“Your money or your life !”
The influence of injury and fine expectations on helmet adoption among motorcyclists in Delhi

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PRELIMINARY DRAFT

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Abstract

In this paper I study the individual decision of wearing a helmet using original data collected among motorcyclists in New Delhi in 2011. The data measures the motorcyclists' subjective expectations of medical expenditures and fines. In my empirical analysis, I first investigate to what extent injury and fine expectations impact helmet adoption depending on the type of trip. I show that expectations of injuries are correlated with helmet use for long distance journeys while expected fines are rather linked with helmet adoption for short distance trips either on main roads or within residential neighborhoods. I use geographical fixed effects to control for area related specificities which could bias my estimates, such as differences in police presence, quality of roads or health infrastructures. I then explore whether previous personal experiences influence individuals' beliefs. I show that having experienced a road crash or a police arrest modifies motorcyclists' expectations. Nonetheless, differences across individuals may be partly due to actual differences in health hazards and police enforcement intensity. Finally, in view of designing policies, I assess the impact of different safety measures which raise either expected medical expenditures or expected fines. The increase of police threat, through enforcement, information and fine levels are likely to increase helmet adoption among motorcyclists. Information campaigns stressing the utility of helmet to avoid severe injuries even for motorbike trips nearby one's home should have a similar effect.

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1 Introduction

Every five minutes in India someone dies from a road traffic accident (NCRB, 2011). This phenomenon is expected to escalate to one death every three minutes by 2020. Many of these fatalities are nevertheless preventable. While Hsiao et al. (2013) found that 62% of Indian road casualties suffered from a cerebral trauma;[1] Liu et al. (2008) highlighted that standardized quality helmets efficiently reduce risk of mortality and injuries by 40% and 70% respectively. Besides road infrastructures or the quality of motorized vehicles, behaviors adopted by road users are actually a crucial lever to reduce the frequency and severity of road traffic accidents. Indeed, individual characteristics and attitudes toward risk may play a role in road habits, risk exposure and conduct while traveling. Grimm and Treibich (2014) studied the influence of individual risk aversion on helmet use and choice of speed among motorcyclists. Their results suggest that risk averse drivers are more likely to wear a helmet. Nevertheless, safety behaviors adopted on the road correspond to “economic decisions involving uncertainty” that are, according to Delavande et al. (2011a), “shaped not only by preferences but also by expectation of future outcomes”. Given the important share of motorcyclists in the traffic mix and among road fatalities in developing countries, a better understanding of the individual decision process of this particular group would definitively help design appropriate and efficient policies. In order to fill this gap, this paper considers individuals’ heterogeneity regarding expected consequences of not using a helmet. More precisely, it provides empirical evidence on the relation between helmet adoption and expectations of injuries and fines among motorbike users in New Delhi, as well as insights into the way these beliefs are shaped.

In recent years, a growing literature of applied development economics has started to investigate the impact of subjective expectations on probabilities and outcomes in the individual decision making process in areas like investment, education, health and entrepreneurship (see for instance Attanasio, 2009; Delavande and Kohler, 2009; Dominitz and Manski, 1997b; McKenzie et al., 2007). As all other uncertain decisions, road safety conducts are likely to be the result of a combination of factors among which perceptions and beliefs play a key role. These include the subjective probability to be caught by the police for infringing road rules, or, in case of an accident, be injured and suffer financial, physical and psychological losses.

Awareness programs on road dangers have extensively used shocking ads in order to raise citizens’ expectations of negative outcomes in case they should choose not to use a seat belt or a helmet. Nevertheless, given the low probability of accident occurrence on a given trip, individuals still face difficulties in internalizing this risk and adapting their behaviors. Many countries have therefore chosen to bind attitudes by law. In low and middle income countries, where two wheelers represent up to 70% of all motorized vehicles, an increasing number of governments have implemented compulsory helmet legislations. This, to urge motorcyclists to protect them-

[1] Their study is based on a nationally representative survey of 1.1 million homes.

selves. In India, for instance, a legislation was enacted in 1988 (Motor Vehicle Act). However, it is the responsability of each and every Indian state to implement and enforce the law. The effect of such a punitive measure on road safety attitudes may thus vary substantially across the country depending on the actual and perceived strength of its enforcement.[2] This can be captured by the subjective probability of being caught by the police if infringing the law and the subsequent expected fines.

In this study, elicited expectations of injury and fine if one does not use a helmet were obtained through a unique dataset collected among motorcyclists in New Delhi in 2011. The methodology, which will be presented in detail below, comes from studies on investment in education (Attanasio, 2009), migration decisions (McKenzie et al., 2007) or health prevention exams (Delavande, 2008). This questionnaire allows me to estimate the impact of injury and fine expectations on road safety behaviors, in particular helmet adoption. Moreover, information gathered on previous experiences of road crash and traffic police arrest enables me to investigate how individuals form their beliefs on the consequences of not using a helmet. Finally, based on my findings, the impact of various road safety measures on helmet use are simulated. This will provide evidence as for the possible ways to improve road safety in large metropolitan cities in developing countries.

The remainder of the paper is organized as follows. Section 2 summarizes the road safety literature, with a focus on the work done at the micro-economic level. In particular, I stress why information on subjective probabilities and outcomes could help the understanding of observed conducts of road users. Then, the methodological literature on the measurement of subjective expectations of probabilities and outcomes is introduced. Section 3 presents the data and the survey methods used to draw expectations out. Some descriptive statistics are also reported. In section 4, I discuss the channels through which personal experiences may impact the formation and updating of beliefs as well as the role of the latter in the decision process regarding helmet adoption by motorcyclists. Section 5 reports the empirical strategy and findings. In this analysis, I first look at the extent to which expectations of medical expenditures and fines influence helmet use depending on the type of trip. In a second step, I explore the influence of previous experience of road crash or of police arrest on expectations. The impacts of different policy measures raising either expected medical costs or expected fines are reported in section 6. Section 7 concludes.

[2] In the last Global Status Report on Road Safety WHO (2013), the Indian rate of enforcement of helmet law appears to be very low (2 on a scale going from 0 to 10). Nonetheless, this figure does not reflect the potential variation across Indian states.

2 Literature review

2.1 Studies on motorcycle safety

Studies implemented in developed countries have examined the effectiveness of compulsory helmet legislations. Using U.S. longitudinal data, Dee (2009) thus found that a universal helmet law reduces motorcyclist fatalities by 27 percent. As for French et al. (2009), they compared the capacity of different safety policies to reduce both fatal and non fatal road injuries and showed that legislations making helmet use mandatory outperform alcohol policies as well as speed limit measures or education programs targeted to riders. It is worth highlighting that motorbike users' differ in terms of demographics, uses and engine sizes between the U.S.A. or Europe and developing countries, such as India. In low income countries for instance, most drivers ride scooters or mopeds, and this on rather short distances. Given the specificities of motorcyclists and the traffic environment in which they evolve, contextualized evaluations are required. Nonetheless, to my knowledge, and despite the implementation of compulsory helmet legislations in many developing countries, studies estimating the efficiency of such regulation have not yet been undertaken in these regions.

In addition, very few studies have investigated the determinants of road safety habits. One exception is Ritter and Vance (2011) who looked at the socio economic characteristics influencing voluntary helmet use among German cyclists. The scarcity of behavioral analysis can be explained by the absence of data on road habit issues. Indeed, micro level data on road safety behavior are all but inexistent, partly because this issue has been less prioritized by the authorities. This considerably limits research on the topic. We started filling the gap in 2011 by collecting information on road habits among motorcyclists in New Delhi. Information on socio demographic characteristics, preferences toward risk and beliefs were also gathered. In a previous paper (Grimm and Treibich, 2014), we focused on the influence of risk aversion on helmet use and choice of speed and on the existence of risk compensation behaviors. We found that among drivers, individuals who are more risk averse are significantly more likely to use a helmet. As to passengers, their use of a helmet depends on the environment they face (driver's characteristics or traveling speed for instance).

While Grimm and Treibich (2014) assumed that probabilities of accident and subsequent injuries are identical for all motorcyclists, this paper takes into account the possible heterogeneity in expectations individuals may have regarding the consequences of not using a helmet. Indeed, besides their risk aversion, the discomfort of wearing a helmet, the protection it offers in case of a crash (in terms of probability and severity of the injury) or the capacity of avoiding police sanctions are various dimensions that may enter the individual decision process regarding helmet adoption and which plausibly differ from one person to the other. Introducing expectation data in the analysis allows to disentangle explanations based on preferences and those based on beliefs. More adequate behavioral interventions might then be suggested.

Both the fear of negative health outcomes and the threat of financial sanctions may influence motorcyclists' behavior toward helmet use. Elicited probabilities of injury and subsequent medical expenditures on the one hand, and probability of police halt and financial penalties on the other hand have been gathered using similar methodologies to the ones already extensively used in the literature (see Delavande et al., 2011a; Manski, 2004, for reviews). In other words, the "frequency" and the "severity" dimensions have been elicited through our survey. This paper discusses the possible mechanisms at play in the formation of beliefs and their theoretical impact on helmet use. Based on a unique dataset, I then empirically test these relations.

To summarize, behavioral studies on road safety conducts investigating the influence of educational and repressive policies, in particular in developing countries, have not yet been undertaken. Individuals' beliefs regarding the gains and costs of not using a helmet are certainly an important dimension to explore in the safety decision process. Moreover, the formation or updating of road related subjective expectations as well as the influence of the latter on helmet adoption are questions which remain overlooked. To fill these gaps, I first study to what extent expectations of medical expenditures and fines impact helmet adoption in different trip circumstances. Second, I explore the role of personal experiences on the observed heterogeneity in beliefs across individuals, and third I estimate the impact on helmet use of various safety measures modifying expectations. I report in the following subsection the various methods used in the literature to elicit this specific type of information.

2.2 Measurement of subjective expectations

Despite the development of elicitation methodologies, in particular in psychology, economic empirical studies of individual choices have often only focused on preferences, while individuals' beliefs were assumed homogenous. However, as pointed by Manski (2004), expectations may vary from one person to the other and different combinations of expectations and preferences may lead to the same observed behavior. By collecting data on individuals' expectations regarding the occurrence of specific events and their subsequent outcomes, researchers aim at relaxing the homogeneity assumptions made on expectations. Moreover, Tversky and Kahneman (1974)'s results suggested that individuals tend to use heuristic rules to process data. These findings brought concerns regarding the assumption of rational and homogenous expectations across agents.

Attanasio (2009) highlighted that a careful design of questionnaires should enable to elicit information on probabilities and distribution of future variables. He added that such procedure is important for economic welfare and relevant to determine economic choice. Because of lower cost and higher willingness of individuals to spend time on answering surveys in developing countries, such data collection has particularly increased in these regions. Detractors have called into question the quality of these datasets putting forward the limited formal education of some respondents and their unfamiliarity with the formal concept of probability. Delavande et al. (2011a) refuted these arguments based on a survey of recent contributions to the literature on the measurement of subjective expectations in developing countries. They showed that elicitation of probability is feasible in low income countries despite the average low level of education of the respondents. Furthermore, they argue that probabilities are preferable to point estimates or qualitative scales, in particular Likert scales. These authors also provided advice regarding the methods to be used in the questionnaire to limit numeracy difficulties. For instance, visual aids (balls, beans, sticks) could be used in low income countries where probability concepts might be too abstract for the respondents. When such tools were used only few people gave degenerated forecasts, supporting the idea that individuals understand the questions asked (cf. Luseno et al., 2003; Lybbert et al., 2007).

Initial formulation of questions eliciting continuous variables, such as future earnings or retirement benefits, enabled to obtain only one value of the outcome of interest, leaving unclear whether the respondent gave the minimum, the maximum, the median or the average of what he expects. Different methods have been used since then to draw out the distribution of the outcome of interest. Attanasio (2009), for instance, asked respondents the minimum and maximum amounts they could earn throughout their career. Enumerators then computed the midpoint M and asked *"from 0 to 100, what is the probability that your earnings at that age will be at least M?"*. Similarly, Dominitz and Manski (1997a) used the following income expectation question, included in the Survey of Economic Expectations: *"what do you think is the percent chance that your total household income, before taxes, will be less than Y over the next 12 months?"*. Four income thresholds in increasing order were presented to the individual. The thresholds about which a given respondent was queried were determined by the respondents' answer to a pair of preliminary questions asking for the lowest and highest possible income that the household might experience in the next year. These two methodologies generate flexible thresholds, a way of avoiding the anchoring problem which appears when using pre determined intervals among population differing regarding their wealth. When analyzing the data on expected continuous variables, Das and Donkers (1999) and Dominitz and Manski (1997a) chose a lognormal distribution with a two dimensional parameter vector: the median (to characterize the central tendency) and the interquartile range (to characterize its dispersion). As for Guiso et al. (1992), they opted for the ratio of the standard deviation to the mean of the subjective real income distribution to measure the uncertainty of subjective earnings.

Finally, Delavande et al. (2011b) conducted an experiment in India to test the sensivity of elicited expectations to variation in three dimensions of the elicitation methodology: (i) the number of beans,[3] (ii) the design of the support (pre determined vs. self anchored) and (iii) the ordering of questions. While more accuracy was obtained by using more beans and a larger number of intervals with a pre determined support, the results remained very robust to

[3]Beans are used as visual aids by respondents.

variations in the elicitation design.

I now proceed with the presentation of the dataset.

3 Data

3.1 Road safety survey

With the help of a local survey firm,[4] we implemented a representative household survey in Delhi in 2011 targeting motorcyclists. Besides socio demographic characteristics, data on risk aversion, perception of road rule enforcement and of road risks were gathered along with helmet use, previous involvement in road traffic crashes or traffic police arrests. Finally, we attempted to elicit the subjective expectations of medical expenditures and fines, based on the methodologies developed in the literature and describe in more detail below in section 3.2.

To ensure representativeness of Delhi's population, the following sampling design was adopted: (i) New Delhi was divided into five zones, (ii) in each zone, ten polling booths were randomly drawn, (iii) the location of each of these polling booths represented the starting point from which every fifth household was selected for the interview. Around each polling booth, 30 households were interviewed, leading to a total of 1,502 households. In 545 of them at least one member had traveled by motorbike in the previous four weeks. Up to three drivers or passengers per household could answered the survey. In the end, 902 motorbike users agreed to reply to our questions.

Our respondents are 36 years old on average, two thirds of them are men and 70% pray daily. 97% of the drivers are men while they only represent 25% of the passengers. Regarding road safety efforts, while men use full face helmets, women more often opt for a half helmet. Motorcyclists were asked about their helmet use in three different circumstances. On average, motorbike users are more likely to declare wearing a helmet for long trips[5] (81%) than for short trips on main roads (61%) or trips in residential neighborhoods[6] (54%). Nonetheless, significant differences in helmet use are observed between men and women, drivers and passengers and motorcyclists who frequently or occasionally use this mode of transportation. Drivers without passengers travel at a higher speed on average. More than 60% of the passengers declare being three or more people when they use the motorbike. 46% of the respondents declare to frequently circulate on a motorbike, 64% use it mainly to commute to work. Finally, 7% of the interviewed motorcyclists have already been involved in a road crash, they are about the same percentage to have been sanctioned by the traffic police.

[4] Sigma Research and Consulting: http://www.sigma-india.in

[5] Long trips are defined as journeys lasting more than 15 minutes.

[6] Residential neighborhoods correspond to residential areas with small food and clothes markets.

3.2 Eliciting expectations of medical expenditures and fines

3.2.1 Methodology implemented in the survey

In our survey, both the subjective probability of being involved in a road accident and injured and the subjective probability of being stopped by the police were elicited by asking respondents to use an 11 point response scale going from 0 "this event will never happen" to 10 "this event will surely happen". To begin with, five general questions were asked in order to control for the understanding of the scale (further detail regarding these "check" questions are included in the Appendices).[7] Then, respondents were invited to consider two cases: (i) the way they generally travel and (ii) a situation where they are not using a helmet. For each of these situations they gave their subjective probability of injury. Similarly, we elicited the subjective probability of police halt for the two previous situations[8] and "for no reason". The latter refers to the case where no road rule is broken by the motorcyclist. Indeed, the discretionary power of police officers may prevent people from adopting safe attitudes if they think their effort will not be rewarded.[9] If the individual answered that the probability of occurrence of either injury or police halt while not using a helmet was strictly higher than zero, the interviewer proceeded with questions regarding the subsequent medical expenditures or fines. More precisely, pre determined amounts were used and individuals were asked the probability that outcomes would range below each threshold. The exact formulation used was the following: *"Thinking about the medical expenditure (the fine) you would have to pay if you were injured in a road crash (stopped by the police) right now without wearing a helmet, what do you think is the percent chance that this amount will be less than X INR?"*. The enumerator kept proposing higher amounts till the respondent answered 100%. The main drawback of using one unique and fixed scale to elicit the distribution of a continuous variable, in particular among a heterogenous population, is the possibility that the range offered doesn't correspond to the intervals the individual has in mind. By asking each respondent about the range of values which is relevant for him, we would instead create a self anchored support. In our case, expected medical expenditures, for instance, may vary quite substantially according to the individual's wealth but also to his access to medical care, in particular whether he has health insurance or not. Taking into account this potential anchoring issue, in the initial version of the questionnaire the respondent was first asked about the minimum and maximum amounts of medical expenditures and fines expected. The inquirer then computed three thresholds and asked what was the percent chance the individual would have to pay less than each of these thresholds (the three computed thresholds and the maxi-

[7] We use similar questions as Delavande and Kohler (2009). When performing robustness checks, I exclude from the sample individuals who did not answer correctly to the check questions (see results in section 5.1.3 and Table 18).

[8] While no horizon was introduced in the questions regarding the probability of being involved in an accident and injured, a one month horizon was to be considered by the respondent regarding the probability of being caught by the traffic police.

[9] This disincentive can't be captured by the first situation (general road habits) where helmet users may infringe the law in many different ways (not using a helmet, but also overspeeding, jumping a traffic light, etc...).

mum) following the elicitation methodology used for instance by Dominitz and Manski (1997a). Nevertheless, the pilot phase revealed the interviewer's difficulties in computing the intervals, which also increased the duration of the interview and exacerbated interviewee's fatigue. This led us to opt for pre determined scales.

3.2.2 Probability of injury and subsequent medical expenditures

Starting with the potential injuries, two situations were presented to the interviewees. In the first one, they were asked to consider the way they usually travel on their motorbike ("in general") and a second one where they would not use the helmet ("if no helmet").[10] In each case, respondents were asked to establish the likelihood they would be involved in an accident and injured using a scale going from 0 to 10. Answers were divided by ten in order to obtain values between 0 and 1 which can be related to probabilities.

Table 1 provides the distribution of subjective probabilities of injury in the two situations of interest. Notably, the "no helmet" variable is on average higher and has fatter tails than the "in general" probability. The graph on the left of Figure 1a draws the distribution of subjective probability of being hurt if not wearing a helmet. This distribution is broken down by different socio demographic characteristics and preferences toward risk in Figure 2a. This subjective probability seems to vary substantially among respondents, even for individuals of similar gender, education, religion or presenting the same level of risk aversion.

[10] One could argue that we should have elicited probabilities of being injured with and without helmet in order to derive the individuals' perceived health utility of wearing a helmet. Nonetheless, we thought that asking these two questions would have exacerbated the social desirability bias. Controlling by the type of injuries individuals have in mind and the answer to the "in general" question should allow me to capture the perceived utility of helmet. As a matter of fact, helmet use questions came before the elicitation of subjective probabilities and outcomes.

Table 1: Distribution of subjective probabilities of injuries and police arrest

	percentile					
	25^{th}	50^{th}	75^{th}	mean	std. dev.	*observations*
Probability of injury						
in general	0.2	0.4	0.5	0.37	0.25	*841*
if no helmet	0.4	0.5	0.9	0.58	0.31	*836*
Probability of arrest						
in general	0.2	0.4	0.5	0.39	0.29	*840*
if no helmet	0.4	0.7	1	0.65	0.34	*878*
for no reason	0.1	0.3	0.5	0.36	0.30	*845*

FORMULATION OF QUESTIONS

Probability of injury

in general - *"Think about the way you generally travel on the motorcycle. Given this, how likely do you think that you have an accident in which you get injured?"*

if no helmet - *"In case you are not wearing a helmet, how likely do you think that you have an accident in which you get injured?"*

Probability of police arrest

in general - *"Think about the way you generally travel on the motorcycle, what is the likelihood that you will be stopped by the police in the next month?"*

if no helmet - *"If you do not use the helmet at all during the next month, what is the probability the police stops you at least once over the period?"*

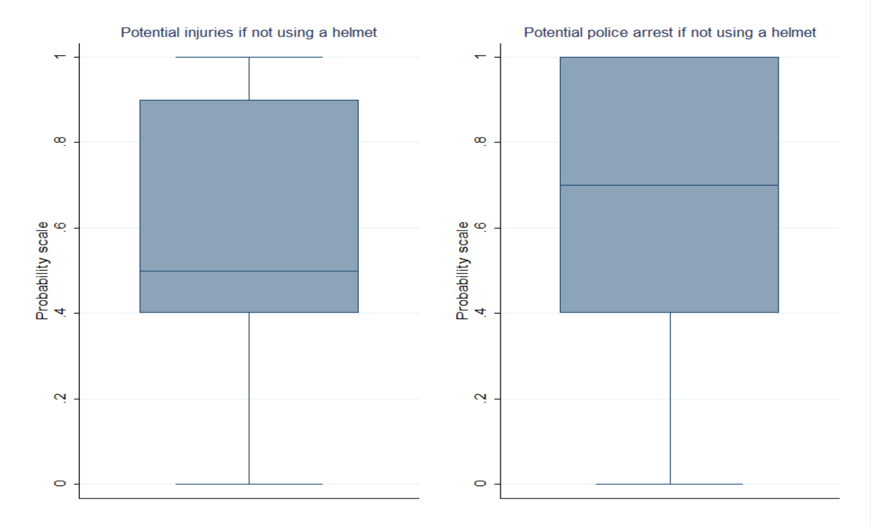
for no reason - *"According to you, what is the likelihood you will be stopped by the police for no reason in the next month?"*

Answer scale

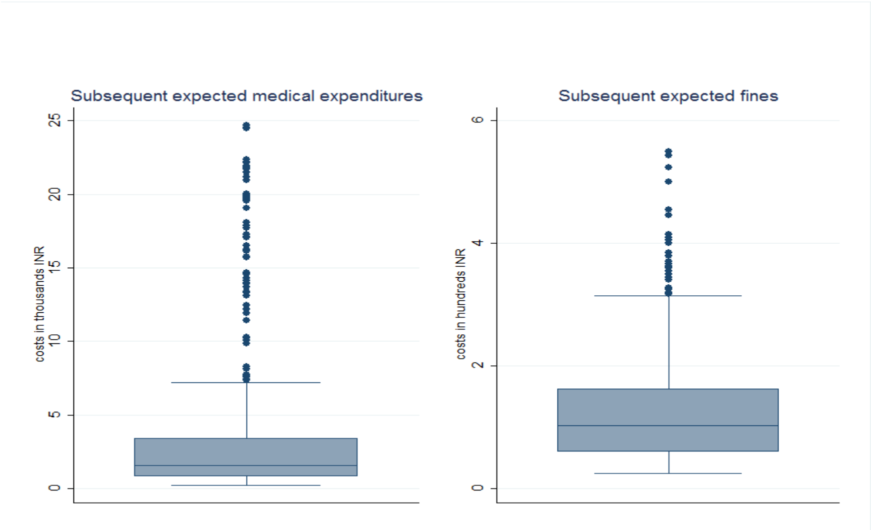
Respondents answered using a 11 point scale going from 0 "this event will never happen" up to 10 "this event will surely happen". I then divided their answer by 10 to obtain probabilities, between 0 and 1.

Figure 1: Heterogeneity in beliefs

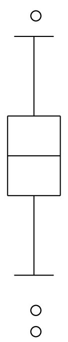
a. Subjective of probabilities if non use of helmet



b. Subsequent expected outcomes



Box plot legend:



upper adjacent value

75th percentile

median

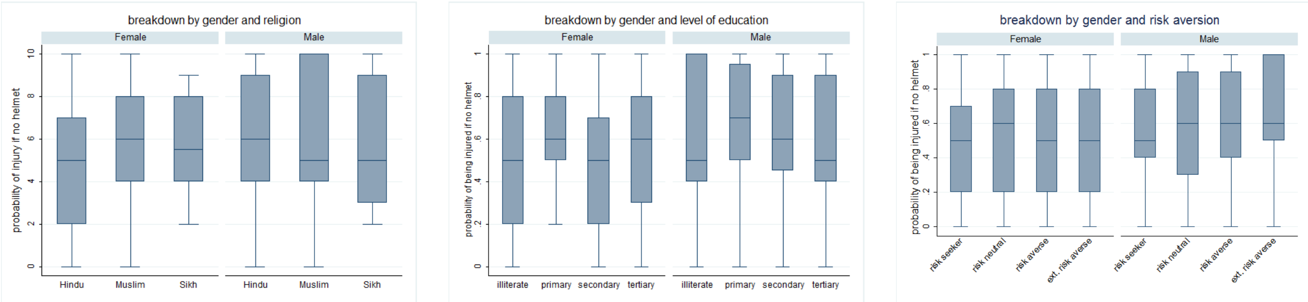
25th percentile

lower adjacent value

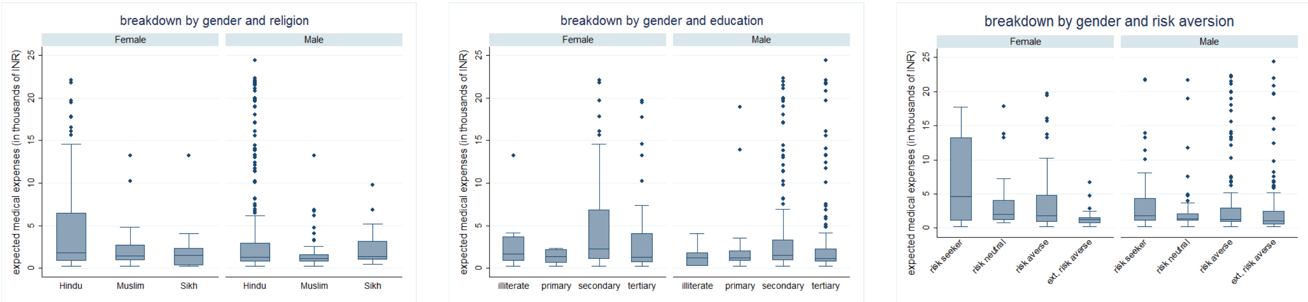
outside values

Figure 2: Heterogeneity in beliefs breakdown by socio-demographics

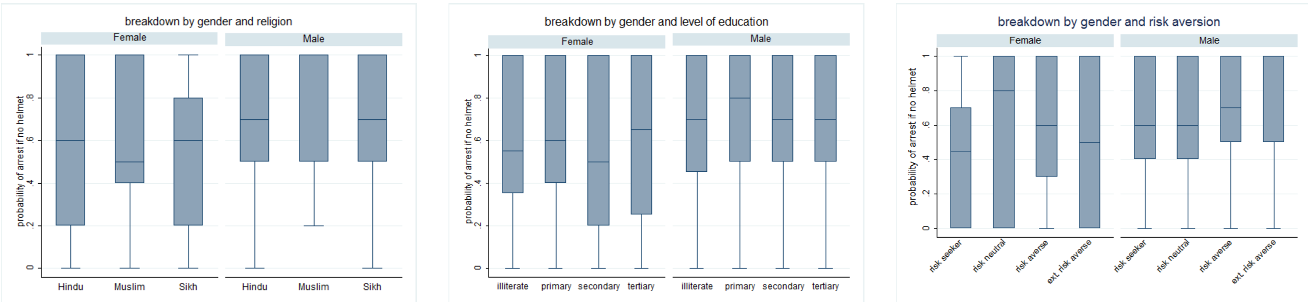
a. Regarding potential injuries if not using a helmet



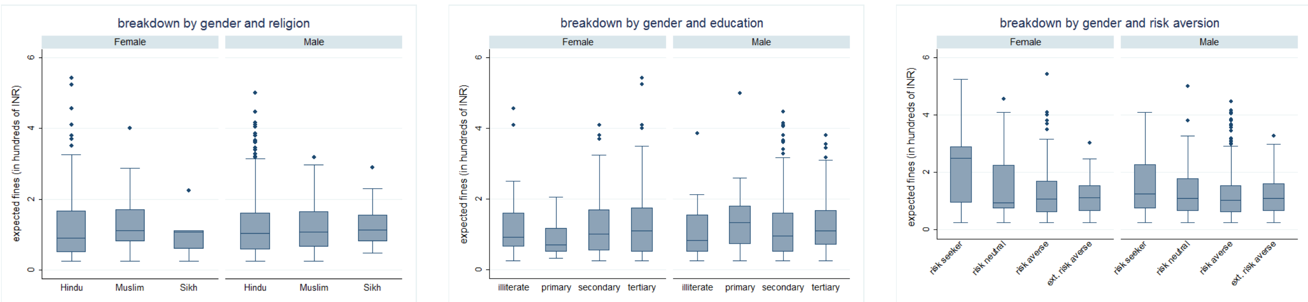
b. Regarding subsequent expected medical expenditures



c. Regarding potential police arrests if not using a helmet



d. Regarding subsequent expected fines



Notes: Answers to the self-assessed risk aversion in general question have been used to build the above graphs.

Following the question regarding the likelihood of being injured, respondents were asked which type of injury would most likely happen in each of the two cases ("in general" and "if no helmet"). Trauma to inferior and superior members are the most commonly cited injuries. However, based on data from one of the biggest hospitals in Delhi, Kumar et al. (2008) highlighted that more than 60% of road related fatalities sustained head injuries. Cerebral trauma is mentioned by only 7% of my sample when considering the "in general" case.[11] This share goes up to 48% of respondents in case the individual is not using a helmet. Nevertheless, this figure is likely to cumulate actual beliefs and the fact that respondents answer what they think they should say.

If the individual said that there was a non zero probability of being in an accident and getting injured if he didn't wear a helmet, he was then interrogated about the medical expenditures he would subsequently encounter. More precisely, respondents were asked the percent chance the medical expenditures would be less than a series of fixed amounts going from 500 INR up to 200,000 INR. Based on the elicited cumulative distribution function, I built the expected cost for each respondent using the following methodology. Let's denote p_{ik} the percent chance that the cost will be less than the amount C_k for individual i. The motorcyclist's expected cost $E_i(C)$ is then equal to :

$$E_i(C) = \sum_{k=1}^{n} (p_{ik} - p_{ik-1}) \cdot \left(\frac{C_k + C_{k-1}}{2} \right)$$

with $\frac{C_k + C_{k-1}}{2}$ the central value of each interval and $p_{ik} - p_{ik-1}$ the percent chance associated to each interval. Initial values C_0 and p_{i0} are equal to zero.

Let's take the example of a respondent who answered that there was a 20% chance the health expenses would be less than 500 INR, 50% chance that they would be less than 1,000 INR and 100% chance that they wouldn't exceed 1,500 INR. Following the above formula, this person's expected medical expenditures amounted to 900 INR ($0.2 \times 250 + 0.3 \times 750 + 0.5 \times 1{,}250$).

The average expected medical cost is 5,189 INR.[12] We observe a lot of heterogeneity across motorcyclists, the standard deviation being equal to 9,012 INR (cf. Table 2). Based on provided answers, the 25$^{\text{th}}$ and the 75$^{\text{th}}$ percentiles were derived through linear extrapolation. When a respondent gave for the first proposed amount a higher percentage than 25% or 75%, the lowest amount of medical expenditures (500 INR) was imputed to the related percentile. Interquartile range (75$^{\text{th}}$ percentile - 25$^{\text{th}}$ percentile) captures the uncertainty individuals have regarding the potential financial costs. Uncertainty regarding potential medical expenditures appears to vary a lot across respondents. Some individuals may consider both minor and extremely severe injuries when answering the outcome question while others may have a clear opinion of what type of injuries they would face. Expectation and uncertainty parameters of medical expenditures are significantly correlated with the type of injuries a person thinks he would suffer

[11] No significant differences are detected when comparing motorcyclists who declare using or not the helmet and this no matter the trip circumstance considered.

[12] I unfortunately can't compare this figure with actual medical expenses faced by road victims due to unavailability of hospital data.

from if he wasn't wearing a helmet at the time of the crash. More precisely, they are positively related to head trauma and negatively correlated with injuries to superior or inferior members.

Table 2: Summary statistics of expected medical expenditures and fines

	observations	mean	std. dev.	median	minimum	maximum
Expected costs (in INR)						
medical expenditures	*772*	5,189	9,012	1,688	250	64,003
fines	*760*	129	103	105	25	783
Interquartile range (in INR)						
medical expenditures	*772*	6,718	15,039	1,500	0	94,000
fines	*760*	112	109	88	0	500

FORMULATION OF QUESTIONS
Medical expenditures
"Thinking about the medical expenditure you would have to pay if you were injured in the road crash right now without wearing a helmet, what do you think is the percent chance that this amount will be less than X INR ?"
A serie of fixed amounts going from 500 INR up to 200,000 INR were proposed, the enumerator kept on proposing higher amounts till the respondent answered 100%.

Fines
"Thinking about the fine you would have to pay if you were stopped by the police right now without wearing a helmet, what do you think is the percent chance that this amount will be less than X INR ?"
A serie of fixed amounts going from 50 INR up to 1,000 INR were offered.

Variables built
1. Based on provided answers, the expected cost $E_i(C)$ was computed: $E_i(C) = \sum_{k=1}^{n}(p_{ik} - p_{ik-1}) \cdot \left(\frac{C_k + C_{k-1}}{2}\right)$, with p_{ik} the percent chance that the cost will be less than the amount Y_k for individual i, $\frac{C_k + C_{k-1}}{2}$ the central value of each interval and $p_{ik} - p_{ik-1}$ the percent chance associated to each interval. Initial values C_0 and p_{i0} being equal to zero.

2. The interquartile range, which corresponds to the difference between the 75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles, has also been computed. Based on provided answers, the 25$^{\text{th}}$ and the 75$^{\text{th}}$ percentiles were derived through linear extrapolation. When a respondent gave for the first proposed amount a higher percentage than 25 or 75, the lowest amount of medical expenditures (500 INR) was imputed to the percentile.

3.2.3 Probability of police arrest and subsequent fines

The mandatory helmet law aims at providing incentives toward helmet use through financial penalties. Nonetheless, such sanctions are likely to modify motorcyclists' behavior only if they are credible and sizeable enough. To capture the actual beliefs of motorcyclists regarding helmet legislation, respondents were asked about their perception of road rules enforcement. More precisely, their subjective probabilities of being stopped by the police in three different situations were assessed. In addition to the "in general" and "if no helmet" cases, individuals were asked the likelihood they would be stopped by the police for no reason (situation hereinafter labelled "for no reason"). It seemed important to set this third case given that unfair and random police sanctions may have an unproductive and potentially adverse effect on safety decisions. From Table 1, it appears that the mean of the perceived probability of being stopped by the police in the "no helmet" situation is much higher than "in general" or "for no reason" (0.65 vs. 0.36-0.39). The variance is also a bit higher.

As previously, when the respondent said that there was a strictly positive probability of being stopped by the police when not wearing a helmet, his expectations regarding the fine amount were elicited by the interviewer. More precisely, interviewees were asked the percent chance the financial penalties would be less than a series of fixed amounts going from 50 INR up to 1,000 INR; the official fine for infringing the helmet law being 100 INR. Following the same methodology as the one used to derive the expected medical expenditures, expected fines have been computed for each individual. The individual's uncertainty regarding the level of financial penalties has also been derived by computing the interquartile range. On average, motorcyclists slightly overestimate the financial sanctions, the observed mean of expected fines across respondents in the sample being 129 INR (cf. Table 2).[13] Nonetheless, the variation in answers is quite important and half of the respondents have expectations which do not exceed the official fine. The dispersion parameter also indicates that the level of the official fine is somewhat unclear for many individuals given that on average interviewees gave an interquartile range which is higher than the official fine (112 INR).

After this presentation of the collected data, and before turning to the empirical analysis, I discuss in the next section the potential mechanisms at play in the formation of the subjective expectations of injury and fine as well as the expected role of such beliefs in the decision to wear a helmet or not.

4 Mechanisms at play

I approach the problem from the theoretical side. This discussion will serve to guide the following empirical analysis.

First, I consider the formation and updating of individuals' beliefs regarding the medical expenditures and fines they expect to pay if they don't use a helmet. In particular, I look whether personal experiences of road crash or traffic police arrest influence motorcyclists' expectations. In a second step, I discuss the theoretical role of expectations on the decision of helmet use

[13] One may argue that the proposed pre determined scale may have biased answers upward given that it starts at 50 INR. Nevertheless, respondents were not told the maximum offered amount (1,000 INR) and 75% of interviewees said the maximum possible fine was below 300 INR (90% below 500 INR). I acknowledge however that it could have been preferable to have a scale starting at 25 INR and increasing by a smaller amount. This would have allowed me to obtain more accurate information. Moreover, I cannot rule out the possibility that respondents also include in the financial consequences of being caught by the police for helmet non use additional fines related to other road regulations they would have simultaneously violated.

along with additional variables which may directly impact the adoption of a head protection device.

4.1 Influence of previous experiences on expectations

From every motorbike trip, individuals obtain new information with respect to the health and financial risks they face from not using a helmet. This new information can, as defined by Haselhuhn et al. (2012), come from a traffic accident they witness (information via observation) or from being involved in a road crash themselves (information via personal experience). Motorcyclists are also likely to modify their beliefs after hearing the story of someone who suffered from road injuries (information via description).

Being involved in an accident and injured or being caught by the police while not wearing a helmet certainly increase the subjective probabilities that such events occur. Nonetheless, the effect of personal experiences on expected medical costs and expected fines are more ambiguous. More precisely, whether personal experience increases or decreases expected outcomes depends on (i) the individual's prior belief and (ii) the severity of the loss the person faces. In other words, if a person, who expected to face tremendous medical expenditures in case of a road crash, is involved in a minor accident, he will certainly correct his expectations downward. If instead, the motorcyclist thought that he would not be injured at all, he will rather modify his beliefs upward. Furthermore, a person is likely to decrease or increase the expected fine to be paid in case of police halt if he was respectively able to corrupt or not the police officer. Finally, a same road experience may have different lasting effects depending on the frequency at which the victim uses the motorbike after the event.

One may think of many other variables which may play a role in the formation of individuals' expectations. Older people have had more time to experience road accident or police arrest. As for women, given their low participation in the labor market, they are much less exposed to motorbike risks. Despite the influence of socio demographics, I mainly focus, in my empirical analysis, on previous experiences. Due to the cross section data at hand, I acknowledge that I am neither able to properly study the updating process nor to estimate accurately the impact of a road crash or a police arrest on one's expectations.[14] Nevertheless, I can look whether individuals who experienced a traffic accident or who have been sanctioned by the traffic police report significantly different beliefs regarding injuries and fines.

4.2 Potential influence of expectations on helmet adoption

Unconditional expected costs

When investigating the impact of expectations on helmet adoption, it seems relevant to consider the product of the subjective probabilities and subsequent expected outcomes rather than the

[14] Panel data could permit to estimate the influence of such events by comparing before and after level of expectations.

two dimensions separately. Indeed, on the one hand, two motorcyclists who think they will certainly be caught by the police if they don't wear a helmet but who have different expectations in terms of fines to be paid may not adopt the same conduct. On the other hand, a motorcyclist who thinks that he has a low probability of being injured but that he will suffer from severe injuries, should this occur, and a person who believes he has a high probability of accident but the subsequent medical expenditures will be rather small may opt for the same attitude toward helmet use. This product of variables is called unconditional expected costs in the empirical analysis.

Different influence of expectations depending on trip circumstances

Helmet use is a renewed decision, i.e. individuals decide to use a helmet or not before each of their motorbike trips. The characteristics of each journey (its length, the type of roads taken, etc.) are therefore likely to influence the use of head protection. Habits and routines may also to some extent be adopted by motorcyclists who will always use the helmet in some circumstances and never in others. Very short trips in small streets are commonly assumed to be less dangerous in terms of injuries. While statistics from developed countries showed that a large share of accidents occur very close to the victims' home,[15] road users often only consider the risk of injuries in long distance trips on big roads where a lot of vehicles circulate at a high speed. A reason for that may be the willingness not to take into account all the risks, so as to limit the stress generated by the fear of injuries. Indian motorcyclists may follow a similar reasoning. Furthermore, the probability of crash remains low for short distance trips when compared to the number of times a person takes the same path. Given this difficulty in internalizing all the health risks constantly faced, it would not be surprising that expectations of injuries only influence helmet use in long trips on main roads. On the contrary, traffic police operates throughout the city, both on main inner city roads and within neighborhoods. Therefore, the threat of financial penalties is more likely to impact helmet use on short distance trips.

Additional variables impacting the expected costs and gains of helmet use

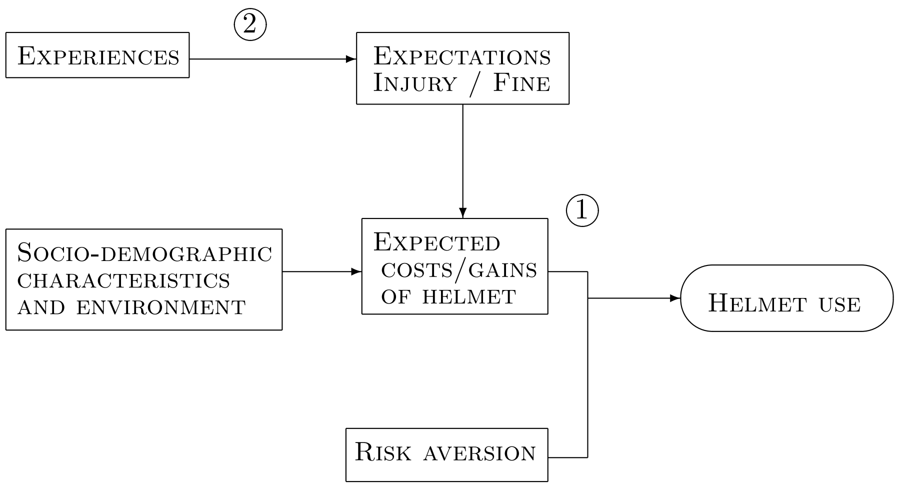
Other important determinants of helmet use include preferences toward risk. Indeed, a more risk averse individual will prefer to adopt a safe conduct to avoid the potential loss. Results from a previous paper (Grimm and Treibich, 2014) show that, indeed, more risk averse drivers wear a helmet more often. However, this relation is not found for passengers. Age is likely as well to affect the individual's time preference rate through the horizon over which the person discounts the consequences of a negative event. As for the level of education, it may capture

[15] This is the case of France where 75 % of road casualties are locals, pedestrians or occupants of vehicles registered in the district. A peak of mortality is also observed around 6 pm, when people return from work (www.securite-routiere.gouv.fr). Unfortunately, to my knowledge, no such data is available for the city of Delhi or at the Indian national level.

the person's ability to collect and deal with information regarding road risks. Income earners, in particular heads of households, married people and individuals with children, may also opt for a safer conduct because of their family responsibilities and the additional financial consequences implied by a temporary or permanent incapacity to work. Moreover, access to health care may also matter, through the mitigation of negative health consequences. Finally, people who believe that their life is in the hand of a superior force and that their date of death is already written may decide not to use a helmet despite high expectations of injuries.

Figure 3 summarizes the main channels through which individuals may form their expectations of injury and fine and then choose whether to wear a helmet or not, in different traveling circumstances. The discussion above aimed at highlighting the role of previous experiences in the formation and updating of individuals' beliefs regarding injury and fine in case one doesn't use a helmet as well as the potential role of these expectations on helmet adoption. This guides my empirical analysis. In particular by helping me to decide which explanatory variables should be introduced in the different regressions of my empirical study.

Figure 3: Formation of expectations and their influence on helmet adoption



Research questions:

1 To what extent expectations influence helmet use decision?

2 Do individuals' experiences modify their expectations?

5 Empirical analysis

I now empirically test the mechanisms previously brought to light. I first look at the extent to which expectations influence helmet adoption and whether the beliefs regarding injury and fine impact the use of a head protection device in different ways depending on the circumstances of the motorbike trip. In a second step, I explore the influence of previous experiences on subjective probabilities, expected financial consequences and the uncertainty regarding these costs.

5.1 To what extent do expectations influence helmet adoption?

5.1.1 Empirical specification

I investigate here whether fear of injuries and police threat actually make motorcyclists adopt safer road behaviors, in particular toward helmet use.

Dependent variables

As already mentioned, in our survey, two traveling dimensions were considered for helmet use: the type of roads and the length of the motorbike trip. More precisely, three different circumstances were presented to the respondents: trips (i) in residential neighborhoods, (ii) on the main roads for short distances and (iii) on the main roads for long distances. While the first situation refers to narrow streets in residential or market areas, the two last cases correspond to travels on large boulevards where the traffic is often heavy. The richness of the data collected allows me to look at the role of different types of expectations (medical expenditures vs. fines) and in particular whether some beliefs have more impact on specific trip situations.

Variables of interest

My variables of interest are the products of the subjective probabilities of being hurt or stopped by the police if not wearing a helmet, and the related subsequent expected costs. In addition to the argument presented in the previous section, this choice is motivated by the fact that no information regarding expected outcomes is available for people who gave a zero probability for the negative event to occur. I set the unconditional expected costs to zero for those individuals.[16] One may also argue that it is the variance in potential financial consequences or its maximum amount, rather than its expected level, which influence the conduct adopted by motorcyclists. Interquartile range and highest values of outcomes are therefore considered as variables of interest in my robustness checks.

[16] An analysis looking at the two dimensions seperately could be done on the subsample of motorcyclists who gave a non zero subjective probability of being injured and being caught by the police while not wearing a helmet.

Local effects

When studying the relation between expected medical costs and fines on helmet use, local specificities may actually bias the estimates.[17] More precisely, a greater police presence or more numerous road traffic accidents in one neighborhood may lead to an overestimation of the true relation existing between expectations and helmet adoption. On the contrary, better roads, the presence of health centers or more corruptible police officers may lead to an underestimation of the true coefficient. In other words, some unobservable characteristics at the geographical level are likely to be correlated with the independent regressors of interest. However, the direction of this bias is ambiguous.

Identification strategy

New Delhi is divided into 47 police zones, called "circles". A specific police budget and man power is allocated to each of these areas. 32 different circles are present in our survey. On average 28 motorcyclists have been interviewed per circle.[18] I take advantage of this geographical division of the city to capture the local effects. Before implementing this kind of empirical strategy, it is important to make sure that there is enough variation within circles; this in order to avoid making hasty conclusions. Based on the analysis of the intra circle heterogeneity, it seems that dependent and independent variables vary quite substantially, even within one area (cf. Table 12 in Appendix A).

I therefore estimate the following specification:

$$\text{Helmet use}_{it} = \beta_m \cdot UEC_i^{med} + \beta_f \cdot UEC_i^{fine} + \sum_j \gamma_j \cdot X_{ij} + \mu_c + \varepsilon_{it}$$

with i referring to the individual and t to the type of trip. Helmet use$_{it}$ is a binary variable. UEC_i^{med} and UEC_i^{fine} are the unconditional expected medical costs and the unconditional expected fines respectively. X is a set of socio demographic characteristics. Finally, μ_c is a circle fixed effects and coincide with the police zone where the respondent's residence is located.

I run probit regressions including circle dummies and linear probability models with circle fixed effects. I cluster all standard errors at that level to control for potential autocorrelation in the error terms. My variables of interest are the unconditional expected costs. I include several individual characteristics which are likely to be correlated to both expectations and helmet adoption and which thus may bias my estimates. More precisely, I introduce gender, age, education level, marital status, number of children, household monthly income, personal contribution to the family revenues, religious beliefs, preferences toward risk and health insurance.

[17]This issue is actually not relevant when looking at the influence of risk aversion on road safety efforts (helmet use and choice of speed), as done in Grimm and Treibich (2014). Indeed, in that case, it is rather the interviewers themselves who potentially influence the declared helmet use and the elicited risk aversion and not the local environment.

[18]However, this number varies from a minimum of 5 to a maximum of 141. The median is 24.

Indeed, as pointed out in the previous section, these variables are likely to be correlated with helmet adoption (through the expected costs and gains of helmet use) and to individuals' beliefs regarding risk of injury and fine (through the likelihood that the person has already experienced a road crash or a police arrest). Introducing circle fixed effects in the estimations allows me to capture the previously mentioned specificities of each area along with the behaviors adopted by respondents' neighbors and the socio economic status of each residential locality. However, as Manski (1993) pointed out in his reflection problem, these various effects are difficult to disentangle given that people with similar tastes and characteristics may select themselves into the same circles. Therefore, the absence of significant impact of some of the explanatory variables might be actually due to their too limited variation within a circle. From Table 12, we note that for some of the socio demographic characteristics this may be a concern. Furthermore, while circle effects pick up part of the differences in actual risks faced by individuals in different neighborhoods, it does not annihilate them completely. This because of, for instance, different traveling hours, different routes taken or different driving skills of motorcyclists living in the same police zone.

5.1.2 Results

I first introduce the unconditional expected medical expenditures and the unconditional expected fines in an additive way (see odd columns of Table 3). In a second step, I account for the correlation existing between the two types of beliefs[19] by introducing an interaction term (see even columns of Table 3). Police threat and fear of injuries appear to impact helmet use in different ways, depending on the traveling situation considered. Indeed, it seems that expectations with respect to fines increase helmet use on short distance trips. On the contrary, higher expected medical expenditures lead to greater helmet adoption on long distance trips only. Probit and linear probability estimates give similar results. The linear probability model provides coefficients which are easier to interpret. I therefore focus on those estimates when interpreting the results. With this latter method, I obtain that a raise of 1,000 INR in the unconditional expected medical costs increases by a bit less than 0.9% the probability that the person wear a helmet. A raise of 100 INR in the unconditional expected fines increases by respectively 8% and 6.8% the probability of using a helmet for short trips on main roads and trips in residential neighborhoods.

Table 4 reports the results obtained for the additional explanatory variables introduced in the regressions presented in the even columns of Table 3. Men are significantly more likely to use a helmet than women, and Sikhs significantly less likely than motorcyclists belonging to other religious communities. More precisely, when considering long trips, the probability of using a helmet increases by 40% if the motorcyclist is a man and decreases by 27% if he or she is a Sikh. These findings are not surprising given that the Sikhs successfully lobbied against

[19] The pairwise correlation coefficient is significant at 1% level of confidence and is equal to 0.236.

Table 3: Influence of expectations on helmet use - using unconditional expected costs

Helmet use	on main roads				trips in the neighborhoods	
	long trips		short trips			
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Probit estimations with circle dummies						
UEC medical expenditures (th. INR)	0.042	0.075**	0.001	0.004	0.002	0.025
	(0.031)	(0.031)	(0.016)	(0.017)	(0.015)	(0.022)
UEC fines (hund. INR)	0.032	0.122	0.356***	0.365***	0.154*	0.227**
	(0.117)	(0.125)	(0.122)	(0.131)	(0.083)	(0.092)
UEC medical expenditures × UEC fines		-0.020**		-0.002		-0.014
		(0.010)		(0.010)		(0.009)
Pseudo R^2	0.375	0.379	0.342	0.342	0.279	0.282
observations	*610*	*610*	*663*	*663*	*660*	*660*
Panel B - LPM estimations with circle fixed effects						
UEC medical expenditures (th. INR)	0.005	0.009**	-0.000	0.001	0.001	0.008
	(0.018)	(0.018)	(0.017)	(0.019)	(0.022)	(0.023)
UEC fines (hund. INR)	0.012	0.024	0.077***	0.081***	0.049**	0.068***
	(0.012)	(0.018)	(0.015)	(0.019)	(0.017)	(0.023)
UEC medical expenditures × UEC fines		-0.003*		-0.001		-0.004
		(0.001)		(0.001)		(0.003)
Hausman test OLS vs. FE (p-value)	0.000	0.001	0.093	0.432	0.000	0.970
R^2 (within)	0.297	0.300	0.261	0.262	0.243	0.247
observations	*670*	*670*	*673*	*673*	*665*	*665*

Notes: *** 1%, ** 5% and * 10% significance. Clustered standard errors are reported in parenthesis. Controls are marital status, # of children, head of hh, gender, age, income, education level, contribution to income, Sikh, caste, risk aversion, health insurance and existence of a superior force.

the use of helmet on the ground that it goes against their religious beliefs. They managed to be exempted from this obligation by the Delhi government. De facto, the helmet law is not enforced for any woman due to the difficulty to distinguish a Sikh from a Hindu or a Muslim. Having a health insurance has a significant and negative impact on helmet use only for long distance trips when not controlling for the circle of residence (Table not shown). The absence of effect of access to health care on helmet use may actually be explained by the inefficiency of ambulatory services. According to Hsiao et al. (2013), 58% of all road traffic injury deaths in India occur on the scene of the collision, either immediately or while waiting for the emergency ambulance to come. Interestingly, we note that the more risk averse individuals are, the les likely they use a helmet on long distance trips; the coefficients are actually not significant once local effects are introduced. No effect of income or impact of education are detected.

Table 4: Influence of expectations on helmet use - additional explanatory variables

Helmet use	on main roads				trips in the neighborhoods	
	long trips		short trips			
	(1)	(2)	(3)	(4)	(5)	(6)
Panel (cf. Table 3)	B	A	B	A	B	A
UEC medical expenditures (th. INR)	0.009**	0.075**	0.001	0.004	0.008	0.025
	(0.004)	(0.031)	(0.005)	(0.017)	(0.006)	(0.022)
UEC fines (hund. INR)	0.024	0.122	0.081***	0.365***	0.068***	0.227**
	(0.018)	(0.125)	(0.019)	(0.131)	(0.023)	(0.092)
UEC medical expenditures × UEC fines	-0.003*	-0.020**	-0.001	-0.002	-0.004	-0.014
	(0.001)	(0.010)	(0.001)	(0.010)	(0.003)	(0.009)
Male (=1)	0.405***	1.777***	0.415***	1.490***	0.385***	1.172***
	(0.052)	(0.194)	(0.061)	(0.229)	(0.071)	(0.248)
Married (=1)	-0.003	-0.071	0.044	0.205	0.012	0.067
	(0.045)	(0.226)	(0.056)	(0.203)	(0.072)	(0.258)
# of children	0.005	0.078	-0.006	-0.029	-0.012	-0.053
	(0.016)	(0.093)	(0.016)	(0.061)	(0.020)	(0.073)
Head of HH (=1)	0.002	-0.094	0.043	0.160	0.055	0.194
	(0.040)	(0.311)	(0.048)	(0.189)	(0.049)	(0.170)
Age (in years)	-0.003	-0.014	-0.002	-0.009	-0.002	-0.007
	(0.002)	(0.014)	(0.002)	(0.007)	(0.001)	(0.005)
Level of education (3 groups)	-0.012	-0.043	0.048	0.143	0.051	0.156
	(0.029)	(0.154)	(0.029)	(0.114)	(0.031)	(0.110)
Household monthly income, *ref: less than 10,000 INR*						
10,000 to 20,000 INR	-0.009	0.053	-0.003	0.034	0.025	0.062
	(0.041)	(0.255)	(0.046)	(0.172)	(0.053)	(0.186)
above 20,000 INR	0.016	0.105	0.096	0.422	0.096	0.327
	(0.043)	(0.241)	(0.064)	(0.279)	(0.078)	(0.288)
Share of one's contribution to income	0.053	0.353	0.005	0.018	0.065	0.263
	(0.070)	(0.482)	(0.085)	(0.317)	(0.076)	(0.261)
Sikh (=1)	-0.271*	-1.222**	-0.223	-0.975*	-0.219	-0.959*
	(0.140)	(0.578)	(0.141)	(0.503)	(0.131)	(0.532)
Belongs to a low caste (=1)	-0.031	-0.230	-0.080*	-0.327*	-0.060	-0.215
	(0.044)	(0.225)	(0.045)	(0.169)	(0.054)	(0.185)
Has health insurance (=1)	-0.002	-0.109	-0.018	-0.078	-0.039	-0.076
	(0.028)	(0.163)	(0.048)	(0.181)	(0.054)	(0.186)
Believes fate is in god's hands (=1)	0.002	-0.011	-0.063	-0.193	-0.134	-0.399
	(0.030)	(0.161)	(0.078)	(0.272)	(0.080)	(0.258)
Risk aversion score	-0.028	-0.111	0.012	0.059	-0.001	0.005
	(0.026)	(0.138)	(0.027)	(0.097)	(0.029)	(0.105)
R^2	0.300		0.262		0.247	
Pseudo R^2		0.379		0.342		0.282
observations	*670*	*610*	*673*	*663*	*665*	*660*

Notes: *** 1%, ** 5% and * 10% significance. Clustered standard errors are reported in parenthesis.

5.1.3 Differenciated influence of expectations on helmet use

Socio demographic characteristics of individuals, in particular gender and income are likely to modify the influence of expectations on helmet adoption. In order to study such differenciated effects, I interact the unconditional expected costs with gender, level of income and preferences toward risk. Results are reported in Tables 5 and 6. Interestingly, I find that among women a raise of 1,000 INR in the unconditional medical expenditures increases the probability of using a helmet on short trips on main roads by 1.4%. Moreover, among the poorest individuals (31% of the sample), a raise of 100 INR in the unconditional expected fines increases the probability of wearing a helmet by 12.4% against an increase by only 6.3% among the wealthiest individuals (17% of the sample). Finally, the impact of unconditional expected fines on helmet use for short trips on main roads decreases with the level of risk aversion of motorcyclists (Table not shown). This finding may be explained by the fact that preferences toward risk already partly influence the behavior of more risk averse motorcyclists.

Table 5: Differenciated influence of expectations on helmet use by gender

Helmet use	on main roads				trips in the neighborhoods	
	long trips		short trips			
	(1)	(2)	(3)	(4)	(5)	(6)
Male (=1)	0.405***	0.420***	0.415***	0.473***	0.385***	0.385***
	(0.052)	(0.060)	(0.061)	(0.059)	(0.071)	(0.063)
UEC medical expenditures (th. INR)	0.009**	0.018*	0.001	0.014**	0.008	0.016
	(0.004)	(0.009)	(0.005)	(0.007)	(0.006)	(0.012)
Male × UEC medical expenditures		-0.012		-0.018**		-0.012
		(0.009)		(0.007)		(0.011)
UEC fines (hund. INR)	0.024	0.006	0.081***	0.079**	0.068***	0.039
	(0.018)	(0.045)	(0.019)	(0.035)	(0.023)	(0.029)
UEC medical expenditures × UEC fines	-0.003*	-0.003	-0.001	-0.001	-0.004	-0.004
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Male × UEC fines		0.025		-0.002		0.041
		(0.052)		(0.045)		(0.034)
R^2	0.300	0.304	0.262	0.270	0.247	0.250
observations	*670*	*670*	*673*	*673*	*665*	*665*

Notes: *** 1%, ** 5% and * 10% significance. Additional controls are marital status, # of children, head of hh, age, education, income, contribution to income, Sikh, caste, risk aversion, health insurance and existence of a superior force. LPM estimations with circle fixed effects (cf. Table 3, Panel B - columns (2), (4) and (6)).

Table 6: Differenciated influence of expectations on helmet use by income

Helmet use	on main roads				trips in the neighborhoods	
	long trips		short trips			
	(1)	(2)	(3)	(4)	(5)	(6)
Monthly household income, *ref: above 20,000 INR (rich)*						
less than 10,000 INR (poor)	-0.016	-0.055	-0.096	-0.159**	-0.096	-0.149
	(0.043)	(0.060)	(0.064)	(0.075)	(0.078)	(0.094)
between 10,000 and 20,000 INR (middle)	-0.025	-0.036	-0.099**	-0.101	-0.070	-0.151***
	(0.040)	(0.050)	(0.041)	(0.063)	(0.048)	(0.055)
UEC fines (hund. INR)	0.024	0.014	0.081***	0.063**	0.068***	0.011
	(0.018)	(0.035)	(0.019)	(0.027)	(0.023)	(0.036)
poor $\times$ UEC fines		0.039		0.061*		0.056
		(0.035)		(0.030)		(0.048)
middle $\times$ UEC fines		0.010		-0.002		0.087**
		(0.034)		(0.034)		(0.033)
R^2	0.300	0.309	0.262	0.268	0.247	0.251
observations	*670*	*670*	*673*	*673*	*665*	*665*

Notes: *** 1%, ** 5% and * 10% significance. Additional controls are marital status, # of children, head of hh, age, education, gender, contribution to income, Sikh, caste, risk aversion, health insurance and existence of a superior force. LPM estimations with circle fixed effects (cf. Table 3, Panel B - columns (2), (4) and (6)).

5.1.4 Robustness checks

In order to provide evidence for the reliability of my results, I implement different robustness checks, the results of which are reported hereinafter.

Considering alternative information of the expected outcomes' distribution

One may argue that it is the variance in potential financial consequences or its highest possible value (i.e. the costs corresponding to the worst case scenario the individual has in mind), rather than its expected level, which motivates the conduct adopted by motorcyclists. When replacing expected costs by the interquartile range, the 75$^{\text{th}}$ percentile or the maximum value, I find similar results regarding the influence of expectations on helmet use (cf. Table 14).

Tackling the reverse causality issue

One main concern regarding the previous results is the possibility that individuals who decide not to wear a helmet may report lower expectations of negative consequences in order to reduce the stress induced by the behaviors they choose to adopt. This effect is known as cognitive dissonance and has been first highlighted by Akerlof and Dickens (1982). In order to tackle the reverse causality issue previously mentioned, I try to show that helmet use does not cause subjective expectations regarding injury or fine. I take advantage of a regulation implemented in Delhi since July 2009 that makes it compulsory to provide a helmet with every new motorbike that is sold. I regress helmet use on unconditional expected costs instrumenting the former variable by mandatory helmet provision. More precisely, the instrument takes value one if the respondent is a driver and rides a motorbike purchased first hand less than two years ago. I assume that this variable is indeed exogenous and unrelated with any omitted variable. Results presented in Table 15 show that the instrumental variable (helmet provision) is positively and significantly correlated with the endogenous regressor (helmet use) and that helmet adoption does not explain fine or injury expectations.

Individual omitted characteristics

I acknowledge that some individual's characteristics (such as optimism, overconfidence regarding one's driving skills, level of speed or road habits) still remain unobserved and might bias my results. Optimism, for instance, is likely to reduce the subjective probability of accident and the size of injury. Similarly, overconfident drivers are likely to think they are able to avoid both police officers and road crashes. These two as yet unobserved characteristics are negatively correlated with expectations regarding the usefulness of a helmet. On the contrary, the velocity at which motorcyclists travel may influence both expectations of medical expenditures and helmet adoption. Speed certainly increases the probability of accident and the severity of injuries. If low speed and helmet use are substitutes, individuals with high expectations of injuries may decide to reduce their speed instead of wearing a helmet. The estimates would in that case be an overestimation of the true relation between beliefs and head protection use. In Table 16 (Appendix D), I add the following variables to the previous specifications: average speed (Panel 1), road habits (Panel 2) and confidence on one's driving skills (Panel 3 for the drivers subsample). Similar results are found regarding the influence of expectations on helmet adoption. In addition, we note that expectations of fines also increase helmet use on long distance trips when average speed or confidence are included in the regressions. Moreover, speed appears to be positively correlated with helmet use on long journeys. Individuals who frequently use a motorbike are significantly more likely to wear a helmet when traveling on main roads. Finally, drivers who believe they drive better than others are less likely to use a helmet for long trips or trips in neighbourhoods. Adding these different characteristics leads to a reduction of the sample but findings are consistent with the previous results providing that my attempts to control for omitted local environmental variables have already given reliable estimates.

Excluding individuals who did not seem to understand the probability scale
The understanding, by all respondents, of the probability scale used to derive subjective probabilities may be questioned. Before eliciting subjective expectations of probabilities and outcomes regarding injury and fine, several questions were asked to interviewees in order to be able to verify whether they properly understood the probability scale (cf. Appendix E). I compare the results reported in the even columns of Table 3 to the coefficients obtained if excluding individuals who did not correctly answered to the check questions (see Table 18). Similar findings of the influence of expectations on helmet adoption are found for the different samples considered (excluding individuals who answered incorrectly to one or several check questions). The absence of a significant effect of unconditional expected fines on helmet use for short distance trips in column (6) is plausibly only due to the reduced size of the sample (306 observations against 670 in the main analysis).

5.2 Do individuals' experiences modify their expectations?

5.2.1 Empirical specification

I subsequently consider the subjective probabilities, the expected costs and the uncertainty regarding these costs which is captured by the interquartile range. I run ordinary least square regressions with and without circle fixed effects. The former estimations capture the differences in health hazards and police enforcement intensity across police zones. Given that for several of my variables of interest no variation is found within a circle (cf. Table 13), the results from the regressions without circle fixed effects are likely to be more reliable. In all regressions, I control for the frequency and the purpose of motorbike use in order to control, at least partly, for the probability that the motorcyclist experienced either a road crash or a police arrest. In addition, religious practices are also included in the analysis as they may actually alter individuals' beliefs.

5.2.2 Influence of road traffic experiences on injury expectations

Both personal and relatives' experiences of road crash are introduced as dummy variables in the analysis. As mentioned previously, the purpose and the frequency of motorbike use control for possible differences in road risks and therefore for the probability of being involved in an accident.[20] Furthermore, the trauma caused by one experience of crash is likely to have a smaller impact on people who frequently use this mode of transportation and who balance this negative event with many safe journeys. I thus introduce an interaction term between frequency of motorbike use and personal involvement in a road accident.

Table 7 reports the results found for the different specifications described above. It appears that knowing someone who has been involved in an accident increases by 0.09 the subjective probability of being injured in a road crash if not using a helmet, while personal experience has no significant impact. Different reasons may explain this finding. First, personal involvement in a traffic accident may correspond to very different events. Second, a sample selection may be at play as individuals who suffered from severe road injuries may no longer use a motorbike or may not even have survived the crash.[21] Third, remembering that a friend or a family member got caught in a traffic accident is more likely if this crash was quite severe. As expected, frequent use of a motorbike decreases the impact of personal road crash on the subjective probability of being injured. Interestingly, involvement in an accident decreases the uncertainty related to medical costs. Following an accident, individuals actually seem to have a clearer idea of the health risks they face. While praying daily decreases one's subjective probability of being injured in a road crash when not using a helmet, expected medical expenditures and variation in these costs are higher among religious individuals who personally experienced a road accident than among those who didn't.

Finally, differences in road quality and incidence of road crash between neighborhoods may partly explain the level of expectations as the influence of knowing a person who got caught in an accident vanishes once circle fixed effects are introduced. In 15 circles out of 32, none of the respondents knew a person who got involved in a road traffic accident. This may either support the quality of roads argument or imply that fixed effects estimations cannot capture the effect of knowing someone who got caught in a crash because individuals are rather homogenous within areas.

[20] In my sample, individuals who frequently use a motorbike are more likely to have personally experienced a road crash.

[21] While information on the severity of the accident was gathered, very few individuals (2% of the sample) were involved in a severe crash.

Table 7: Determinants of injury expectations

	subjective probability of injury if no helmet		subsequent outcomes			
			expected costs		interquartile range	
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced a road crash (=1)	0.078	0.042	-6.092***	-5.377**	-9.576***	-8.266**
	(0.080)	(0.052)	(1.366)	(2.146)	(2.553)	(3.607)
Has a relative involved in a road crash (=1)	0.093**	0.030	1.554	2.275	2.070	3.226
	(0.041)	(0.040)	(1.814)	(1.500)	(2.910)	(2.149)
Uses the moto to commute to work (=1)	0.044*	0.068***	-0.124	0.071	0.411	0.758
	(0.025)	(0.019)	(0.770)	(0.583)	(1.278)	(0.851)
Uses the moto frequently (=1)	0.071***	0.053**	-2.450***	-0.676	-3.804***	-1.254
	(0.025)	(0.023)	(0.723)	(1.064)	(1.192)	(1.769)
Experienced a road crash × Uses the moto frequently	-0.151**	-0.125	4.425**	2.263	7.670*	4.119
	(0.073)	(0.080)	(2.176)	(2.129)	(4.330)	(4.422)
Prays daily (=1)	-0.142***	-0.069***	-1.300*	-1.059	-1.714	-1.420
	(0.024)	(0.023)	(0.771)	(0.759)	(1.285)	(1.208)
Experienced a road crash × Prays daily	0.094	0.065	5.128***	5.668**	9.639***	10.401**
	(0.087)	(0.072)	(1.811)	(2.210)	(3.484)	(4.183)
Specification	OLS	FE	OLS	FE	OLS	FE
Hausman test OLS vs. FE (p-value)		-		-		0.000
R^2	0.077		0.028		0.026	
R^2 within		0.048		0.017		0.018
observations	*828*	*828*	*765*	*765*	*765*	*765*

Notes: Robust standard errors are reported in parenthesis. *** 1%, ** 5% and * 10% significance.

Remark: The difference in the number of observations comes from the fact that individuals who gave a zero probability of injury did not answer to the medical expenditure questions. Moreover some respondents who gave a non zero probability did not reply to the outcome questions.

5.2.3 Influence of interactions with the traffic police on fine expectations

I now turn to the influence of personal experiences on fine expectations. Besides previous police arrests for infringing road rules, individuals' subjective probability of being stopped by the police for no reason and the possibility of bribing police officers are my variables of interest. The former may capture the discretionary power of the police and the latter the bargaining power of the motorcyclist.[22] Both can be considered as proxies for previous interactions with traffic forces and might impact individuals' expectations. As previously, road exposure and religious practices are introduced in all regressions.

From Table 8, it seems that having been already sanctioned by the traffic police increases both the subjective probability of being caught if infringing the helmet law and expected fines. Moreover, uncertainty with respect to the financial penalty is also higher for those motorcyclists. This latter effect may be explained by repeated sanctions of different amounts.

Many of the impacts found vanish when circle fixed effects are considered. Differences in expectations may therefore also come from actual differences in police enforcement intensity in each circle. Nontheless, I acknowledge that this result may be simply caused by the reduced variation within a circle. In 11 circles, none of the respondents reports having been stopped by the traffic police.

[22] Expectations and opinion on the work made by the traffic police may actually be both related with a third variable which reflects the individual's acceptance of authorities and their power.

Table 8: Determinants of fine expectations

	subjective probability of injury if no helmet		subsequent outcomes			
			expected costs		interquartile range	
	(1)	(2)	(3)	(4)	(5)	(6)
Has been sanctionned by the police (=1)	0.086*	0.032	0.598**	0.538*	0.516**	0.469*
	(0.046)	(0.035)	(0.244)	(0.297)	(0.214)	(0.273)
Discretionnary power of police †	0.271***	0.189***	0.281**	0.168	0.492***	0.206
	(0.041)	(0.061)	(0.123)	(0.198)	(0.144)	(0.243)
Police officers can be bribed (=1)	-0.045*	-0.041	-0.085	-0.126	-0.093	-0.153
	(0.023)	(0.025)	(0.081)	(0.100)	(0.084)	(0.100)
Uses the moto to commute to work (=1)	0.011	0.034*	0.002	0.045	0.009	0.038
	(0.027)	(0.018)	(0.086)	(0.084)	(0.091)	(0.083)
Uses the moto frequently (=1)	0.029	0.038	-0.098	-0.051	0.010	0.023
	(0.026)	(0.027)	(0.083)	(0.090)	(0.087)	(0.077)
Prays daily (=1)	-0.050**	-0.041	-0.137	-0.006	-0.224**	-0.120
	(0.025)	(0.029)	(0.089)	(0.074)	(0.101)	(0.097)
Specification	OLS	FE	OLS	FE	OLS	FE
Hausman test OLS vs. FE (p-value)		0.000		0.000		0.000
R^2	0.076		0.030		0.041	
R^2 within		0.050		0.028		0.028
observations	*821*	*821*	*702*	*702*	*702*	*702*

Notes: Robust standard errors are reported in parenthesis. *** 1%, ** 5% and * 10% significance.
Remark: The difference in the number of observations comes from the fact that individuals who gave a zero probability of arrest did not answer to the questions on fines. Moreover some respondents who gave a non zero probability did not reply to the outcome questions. † Probability of arrest by the traffic police for no reason.

5.2.4 On the direct influence of experiences on helmet use

In the analysis above, I assume that experiences only influence helmet adoption indirectly through expectations, these being updated based on the new information the individual gets from a road traffic accident or a police arrest.

Nonetheless, the event *per se* is likely to impact the safety conduct adopted by motorcyclists. Haselhuhn et al. (2012) used data on video rental fines and showed that, controlling for the level of information regarding the financial sanctions of a delay in returning the video, previous experience with a fine significantly improves the future compliance rate. Using the same specification as the one presented in the Panel B of Table 3, I introduce road crash and police arrest as explanatory variables along with interaction terms between (i) road accident and unconditional expectated medical costs and (ii) police arrest and unconditional expected fines. From Table 9, we note that the effect of injury expectations on helmet use for short trips appears to be lower among individuals who have been involved in a traffic accident. The effect of fine expectations on helmet use for trips in the residential neighborhoods among individuals who have been caught by the traffic police doubles compare to its effect among those who have never been in that situation. This last result shows the importance of combining information and enforcement to make motorcyclists adopt safe behaviors.

Table 9: Differenciated influence of expectations on helmet use by previous experiences

Helmet use	on main roads				trips in the neighborhoods	
	long trips		short trips			
	(1)	(2)	(3)	(4)	(5)	(6)
UEC medical expenditures (th. INR)	0.009**	0.009*	0.001	0.003	0.007	0.007
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
UEC fines (hund. INR)	0.022	0.023	0.078***	0.095***	0.069***	0.052**
	(0.018)	(0.025)	(0.019)	(0.026)	(0.023)	(0.026)
UEC medical expenditures × UEC fines	-0.003*	-0.003*	-0.001	-0.002	-0.004	-0.004
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Road crash (=1)		-0.048		-0.014		-0.095
		(0.059)		(0.061)		(0.065)
Road crash × UEC medical expenditures		-0.002		-0.010**		0.001
		(0.004)		(0.004)		(0.005)
Police arrest (=1)		0.037		0.047		-0.107
		(0.051)		(0.072)		(0.098)
Police arrest × UEC fines		-0.003		-0.048		0.064*
		(0.029)		(0.036)		(0.035)
R^2	0.290	0.292	0.259	0.263	0.246	0.250
observations	*670*	*670*	*665*	*665*	*657*	*657*

Notes: *** 1%, ** 5% and * 10% significance. Additional controls are gender, marital status, # of children, head of hh, age, education, gender, contribution to income, Sikh, caste, risk aversion, health insurance and existence of a superior force. LPM estimations with circle fixed effects (cf. Table 3, Panel B - columns (2), (4) and (6)).

6 Policy implications

In order to be able to formulate policy recommendations, I now consider different road safety policies which are likely to influence individuals' expectations of injuries and fines when not wearing a helmet, and estimate their impact with respect to helmet use.

6.1 Raising expectations of fines

I first study policies which impact expectations of fines if infringing the helmet law, either through the information on the official level of fine, its perceived enforcement or its level *per se*.

Based on the results of even columns from Panel A of Table 3,[23] Table 10 reports the estimated impact on helmet use if motorcyclists perfectly know the current level of fine (Scenario 1), if the official fine is raised up to 500 INR (Scenario 2), if individuals perfectly know the current level of fine and expect to always be caught by the police when not wearing a helmet (Scenario 3), and if perfect enforcement and information is associated with a higher official fine of 500 INR (Scenario 4). The chosen multiplicator factor of fines ($\times 5$) coincides with an amendment of the Motor Vehicle Act currently under discussion in the Indian Parliament. As expected from the empirical analysis, larger gains regarding helmet adoption are obtained on short distance trips, in particular on main roads. The limited increase in helmet use for longer trips can be explained both by a bigger role of expected injuries in this particular decision and by the smaller room for improvement in this type of trip. A larger impact is found when raising the official fine substantially. More precisely, scenarios 2 and 4 lead to an increase of 20% to 30% of helmet use for short distance trips.

When comparing previous police arrests experienced by respondents with administrative traffic police data, we note that the number of offences for not using a helmet in 2011 per police zone is positively correlated with the share of respondents living in that area who declare they have been stopped by the police for infringing the helmet law. Nonetheless, traffic offence data is negatively correlated with the subjective probability of being checked by the police. According to these figures, it seems important not only to publicize the financial penalties individuals may face when not using a helmet but also to increase the actual enforcement of helmet legislation. Similar findings are found by Lu et al. (2012). These authors implemented a randomized experiment in China and showed that telling drivers that they have been catched by the electronic devices deters them from infringing the road rules in the future while providing them with information on the likelihood of punishment does not.

[23]We use coefficients from the probit estimations when predicting helmet use to ensure that itsprobability is not superior to one.

Table 10: Estimated helmet use for changes in expectations of fines

Helmet use	on main roads for long trips		on main roads for short trips		for trips in the neighborhood	
observations	*610*		*663*		*660*	
Current UEC fines (INR)	90		93		93	
Observed helmet use (%)	78.20		59.58		53.03	
Observed - predicted helmet use (average)	-0.003		-0.004		-0.005	
% change in helmet use						
Scenario 1 EC = 100 INR	+ 0.13%		- 3.17%		- 1.09%	
Scenario 2 EC = 500 × info. coeff.	+ 3.16%		+ 22.70%		+ 20.61%	
Scenario 3 UEC = 100 INR	+ 0.99%		+ 2.55%		+ 2.61%	
Scenario 4 UEC = 500 INR	+ 6.99%		+ 33.16%		+ 27.98%	
Helmet use (%) if						
Scenario 1 EC = 100 INR	78.30	+0.10pts	57.75	-1.83pts	52.46	-0.57pts
Scenario 2 EC = 500 × info. coeff.	80.75	+2.55pts	77.08	+17.50pts	66.80	+13.77pts
Scenario 3 UEC = 100 INR	78.98	+0.78pts	61.14	+1.56pts	54.45	+1.22pts
Scenario 4 UEC = 500 INR	84.08	+5.88pts	89.14	+29.56pts	73.63	+20.60pts

Notes: Computations based on probit regression with circle dummies (cf. Table 3, columns (2), (4) and (6)).
Scenario 1: perfect information, individuals expect to pay 100 INR, i.e. the official fine.
Scenario 2: raising the official fine up to 500 INR, but keeping enforcement and information level as it is.
Scenario 3: perfect information and enforcement with current level of fine.
Scenario 4: perfect information and enforcement with an official fine at 500 INR.

6.2 Raising expectations of medical expenditures

I now focus on different scenarios of expectations of medical costs and relate them to policies such as awareness campaigns regarding the road mortality rate or the usefulness of a helmet.

Unfortunately, I don't have access to any official data regarding the actual health expenditures road victims have to pay. I therefore simply consider different scenarios with increasing unconditional expected medical costs and estimate the helmet use associated to each of these levels of expenditures for different motorbike trips. Table 11 reports the simulated percentage of use. While no increase in the share of motorcyclists wearing a helmet is found on short distance trips, doubling the expectations of injury costs (from 2,400 to 5,000 INR) raises the use of a head protection device for long distance trips by 3.5 percentage points. A share of 98.2% of motorcyclists using a helmet, implying an increase of 20 percentage points, is obtained when multiplying by 20 the individuals' beliefs. These results suggest that awareness campaigns stressing the high cost of road injuries in case of an accident and in particular if not using a helmet might be useful to increase helmet use among motorcyclists in Delhi. Lewis et al. (2007) summarized the literature on road safety media campaigns and concluded that the impact of shocking advertisement is rather mixed and inconsistent. Fear campaigns must therefore be used with caution. Using factual information or humor might be alternative options.

Finally, highlighting the risk one faces even in short distance trips could raise the use of helmets among individuals who use a motorbike only in the vicinity of their homes. When imputing the estimated impact of unconditional expected medical costs found for long trips to helmet use on short distance ones (scenario 8), it appears that if individuals thought that short distance journeys imply similar health risks as longer trips, an increase of around 6% in helmet use would be observed.

Table 11: Estimated helmet use for changes in expectations of medical expenditures

Helmet use	on main roads: for long trips		on main roads: for short trips		for trips in the neighborhood	
observations	*610*		*663*		*660*	
Current UEC medical expenditures (INR)	2,408		2,704		2,755	
Observed helmet use (%)	78.20		59.58		53.03	
Observed - predicted helmet use (average)	-0.003		-0.004		-0.005	
% change in helmet use						
Scenario 5 UEC = 5,000 INR	+ 4.30%		+ 0.98%		+ 3.23 %	
Scenario 6 UEC = 10,000 INR	+ 9,12%		+ 1.37%		+ 6.12%	
Scenario 7 UEC = 50,000 INR	+ 20.37%		+ 4.38%		+ 23.07%	
Scenario 8 $\hat{\beta}^{long}_{UECinj}$	-		+ 5.22%		+ 6.26%	
Helmet use (%) if						
Scenario 5 UEC = 5,000 INR	81.71	+3.51pts	60.17	+0.59pts	54.80	+1.77pts
Scenario 6 UEC = 10,000 INR	86.05	+7.85pts	60.41	+0.83pts	56.49	+3.46pts
Scenario 7 UEC = 50,000 INR	98.21	+20.01pts	62.31	+2.73pts	68.93	+15.90pts
Scenario 8 $\hat{\beta}^{long}_{UECinj}$	-		62.86	+3.28pts	56.57	+3.54pts

Notes: Computations based on probit regression with circle dummies (cf. Table 3, Panel A - columns (2), (4) and (6)).

7 Conclusion

Road mortality is a growing burden in many developing countries. To counteract this trend, an increasing number of low and middle income countries have started to implement mandatory helmet regulations. Yet, helmet use remains low in a majority of African and Asian countries, where motorcyclists represent an important share of both traffic mix and road casualties. Understanding the mechanisms leading to the adoption of a helmet by motorcyclists is therefore key to implementing efficient safety measures in these regions.

This paper studies motorbike users' decisions whether to wear a head protection or not using original data collected in a low income country metropolitan city, New Delhi. More precisely, I investigate the impact of subjective expectations of injury and fine when not wearing a helmet; this, in various traveling situations differing by the length of the trip and the type of roads taken. Both fear of injuries and police threat are indeed likely to play a role in the safety conduct adopted by motorcyclists.[24] I therefore investigate whether one type of belief is more likely to be associated with the adoption of a helmet for a specific type of travel. In the empirical analysis, I find that while expectations regarding medical expenditures increase the adoption of helmet on long distance trips on main roads, it is rather the threat of police sanctions which explains helmet use on short distance journeys. Differenciated effects are found for helmet use on short distance trips on main roads between gender and income groups. In particular, expected medical costs influence the decision of using a helmet for women but not for men. Moreover, the influence of financial penalties is twice as big among the poorest individuals as among the wealthiest ones. I then explore the factors which may explain the observed differences in beliefs across individuals and show that road exposure and previous experiences of road related risks impact the formation of motorcyclists' beliefs. Nonetheless, differences across individuals seem also to come from differences in actual health hazards and police enforcement intensity.

In view of designing policies, various measures impacting expectations of injury or fine have been considered and their impact on helmet use have been assessed. Based on these predictions, different policy directions can be suggested. First, the increase of police threat through enforcement, information or fine levels should increase helmet use in short distance journeys. As a matter of fact, combining these measures should be even more effective. Second, information campaigns stressing the usefulness of a helmet to avoid severe injuries (implying important health expenditures) even for motorbike trips nearby one's home are also likely to make motorcyclists adopt safer conducts.

[24] By using the slogan *"Protect yourself from hefty fines and serious injuries. Wear a helmet."* in its 2012 road safety campaign, the Cambodian government actually intented to impact both dimensions.

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8 Appendices

Appendix A. Variation within circles

Table 12: Variation within circles - expectations and helmet use

	Observations			Mean	Standard deviation			# of circles without
	N	n	T-bar	overall	overall	between	within	variation†
HELMET USE								
Long trips on main roads (%)	670	32	20.94	80.15	39.92	12.62	38.03	4
Short trips on main roads (%)	673	32	21.03	59.44	49.14	24.05	44.86	2
Trips in neighborhoods (%)	665	32	20.78	53.38	49.92	20.59	46.66	2
EXPECTATIONS								
UEC medical costs (INR)	673	32	21.03	2,729	5,087	2,357	4,636	0
UEC fines (INR)	673	32	21.03	93	102	58	86	0
SOCIO-DEMOGRAPHICS								
Male (%)	673	32	21.03	69.54	46.06	14.78	44.18	2
Age (in years)	673	32	21.03	36.01	12.86	4.42	12.48	0
Level of education (3 groups)	673	32	21.03	2.26	0.65	0.40	0.60	2
Household monthly income								3
less than 10,000 INR (%)	673	32	21.03	32.84	47.00	28.96	41.66	
10,000 to 20,000 INR (%)	673	32	21.03	34.47	47.56	20.85	43.99	
above 20,000 INR (%)	673	32	21.03	16.94	37.54	18.80	33.78	
Share of one's contribution to income$^{\diamond}$	673	32	21.03	0.38	0.38	0.13	0.37	0
Head of HH (%)	673	32	21.03	38.48	48.69	14.90	47.73	1
Married (%)	673	32	21.03	72.96	44.45	11.70	43.21	0
Number of children	673	32	21.03	1.47	1,32	0.47	1.27	0
Sikh (%)	673	32	21.03	4.31	20.32	11.04	18.68	22
Belongs to a low caste (%)	673	32	21.03	37.30	48.40	26.85	43.91	5
Believes his life is in god's hands (%)	673	32	21.03	89.90	30.16	9.93	28.77	15
Risk aversion score$^{\diamond\diamond}$	673	32	21.03	2.72	0.78	0.43	0.70	0
Has a health insurance (%)	673	32	21.03	12.93	33.58	14.71	31.76	7

Notes: T-bar is the average number of respondents per circle (N/n). This table shows the statistics for the sample used in my analysis. $^{\diamond}$ this variable takes values from 0 to 0.9. $^{\diamond\diamond}$ the risk aversion score takes values from 1 to 4. † Total number of circles is 32.

Table 13: Variation within circles - previous experiences and expectations

	Observations			Mean	Standard deviation			# of circles without variation†
	N	n	T-bar	overall	overall	between	within	
EXPECTATIONS								
probability of injury◇	836	32	26.13	0.58	0.31	0.20	0.26	0
expected medical costs (in INR)	772	32	24.13	5,189	9,012	4,217	8,013	0
IQR of medical costs (in INR)	772	32	24.13	6,718	15,039	6,162	13,763	0
probability of police arrest◇	878	32	27.44	0.65	0.34	0.20	0.29	1
expected fines (in INR)	760	32	23.75	129	103	60	85	0
IQR of fines (in INR)	760	32	23.75	112	109	67	92	0
PREVIOUS EXPERIENCES								
Experienced a road crash (%)	836	32	26.13	7.04	26.22	7.46	25.44	11
Has a relative involved in a road crash (%)	836	32	26.13	6.70	25.01	12.39	23.39	15
Has been sanctionned by the police (%)	867	32	27.09	7.04	25.59	9.81	24.85	11
Discretionnary power of police◇	841	32	26.28	0.36	0.30	0.19	0.25	1
Police officers can be bribed (%)	869	32	27.16	36.48	48.16	21.86	44.59	1
ROAD HABITS								
Uses the moto to commute to work (%)	833	32	26.03	65.07	47.70	14.35	46.09	0
Uses the moto frequently (%)	835	32	26.09	44.55	49.73	20.27	46.70	0
RELIGIOUS PRACTICES								
Prays daily (%)	832	32	26	71.80	44.93	16.80	42.21	1

Notes: T-bar is the average number of respondents per circle (N/n). † Total number of circles is 32.
◇ This variable takes values from 0 to 1.

Appendix B. Considering alternative information of the distribution of expected outcomes

Table 14: Influence of expectations on helmet use - using alternative distribution's information

Helmet use	on main roads				trips in the neighborhoods	
	long trips		short trips			
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	LPM	probit	LPM	probit	LPM	probit
Circle effects	yes	yes	yes	yes	yes	yes
observations	*670*	*610*	*673*	*663*	*665*	*660*
Panel 1 - Interquartile range (IQR)						
UIQR medical expenditures (th. INR)	0.007***	0.117***	0.001	-0.000	0.007*	0.022
	(0.002)	(0.036)	(0.003)	(0.011)	(0.004)	(0.013)
UIQR fines (hund. INR)	0.039	0.203	0.092***	0.331**	0.085***	0.284***
	(0.023)	(0.126)	(0.028)	(0.135)	(0.023)	(0.083)
UIQR medical expenditures × UIQR fines	-0.004***	-0.052***	-0.001	0.001	-0.004	-0.014
	(0.001)	(0.014)	(0.001)	(0.005)	(0.003)	(0.009)
R^2	0.303		0.267		0.254	
Pseudo R^2		0.390		0.343		0.288
Panel 2 - 75^{th} percentile (P75)						
UP75 medical expenditures (th. INR)	0.005***	0.054**	0.000	0.001	0.006	0.019
	(0.002)	(0.023)	(0.003)	(0.009)	(0.004)	(0.014)
UP75 fines (hund. INR)	0.020	0.098	0.062***	0.258***	0.049***	0.160***
	(0.014)	(0.086)	(0.015)	(0.096)	(0.015)	(0.059)
UP75 medical expenditures × UP75 fines	-0.011**	-0.012***	-0.001	-0.002	-0.002	-0.006
	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.004)
R^2	0.299		0.265		0.249	
Pseudo R^2		0.379		0.343		0.284
Panel 3 - Maximum value (MAX)						
UMAX medical expenditures (th. INR)	0.002***	0.019**	0.001	0.001	0.001	0.003
	(0.001)	(0.008)	(0.001)	(0.004)	(0.001)	(0.005)
UMAX fines (hund. INR)	0.016	0.066	0.500***	0.184**	0.039**	0.125**
	(0.011)	(0.063)	(0.014)	(0.074)	(0.015)	(0.055)
UMAX medical expenditures × UMAX fines	-0.000	-0.002	-0.000	0.001	-0.000	-0.002
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
R^2	0.303		0.269		0.247	
Pseudo R^2		0.383		0.347		0.281

Notes: *** 1%, ** 5% and * 10% significance.
Controls are marital status, # of children, head of hh, gender, age, income, education level, contribution to income, Sikh, caste, risk aversion, health insurance and existence of a superior force.

Appendix C. Tackling reverse causality

Table 15: Reverse causality tests

	UEC inj. (1)	UEC fine (2)	UEC inj. (3)	UEC fine (4)	UEC inj. (5)	UEC fine (6)
Helmet use						
Long trips on main roads	1.890	1.204				
	(9.252)	(1.766)				
Short trips on main roads			0.730	0.417		
			(3.225)	(0.594)		
Trips in the neighbourhood					2.318	0.941
					(7.107)	(1.307)
observations	*670*	*670*	*673*	*673*	*665*	*665*

	on main roads		for trips in
	for long trips	for short trips	neighborhoods
First stage			
Helmet provision (=1) †	0.063***	0.182***	0.091*
	(0.021)	(0.044)	(0.054)
Weak identification test ‡	9.167	16.887	2.816
F statistic	12.07***	15.94***	17.99***
R^2	0.281	0.236	0.252
observations	*670*	*673*	*665*

Notes: *** 1%, ** 5% and * 10% significance. Controls are marital status, # of children, head of hh, gender, age, income, education level, contribution to income caste, risk aversion, health insurance and existence of a superior force. † helmet provision is a dummy variable which takes value 1 if the respondent is a driver and rides a moto purchased in first hand less than 2 years ago and 0 otherwise. ‡ Kleibergen-Paap rk Wald F statistic.

Appendix D. Individual omitted characteristics

Table 16: Influence of expectations on helmet use - omitted individual characteristics

Helmet use	on main roads				trips in the neighborhoods	
	long trips		short trips			
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	LPM	probit	LPM	probit	LPM	probit
Circle effects	yes	yes	yes	yes	yes	yes
Panel 1 - adding average speed						
UEC medical expenditures (th. INR)	0.011**	0.129**	-0.000	-0.002	0.008	0.027
	(0.004)	(0.055)	(0.005)	(0.017)	(0.007)	(0.026)
UEC fines (hund. INR)	0.049***	0.341**	0.086***	0.477***	0.081***	0.281**
	(0.015)	(0.146)	(0.018)	(0.149)	(0.024)	(0.113)
UEC medical expenditures × UEC fines	-0.002*	-0.014	-0.000	-0.005	-0.005	-0.016
	(0.001)	(0.022)	(0.001)	(0.012)	(0.003)	(0.009)
Average speed (kph)	0.002***	0.022***	-0.001	-0.001	-0.000	0.000
	(0.001)	(0.008)	(0.001)	(0.005)	(0.001)	(0.004)
R^2	0.320		0.268		0.242	
Pseudo R^2		0.449		0.372		0.304
observations	*525*	*422*	*527*	*499*	*522*	*507*
Panel 2 - adding road habits						
UEC medical expenditures (th. INR)	0.009**	0.073**	0.001	0.003	0.008	0.024
	(0.004)	(0.031)	(0.005)	(0.017)	(0.006)	(0.022)
UEC fines (hund. INR)	0.023	0.124	0.078***	0.356***	0.066***	0.220**
	(0.018)	(0.131)	(0.019)	(0.131)	(0.023)	(0.093)
UEC medical expenditures × UEC fines	-0.003	-0.020**	-0.001	-0.001	-0.004	-0.013
	(0.002)	(0.010)	(0.001)	(0.010)	(0.003)	(0.009)
Uses the moto frequently (=1)	0.064*	0.567***	0.090*	0.331*	0.048	0.145
	(0.032)	(0.202)	(0.047)	(0.180)	(0.044)	(0.148)
Uses the moto to commute to work (=1)	0.029	0.234*	0.018	0.154	0.023	0.146
	(0.031)	(0.132)	(0.048)	(0.170)	(0.037)	(0.123)
R^2	0.303		0.267		0.248	
Pseudo R^2		0.393		0.348		0.283
observations	*668*	*608*	*671*	*661*	*663*	*658*
Panel 3 - adding confidence on one's skills (sample of drivers)						
UEC medical expenditures (th. INR)	0.006*	0.242***	-0.002	-0.009	0.011*	0.037*
	(0.003)	(0.074)	(0.006)	(0.016)	(0.006)	(0.022)
UEC fines (hund. INR)	0.022**	0.862**	0.068***	0.413**	0.090***	0.380***
	(0.011)	(0.373)	(0.022)	(0.187)	(0.026)	(0.123)
UEC medical expenditures × UEC fines	-0.002**	-0.091***	0.000	-0.003	-0.006**	-0.024***
	(0.001)	(0.021)	(0.001)	(0.008)	(0.002)	(0.008)
Thinks he has better driving skills than	-0.046**	-0.578	-0.029	-0.172	-0.084**	-0.405**
other drivers (=1)	(0.021)	(0.415)	(0.040)	(0.153)	(0.041)	(0.159)
R^2	0.247		0.151		0.163	
Pseudo R^2		0.517		0.305		0.304
observations	*393*	*169*	*393*	*317*	*389*	*336*

Notes: *** 1%, ** 5% and * 10% significance.
Controls are marital status, # of children, head of hh, gender, age, income, education level, contribution to income, Sikh, caste, risk aversion, health insurance and existence of a superior force.

Appendix E. Excluding individuals who did not understand the probability scale

Five general questions were asked to respondents in order to control for their understanding of the scale.

First, we check the understanding of the probability concept:

1. *"Imagine I have 5 balls, one of which is red and four of which are blue. If you pick one of these balls without looking, how likely it is that you will pick the red ball?"* - variable named "red ball" below.

Two nested questions were also asked:

2. *"How likely are you to go to the market sometime in the next two days?"* - variable named "2 days" below.

3. *"How likely are you to go to the market sometime in the next two weeks?"* - variable named "2 weeks" below.

The variable called "nested" takes value 1 if the individual gave consistent answers to above two questions.

Finally, we aimed at check whether the entire scale was used by the respondent and therefore asked about events for which everybody should reply the extreme values of the scale:

4. *"How likely do you think it is that you will go out of the house for any reason in the next month?"* - variable named "outside" below. This question turned out to be misleading, while we meant outside the house, some respondents understood out of the city. This confusion explain the unexpected results presented in Table 18.

5. *"How likely is it that Christmas will fall in the month of June?"* - variable named "christmas" below.

Only 4 respondents have no correct answer. 52% of interviewees provided only one or no inconsistent answer. 36% gave two consistent replies out of four.

Table 17: Check questions

	probability concept	**nested questions**		**extreme values**	
	red ball	2 days	2 weeks	outside	christmas
event will not happen (%)	3.05	2.83	1.36	6.59	**96.06**
1	8.77	3.28	1.36	6.14	0.48
2	**24.24**	4.87	1.25	4.89	0.48
3	9.99	3.74	3.28	2.05	0
4	15.35	3.96	2.60	1.14	0.48
5	26.55	12.46	6.46	7.61	1.08
6	5.97	4.53	4.19	3.07	0
7	2.68	7.47	8.61	6.02	0
8	1.34	8.04	9.29	8.07	0.36
9	0.37	4.87	6.91	6.59	0.12
event will happen	1.71	43.94	54.7	**47.84**	0.96
Share of correct answers	24.24	84.60		47.84	96.06
observations	*821*	*883*	*883*	*880*	*837*

Notes: In bold are indicating the share of individuals who provide the expected answer to each question. *Remark:* 84.60% of respondents said that the probability that they will go to the market in the next two weeks was higher or equal as the probability they will go within two days.

Table 18: Keeping individuals who understood the probability scale

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all	christmas	nested	outside	christmas OR nested	christmas AND nested
Panel: Helmet use for long trips on main roads						
UEC medical expenditures (th. INR)	0.009**	0.009**	0.010**	0.006	0.009**	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
UEC fine (hund. INR)	0.024	0.020	0.019	0.025	0.020	0.013
	(0.018)	(0.019)	(0.018)	(0.030)	(0.019)	(0.019)
UEC medical expenditures × UEC fines	-0.003*	-0.003*	-0.003*	-0.003	-0.003*	-0.003*
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
R^2	0.636	0.284	0.290	0.445	0.294	0.283
observations	*670*	*629*	*552*	*306*	*647*	*521*
Panel: Helmet use for short trips on main roads						
UEC medical expenditures (th. INR)	0.001	0.002	0.003	-0.002	0.002	0.003
	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.003)
UEC fine (hund. INR)	0.081***	0.077***	0.0075***	0.075	0.076***	0.070***
	(0.019)	(0.019)	(0.014)	(0.049)	(0.019)	(0.015)
UEC medical expenditures × UEC fines	-0.001	-0.001	-0.002*	0.001	-0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
R^2	0.262	0.267	0.289	0.352	0.266	0.299
observations	*673*	*632*	*555*	*308*	*650*	*524*
Panel: Helmet use for trips in residential neighborhoods						
UEC medical expenditures (th. INR)	0.008	0.008	0.008	0.005	0.008	0.008
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
UEC fine (hund. INR)	0.068***	0.067***	0.069***	0.050	0.066***	0.068***
	(0.023)	(0.024)	(0.022)	(0.037)	(0.023)	(0.024)
UEC medical expenditures × UEC fines	-0.004	-0.004	-0.004	0.000	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
R^2	0.247	0.256	0.257	0.360	0.251	0.270
observations	*665*	*625*	*548*	*304*	*642*	*518*

Notes: *** 1%, ** 5% and * 10% significance. Controls are marital status, # of children, head of hh, gender, age, income, education level, contribution to income caste, risk aversion, health insurance, helmet ownership and existence of a superior force. Estimations in column (1) corresponds to even columns of Panel B in Table 3.