Social comparisons, status and driving behavior*

Yan Chen[†] Fangwen Lu[‡] Jinan Zhang[§]

February 24, 2016

Abstract

The establishment of desirable social norms is an integral part of a well-functioning civil society. While recent evidence has demonstrated that social comparison can affect behavior in a variety of contexts, it is not clear what *type* of comparative social information is most effective. Using a large-scale field experiment to study driving practices, we sent text messages containing different types of social information to drivers in Tsingtao, China. We find two types of social information to be particularly effective in reducing traffic violations: the driving behavior of those similar to oneself and the driving behavior of those with high-status cars. Our results indicate that the combination of descriptive norms with social status is a cost-effective yet powerful intervention for establishing better driving behavior in emerging markets.

JEL: C93, D83

Keywords: social comparison, status, randomized field experiment

*We would like to thank Jiang Jiang, Ming Jiang, Nancy Kotzian, Erin Krupka, Steve Leider, Yusufcan Masatlioglu, Tanya Rosenblat, Carrie Xu, Yesim Orhun and seminar participants at Peking University, Renmin University, Tsinghua University, the University of Michigan, and the 2014 International Meetings of the Economic Science Association (Honolulu, HI) for helpful discussions and comments. We thank the Tsingtao Police Department for their collaboration, especially Bin Yan and Peng Xu for their support in implementing the experiment. The financial support from the National Science Foundation through grant no. BCS-1111019 to Chen and the Natural Science Foundation of China through grant no. 71203226 to Lu is gratefully acknowledged. The research has been approved by the University of Michigan IRB.

[†]School of Information, University of Michigan, 105 South State Street, Ann Arbor, MI 48109-2112, USA. Email: yanchen@umich.edu.

[‡]School of Economics, Renmin University of China, 59 Zhongguancun Street, Beijing 100872, China. E-mail: lufangwen@gmail.com. Lu is the corresponding author.

[§]Center for East Asian Studies, Stanford University, Stanford, CA 94305-6072, USA. E-mail: jnzhang@stanford.edu.

> It is not only the superior who causes himself to be copied by the inferior, the patrician by the plebeian, the nobleman by the commoner, the cleric by the layman, and, at a later period, the Parisian by the provincial, the townsman by the peasant, etc., it is also the inferior who, in a certain measure, much less, to be sure, is copied, or is likely to be copied, by the superior. – Gabriel Tarde (1888, page 187)[1]

1 Introduction

Social information has been shown to affect behavior in a variety of domains. It is well-documented that social comparisons can cause people to reduce household water consumption (Ferraro and Price 2013) and overall energy consumption (Allcott 2011, Allcott and Rogers 2014), increase contributions to public goods in online communities (Chen, Harper, Konstan and Li 2010), and influence voter turnout (Gerber and Rogers 2009).[2] Despite the increased interests in social comparison research, several open questions remain. In particular, what type of social information is most effective to influence behavior? Who are influenced by social comparisons? And lastly, what is the role of status in social comparisons?

While sociologist Gabriel Tarde acknowledged that the superior could both influence and be influenced by the inferior, he asserted that “the radiation of examples from above to below is the only fact worth consideration" (Tarde 1888, page 188). In this paper, we systematically evaluate the role of status in social comparison in a large-scale field experiment designed to reduce traffic violations, an important domain with global policy implications.

Traffic fatalities have become a global problem. In 2010 alone, 1.24 million people were killed on the roads in various countries in the world. Of these, 80 percent were in middle-income countries, where only 50 percent of the world’s registered vehicles were owned and driven (United Nations General Assembly 2013). In addition to the loss of life, these accidents result in billions of dollars in costs for drivers and insurers (Jacobs, Aeron-Thomas and Astrop 2000). The growing awareness of the devastating scale of road traffic injuries as a global public health and development concern prompted the governments of the world to declare 2011–2020 as the Decade of Action for Road Safety (World Health Organization 2013).

Many measures have been proposed to reduce fatalities from road accidents, including increasing road capacity; passing stricter road safety laws; increasing penalty for drinking and driving; increasing the use of seat belts, helmets and child restraints; and improving post-crash responses (World Health Organization 2013). However, implementation of these measures takes time and resources. This study explores alternative ways to increase road safety through social comparison.

[1] Gabriel Tarde (1843-1904), a French sociologist, is considered one of the founding fathers of sociology.

[2] We review this literature in detail in Section 2.

Specifically, our study focuses on China. Car ownership in China has an annual growth rate of 24% in recent years and China is projected to overtake the United States as the country with the largest car fleet in the world by 2030 (Chamon, Mauro and Okawa 2008). As private car ownership is a relatively recent phenomenon in China, social norms about driving have not yet been established. Consequently, the use of social comparison can be particularly effective in influencing behavior (Buunk and Mussweiler 2001).

In this paper, we systematically vary and evaluate the role of status on driving behavior in our interventions. The use of status-based social comparison to influence driving behavior in China is particularly promising, as the type of car one drives increasingly reflects one's social status (Barton 2011, Branigan 2012). As status symbols, cars signify not only stability and maturity, but also marriageability in a society with rising sex ratios.[3] Therefore, in our study, we link social information with car status to influence driving behavior.

Based on social comparison theories in economics and psychology, as well as empirical findings from lab and field experiments, we implement a large-scale field experiment in Tsingtao, a prosperous coastal city in China. In our field experiment ($n = 395,204$), we send a text message to 75,247 drivers who had received at least one ticket in the first nine months of 2013 that indicates one of the following: his or her own number of tickets, the average number of tickets among drivers of the same car brand, or the average number of tickets among drivers of a high-, medium-, or low-status car. Our results show that, compared to the control condition, drivers with an above-average number of violations reduce their future violations by 6% after receiving information on the average number of violations for drivers of their own car brand. This result replicates the effect of descriptive norms of similar others found in the lab and field. Furthermore, we find that drivers reduce their future violations by 5% after receiving information on what drivers of high-status cars do. The effect is the largest among drivers of an economy car who reduce their future violations by 9%. Our finding provides empirical evidence for Tarde's claim that social influence is channeled by status: it descends from the social superior to social inferior.

What tangible actions do drivers take in response to our intervention? Looking at the effects of our intervention on the types of traffic violations, we find that the most significant effect is the reduction of the number of speeding tickets, indicating that social information might have made drivers pay more attention while driving.

To our knowledge, this is the first large-scale field experiment that evaluates the role of status in social comparison interventions. Our findings have both theoretical and practical implications. First, it underscores the importance of status in social comparisons by demonstrating that drivers of low-status cars have the largest behavioral response to the descriptive norm of high-status drivers. Second, in the domain of traffic safely and potentially in other domains as well, the behavior of

[3] The rising sex ratio has been proposed as one of the motives for household savings in China (Wei and Zhang 2011).

high-status individuals can serve as the guiding model for the rest of the society. Lastly, our intervention with personalized text messages is a cost-effective way to achieve socially more desirable outcomes.

2 Literature Review

Our experiment is based on the idea that social comparisons impact how people behave. This section presents a discussion of the theoretical and experimental literature behind this idea.

A large body of literature in both social psychology (Festinger 1954) and economics (Akerlof 1980) demonstrates that social comparisons affect behavior by providing us with a specific guideline of what constitutes the “right behavior" in various contexts. These effects are especially strong in ambiguous situations or when norms have not yet been established (Buunk and Mussweiler 2001, Suls, Martin and Wheeler 2002), a condition which is likely to be true for drivers in emerging markets.

Furthermore, when information regarding prevalent behavior is available, people exhibit a tendency to copy this behavior, a phenomenon referred to as conformity (Asch 1956, Akerlof 1980, Jones 1984, Bernheim 1994). In economics, this phenomenon can be modelled as interdependent preferences, where utility functions depend on not only the absolute value of consumption, but also the average level of consumption (Duesenberry 1949, Pollak 1976) or ordinal rank in the distribution of consumption (Frank 1985, Robson 1992, Hopkins and Kornienko 2004).

While most of the empirical studies of social comparisons are conducted in the laboratory, using dictator games (Cason and Mui 1998, Krupka and Weber 2009, Duffy and Kornienko 2010), ultimatum bargaining games (Knez and Camerer 1995, Duffy and Feltovich 1999, Bohnet and Zeckhauser 2004, Ho and Su 2009), or coordination games (Eckel and Wilson 2007), several studies have used natural field experiments. These field experiments have been conducted in such diverse contexts as university, public radio and United Way fundraising campaigns (Frey and Meier 2004, Shang and Croson 2009, Kessler 2013), online community movie ratings (Chen et al. 2010), voting (Gerber and Rogers 2009), retirement savings (Beshears, Choi, Laibson, Madrian and Milkman forthcoming), residential water consumption initiatives (Ferraro and Price 2013), and online job recruiting (Gee 2014). Similarly, descriptive social norms have been used to reduce overall energy consumption among households across the United States (Allcott 2011, Allcott and Rogers 2014).

Two studies have examined the use of social forces to improve traffic safety. In a field experiment in Kenya, messages encouraging passengers to speak up against bad driving are placed on long-distance mini-buses. This intervention is shown to have reduced insurance claims by a half to two-thirds (Habyarimana and Jack 2011). In a recent field experiment in Tsingtao, researchers find that only drivers who receive messages on their traffic tickets reduce their subsequent traffic violations, with informative messages on enforcement or safe driving having no significant effect (Lu, Zhang and Perloff 2013). Given that our experiment was conducted in the same city, it is important to compare the two studies. In Lu et al. (2013), all text messages were sent in April 2012, 18 months before ours. Furthermore, less than 5% of the drivers in our experiment received a treatment message in the earlier study, which shows that the treatment effect faded away in eight weeks. Therefore, we think that driver behavior in our study is unlikely to be affected by the earlier study, given the 18-month gap between the two.

Our study adds a new element to the social comparisons and social influence literature by interacting social information with status and demonstrates effects of status-driven social comparisons. Research in both sociology and cultural anthropology has shown that people model the behavior of high-status individuals (Henrich and Gil-White 2001). Inducing status in the laboratory following the procedure in Ball, Eckel, Grossman and Zame (2001), Eckel and Wilson (2007) find that observing a high-status player enhances coordination on an efficient equilibrium more often than observing a low-status individual. Using the same procedure, in a sequential public goods experiment, Kumru and Vesterlund (2010) find that low-status followers are likely to mimic donations by high-status leaders, which encourages high-status leaders to give. Inspired by these findings from the laboratory, we investigate whether status-driven social comparisons change how people actually drive.

3 Experimental Design

Our field experiment was implemented in Tsingtao (qīng dǎo), a coastal city in the Shangdong Province of eastern China, with a population of over 8.7 million (2010 Chinese Census). Tsingtao is a major seaport, naval base, and industrial center. Its per capita GDP ranks 28 among 287 regional-level Chinese cities in 2011, 2.35 times the national average. Like other major cities in China, Tsingtao has experienced rapid economic growth and car ownership in recent years.

3.1 Sample selection

Our experiment was conducted with the help of the Tsingtao Police Department in October 2013. As of January 1, 2013, there were 1,290,724 registered cars in Tsingtao. We used the following criteria to get our sample: (1) a private owner (1,059,692 cars); (2) associated with a valid cell phone number (973,161 cars); and (3) at least one traffic violation ticket (excluding parking tickets) in the first nine months of 2013 (433,136 cars). Among these, we drop cars if three or more cars share the same cell phone number (397,008 cars remaining), if the car owner was born before 1939 or after 1996, if the owner's district or county could not be identified (395,687 remaining), or if fewer than 30 cars shared the same brand (395,204 cars remaining). This gave us a final sample of 395,204 cars.

Table 1: Summary Statistics

Variable	Mean	Std.	Min	Max
Male driver	0.74	0.44	0	1
Driver age	39.59	9.48	17	74
Car age	3.97	2.97	1	27
Registered in urban district	0.30	0.46	0	1
Sharing a phone number with other car(s)	0.09	0.29	0	1
Monthly Violations 01/01-09/30/2013:				
Number of violations	0.28	0.32	0.11	16
Having 1 violation (0/1)	0.05	0.06	0	1
Having 2 violations (0/1)	0.02	0.05	0	1
Having $\geq$ 11 violations (0/1)	0.00	0.02	0	1
Number of violations 10/25-11/24/2013:	0.17	0.54	0	30

Table 1 presents the summary statistics for our sample, including gender, driver age, car age, whether the car has an urban registration, and whether the car shares a phone number with other cars. The lower panel of the table documents the monthly traffic violation statistics for our drivers in the first nine months of 2013, as well as in the month after our experimental intervention. Note that three-quarters of the drivers in our sample are male, a number consistent with the national average in China (78.5%).[4] The monthly average number of traffic violations for our drivers in the first nine months of 2013 is 0.28. We also note that the maximum number of monthly violations is high in our sample. We will discuss in detail how we handle the outliers in Section 4.

3.2 Experimental conditions

We randomly divide the sample into five treatment groups ($75,247$ cars) and one control condition ($319,957$ cars). These sample sizes are derived using the desired minimum treatment effect of a 7-percent reduction, a Type I error rate of 0.05, and statistical power of 0.80, using the variance from a related prior field experiment (Lu et al. 2013).

While drivers in the control condition were not contacted during the experiment, for each treatment, we sent one of five text messages. Each text message consists of two parts. Part 1 is common to all treatments,

[4]Source: http://m.news.cntv.cn/2013/12/01/ARTI1385892983879806.shtml, retrieved on December 8, 2014.

Tsingtao Police: Your car with licence number [ ] had [ ] traffic violations in the first three quarters of 2013.

The five treatments also received one of the following in the second part of the text message:[5]

1. Own-ticket treatment ($n = 15,009$):

   Tsingtao Police: Please drive safely for the sake of yourself and others.

2. Own-brand treatment ($n = 15,090$):

   Tsingtao Police: Your car brand had an average of [ ] traffic violations. Your number of violations is [above/about the same as/below] your brand average. Please drive safely for the sake of yourself and others.

3. High-status treatment ($n = 15,066$):

   Tsingtao Police: Your car brand had an average of [ ] traffic violations. Among (drivers of) high-end cars, some drivers had fewer violations. Their car brand had an average of 0.6 violations, which is [above/below] your brand average. Please drive safely for the sake of yourself and others.

4. Medium-status treatment ($n = 15,009$):

   Tsingtao Police: Your car brand had an average of [ ] traffic violations. Among (drivers of) middle-range cars, some drivers had fewer violations. Their car brand had an average of 0.6 violations, which is [above/below] your brand average. Please drive safely for the sake of yourself and others.

5. Low-status treatment ($n = 15,073$):

   Tsingtao Police: Your car brand had an average of [ ] traffic violations. Among (drivers of) economy cars, some drivers had fewer violations. Their car brand had an average of 0.6 violations, which is [above/below] your brand average. Please drive safely for the sake of yourself and others.

All statistics given to the drivers are real. The model high-end, middle-range and economy car brands, Rolls-Royce, Škoda and Fukang respectively,[6] each averaged 0.6 violations per driver in

[5]We translate the Chinese text message into English as literally as possible. Words in parentheses, e.g., (drivers of), are added in the English translation to ensure grammatical correctness.

[6]Škoda is a car brand manufactured in the Czech Republic and owned by the Volkswagen Group. Fukang is an economy car produced in China by the Dongfeng Peugeot-Citroën Automobile group, a joint venture between the French PSA Peugeot Citroën and the Chinese manufacturer Dongfeng.

the first nine months of 2013.[7] As the average number of violations is the same across the three status treatments, any differential treatment effect is unlikely to be driven by anchoring. Furthermore, as each driver in our sample has had at least one violation in the past nine months, the 0.6 average is also lower than each driver's actual number of violations and thus represents a socially desirable target. In all treatments, we align what people typically do (descriptive norms) with what is typically approved by the police (injunctive norms) to achieve a more socially desirable outcome (Cialdini 2003). In the three status treatments, we bring in intergroup comparison, a technique to make one's own group identity salient. The injunctive norm (0.6 violations) can be interpreted as the "ideal" in the social identity model of Akerlof and Kranton (2000).

For the own-brand treatment, since the number of a driver's tickets is an integer whereas the brand average is rounded using one decimal point, the group whose number of violations is "about the same as" the brand-average contains only 443 cars, or 2.94% of the sample. In our regression analysis, we combine this group with the "below average" group. For the inter-group status treatments, drivers whose brand average number of violations is below 0.6 account for 5.3% of our total sample.

Table 2 presents tests of randomization based on each observable characteristic. P-values for tests of equality between the control and the pooled treatment groups are presented in the last column. None of the p-values is below 0.10, indicating that our randomization works.

All text messages were sent over a two-day period (15,309 messages in the morning, and 29,892 in the afternoon of October 23, and 30,046 messages in the morning of October 24). A roughly equal number of messages were sent to each treatment in each batch. The cost of the text message is 0.14 CNY (Chinese Yuan) per message, and each message was sent in two parts due to the number of character constraints per part.[8] After we sent the text messages, we waited for a month to see if drivers changed their behavior.

3.3 Car Status Survey

One important aspect of our experiment design and analysis is the perception of the status of various car brands. Following the procedure to check the racial distinctiveness of applicant names in Bertrand and Mullainathan (2004), we conducted a survey in public areas frequented by drivers, including two gas stations and a shopping mall parking lot, all located in downtown Tsingtao.[9] Six

[7] In our original experimental design, we explicitly mentioned the model car brand. However, the Tsingtao Police asked us to replace, "Rolls-Royce [Škoda or Fukang] drivers had an average of 0.6 violations" with "Their car brand had an average of 0.6 violations," so as not to appear promoting certain car brands.

[8] The exchange rate was $1 = 6 CNY at the time of the experiment.

[9] The addresses of the two gas stations are 76 Hong Kong East Boulevard, and 112 Hong Kong Central Boulevard, respectively. The shopping mall, Tsingtao Dong Tai Jia Shi Ke, is located at 72 Hong Kong Central Boulevard,

Table 2: Tests of randomization

	Control	Own-ticket	Own-brand	High-status	Medium	Low	P-value
Male driver	0.74	0.74	0.74	0.74	0.75	0.74	0.37
	(0.44)	(0.44)	(0.44)	(0.44)	(0.43)	(0.44)	
Driver age	39.58	39.59	39.66	39.63	39.6	39.73	0.44
	(9.47)	(9.46)	(9.53)	(9.49)	(9.49)	(9.52)	
Car age	3.97	3.99	3.96	4.01	4	3.98	0.60
	(2.97)	(2.95)	(2.94)	(3.00)	(3.04)	(2.96)	
Urban district	0.3	0.31	0.3	0.3	0.3	0.31	0.64
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	
Sharing cell phone number	0.09	0.1	0.09	0.09	0.09	0.1	0.64
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	
Violations 01/01-09/30/2013							
Number of violations	2.5	2.52	2.51	2.5	2.5	2.53	0.81
	(2.83)	(2.79)	(2.95)	(2.75)	(2.93)	(2.85)	
Number of unhandled violations	1.56	1.56	1.54	1.56	1.54	1.61	0.25
	(2.58)	(2.53)	(2.62)	(2.50)	(2.60)	(2.65)	
Having 1 violation (0/1)	0.48	0.47	0.48	0.48	0.48	0.47	0.72
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Having 2 violations (0/1)	0.22	0.22	0.22	0.22	0.22	0.22	0.93
	(0.42)	(0.42)	(0.42)	(0.41)	(0.42)	(0.42)	
Having 11+ violations (0/1)	0.02	0.02	0.02	0.02	0.02	0.02	0.25
	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	
Sample size	319,957	15,009	15,090	15,066	15,009	15,073	

Notes: Standard errors appear in parentheses. P-values test the equality among the control and treatment groups.

trained surveyors conducted the survey in two days in September 2014.[10]

At each gas station, a surveyor approaches one of the drivers waiting in line, introduces herself as an investigator of a research project by Renmin University, and gives the driver a hand drawn postcard of Renmin University as a gift.[11] The surveyor then briefly describes the questionnaire and the main purpose of this survey. She then hands over the questionnaire to the driver, who completes it. It usually takes three to five minutes to survey a driver. Surveys conducted at the shopping mall parking lot follows a similar procedure. A total of 98 drivers complete the survey, each rating 28 car brands.

We use four versions of the survey, each containing 28 different car brands. Thus a completion of the four versions categorizes all 112 brands in our sample. For each car brand, a respondent is asked to identify the car as “high-end," “middle-range," “economy," or “not familiar with." Each car brand is independently rated by approximately 25 respondents. The English translation of one version of the questionnaire, as well as the median rating of each car brand tabulated in Table 8 are included in the Appendix. As a robustness check, we compare the median rating from our survey with (1) an expert’s rating, and (2) the median sale prices for the typical model of each car brand,[12] and find strong correlations in both cases.[13] In subsequent analysis, we will use the median rating from our survey to determine a car’s status category.

4 Experimental Results

Our study on social comparisons, status and driving behavior provided some interesting results. Table 3 presents the number of traffic violations over the one-month window after our intervention. The distribution is extremely skewed. Cars with 0, 1, or 2 violations account for more than 99% of all the cars in the sample. There are also cars committing up to 30 violations in one month. Those cars are likely to be driven in unusual situations. For example, a driver could accumulate many speeding tickets in one trip if she did not notice the speed limit. In fact, our random assign-

Tsingtao.

[10] The surveyors include the third author, his friend, and four undergraduate students from Tsingtao University. The third author trained the five surveyors for an hour. Then each surveyor conducted at least one simulated survey of a randomly chosen student on the campus of Tsingtao University before conducting their first real survey at the gas station.

[11] The postcard costs around 1 CNY.

[12] We obtain car sales prices for 86 (out of 112) brands in our sample from two websites, www.autohome.com.cn and car.bitauto.com, retrieved on December 8, 2014.

[13] Of the 112 brands in our sample, the survey respondents (expert) rate 14, 23, 75 (14, 24, 74) brands as high-end, middle-range, and economy cars, respectively. Regressing median survey rating on expert rating yields a coefficient of 0.90 ($p < 0.01$) and $R^2 = 0.81$. Similarly, regressing median survey rating on median price yields a coefficient of 0.82 ($p < 0.01$) and $R^2 = 0.67$.

ment balances the outliers across treatments ($p > 0.10$ for all pairwise comparisons using Poisson regressions). Notwithstanding its equal distribution, the extreme values could still bias the estimation by enlarging the standard errors. To test the sensitivity of our results to these outliers, we report our analysis using raw, top-coded and logarithmically transformed data.

Table 3: Distribution of the Number of Traffic Violations

Violations	Number	Percent	Cumulative
0	345,852	87.51	87.51
1	38,418	9.72	97.23
2	7,510	1.90	99.13
3	2,113	0.53	99.67
4	710	0.18	99.85
5	295	0.07	99.92
6	129	0.03	99.96
7	62	0.02	99.97
8	41	0.01	99.98
9	18	0.00	99.99
10	21	0.01	99.99
11	3	0.00	99.99
12	16	0.00	100
13	3	0.00	100
14	2	0.00	100
15	1	0.00	100
16	1	0.00	100
18	3	0.00	100
19	2	0.00	100
20	2	0.00	100
26	1	0.00	100
30	1	0.00	100
Total	395,204	100	

So which text messages had an impact? Table 4 presents Poisson and OLS regressions on our treatment effects.[14] The dependent variable is V_i, the number of traffic violations in the month after our text message intervention. The independent variables include own-ticket, own-brand,

[14]Poisson regressions are used as our dependent variable is a count of traffic tickets. We have repeated all regression analysis using OLS and found similar results.

high-status, medium-status, and low-status treatment dummies, with the control dummy omitted as the basis for comparison. Specification (1) presents the treatment effects for all drivers, whereas specifications (2) to (5) additionally control for driver's age, car age, urban district (compared to rural district) and the log number of violations in the first nine months of 2013.

Since the post-experiment number of violations is extremely skewed (Table 3), we adopt two commonly used methods to deal with the extreme values. The first is to top code the extreme values. Specification (3) presents the estimation result if the number of traffic violations is top-coded at 2, i.e., $\bar{v} = 2$ for $V_i > \bar{v}$, at which less than 1% of cars have their number of violations top-coded, resulting in almost no change in the estimated coefficient for the high-status treatment. This suggests the high-status treatment group and the control group are similarly recoded, supporting the validity of the random assignment. Meanwhile, the standard error decreases from 0.028 to 0.023. Alternatively, specification (4) uses $\bar{v} = 6$ as the cutoff for top coding, which is ten standard deviations away from the mean. Both (3) and (4) show that the high-status treatment significantly reduces traffic violations by about 5%.[15]

A second method to deal with extreme values is to take a logarithmic transformation of the skewed variable. As there are many zeroes, we take $\ln(V + 1)$ and use an OLS specification. Specification (5) suggests that the high-status treatment has a significant effect in reducing the log violations, with an effect size again around 5%, similar to that obtained from the Poisson regressions.[16]

Summarizing the main treatment effects in Table 4, we find that, after receiving a text message about their own number of traffic violations, drivers in the own-ticket treatment have the same number of traffic violations as those in the control condition. Therefore, without additional social information, a text message with only each driver's traffic violation information, and a police reminder to drive safely, has no effect on subsequent traffic violations.[17] Likewise, drivers in the own-brand treatment have the same number of traffic violations as those in the control condition, although theory predicts heterogeneous treatment effects which we will explore later. In compari-

[15]The significance survives any top coding for $2 \leq \bar{v} \leq 8$ at the 5% level. Beyond $\bar{v} = 8$, the statistical significance decreases to the 10% level.

[16]To calculate the magnitude of the reduction effect in specification (5), let h and c denote the number of violations for the high-status and the control group, respectively. Let b equal the coefficient for the high-status treatment, -0.0047. Therefore, from $\ln(h+1) - \ln(c+1) = b$, we obtain $(h-c)/c = (e^b - 1)(1 + 1/c) = (e^{-0.0047} - 1)(1 + 1/0.107) = -0.049$. We take $c = 0.107$ so that $\ln(c + 1)$ equals the average in the control group.

[17]In comparison, Lu et al. (2013) find a significant effect when their text message reveals the number of violations within the last two to three months, as such information is likely to be new for drivers. Indeed, they find if a driver already knows those violations before receiving the message, then the message has no effect. In our study, since the text message iterates traffic violations during the past nine months, it is likely that many drivers already know about these violations. Results from the two studies indicate that text message on own ticket information has an effect only when it provides new information.

Table 4: Treatment effects

Dependent variable: Post-experimental number of violations (V)					
	(1)	(2)	(3)	(4)	(5)
	V	V	$V_{\bar{v}=2}$	$V_{\bar{v}=6}$	$\ln(V+1)$
Own-ticket treatment	-0.004	-0.008	-0.006	-0.005	-0.0010
	(0.027)	(0.026)	(0.023)	(0.025)	(0.002)
Own-brand treatment	-0.030	-0.032	-0.027	-0.032	-0.0030
	(0.027)	(0.026)	(0.023)	(0.026)	(0.002)
High-status treatment	-0.046	-0.045	-0.046**	-0.052**	-0.0047**
	(0.029)	(0.028)	(0.023)	(0.025)	(0.002)
Medium-status treatment	-0.015	-0.014	-0.013	-0.012	-0.0009
	(0.026)	(0.026)	(0.023)	(0.025)	(0.002)
Low-status treatment	-0.017	-0.026	-0.023	-0.026	-0.0023
	(0.027)	(0.026)	(0.023)	(0.025)	(0.002)
Driver age		0.002***	0.003***	0.003***	0.0003***
		(0.001)	(0.000)	(0.001)	(0.000)
Car age		-0.015***	-0.019***	-0.017***	-0.0017***
		(0.002)	(0.002)	(0.002)	(0.000)
Urban district		-0.162***	-0.160***	-0.160***	-0.0153***
		(0.011)	(0.010)	(0.011)	(0.001)
Log # violations in the first nine months		0.774***	0.679***	0.756***	0.0869***
		(0.007)	(0.005)	(0.006)	(0.001)
Constant	-1.778***	-2.419***	-2.434***	-2.414***	0.0478***
	(0.006)	(0.022)	(0.020)	(0.021)	(0.002)
Number of Observations	395,204	395,204	395,204	395,204	395,204
R^2					0.048

Notes: Poisson (OLS) regressions are reported in 1-4 (5), with the control as the omitted category. For Poisson regressions, the corresponding incidence-rate ratio for a variable x_i is obtained by e^{β_i}. Standard errors are clustered at the level of the cell phone number.

son, of the three intergroup comparison treatments, the high-status treatment significantly reduces post-experiment traffic violations by 5% (specifications 3, 4 and 5).

Furthermore, as a car is considered a status symbol in China, we expect that social information regarding the average number of violations among drivers of a high-status car should have the most influence on drivers of medium- and low-status cars. Furthermore, because of the rising sex ratio (Wei and Zhang 2011), we expect that male drivers might respond more strongly to the high-status treatment. This leads us to explore the heterogeneous treatment effects on subpopulations.

Table 5 reports the heterogeneous treatment effects on female (1) and male drivers (2), and drivers of high-end (3), middle-range (4), and economy cars (5). The dependent variable is again the post-experiment number of violations, whereas the independent variables include the treatment dummies, demographic variables, and the log number of violations in the first nine months. In this analysis, car status is categorized based on the median rating in our gas station surveys. We find that the high-status treatment has a larger effect on male drivers ($1 - e^{-0.073} = 7\%$ reduction, specification 2), and an even larger effect on drivers of economy cars ($1 - e^{-0.096} = 9\%$ reduction, specification 5), compared to the control group.

Result 1 (Inter-group comparison: status)**.** *After receiving a text message about the average violations of drivers of high-status cars, drivers reduce their traffic violations by 5% compared to the control group. Among them, male drivers reduce their traffic violations by 7%, whereas drivers of economy cars reduce their violations by 9% compared to the control group.*

Result 1 indicates that intergroup comparisons are only effective when the "ideal" has high status. We further find a gender difference in responses to status triggers, which have been found in cross-cultural studies on contest behavior that show men reacted more strongly to status cues in the laboratory (Huberman, Loch and ÖNçüler 2004). Of these, the size of the effect almost doubles for drivers of an economy car.

We next examine whether drivers change their behavior based on the average number of violations incurred by people who drive the same car brand. Based on social comparison theory (Festinger 1954, Akerlof 1980), we expect that, in the own-brand treatment, drivers with an above (below)-average number of violations will decrease (increase) their number of violations after receiving a text message about the average number of violations incurred by drivers of their own car brand.

In Table 6, specifications (1) and (2) examine the treatment effects on drivers with a below-average number of violations, whereas (3) and (4) examine the same effects on drivers with an above-average number of violations. We find that the own-brand dummy is positive but insignificant in (1) and (2), negative and marginally significant in (3), but significant in (4) after controlling for demographics and past driving history:

Table 5: Heterogeneous treatment effects: Gender and car status

Dependent variable: Post-experimental number of violations (V)

	(1) Female	(2) Male	(3) High-end	(4) Middle-range	(5) Economy cars
Own-ticket treatment	-0.009	-0.008	0.025	-0.001	-0.032
	(0.049)	(0.030)	(0.100)	(0.034)	(0.043)
Own-brand treatment	-0.064	-0.020	0.075	-0.029	-0.059
	(0.048)	(0.031)	(0.098)	(0.035)	(0.044)
High-status treatment	0.032	-0.073**	0.051	-0.026	-0.096**
	(0.053)	(0.033)	(0.097)	(0.039)	(0.044)
Medium-status treatment	-0.076	0.005	-0.118	0.029	-0.047
	(0.050)	(0.030)	(0.101)	(0.035)	(0.040)
Low-status treatment	-0.031	-0.024	0.043	-0.028	-0.043
	(0.049)	(0.031)	(0.098)	(0.036)	(0.039)
Driver age	-0.000	0.003***	-0.001	0.001	0.002**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Car age	-0.009**	-0.016***	-0.013*	-0.006**	-0.019***
	(0.004)	(0.002)	(0.007)	(0.003)	(0.003)
Urban district	-0.245***	-0.128***	-0.211***	-0.226***	-0.185***
	(0.021)	(0.013)	(0.039)	(0.015)	(0.021)
Log # violations in	0.751***	0.781***	0.682***	0.753***	0.744***
the first nine months	(0.015)	(0.008)	(0.025)	(0.010)	(0.012)
Constant	-2.282***	-2.460***	-1.827***	-2.310***	-2.476***
	(0.044)	(0.026)	(0.093)	(0.030)	(0.035)
Number of Observations	102,124	293,080	17,191	195,563	182,450

Notes: Poisson regressions are reported, with the control as the omitted category.
The corresponding incidence-rate ratio for a variable x_i is obtained by e^{β_i}.
Standard errors are clustered at the level of the cell phone number.

Table 6: Heterogeneous treatment effects: Above- and below-average drivers

Dependent variable: Post-experimental number of violations				
	Drivers with below-average violations		Drivers with above-average violations	
	(1)	(2)	(3)	(4)
Own-ticket treatment	0.055	0.056	-0.019	-0.026
	(0.053)	(0.053)	(0.031)	(0.030)
Own-brand treatment	0.067	0.061	-0.053*	-0.062**
	(0.052)	(0.052)	(0.032)	(0.031)
High-status treatment	-0.096*	-0.100*	-0.035	-0.031
	(0.053)	(0.053)	(0.033)	(0.032)
Medium-status treatment	0.062	0.065	-0.036	-0.036
	(0.052)	(0.052)	(0.031)	(0.030)
Low-status treatment	-0.090*	-0.095*	-0.002	-0.009
	(0.054)	(0.054)	(0.031)	(0.029)
Driver age		0.003***		0.002***
		(0.001)		(0.001)
Car age		-0.004		-0.015***
		(0.004)		(0.002)
Urban district		-0.286***		-0.152***
		(0.022)		(0.013)
Log number of violations in the first nine months		0.976***		0.864***
		(0.053)		(0.008)
Number of Observations	126,979	126,979	268,225	268,225

Notes: Poisson regressions are reported, with the control as the omitted category.
The corresponding incidence-rate ratio for a variable x_i is obtained by e^{β_i}.
Standard errors are clustered at the level of the cell phone number.

Result 2 (Within-brand comparison: descriptive norm)**.** *After receiving a text message with the average number of violations for drivers of their own car brand, drivers with an above-average number of traffic violations have significantly fewer violations than those in the control group, equivalent to a 6% reduction, whereas the effects on drivers with a below-average number of violations are insignificant.*

We fail to reject the null for drivers with a below-average number of violations, which could be due to the asymmetry in sample sizes (126,979 versus 268,225) or to the social desirability of fewer violations. Since fewer violations are both socially and individually desirable, this result shows that, overall, drivers conform to socially efficient outcomes. The asymmetric response to a descriptive social norm is also consistent with prior field experiments that show people who contribute less to the public good than the average are more likely to increase their contributions when informed of the average (Chen et al. 2010). It is likely that the perceived similarity between a driver and the average driver of one's own brand motivates the reduction of traffic violations (Mussweiler and Ockenfels 2013).

Overall, we find that certain types of social information make people reduce their traffic violations. This holds when they compare themselves to those who drive the same type of car. It also holds when they compare themselves to that of high-status car owners, with the largest effect among drivers of economy cars.

Our analysis also gives a glimpse into who is more or less likely to incur a traffic violation (Tables 4 to 6). All else being equal, older drivers have more traffic violations; drivers of older cars have fewer violations; and drivers registered in the urban districts have fewer traffic violations, probably because urban traffic precludes speeding. Furthermore, drivers with more violations in the first nine months of 2013 have more violations in the month after our intervention. While skills such as reaction time might be difficult to change, attention and effort can be changed. Looking at the effects of our treatments on various types of traffic violations among male drivers (Table 7), we find that the most significant effect in our intervention is on speeding (specification (6)), indicating that social information might have made drivers pay more attention while driving.

5 Discussion

Our large-scale field experiment on the effectiveness of social comparison intervention shows that social information can reduce traffic violations. We find two types of social information to be particularly effective in reducing traffic violations. The first type is the within-brand comparison. When informed of the average number of violations for drivers of the same car brand, drivers with an above-average number of violations reduce their violations by 6%. However, our safer

Table 7: Treatment Effects on Violation Types (Male sample only)

	Dependent variable: Post-experimental number of violations					
	All	Forbidden Line	Turn Lane	Wrong Lane	Traffic Light	Speeding
	(1)	(2)	(3)	(4)	(5)	(6)
Own-ticket treatment	-0.008	-0.007	-0.015	-0.03	-0.207	0.035
	(0.030)	(0.064)	(0.065)	(0.090)	(0.133)	(0.053)
Own-brand treatment	-0.02	-0.064	0.02	-0.117	-0.04	-0.066
	(0.031)	(0.066)	(0.077)	(0.092)	(0.127)	(0.054)
High-status treatment	-0.073**	-0.075	-0.046	-0.037	-0.131	-0.128**
	(0.033)	(0.064)	(0.080)	(0.089)	(0.134)	(0.053)
Medium-status treatment	0.005	-0.08	-0.046	-0.054	-0.079	0.067
	(0.030)	(0.061)	(0.067)	(0.093)	(0.126)	(0.051)
Low-status treatment	-0.024	-0.026	-0.071	-0.181*	0.086	0.029
	(0.031)	(0.065)	(0.066)	(0.098)	(0.115)	(0.054)
Driver age	0.003***	0.009***	0.005***	0.009***	-0.005*	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)
Car age	-0.016***	-0.008*	0.008*	-0.019***	0.023***	-0.039***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.009)	(0.004)
Urban district	-0.128***	-1.226***	0.157***	-0.995***	-0.297***	0.011
	(0.013)	(0.039)	(0.028)	(0.052)	(0.060)	(0.022)
Log violations	0.781***	0.667***	0.781***	0.861***	0.772***	0.890***
	(0.008)	(0.015)	(0.019)	(0.021)	(0.037)	(0.013)
Number of observations	293,080	293,080	293,080	293,080	293,080	293,080

Notes: Poisson regressions are reported, with the control as the omitted category.
The corresponding incidence-rate ratio for a variable x_i is obtained by e^{β_i}.
Standard errors are clustered at the level of the cell phone number.
Forbidden Line refers to violations of marking lines with instructions.
Turn Lane refers to refusing to turn on a turn lane.
Wrong Lane refers to driving on the wrong lane.
Traffic Light refers to disobeying traffic light.

drivers do not change their behavior significantly, indicating that aligning descriptive norms of similar others with injunctive norms (the police reminder to drive safely) can be a powerful and cost-effective way to reduce traffic violations.

The second type of social information which works effectively combines descriptive norms with status. We find that information about drivers of high-status cars reduces the number of tickets received by 5%, with the largest effect on drivers of economy cars, who reduce their violations by 9% compared to the control group. The combination of descriptive norms with social status is a new venue for research in social influence, with practical policy implications for establishing better social norms for driving behavior in emerging markets.

Beyond the traffic context, our finding that social influence is channeled by status provides empirical support for Tarde's (1888) assertion that social influence descends from high-status to low-status individuals. Furthermore, it provides limiting conditions on Tarde that not every group might be equally affected by status-driven social comparisons. More field experiments and theoretical work should be conducted to map out the limits of status-driven social comparisons.

Appendix. Car Status Survey

We include the Chinese translation of one of the four versions of the survey. All four versions follow the same format, differing only in the car brands included.

A Survey on Car Brand Recognition

I am a member of the Driving Behavior Research Project at the Renmin University of China. We would like to know the public's familiarity with various car brands. Thank you for your cooperation! This is a small gift for you, a hand-drawn postcard designed by the students (of Renmin University).

1. What is the brand of your car? ___
2. If we divide cars into (1) high-end, (2) middle-range, or (3) economy cars, which category does your car fall into? ___
3. Please categorize each of the following car brands into (1) high-end; or (2) middle-range; or (3) economy cars. As some car brands are rare, you may answer (4) not familiar with.

Car Brand	Category	Car Brand	Category	Car Brand	Category	Car Brand	Category
Wanfeng		Iveco		Jieshida		Fudi	
Golden Dragon		Gonow		Rolls-Royce		Isuzu	
Lexus		Ssangyong		Dadi		Buick	
Zhonghua		Hyundai		Langfeng		Jiefang	
Luxgen		Land Rover		Kama		Great Wall	
BMW		BAIC		Xinkai		Hanjiang	
Huali		Toyota		Dongfeng		Jinbei	

Table 8: Car Status Categorization Based on Gas Station Surveys

High-status	Median-status	Low-status	Low-status	Low-status
Audi	Acura	Ao Luka	Hyundai	Suzuki
BMW	Buick	BAIC	Isuzu	Tianma
Cadillac	Chevrolet	Baojun	Iveco	Tianye
Chrysler	Citroen	BYD	JAC	Tongjiafu
Infiniti	Daewoo	Changan	Jiangnan	Trumpchi
Jaguar	Dodge	Changhe	Jiaxing	Vizi
Land Rover	FAW	Chery	Jiefang	Wanfeng
Leopard	Ford	Dadi	Jieshida	Weile
Lexus	Heibao	Daihatsu	Jinbei	Wuling
Mercedes-Benz	Honda	Dongfeng	JMC	Xiali
Phaeton	Jeep	Earth	Kama	Yangzi
Rolls-Royce	Kia	Englon	Karry	Yantai
Porsche	Lawns	Feidie	Langfeng	Yuejin
	Luxgen	Fiat	Lifan	Zhonghua
	Mazda	Fudi	Xinkai	Zotye
	MG	Fukang	Lotus	
	Mitsubishi	Fukuda	Meiya	
	Mustang	Geely	Oulin	
	Nissan	Golden Dragon	Qingqi	
	Opel	Gonow	Riich	
	Peugeot	Great Wall	Roewe	
	Red Flag	Hafei	Sanxing	
	Renault	Haima	Shifeng	
	Skoda	Hanjiang	Shuanghuan	
	Subaru	Huali	Smart	
	Toyota	Huanghai	Songhua River	
	Volkswagen	Huatai	Southeast	
	Volvo	Huayang	Ssangyong	

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