)
Has price constraints		-0.084***	-0.084***	-0.083***
		(0.031)	(0.031)	(0.031)
Proactive towards fuel economy and		-0.064**	-0.077***	-0.073**
lifetime costs		(0.029)	(0.029)	(0.029)
Religious principles, holds on to			-0.095***	-0.082***
family's traditions			(0.030)	(0.031)
Out-going, likely to buy latest tech			0.003	0.004
innovations			(0.030)	(0.031)
Would rather buy latest iphone today,			0.073***	0.069**
enjoys life			(0.027)	(0.028)
Loss averse				-0.099
				(0.096)
WTT Risk = Medium				-0.065
				(0.072)
WTT Risk = High				0.043
				(0.077)
Present bias (beta)				0.460
				(0.427)
Annualised discount factor				-0.086
				(0.175)

Estimation results of linear probability models. The binary outcome variable is equal to one for a respondent who exhibits herd behavior, and is zero otherwise. The reference levels for categorical variables are: 'Less than Rs. 30,000' (household income); 'High school or below' (education category); and 'WTT Risk = Low' (WTT Risk, or Willingness-to-take risk). *,** and *** respectively denote significance at 10%, 5% and 1% levels.

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