Traffic campaigns, overconfidence and emotions: an experimental approach

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Abstract

Concern about traffic issues has increased considerably in recent years. Human behavior is primarily responsible for the occurrence of traffic accidents. This work aims to develop specific metrics and study methodologies to trace individuals' behaviors and, thus, to seek effective measures to reduce traffic infractions and traffic risk exposure. This study aims to measure the impact of individuals' decision making by inducing mood swings and measuring individual perceptions related to the traffic area. We conduct a laboratory experiment with undergraduate students. The results indicate that punitive and strong scenes traffic campaigns are effective in reducing drivers' overconfidence, making them more aware of their role in traffic.

Keywords: Traffic campaigns, mood inducement, emotions, decision making, traffic.

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1. Introduction

Human behavior is primarily responsible for the occurrence of traffic accidents, but there is still a lack of specific metrics and methodologies to study traffic accidents and the actions that lead individuals to commit them.

Concern about traffic issues has increased considerably in recent years as a result of the high number of accidents caused by mechanical problems with vehicles, weak road signs, and road maintenance, lack of surveillance or traffic behavior of drivers. Concerning drivers, more specifically, several factors can contribute to the emergence of inappropriate traffic behaviors, such as the lack of traffic education, minimum knowledge of driving, and also personality characteristics and functioning of drivers.

Human behavior is tested in several everyday traffic situations, requiring drivers' decisions and choices. Often drivers are subjected to stress and hazardous conditions and must act according to their impulses, intuitions, and emotions. Thus, it is necessary to take into account these reactions in the design of public policies that aim to reduce the number of traffic accidents on highways. Specifically, the use of alcoholic beverage and the handling of cellular devices in the direction are the cause of many traffic accidents in highways and roads in many countries.

We conduct a general experiment to analyze how different traffic campaigns may impact overconfidence on driving behavior. We use it as a case study in Brazil. According to the Brazilian Association of Traffic Medicine (Abramet), the use of the cell phone while driving is already the third most significant cause of death in traffic. A hundred and fifty die every day, and almost fifty-four thousand every year. Abramet studies show that people spend between 8 and 9 seconds to answer a phone call, between listening to the request, locating the phone, picking up, unlocking and answering. If the driver is at 80 km/h, he will travel almost two blocks inattentive to traffic. In the case of text messages, it takes people 20 to 23 seconds to respond to an underlying message. If the driver is at 60 km/h, he will travel almost four blocks dividing the attention between the traffic and the cell phone.

Concerning drunken driving, Abramet estimates that 54 % of Brazilian drivers make use of alcohol before picking up the steering wheel. The National Health Survey of the Ministry of Health, in partnership with the Brazilian Institute of Geography and Statistics (IBGE), indicates that 24.3 % of drivers say they take over the vehicle after drinking alcohol.

Pursuant to Law No. 9,503 of September 27, 1997, which instituted the Brazilian Traffic Code - CTB, driving under the influence of alcohol or any other psychoactive substance that determines dependence constitutes a severe violation (whose value is R$ 293.47) and has a fine (ten times), in the amount of R$ 2,934.70, and suspension of the right to drive for 12 (twelve) months. Its administrative measure is the collection of the document of habilitation and retention of the vehicle. In case of a repeat offense within a period of up to 12 (twelve) months, the fine shall be doubled. Already to handle or handle a cell phone is a severe infraction, whose fine is R$ 293.47, according to the single paragraph of article 252 of the CTB. An increase in the value of fines occurred in 2016.

The Act became more severe to draw the attention of drivers, but the main objective of these measures would be to raise awareness of the population. However, is this change in the values of traffic tickets effective in reducing the number of offenses? What measures of inspection and recognition can change the behavior of drivers on Brazilian highways and roads? Is it possible to reduce drivers' overconfidence and make them more aware of their role and risk in traffic?

Some authors show the importance of looking at measures that go beyond legislation and education in traffic, pointing to the effectiveness of using, for example, social marketing to reduce alcohol intake in the direction (Rothschild et al. 2006). After all, often only reducing the blood alcohol concentration rates allowed by legislation does not reduce traffic deaths, and in fact may even increase them, because as marginal penalties fall, drivers who drink alcohol while driving may relax their efforts to comply with the law, and this overcomes the effect of reducing the consumption of calmer law-abiding drivers (Grant, 2016). Thus, it is important to study which measures are effective in reducing traffic accidents.

In analyzing the literature on behavioral economics and the economics of transport, we note that only a few studies have explored the relationship between traffic decision making and individual behavior. Not to say to take into account the influence of feelings and emotions in drivers' decision making. This issue is especially relevant in which concerns driving after the ingestion of alcoholic beverages and handling the cellular device while driving — such recurring infractions are causing many traffic accidents on highways and roads in Brazil.

In this sense, this paper seeks to overcome this deficiency and to corroborate for the formulation of public policies that aim to reduce traffic accidents on Brazilian highways and roads. Specifically, we deal with two very current themes that cause many deaths in traffic: the handling of the cell phone while driving and the consumption of alcoholic beverages before driving. We note that many traffic campaigns and measures aim to provide more excellent traffic safety and reduce deaths and accidents on Brazilian highways and roads. However, little do we know whether these campaigns and actions are effective in changing drivers' behavior in traffic.

This paper seeks, through the application of an experiment with undergraduate students, to measure the impact of individuals' decision making by inducing mood swings. We draw the profile of the drivers to show if there is a difference in driver behavior, involvement in traffic accidents, risk propensity, and altruistic behavior. We also find that the traffic safety measures that most impact on the behavior change of the individuals. We intend to verify which type of traffic campaign most impacts behavior and reduces the overconfidence of drivers.

By conducting experiments that consist of the application of videos of traffic campaigns, followed by the use of questionnaires, this work shows that it is possible to change the behavior of individuals through the induction of humor. Traffic campaigns with hard images and punitive content have proven effective in reducing drivers' overconfidence, making them more aware and alert of their role in traffic and in reducing traffic accidents. Also, the profile and characteristics of drivers influence their indexes of overconfidence, revealing that younger, left-handed and ambidextrous people have a lower index of overconfidence.

There are several contributions that these results bring to public policy makers in traffic, especially to reduce traffic accidents. A better understanding of the drivers' profile and the cognitive and behavioral factors that lead them to commit traffic violations is essential for developing strategic public policies.

This paper is structured as follows. Section 2 describes the literature review, while 3 presents the data and discusses the methodology. In 4 we show the empirical results. Some public policy implications are discussed in Section 5, whereas 6 concludes the paper.

2. Literature Review

Traffic safety depends on the integrated and complex relationship between its various components: driver behavior, traffic, vehicle, environment, and road infrastructure. The element that, according to statistics, seems to be the most important, since it is responsible for most accidents, is the behavior of drivers in traffic. Bucchi et al. (2012) analyze the interaction of road and human safety factors to identify a driver's personality, attitude, skill, and reliability. Employing methods used in psychology, we investigate the process of construction of the character of the driver by studies of the processes of perception, learning, and memory. Chen et al. (2017) finds that two types of information are useful in influencing the reduction of traffic transgressions in emerging economies: the behavior of drivers similar to the individual and the practice of drivers of high-status cars.

The accuracy of drivers' perceptions of risk has always been a recurring topic in traffic safety surveys, most of which analyze how people assess traffic risks and how these perceptions affect traffic behavior (Svenson (1978)).

Johansson & Rumar (1968) seek to explain how well pedestrians and drivers understand the limits of their visibility at night through an experimental study of 413 drivers at 14 locations in Sweden, showing that the average visible distance is 23 meters, and safe approach speed varies between 25 km/h and 50 km/h, depending on the conditions chosen. Cohen (1960) shows how alcoholic drink users perceive the effects of alcohol on their judgment and abilities. O. (1970) discusses how drivers estimate the time they save driving faster than average. Bick & Hohenemser (1980) shows that when they identify significant inaccuracies, it may be possible to correct them by information campaigns or system redesign. For example, Shinar et al. (1980) painted stripes on a dangerous curve to making it sharper than it was, causing the drivers to slow down.

We can infer that these studies deal with local risks and tactical decisions to consider them. Another level of risk perception involves drivers' feelings and emotions about the risk of driving.

Over the last few years, there is greater importance given to emotions in decision making (Loewenstein & Lerner (2003); Isen (2008)). Specifically, Isen (2008) shows that emotions play an essential role and a salutary effect. Studies show the influence of positive impact on several aspects, for example, to increase work performance and productivity (Erez & Isen (2005)); increase loss aversion (Isen et al. (1988)), and increase risk aversion (Isen & Geva (1987)). Other studies also show that a mild positive effect significantly reduces the time preference of the subjects and the measure of temporal choice after the induction of a mood in the individuals (Ifcher & Zarghamee (2011)).

There is a large body of research that studies the impact of a smooth, positive effect on decision making in recent years. Several authors have conducted controlled experiments that demonstrate that the mild positive influence can have beneficial effects on decision making, increasing cognitive flexibility, work effort, utility and creativity (Lyubomirsky et al. (2005); Isen (2008)). Besides, the soft positive impact does not seem to impede decision making, as many would expect. For example, there is no experimental evidence that a mild positive effect causes impulsive or overly optimistic behavior (Isen (2007)).

Several procedures can be used to induce emotions or mood in laboratory experiments, such as images, sounds, body and facial movements, social interactions, hypnosis, medication, music, and odor (Martin (1990)). The use of humor-inducing videos is every day in behavioral economics experiments (Kirchsteiger et al. (2006); Rottenberg et al. (2007)).

There is evidence that videotapes are capable of triggering activation in many of the emotion-related response systems (Palomba et al. (2000); Karama et al. (2002)). Philippot (1993) presents a study showing how a list of 12 films reproduced six stages of different emotions, and reported success in stimulating feelings of joy, sadness, and neutrality. Gross & Levenson (1995) evaluated 16 films that provided eight mixed emotions, indicating progress in stimulating emotions: joy, anger, contentment, disgust, sadness, surprise, neutrality, and, to a lesser extent, fear. Westerman et al. (1996) analyze eleven procedures to induce mood. The literature finds that the use of movies or stories is the most effective means of causing positive effects on individuals. However, studies show that while some videos are capable of inducing humor and the activation of various senses, other videos are incapable of doing that.

There is extensive use of videos of traffic campaigns in an attempt to reduce traffic accidents and alter the behavior of individuals. Specifically, drinking and driving remains a serious road safety concern, despite significant efforts to address the problem (Davey & Freeman (2011); Owens & Boorman (2011); Terer & Brown (2014)), highlighting studies that seek to understand the behavior of people who drink and drive (Sloan et al. (2014)) and its consequences (Otero & Rau (2017)).

There is some preliminary evidence that traffic campaigns can result in reductions in traffic accidents caused by alcohol ingestion (Cameron et al. (1993); Cameron & Vulcan (1998); Murry et al. (1993); Newstead et al. (1995)), showing that non-legal sanctions help reduce this type of traffic violation. However, there is research that points out that the effects of messages encouraging people not to drink and drive may not have any impact after all, through defensive processing mechanisms (Agrawal & Duhachek (2010)), particularly among people less motivated to change their behavior (SWOV (2009)). Freeman et al. (2016), when analyzing the behavior of drivers who drink and drive, through the application of an experiment using questionnaires, verify that the respondents' perceptions of both legal sanctions (seizure of the vehicle, increased severity of the sentence), and as of non-legal sanctions (fear of social or physical damage) are relatively high, with non-legal sanctions higher.

Recent studies have also attempted to explain the behavior of drivers who handle the cell phone while driving (Tucker et al. (2015)). Research has identified several psychological factors associated with this risk behavior. These factors include impulsivity (Quisenberry (2015); Hayashi et al. (2016)), habit of handling cell phones (Bayer & Campbell (2012)), cell phone dependence (Struckman-Johnson et al. (2015)), and tendencies for risky behaviors (Struckman-Johnson et al. (2015)). However, the behavioral and cognitive processes underlying this behavior remain unknown. Even knowing the risks, people continue to carry out this type of behavior (Atchley et al. (2011)). This trend may explain why transit legislation and traffic education have not been able to reduce the committing of this type of infraction (Ehsani et al. (2014); Goodwin et al. (2012)).

To explain risk aversion behaviors using "myopic loss aversion" - MLA, elaborated by Bernatzi & Thaler (1995), Teixeira et al. (2015) conduct a laboratory experiment with university students to show that increased exposure to the hormone testosterone influences human behavior and economic outcomes.

Another variable to be taken into consideration is optimism or overconfidence, which can affect road safety and road safety in the country, affecting the many tactical decisions involved in managing a vehicle in transit. Drivers who feel relatively immune may disregard safety measures, such as wearing seat belts or feel more confident about drinking alcohol, driving with a cell phone or exceeding the speed allowed on the road.

Studies of psychology on overconfidence are common in behavioral economics. Olsson (2014) reviews some of the problems associated with the conclusion that people overestimate the accuracy of their judgments based on observed overconfidence, measured as the difference between the mean subjective probability and the correct proportion.

For a long time, the literature has provided evidence that most drivers believe that they are better than average. Over the years, several papers have sought to show these results empirically and in an applied way. Svenson et al. (1985), through the application of a questionnaire with students from universities in the United States of America and Sweden, show that drivers believe that they are more skillful and safe than average and therefore tend to underestimate the risk of their behavior in traffic. This underestimation replicates a general bias of optimism that people perceive themselves to be less vulnerable than others to a variety of hazards (Weinstein (1980)).

3. Experimental Design and Data

In this section, we describe the experimental design and data pre-processing steps. We also provide an exploratory analysis of the experimental data.

3.1. Experimental design

We design a controlled field experiment to investigate the effectiveness of different educational traffic campaigns videos in shaping drivers' overconfidence levels. We construct a sample that consists of students of a large university in Brasília-DF that hold driving licenses. Our goal is to obtain a representative view of students within the university. Therefore we invite students across campus of all undergraduate courses to participate in the experiment.

It is essential to highlight that we invite students to participate in an experiment that done on campus an hour before the beginning of classes. Students fill a form that consents their use of their data for research purposes and are allowed to leave the experiment at any time. We did not provide any payments for participants. We explained that they would receive a research report a few weeks after the study with overall results.

Our experiment has two sequential steps. In the first, we apply an external stimulus to respondents in the form of educational traffic campaign videos. Immediately after the video, we present a questionnaire to students querying about their characteristics, economic background, own adherence to traffic safety measures in the case of consumption of alcoholic beverages and cell phone handling while driving, and also perceptions of her/his behavior while driving.

To evaluate the efficiency of educational traffic campaigns, we divide our sample into four *similar groups* that different experience levels of external stimuli in the form of videos. In the first group, no footage is applied, and respondents only fill in the questionnaire (*control group*). In the other three groups (*treatment groups*), we show educational traffic campaign videos with the same content but with different forms of exhibition. The objective is to induce humor change in individuals by introducing a small video before they answer the questionnaire. We select three types of traffic awareness videos to encourage drivers not to drink alcohol before driving — first, a video of the Australian school, with intense and life-threatening scenes (*shocking video*). Second, a video of the American school, with punitive content, showing the consequences and penalties of drinking and driving (*punitive video*). Third, a video of the European school, with technical content, explaining the biological effects of alcohol use on the human body (*technical video*).

The advantage of using videos is that they catch the attention of participants more easily. Although threats to the standardization are present in any laboratory procedure, the content of the stimulus, presentation apparatus and viewing conditions are under tight control with the application of videos. The standardization of videos is therefore high, allowing the potential replication of effects between laboratories (Gross & Levenson, 1995). High uniformity, however, does not guarantee that the mood-changing impact of the video will be the same for all participants.

All steps in the experiment are identical, except for the video content to which students are submitted. Videos are about the same length so that video length is not the mood-inducing factor, but the content and presentation of the video. At the beginning of each experiment, students are instructed not to perform any communication with each other, so that results are not biased. The questionnaire is answered by participants immediately after the video, in such a way that no time lapse would hinder the capture of humor provoked by the video.

To mitigate fundamental differences of the control and treatment groups, which could otherwise compromise our results, we randomly assign the treatment and control groups within classes from the same undergraduate course *and* period.[1] We expect courses from the same undergraduate course and the same period be roughly homogeneous in the aggregate. In this way, control and treatment groups should be ap-

[1]Our external intervention in the form of videos is at the class level. Therefore, we cannot assign within the same class but across classes in the same period within the same university.

proximately equivalent ex-ante the application of the external stimulus (video) and selection bias should be minimal.

As robustness, to further refine the similarity between the control and treatment groups, we further subdivide individuals across different classes in the same period. We construct similarity clusters and compare individuals within these clusters that are at various courses in the same period, in which one was assigned to the control group and the other to the treatment group. We use social and bio-characteristics to compose these groups such as age similarity, laterality, marital status, whether it is a frequent driver and suffered drink and cellphone-related fines, age differential between the mother and the student, and emotion.

We assign individuals randomly to participate in the control and treatment groups. Therefore, we mitigate the potential presence of omitted variables that could be driving and biasing our results. Consequently, we can isolate and quantify the effectiveness of educational traffic campaigns in shaping drivers' overconfidence levels. For better representativeness of the population under study, we apply the questionnaire to all undergraduate courses within the university.

3.2. Data

The sample size is an essential concern in behavioral economics experiments, particularly for studies involving controlled trials (List et al., 2011). We choose the sample size using *a priori analysis*. Such analysis provides an efficient method of controlling statistical power one conducts a survey(Cohen, 1988). We use the well-established and freely available G*Power tool to determine the required sample size (Faul et al., 2007). In our case, we base our sample size choice on the usual benchmark in behavioral research: a significance level of 0.05, power adjustment of 0.80, and size effect of 0.5 (List et al., 2011). Under these criteria, we obtain a minimum sample size of about 84 participants.

The experiment is applied to a sample of 400 students, equally divided into four groups: 100 questionnaires administered to the control group and 100 surveys applied to each of the three treatment groups. Respondents are between 19 and 58 years old, 183 (45.8%) are women, and 217 (54.2%) are men. We implemented the experiment in 2018. Respondents had 15 minutes to respond to the questionnaire after the application of the video.

In the following, we discuss the grave concern about the similarity between the control and treatment groups and also define our overconfidence index.

3.2.1. Similarity between the control and treatment groups

One potential concern in our analysis is selection bias, which is the existence of fundamental differences between the control and treatment groups. Selection bias hampers any causal analysis and is a live concern in any empirical study. A way to minimize the selection bias across these groups is through randomization. In this section, we discuss the composition of the control and treatment groups and show that they have, in all investigated dimensions, statistical similarity. This fact suggests that our randomization procedure (in and across university classes) has worked as planned.

Table 3 compares social, biological, economic and driving characteristics across the control and the three treatment groups that experienced video exhibitions. We show that these groups are almost identical in these characteristics, suggesting that our randomization strategy has worked. We also test for statistical differences across the multiple groups for each attribute and report the *p*-value in the last column. The null hypothesis is that the distributions are statistically the same. As we can see, we cannot reject the null hypothesis in all cases except for the gender. Therefore, in our robustness, we will take care of this heterogeneity by also comparing within gender (within estimation).

Table 1: *We compare social, biological, and driving characteristics across the control and the three treatment groups. For categorical variables, we report the number of occurrences followed by the associated percentage in paratheses. For numerical variables, we provide the mean value followed by the associated standard deviation. For each variable, we also test whether the control and treatment group statistics are statistically equivalent and report the associated p-value in the last column. In this comparison, we perform pairwise comparisons adjusting for multiple testing (Tukey when row-variable is normal-distributed and Benjamini & Hochberg method otherwise). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non-normal.*

	No video N=100	Technical video N=100	Punitive video N=100	Shocking video N=100	Overall *p*-value
Categorical Variables					
Drink fines?					0.851
No	97 (97.0%)	94 (94.0%)	96 (96.0%)	95 (95.0%)	
Yes	3 (3.00%)	6 (6.00%)	4 (4.00%)	5 (5.00%)	
Cellphone fines?					0.613
No	89 (89.0%)	91 (91.0%)	88 (88.0%)	85 (85.0%)	
Yes	11 (11.0%)	9 (9.00%)	12 (12.0%)	15 (15.0%)	
Laterality					0.546
Left-handed	7 (7.00%)	9 (9.00%)	10 (10.0%)	13 (13.0%)	
Right-handed	93 (93.0%)	91 (91.0%)	90 (90.0%)	87 (87.0%)	
Marital status					0.719
Married	16 (16.0%)	17 (17.0%)	20 (20.0%)	14 (14.0%)	
Single	84 (84.0%)	83 (83.0%)	80 (80.0%)	86 (86.0%)	
Frequenty driver?					0.249
No	34 (34.0%)	29 (29.0%)	28 (28.0%)	40 (40.0%)	
Yes	66 (66.0%)	71 (71.0%)	72 (72.0%)	60 (60.0%)	
Gender					<0.001
Female	59 (59.0%)	34 (34.0%)	32 (32.0%)	58 (58.0%)	
Male	41 (41.0%)	66 (66.0%)	68 (68.0%)	42 (42.0%)	
Has housekeeper?					0.131
No	85 (85.0%)	93 (93.0%)	82 (82.0%)	85 (85.0%)	
Yes	15 (15.0%)	7 (7.00%)	18 (18.0%)	15 (15.0%)	
Is religious?					0.624
No	37 (37.0%)	31 (31.0%)	39 (39.0%)	33 (33.0%)	
Yes	63 (63.0%)	69 (69.0%)	61 (61.0%)	67 (67.0%)	
Numerical Variables					
Age	25.7 (5.97)	25.7 (5.82)	27.0 (6.48)	26.8 (7.37)	0.313
Driving experience	5.29 (6.87)	5.66 (4.40)	5.31 (5.21)	4.25 (3.50)	0.242
Mother's - student's age	24.7 (6.70)	25.0 (5.24)	24.3 (5.44)	23.9 (4.32)	0.518
Emotion	4.45 (1.57)	4.55 (1.56)	4.56 (1.39)	4.79 (1.34)	0.413

Table 3: *We use eight components to gauge drivers' overconfidence. For each element, the respondent can answer strongly agree with the assertion (+2 points for overconfidence), agree (+1), indifferent (0), disagree (-1), and strongly disagree (-2). We calculate the overall as the average of each of these components, and we report it in the last row of the table. Each intermediate cell represents the average for the specific question (row) and group column), and can range from -2 (underconfidence) to +2 (overconfidence).*

Assertion (question)	**No video**	**Technical video**	**Punitive video**	**Shocking video**
I am confident in driving after drinking alcohol	0.19	0.08	0.27	-0.01
I am confident in driving while in cellphone	0.21	0.12	0.15	0.08
I feel like a driver above the average	0.76	0.65	0.48	0.30
I can drive after ingesting alcohol without major risks because my resistance is above the average	0.05	0.11	0.06	-0.02
I feel that I am more careful and respectful of traffic laws than the average driver	0.81	0.86	0.75	0.50
I feel that I am more aware of traffic than the average driver	0.83	0.95	0.79	0.50
I do not see any problem driving under the influence of alcohol because I am quite resistant	0.02	0.08	0.02	0.03
I do not see any problem driving while in cellphone because I am very alert in traffic	0.03	0.08	0	0.03
Overall	0.181	0.183	0.158	0.088

The proper homogenization between the control and treatment groups allows us to test the effect of different traffic campaign videos in shaping drivers' overconfidence.

3.2.2. Construction of the overconfidence index

We construct our overconfidence based on eight questions that are highlighted in the first column of Table 3. We score each question based on the five possible and standardized answers: strongly agree (+2 points), agree (+1 point), indifferent (no points), disagree (-1), and strongly disagree (-2 points). The overconfidence index is the sum of points achieved by respondents in the eight questions. Respondents with positive overall scores have a degree of overconfidence, while respondents with a negative overall score are underconfident. Zero scores denote average individuals in terms of self-confidence.

Table 3 provides the average scores for each question (row) and group (column), which can range from -2 (strong underconfidence) to +2 (strong overconfidence). Since most scores are positive, respondents have traits of overconfidence, on average, regardless of their assigned groups. In addition, the overall overconfidence (last row) is particularly higher for the control group and the technical video treatment group, suggesting that traffic educational videos with technical content might not be efficient to reduce drivers' overconfidence. The level of overconfidence significantly drops for respondents assigned to the shocking video treatment group, hinting us that educational videos with shocking content may reduce drivers' overconfidence. Punitive videos are in-between technical and shocking videos in terms of reducing drivers' overconfidence. We will test these conjectures using an econometric specification later on, in which we control for several confounding factors that could be driving these plain averages.

Figure 1 depicts boxplots of the overconfidence indices for different social and bio-characteristics of respondents such as (a) gender, (b) marital status, (c) laterality, and (d) driving experience. With no external intervention (control group), we see that women are more overconfident than men in traffic (statistically significant at 5% level), right-handed persons are more overconfident than left-handed persons (statistically significant at 1% level), and drivers with medium or high experience are more overconfident than drivers with low experience (statistically significant at 1% level). We do not find significant differences between single and married persons in the control group. Consistent with Table 3, the median overconfidence indices tend to decrease when we compare treatment groups watched the technical, punitive, and shocking videos (in this order).

4. Feature Selection using Machine Learning

Our questionnaires collect 33 social, biological and economic characteristics of respondents. Many of these attributes may be correlated with each other, which could inflate our standard errors in our econometric analysis exploring the determinants of drivers' overconfidence. To avoid such problem and also to not miss out any important covariate able to strongly explain drivers' overconfidence, we use data-driven machine learning methods to help us select the most important attributes. We only keep attributes identified as most important by the machine learning method that have economic meaning, so as to prevent spurious correlations.

By assumption, we assume that students from the control and treatment groups are roughly similar. However, they are exposed to different external estimuli in the form of educational traffic videos. In this way, our outcome variable—the level of overconfidence—is somewhat contaminated by such exposure. In any machine learning method, data must come from the same distribution and any shifting of the distribution is not appropriate when training and can lead to biased results. As a first step, we remove the effect of such external stimuli used in the design of the control and treatment group by running the following regression:

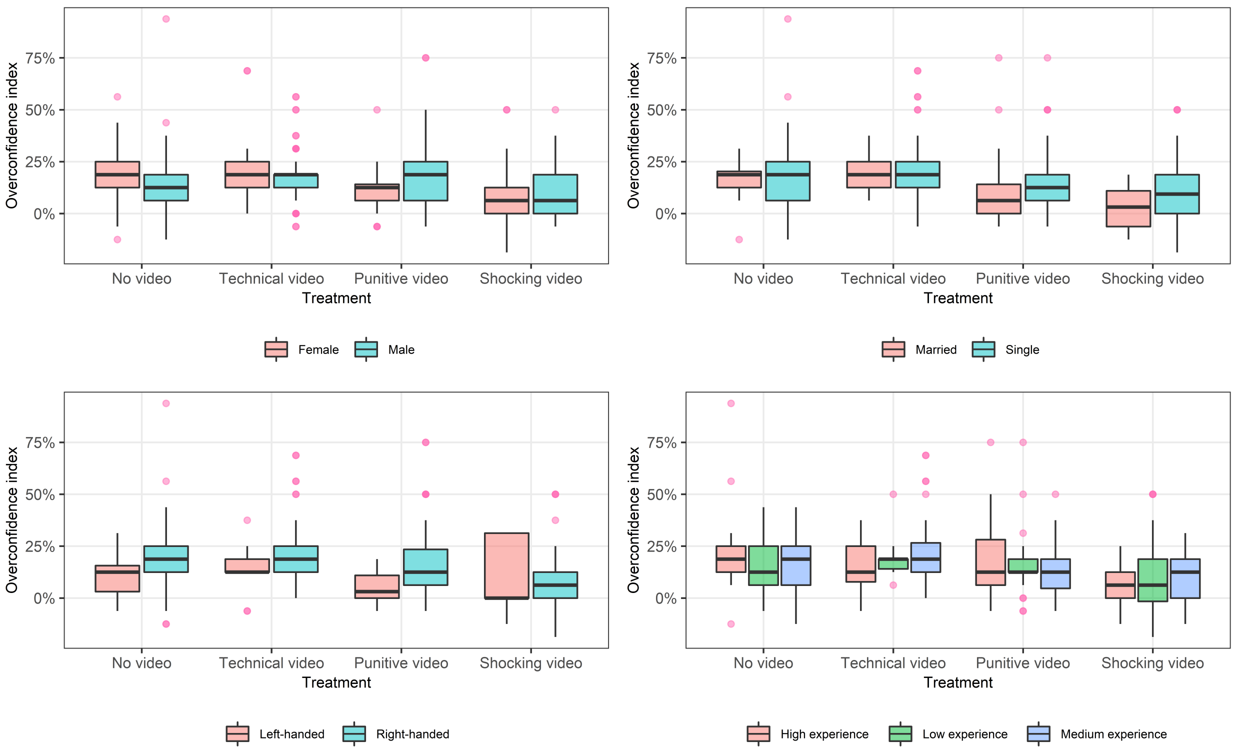

Figure 1: *We present the boxplots of the overconfidence index for different data subsamples. In the x-axis, we segregate by treatment type (no video, technical video, punitive video, and shocking video). The y-axis shows the average overconfidence index for each subgroup. Each panel further subdivides the sample into (a) gender (female, male), (b) marital status (married, single), (c) laterality (left- and right-handed), and (d) driving experience (high, medium, and low experience).*

$$y_i = \alpha + \beta_1 \text{Technical}_i + \beta_2 \text{Punitive}_i + \beta_3 \text{Shocking}_i + \varepsilon_i, \tag{1}$$

in which y_i denotes the level of overconfidence of student i, $\text{Technical}_i, \text{Punitive}_i$, and Shocking_i are non-overlapping dummy variables that are switched on if student i received the corresponding treatment (technical, punitive, or shocking video), and zero otherwise. Since each student only participates a single time, $\text{Technical}_i + \text{Punitive}_i + \text{Shocking}_i = 1$. Students in the control group have $\text{Technical}_i = \text{Punitive}_i = \text{Shocking}_i = 0$, so that the intercept absorbs the average drivers' overconfidence of all the sample. The three dummies absorb any linear deviation of the average drivers' overconfidence of that particular treatment group with respect to the entire sample. The term ε_i is the residual, which captures variations of the level of overconfidence that are not explained by the external stimuli nor the average effect.

Since we are looking to purge out the effect of the external intervention and put the drivers' overconfidence level distribution in common grounds for the control and treatment groups, we use the residual ε_i of specification in (1) to identify the most important attributes in explaining students' overconfidence. Such residual gives an unbiased level of overconfidence, which is not contaminated by the external stimuli. The left-most panel of Figure 2 shows a kernel density plot of the original level of overconfidence of students (y_i in (1)), while the right-most panel shows the same plot but with the unbiased level of overconfidence among students in the control and treatment groups (ε_i in (1)). While the distributions of the level of overconfidence are clearly different, suggesting that the external intervention has an effect on drivers' overconfidence, the distributions become roughly the same if take the residual of specification in (1).

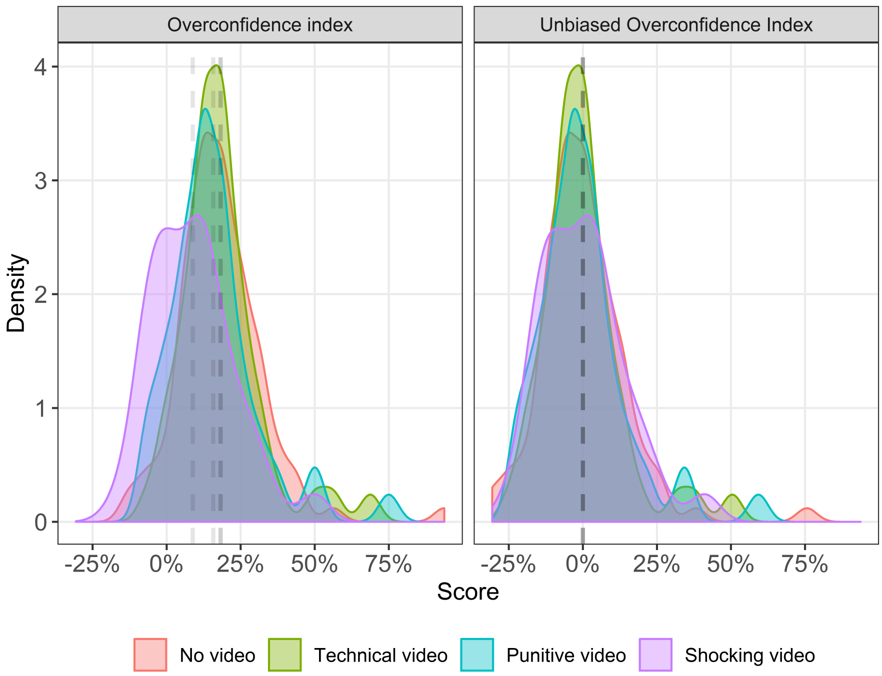

Figure 2: *Kernel density plots of (a) the plain level of overconfidence of students and (b) the residual of the level of overconfidence after controlling for the external video stimuli (term ε_i of specification (1)).*

We use a elastic net regression to estimate the importance of each attribute in the model. Such regression optimally combines L_2-norm (ridge) and L_1-norm (Lasso) regularization and is useful when we have several attributes to choose from and few observations. Standard linear models, such as the OLS, would perform poorly as we are in a high-dimensional space[2] with few observations. Regularization is a natural step to overcome this problem, as it balances model's complexity (number of parameters) and performance. The ridge regularization tends to shrink the coefficients of correlated predictors towards each other while the Lasso tends to pick one of them and discard the others.

To select the most important attributes, we model the unbiased level of overconfidence (ε_i) using all attributes we have as follows:

$$\varepsilon_i = \beta^T \cdot \mathbf{X}_i + \text{error}_i, \tag{2}$$

in which dim($\mathbf{X}$) = 400×34 (400 observations and 33 attributes + 1 constant) and dim(β) = 34×1. Following the elastic net procedure, we select β that minimizes the following loss function $L(\beta)$:

$$L(\beta) = \sum_{i=1}^{n} \left(\varepsilon_i - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \left[(1-\alpha) \frac{\|\beta\|_2^2}{2} + \alpha \|\beta\|_1^2 \right], \tag{3}$$

in which $n = 400$ is the number of observations and $p = 33 + 1$ is the number of attributes; λ is the regularization parameter that penalizes model complexity; and $\alpha \in [0,1]$ controls the mixture between L_2 and L_1 regularization. The first term is the traditional error, measured by the projected and the real unbiased overconfidence level. The second is the regularization term, which has relative weight of λ with respect to the traditional OLS fitting, and comprises a convex linear combination of L_2 regularization (weighted by α) and L_1 regularization (weighted by $1-\alpha$).

Following the machine learning literature, model complexity is given in terms of the total magnitude of the model's free parameters, which are encoded in the vector β. Like Lasso and ridge, we do not penalize the magnitude of the intercept term, which is one of the coefficients inside β. When $\lambda = 0$, the estimation of β reduces to a standard OLS. If $\lambda \neq 0$, then regularization is enabled. In such case, when $\alpha = 0$, Equation (3) simplifies to a ridge regression. In contrast, when $\alpha = 1$, Equation (3) reduces to a Lasso regression.

In the elastic net regression, α takes values in-between 0 and 1. We optimally tune α and λ using a nested cross-validation procedure. Such methodology enables us to tune the regularization parameters while preventing overfitting of the model.[3] We use $k = 10$ folds, repeat such process 100 times, and report the average values. We optimize α over the grid search space $\{0, 0.01, 0.02, \ldots, 1\}$ and λ over $\{0, 1, 2, \ldots, 100\}$. Also, we pre-process all attributes by applying a Z-score standardization, which is a demeaning process followed by a division by the standard deviation of each attribute.

Figure 3 plots the 14 most relevant (out of 33) attributes for explaining the unbiased level of confidence. The optimal regularization parameters were $\lambda = 2$ and $\alpha = 0.545$. We normalize the coefficients in terms

[2]The number of dimensions is equivalent to the number of attributes used in the model. In our case, we have 33 attributes to choose from.

[3]The nested cross-validation procedure involves multiple runs of k-fold cross-validation procedures. Each k-fold cross-validation estimates an unbiased accuracy for a given set of parameters α and λ (inner loop). However, to estimate the optimal λ and α, we need another k-fold cross validation outside the inner k-fold cross-validation procedure (outer loop). In each k-fold cross-validation procedure, we split the data into k non-overlapping folds or subsets. In each run, one fold is held out for performance check while the model is trained with the $k-1$ remaining subsets. For each pair of parameters λ and α, we perform this procedure k times, such that each fold is left for performance check exactly once. In the end, we select the parameters λ and α that maximize the accuracy of the model.

of the most important attribute. The attribute "Drink fines?" is the most powerful predictor of students' level of overconfidence, followed by "Age" and "Cellphone fines." There is an exponential decrease of the importance of attributes, suggesting that few attributes would suffice for the estimation of the level of overconfidence of students. In our econometric specification in the next section, we choose the top 10 attributes.[4]

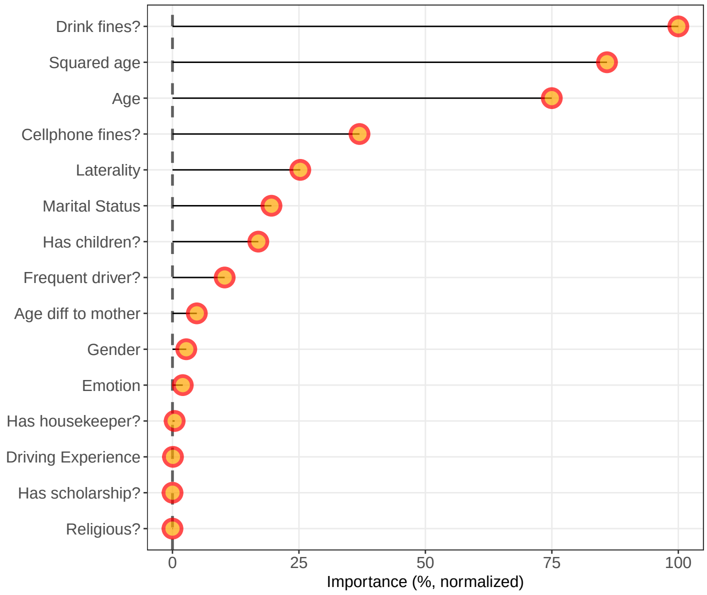

Figure 3: *Feature selection results using an elastic net procedure with L_2 and L_1 regularization. Coefficients are normalized in terms of the most important attribute ("drink fines?").*

5. Results and discussions

In this section, we define our econometric specifications and report our empirical results.

5.1. Measuring the efficiency of different traffic campaign videos in shaping drivers' overconfidence

To test the role of different traffic campaign videos in increasing or reducing drivers' overconfidence, we use the following baseline model:

$$y_{ig} = \alpha_g + \beta_1 \text{Technical}_i + \beta_2 \text{Punitive}_i + \beta_3 \text{Shocking}_i + \gamma^T \text{Controls}_i + \varepsilon_{ig} \tag{4}$$

in which i indexes students and g groups of students. The variable y_{ig} is the overconfidence level of student i in group g; α_g represents fixed effects at different group levels (will be discussed); $\text{Technical}_i, \text{Punitive}_i, \text{Shocking}_i$ are dummies that indicate whether student i is in the treatment group that watched the technical, punitive, or shocking video, respectively. Controls_i are control variables that can influence students' overconfidence level, and ε_{ig} is the standard error term. As baseline model, we measure overconfidence index by the average score students obtain in the set of questions in Table 3 (see Section 3.2.2). As controls, we choose

[4]Observe that the variables below the top 10 approximately do not explain anything of the level of overconfidence of students after controlling for the top 10 attributes.

the ten most relevant predictors of students' overconfidence level as identified by our feature extraction methodology (refer to Section 4), which are:

1. *Drink fines?*: dummy variable that equals 1 if the student has received a fine related to alcohol drinking and 0, otherwise.
2. *Age*: numerical variable describing the age of the student.
3. *Cellphone fines?*: dummy variable that equals 1 if the student has received a fine related to cellphone handling and 0, otherwise.
4. *Right-handed*: dummy variable that equals 1 if the student is right-handed and 0, otherwise.
5. *Single*: dummy variable that equals 1 if the student is single and 0, otherwise.
6. *Has children?*: dummy variable that equals 1 if the student has children and 0, otherwise.
7. *Frequent driver?*: dummy variable that equals 1 is a frequent driver and 0, otherwise.
8. *Age diff to mother*: numerical variable indicating the difference of ages between the mother and the student.
9. *Male*: dummy variable that equals 1 is male and 0, otherwise.
10. *Emotion*: numerical variable that indicates the level of emotion of the student. It ranges from 0 (not emotive at all) to 7 (very emotive).

We estimate (4) using OLS using robust standard errors (Newey & West, 1987). Since we are dealing with a cross-sectional data, such error clustering minimizes heteroskedasticity issues. In addition, if variable x is numerical, then we apply the following logarithmic transformation: $\log(k+x)$, in which $k = 1 + |min(x)|$.[5]

Table 4 reports summary statistics of the overconfidence index and the regressors employed in the model. Even though the overconfidence ranges from -2 to 2, the minimum value is -0.19, and the maximum is 1, suggesting we do not find extreme overconfidence traits in our sample. Also, the mean and standard values of the overconfidence are 0.15 ± 0.15, suggesting that students are, on average, overconfident. Only 4% of respondents received a fine related to alcohol driving before driving and 12% with fines related to cellphone handling during driving. We have a wide range of students' age, going from 19 to 58 with a mean value of 24.46. 90% of students are right-handed, 83% are single, 17% have children, 67% are frequent drivers, and 54% are men. We have a substantial heterogeneity of emotion levels of students, going from the minimum value (1 - not emotive at all) to the maximum value (7 - incredibly emotive). The average emotion level of students is 4.59, indicating a degree of emotiveness of students.

Table 5 presents the results from estimating Equation (4). In the seven econometric specifications, columns (1) to (7), we always introduce the treatment group dummies to test whether traffic campaign videos with the same content but with a different exhibition manner matter. From columns (1) to (6), we add, in an isolated way, controls. In column (7), we introduce all controls at once.

Comparatively to the control group, shocking videos lead to a decrease of 8.9% to 10.1% in respondents' level of overconfidence. The coefficient does not change much as we add more controls, suggesting that the result is robust. In contrast, the level of overconfidence of students that experienced punitive videos is 2.1% to 2.9% less than that of the control group, but not statistically significant when we cluster with robust standard errors. The coefficient measuring the differential of overconfidence of students that watched technical videos is very close to zero and statistically insignificant. Our results indicate that videos of the

[5] The addition of k prevents the application of the logarithmic transformation to a non-positive number (undefined). We also add 1 to prevent the application of the logarithm to a zero number if the domain of x contains a zero.

Table 4: *Summary statistics of the variables used in the econometric specification. Numerical variables are reported before any logarithmic transformation. The first row corresponds to the dependent variable. The remainder denotes the independent variables, which are ordered by feature importance (see Section 4).*

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Overconfidence index	400	0.15	0.15	−0.19	0.10	0.20	1.00
Has drink fines	400	0.04	0.21	0	1	1	1
Age	400	24.46	5.49	19	22	25	58
Has cellphone fines	400	0.12	0.32	0	1	1	1
Right-handed	400	0.90	0.30	0	1	1	1
Single	400	0.83	0.37	0	1	1	1
Has children	400	0.17	0.37	0	1	1	1
Frequent driver	400	0.67	0.47	0	0	1	1
Mother's - student's age	400	24.46	5.49	19	22	25	58
Male	400	0.54	0.50	0	0	1	1
Emotion	400	4.59	1.47	1	4	6	7

Australian school (shocking videos), with strong and life-threatening scenes, are more effective in reducing drivers' overconfidence than videos of the American school (punitive videos), with punitive contents showing the consequences and penalties of drinking and driving, and videos of the European school (technical videos), with technical content.

5.2. The role of emotion in driving overconfidence

Using our sample of students, we have shown in the previous section that traffic campaigns with shocking contents are the most effective in reducing overconfidence. Now, we want to understand further the role of emotion as a driver that amplifies the effectiveness of traffic campaign videos (regardless of the video content).

Ideally, we would need the emotion level of every student before and after watching the videos. Then, we could interact with the emotion level differential with the treatment variable to understand the role of emotion in shaping drivers' overconfidence. As the collection of such information is noisy and very prone to errors and human biases,[6] we opt to use a data-driven approach through the use of the propensity score matching technique.

Our matching rationale is as follows. For each student in the three treatment groups, we match her/him with the *most similar* student in the control group using several social, biological and driving characteristics. Since the control group did not experience any video exhibition, we take the emotion level of the matched student in the control group as the *prior emotion level* of the matched student in the treatment group. We then define the emotion level differential as the *observed emotion level* of the treatment student minus the *matched emotion level* of the control student.

Our specification for the propensity score matching algorithm is:

$$\text{Treatment}_i = \alpha + \gamma^T \,\text{Attributes}_i + \varepsilon_i, \tag{5}$$

in which $\text{Treatment}_i = 1$ if student i is in any of the three treatment groups, and 0 otherwise; Attributes_i is a vector composed of the attributes used to find the most similar student in the control group for each student

[6] Besides, we only have cross-sectional information of students.

Table 5: *This table reports the output from Regression (4). The dependent variable is the log of the overconfidence index of students plus a constant k. We set $k = 1.19$, which is one plus the minimum overconfidence index in absolute values, i.e., $|-0.19|$ according to Table 4. The coefficient estimates of interest are the dummy variables Technical, Punitive, and Shocking videos, which provide elasticities of the efficiency of traffic campaign videos in shaping drivers' overconfidence. We add as controls the ten most predictive variables identified by our machine-learning feature extraction procedure discussed in Section 4. We take the log values of all numerical variables. We use Newey & West (1987)'s robust standard errors and no fixed effects in every specification in this table. Dummies for the three treatment groups are present in every specification. We test different controls from columns (1) to (6) and add all of them in column (7). Statistical significance levels: *** p-value< 0.01, ** p-value< 0.05, * p-value< 0.10.*

Dependent variable:	*log*($k+$ Overconfidence Index)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment groups							
Technical video	0.003	0.001	0.003	0.004	0.003	−0.0004	−0.002
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
Punitive video	−0.025	−0.027	−0.019	−0.024	−0.024	−0.029	−0.021
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Shocking video	-0.100^{***}	-0.104^{***}	-0.090^{***}	-0.097^{***}	-0.101^{***}	-0.099^{***}	-0.089^{***}
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
Control variables							
Has drink fines		0.114^{***}					0.125^{***}
		(0.034)					(0.034)
Has cellphone fines		0.045^{**}					0.031
		(0.022)					(0.022)
log(age)			1.572^{**}				1.498^{**}
			(0.621)				(0.610)
log^2(age)			-0.259^{***}				-0.246^{***}
			(0.096)				(0.094)
Right-handed				0.055^{**}			0.056^{**}
				(0.024)			(0.023)
Single					0.039^{**}		0.014
					(0.019)		(0.026)
Has children						-0.045^{*}	−0.040
						(0.023)	(0.026)
Frequent driver						0.020	0.019
						(0.015)	(0.015)
log(mother's − student's age)						0.006	0.026
						(0.048)	(0.049)
log(Emotion)						−0.003	−0.006
						(0.019)	(0.018)
Male						0.012	0.010
						(0.015)	(0.014)
Constant	−0.016	-0.024^{*}	-2.382^{**}	-0.068^{**}	-0.049^{**}	−0.040	-2.431^{**}
	(0.014)	(0.014)	(1.007)	(0.026)	(0.021)	(0.151)	(1.011)
Observations	400	400	400	400	400	400	400
R^2	0.080	0.123	0.128	0.093	0.090	0.097	0.196
Adjusted R^2	0.073	0.112	0.117	0.084	0.081	0.078	0.167

in the treatment group. We use the top 10 attributes that most explain students' overconfidence discussed in Section 4, except for the emotion level. Since we have 100 students in each of the three treatment groups and only 100 students in the control group, we use matching with replacement.[7]

One underlying hypothesis of this approach is that traffic campaign videos also influence emotion.[8] Moreover, there is a large body of literature showing that emotion influences human behavior, including overconfidence. Therefore, we would have two channels through which traffic video campaigns could influence overconfidence: (i) one direct channel (video $\to$ overconfidence) and (ii) an indirect channel, through emotion (video $\to$ emotion $\to$ overconfidence). We potentially consider the two channels. Since the control group does not experience videos, we only compare the differentials of emotions within the treatment group. Therefore, we are interested in the interaction between the treatment dummies and the emotion differentials of treated students evaluated in respect with their matched control students' emotion levels.

We use the following econometric specification to test the direct and indirect channels:

$$y_{ig} = \alpha_g + \sum_{treat \in \mathscr{T}} \beta_{treat} \cdot \mathbb{1}_{\{i \,\in\, treat\}} + \sum_{treat \in \mathscr{T}} \gamma_{treat} \cdot \mathbb{1}_{\{i \,\in\, treat\}} \times \text{Emotive}_i + \varepsilon_{ig} \tag{6}$$

in which i indexes students and g groups of students; y_{ig} is again the overconfidence level of student i, member of group g; $\mathscr{T} = \{\text{Technical Video}, \text{Punitive Video}, \text{Shocking Video}\}$ is a set containing the subsets of students comprising each of the three treatment groups and $\mathbb{1}_{\{\text{condition}\}}$ is the indicator function that yields 1 if the condition is true, and 0 otherwise. We construct the dummy variable Emotive_i using the emotion differential $\Delta\text{Emotion}_i$, which is the observed emotion of treated student i minus the *a priori* emotion (before video exhibition), which is proxied by the most similar student in the control group via propensity score matching. We set $\text{Emotive}_i = \Delta\text{Emotion}_i \geq \theta$, in which θ is a minimum threshold for emotion differentials. The larger is the differential, the more sensitive the student was to the video exhibition. While the β coefficients capture the direct effect of traffic campaign videos on overconfidence, the γ coefficients absorb the indirect effect through emotion differentials.

The term α_g represents matched group fixed effects. The introduction of such fixed effects makes our analysis within matched groups, i.e., we are comparing each treated student with her/his most similar counterpart in the control group. Therefore, we do not need to use biological, social, and driving characteristics for fixed effects, which are embedded in the matched pair by construction.

Table 5 presents the results from estimating Equation (6). Columns (1) to (6) consider different threshold values (θ) for the Emotive dummy, going from $\theta \geq 1$ to $\theta \geq 6$. Specification 6 is the most conservative and compares only across matched students with large emotion differentials. The indirect channel takes place only when emotion differentials are greater than a threshold of 3 (columns (3) to (6)) and in the treatment group that watched the shocking video content. In these cases, more emotive students are 15.5% to 22.6% less overconfident than non-emotive students within the shocking video treatment group. The indirect channel seems to push down overconfidence much more than the direct channel for students that

[7] Without this bootstrap-like approach, we would have to drop 200 treated students (1:1 matching). In unreported regressions, our conclusions with matching without replacement are the same and can be shared upon request. With replacement, the 300 treated students are matched with 76 control students. The 24 remainder control students are not matched with any treated student.

[8] Even though the average level of excitement is similar across the control and treatment groups (see Table 3), we are here looking at a more granular level, at the student level, which has more extensive heterogeneity. This difference is critical for finding matched control students for each treated student. If videos would not change emotion levels, then the emotion differentials would all be zero. As we will see, this is not the case in our empirical findings.

Table 6: *This table reports the output from Regression (6). The dependent variable is the log of the overconfidence index of students plus a constant k. We set $k = 1.19$, which is one plus the minimum overconfidence index in absolute values, i.e., $|-0.19|$ according to Table 4. We use as comparisons within matched treated students and most similar control students. The most similar control student is found using (5) via propensity score matching. The direct channel part of the table captures the channel (traffic video campaign $\rightarrow$ overconfidence). The indirect channel part capture the channel (traffic video campaign $\rightarrow$ emotion $\rightarrow$ overconfidence). All coefficients are in elasticities. Columns (1) to (6) define the Emotive dummy variable by altering the θ threshold. For instance, in column (1), $\theta = 1$, and so on. We did not find emotion differentials in the technical treatment group for $\theta \geq 5$ and in the punitive treatment group for $\theta \geq 6$ (depicted as horizontal bars). We use Newey & West (1987)'s robust standard errors. Statistical significance levels: *** p-value< 0.01, ** p-value< 0.05, * p-value< 0.10.*

Dependent variable:	$log(k+$ Overconfidence Index$)$					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEmotion	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5	≥ 6
Indirect channel (through emotion)						
Technical video × Emotive	0.011	−0.014	−0.070	−0.008	—	—
	(0.049)	(0.050)	(0.069)	(0.074)		
Punitive video × Emotive	−0.035	−0.062	−0.059	−0.115	−0.296	
	(0.061)	(0.054)	(0.070)	(0.121)	(0.197)	—
Shocking video × Emotive	−0.025	−0.033	-0.208^{**}	-0.226^{*}	-0.172^{***}	-0.155^{***}
	(0.056)	(0.054)	(0.093)	(0.117)	(0.030)	(0.026)
Direct channel						
Technical video	−0.024	−0.011	−0.0004	−0.016	−0.017	−0.017
	(0.037)	(0.029)	(0.023)	(0.026)	(0.024)	(0.024)
Punitive video	−0.004	−0.004	−0.018	−0.020	−0.018	−0.030
	(0.053)	(0.030)	(0.028)	(0.025)	(0.024)	(0.026)
Shocking video	-0.088^{*}	-0.092^{***}	-0.081^{***}	-0.093^{***}	-0.100^{***}	-0.102^{***}
	(0.047)	(0.032)	(0.025)	(0.026)	(0.026)	(0.026)
Fixed effects						
Matched treat-control PSM group	Yes	Yes	Yes	Yes	Yes	Yes
Observations	600	600	600	600	600	600
R^2	0.535	0.539	0.561	0.550	0.552	0.534
Adjusted R^2	0.052	0.061	0.106	0.084	0.091	0.057

Table 7: *Robustness test. This table reports the output from Regression (6). The dependent variable is the log of the overconfidence index of students plus a constant k. We set* $k = 1.19$*, which is one plus the minimum overconfidence index in absolute values, i.e.,* $|-0.19|$ *according to Table 4. The comparisons are within different biological, social, and driving characteristics of students. To compose the Emotive dummy, we take the observed emotion level of the treated student minus the emotion level of the most similar student in the control group via propensity score matching. The direct channel part of the table captures the channel (traffic video campaign → overconfidence). The indirect channel part capture the channel (traffic video campaign → emotion → overconfidence). All coefficients are in elasticities. Columns (1) to (6) define the Emotive dummy variable by altering the* θ *threshold. For instance, in column (1),* $\theta = 1$*, and so on. We did not find emotion differentials in the technical treatment group for* $\theta \geq 5$ *and in the punitive treatment group for* $\theta \geq 6$ *(depicted as horizontal bars). We use Newey & West (1987)'s robust standard errors. Statistical significance levels: *** p-value*< 0.01*, ** p-value*< 0.05*, * p-value*< 0.10*.*

Dependent variable:	$log(k+$ Overconfidence Index$)$					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEmotion	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5	≥ 6
Indirect channel (through emotion)						
Technical video × Emotive	0.026	−0.003	−0.001	0.013	—	—
	(0.023)	(0.021)	(0.024)	(0.030)		
Punitive video × Emotive	0.001	0.009	−0.019	−0.042	−0.049	—
	(0.024)	(0.025)	(0.027)	(0.037)	(0.048)	
Shocking video × Emotive	-0.043^{**}	−0.017	-0.066^{**}	−0.088	-0.177^{***}	-0.209^{***}
	(0.021)	(0.022)	(0.032)	(0.057)	(0.043)	(0.034)
Direct channel						
Technical video	−0.022	−0.003	−0.004	−0.006	−0.004	−0.005
	(0.021)	(0.021)	(0.018)	(0.018)	(0.017)	(0.017)
Punitive video	−0.029	-0.034^{*}	−0.026	−0.025	−0.027	-0.030^{*}
	(0.024)	(0.018)	(0.017)	(0.017)	(0.016)	(0.016)
Shocking video	−0.028	-0.050^{***}	-0.048^{***}	-0.051^{***}	-0.053^{***}	-0.054^{***}
	(0.020)	(0.016)	(0.015)	(0.014)	(0.014)	(0.014)
Fixed effects						
Drink fines?	Yes	Yes	Yes	Yes	Yes	Yes
Age + squared Age	Yes	Yes	Yes	Yes	Yes	Yes
Cellphone fines?	Yes	Yes	Yes	Yes	Yes	Yes
Laterality	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Has children	Yes	Yes	Yes	Yes	Yes	Yes
Frequent driver	Yes	Yes	Yes	Yes	Yes	Yes
Mother's - student's age	Yes	Yes	Yes	Yes	Yes	Yes
Observations	400	400	400	400	400	400
R^2	0.378	0.369	0.377	0.378	0.381	0.376
Adjusted R^2	0.165	0.152	0.163	0.164	0.171	0.168

watched the video with shocking contents. We do not find evidence of emotion influencing overconfidence within the treatment groups that received the technical and punitive video contents.

As robustness, we re-run our specification but using a different comparison strategy. Instead of performing within matched treat-control comparisons, we compare within similar biological, social, and driving characteristics of students. In technical terms, we only need to change the group fixed effects α_g in (6). Table 7 reports the results from re-estimating such equation. Our conclusions remain the same.

5.3. Does the efficiency of different traffic campaign videos differ across genders?

We now analyze whether gender plays a role in the efficiency of different traffic campaign strategies. Our baseline econometric specification stays the same, but now we include an interaction of gender with the treatment variables to capture any potential heterogeneity among men and women. Therefore, we use the following model:

$$y_{ig} = \alpha_g + \sum_{treat \in \mathscr{T}} \beta_{treat} \cdot \mathbb{1}_{\{i \,\in\, treat\}} + \sum_{treat \in \mathscr{T}} \gamma_{treat} \cdot \mathbb{1}_{\{i \,\in\, treat\}} \times \text{Male}_i + \lambda \text{Male}_i + \varepsilon_{ig} \tag{7}$$

in which i indexes students and g groups of students; y_{ig} is the overconfidence level of student i, member of the group g; and the other variables follow the same convention as the previous econometric exercises. Our coefficient of interest is γ, which measures any potential heterogeneity in men's and women's overconfidence levels after watching the same traffic video content but with different exhibition strategies. We also add the marginal term Male_i to capture the average overconfidence level of men that differs from the average overconfidence level of the entire sample (men + women).

Table 8 reports the results of Regression (7). Columns (1) to (6) incrementally add fixed effects that capture biological, social and driving heterogeneities among students. Looking at the interacted terms, we observe that punitive videos are less effective in reducing the overconfidence of men. Women that watched the punitive video have 7.0% to 8.9% less overconfidence that the control group. However, the overall effect of punitive video on men's overconfidence ranges from -1.2% to +1.5%, with no statistically significance (compound effect).

Our findings indicate that shocking videos are an excellent traffic campaign strategy to reduce overconfidence levels regardless of gender. Punitive videos, in contrast, are valid only for women, being ineffective for men. Finally, we find no empirical evidence that technical videos change students' overconfidence.

6. Conclusions

Promoting traffic safety is one of the most important goals for public policymakers in today's society and represents a critical strategic issue to reduce the number of traffic accidents, as according to data from the World Health Organization (WHO) road accidents kill 1.25 million people a year worldwide and are the leading cause of death for people aged 15-29. In Brazil, according to DataSUS, more than 37.3 thousand people die every year in the transit of cities and highways of the country. A significant number of these deaths is caused due to the Handling the cell phone, and the consumption of alcoholic beverage in the direction is generating a substantial amount of deaths.

In this way, pursuing effective public policies to reduce these numbers is of fundamental importance. In this sense, this work stresses the importance of paying attention to the behavior of drivers in traffic, since they are responsible for transgressions and deaths in transit. This work, seeking a broad look at the practice of drivers in traffic, reveals that their behavior can be affected by mood swings. Punitive and strong-minded traffic campaigns have proved effective in reducing drivers' overconfidence, thus providing more conscious

Table 8: *This table reports the output from Regression (7). The dependent variable is the log of the overconfidence index of students plus a constant k. We set* $k = 1.19$*, which is one plus the minimum overconfidence index in absolute values, i.e.,* $|-0.19|$ *according to Table 4. The coefficient estimates of interest are the dummy variables Technical, Punitive, and Shocking videos, interacted with male, which capture any heterogeneity among men and women concerning the efficiency of traffic campaign videos in shaping drivers' overconfidence. We add as controls the ten most predictive variables identified by our machine-learning feature extraction procedure discussed in Section 4, except for gender, which is explicitly in the table. We take the log values of all numerical variables. We use Newey & West (1987)'s robust standard errors and no fixed effects in every specification in this table. We gradually add fixed effects that absorb the biological, social, and driving characteristics of students from columns (1) to (6). Statistical significance levels: *** p-value*< 0.01*, ** p-value*< 0.05*, * p-value*< 0.10*.*

Dependent variable:	$log(k+$ Overconfidence Index$)$					
	(1)	(2)	(3)	(4)	(5)	(6)
Interactions (treatment × gender)						
Technical video × Male?	0.016	0.014	0.002	0.006	0.008	−0.011
	(0.041)	(0.041)	(0.043)	(0.041)	(0.041)	(0.046)
Punitive video × Male?	0.098^{**}	0.100^{**}	0.089^{**}	0.087^{**}	0.082^{**}	0.077^{*}
	(0.042)	(0.041)	(0.043)	(0.041)	(0.041)	(0.045)
Shocking video × Male?	0.049	0.060	0.052	0.051	0.047	0.030
	(0.040)	(0.040)	(0.042)	(0.040)	(0.040)	(0.045)
Non-interacted variables (treatment + gender)						
Technical video	−0.0001	−0.002	0.013	0.011	0.010	0.012
	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.032)
Punitive video	-0.084^{***}	-0.086^{***}	-0.074^{**}	-0.073^{**}	-0.070^{**}	-0.089^{***}
	(0.031)	(0.030)	(0.032)	(0.031)	(0.031)	(0.033)
Shocking video	-0.121^{***}	-0.127^{***}	-0.107^{***}	-0.106^{***}	-0.102^{***}	-0.093^{***}
	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)	(0.028)
Male	−0.030	−0.034	−0.026	−0.025	−0.022	−0.021
	(0.029)	(0.028)	(0.030)	(0.028)	(0.028)	(0.032)
Constant	−0.004					
	(0.018)					
Fixed effects						
Drink fines?	No	Yes	Yes	Yes	Yes	Yes
Age + squared Age	No	No	Yes	Yes	Yes	Yes
Cellphone fines?	No	No	No	Yes	Yes	Yes
Laterality	No	No	No	No	Yes	Yes
Marital Status	No	No	No	No	No	Yes
Has children	No	No	No	No	No	Yes
Frequent driver	No	No	No	No	No	Yes
Mother's - student's age	No	No	No	No	No	Yes
Emotion	No	No	No	No	No	Yes
Observations	400	400	400	400	400	400
R^2	0.096	0.131	0.269	0.271	0.286	0.385
Adjusted R^2	0.080	0.113	0.113	0.188	0.198	0.160

and cautious action in traffic. Also, this work sought to trace the individual characteristics of drivers that influence their perception of risk and the construction of their overconfidence.

Because it is such a current and recurring issue, future research may try to explain these behaviors through field experiments, testing in practice what influences individuals to commit such traffic offenses, and thus contributing to the formulation of public policies.

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