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Traffic violations and economic preferences: Evidence from full-time drivers of a large transportation network company in China

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ABSTRACT

Safety has been a consistent issue with the rise of transportation network companies (TNCs), especially in China with annual revenue exceeding 1.5 trillion CNY. In this paper, we explore intrinsic factors that can influence the risky behavior of TNC drivers by investigating the link between their economic preference parameters and traffic violations. We measure the economic preferences of 160 full-time drivers on a large Chinese TNC platform and examine their violations over the previous 13 months. We have four major findings. First, more risk-averse drivers have less violations. Second, present bias and patience do not affect drivers' risky behavior except that more patient drivers commit more direction|sign violations, which may have been caused by the higher expectation of the gain from such a violation of patient drivers. Third, reciprocity reduces violations of all types. Drivers' belief of other people's pro-social inclination only affects dangerous violations with long duration, i.e., speeding, in which case they take advantage of other people's attentiveness. And finally, we find no evidence of driver fatigue. These results highlight how the advantage of TNC platforms in managing drivers' incentive can affect the negative externality drivers impose through risky driving behavior, and hence provide policy implications.

1. Introduction

Following the enormous growth of information technology, the market scale of Transportation Network Companies (TNCs) has been increasing rapidly over the past decade. In China, the market size of the online car hailing industry has reached 1.5 trillion CNY (approximately 210 billion USD) in 2023, with the number of average daily orders being 26 million. However, criticism of TNC's drivers and business operations has been constant. One of the most common critiques is the possible increased risk of traffic accidents.[1] This concern is of particular importance in China not only because of the huge market scale, but also because traffic death is still a critical issue.[2] Moreover, disputes over responsibility for accidents involving TNC drivers, usually caused by the vague contractual

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[1] Reasons behind these risks include incentive schemes to encourage drivers' labor supply, which may cause driver fatigue; poor background checks for criminal records, etc.

[2] In 2017, traffic injury is rated the 5th leading cause of death in China while the 8th globally.

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relationship between drivers and platforms are common and increase the need to reduce traffic violations by TNC drivers. In 2018, to increase the supervision of TNC drivers, China's transportation department built a centralized system that required all TNCs to upload the real-time data of all registered vehicles. However, this regulation policy has limited binding force on private TNCs. In addition, monitering driving behavior of non-registered vehicles or drivers was even more difficult.[3] The need to find an alternative, decentralized method to reduce TNC drivers' risky driving behavior is urgent.

In this paper, we attempt to analyze the incentives behind professional TNC drivers' inclination to violate traffic laws. As the global survey of Falk et al. (2018) suggests, people's economic preferences are linked to various aspects of their behavior, including professional decisions, financial decisions and prosocial behaviors. Motivated by this line of work, we investigate the relationship between the traffic violation records and economic preferences of full-time professional drivers working for one of China's largest TNCs, under the basic assumption that they act as economic decision makers when committing traffic violations. The results can be used to predict risky driving tendency of TNC drivers, which would benefit both the training of existing drivers and the selection of qualified future drivers.

Our study involved two steps. Following the experimental design of Burks, Carpenter, Goettec, and Rustichini (2009), we first obtained the economic preference parameters of 160 full-time drivers on that platform in January 2018, including risk attitude, time preference, and social preferences.[4] Second, we combine their preference parameters with their traffic violation records over the previous 13 months, including violation type, point deduction and fine, and tested the hypothesis regarding the relationship between different types of violations and economic preference parameters. We focus on four main types of violation that accounted for 80% of all violations: Parking violations, traffic direction|sign violations, traffic light violations and speeding. We then raise testable hypotheses based on the assumption that drivers consider the risk, benefit and cost when deciding whether to commit certain violations. In general, the empirical findings are consistent with our hypotheses.

First, risk aversion significantly reduces the number of dangerous violations, i.e., direction|sign, traffic light violations and speeding. However, for violations that are almost free of danger; i.e., parking violations, contrary to the intuition, the drivers measured to be more risk-averse by high stakes in gain or by loss in both certainty and lotteries have more violations. We conjecture that this reversal is caused by the heterogeneity of drivers' cognitive ability. Drivers with lower cognitive ability may have underestimated the risk of being detected, since the literature relating people's cognitive ability to their risk aversion has identified a negative relationship (Benjamin, Brown, & Shapiro, 2013; Dohmen, Falk, Huffman, & Sunde, 2010). We use the method in Frederick (2005) to support this relationship, and further show that the unintuitive result would disappear when drivers of relatively low cognitive ability are removed from the sample.

Second, present bias does not affect any type of violation, while patience affects only direction|sign violations. Particularly, patient drivers (with a larger time discount factor) commit more direction|sign violations. While this result violates our hypothesis, we conjecture that patient drivers may have a higher expectation of the gain from a direction|sign violation. We find supporting evidence for this conjecture that more patient drivers have higher monthly income. In fact, because this type of violation is not very dangerous but can save time for drivers, and because this platform impose a monthly ranking to provide drivers with monthly bonus, we also find that drivers commit more such violations near the end of a natural month. Although more than 72% of direction|sign violations were committed without passengers, this observation still highlights the negative externality induced by the incentive scheme of TNCs on the general public.

Third, reciprocity reduces all dangerous violations. Drivers' belief about the pro-social inclination of other people only affects speeding violations, in which drivers' with a more positive belief of other people's pro-social inclination commit more speeding violations, indicating that this belief induces them to free-ride other people's attentiveness. This result shows that drivers tend to ignore the positive externality from other people when the violation only last for a few seconds, e.g., direction|sign violations and traffic light violations. However, we also find supporting evidence that the possibility of passengers' leaving a negative review, which is related to drivers' belief about the pro-social inclination of passengers, could regulate drivers' risky driving behavior.

We find no sign of driver fatigue in the data. The first reason is that drivers' average daily service hours and the time gap between orders imply that they were highly unlikely to suffer from fatigue driving in the sample period. The second reason is that as drivers' service hours increases, their marginal inclination of committing parking violations and direction|sign violations significantly decreases. The number of traffic light and speeding violations is not affected by service hours. All these results show no sign of driver fatigue, which have been caused by the platform's close supervision of drivers' hours of labor supply which enables it to dispatch orders based on their accumulated service hours.

This paper contributes to two strands of literature. The first is the literature on measures to reduce traffic violations. From the perspective of increasing the cost of violations, previous studies have investigated the effects of increasing surveillance by implementing traffic light cameras (Retting, Williams, Farmer, & Feldman, 1999, 2014), increasing punishment (Bar-Ilan & Sacerdote, 2004), informing drivers of their outstanding traffic tickets (Habyarimana & William, 2011), motivating people to speak up about bad

[3] For example, according to data published by this system, as of Novermber of 2023, the largest TNC of China (which is Didi) only had 56.4% order compliance rate (referring to the proportion of orders in which both drivers and vehicles are licensed). TNCs with the top 10 traffic violation rates (calculated as a company's total number of traffic violations in a month over its number of registered vehicles) in Guangzhou had from 88% to 119% monthly violation rates. This number may have been under-estimated because of non-registered vehicles or drivers. Please refer to http://www.100ec.cn/home/detail–6634878.html and https://static.nfapp.southcn.com/content/202311/29/c8351112.html

[4] The survey included three sections of questions: Risk aversion, intertemporal choices and a sequential prisoner's dilemma game to reveal social preference.

driving (Hansen, 2015), sending informative text messages (Lu, Zhang, & Perloff, 2016), using social comparison to nudge safe driving (Chen, Lu, & Zhang, 2017) and motivating drivers' cooperativeness. One major difference between this paper and these studies is that they do not distinguish between non-professional and professional drivers, while the factors influencing risky driving behaviors are different for the two groups.[5] For example, professional drivers tend to have rich knowledge of the traffic law. In contrast, according to Lu et al. (2016), 30% of non-professional drivers in China have poor knowledge regarding the chance of being detected when violating and of the associated penalty, and even lack awareness of the installation of electronic police. Moreover, professional drivers suffer less from psychological issues when driving. Finally, the income of professional drivers depends directly on driving, which makes all their decisions regarding driving comparable to economic decision making. Relating the economic preferences of professional drivers to their driving behaviors can generate both practical and theoretical implications for policy making, especially considering that reggulating TNC platforms has become necessary and urgent globally.

The second strand of literature links the behavior of professionals in the field to their economic preferences obtained from lab experiments. List (2006) studies sports card traders, and suggests that reputational concerns may affect cooperativeness in the field, especially for local dealers. Carpenter and Myers (2010) link the choices of volunteer fire fighters in a dictator game to their training hours and their response rates in real fire alarms. Fehr and Leibbrandt (2011) discover that the field behavior of Brazilian shrimpers is generally consistent with their lab behavior in cooperativeness and impatience. Carpenter and Seki (2011) study the relationship between Japanese fishermen's strategic behavior in a public good game and their group performance in production. Burks et al. (2016) find that truck drivers' parallel prosocial tendency is consistent with their lab behavior, but not their altruism towards an outsider. Since we study traffic violations, our results, especially those regarding the reciprocity of drivers and their beliefs about those of others, adds to this literature in investigating how professionals deal with the negative externalities they impose on others and respond to positive externality of others. Our results indicate that reciprocity plays an important and positive role in reducing drivers' dangerous violations. However, the incentive scheme which is designed to induce more effort of the professional drivers can impose additional negative externality on the society.

This paper also contributes practically to policy making and contract design aimed at reducing the risky driving behaviors of TNC drivers. The data of extant studies about traffic violations were obtained before the rise of the ride-sharing industry, which has significantly changed the composition of drivers on the road in cities with a large number of TNC vehicles. Because of the difference between normal drivers and professional drivers, strategies proposed in previous studies may not work as well on TNC drivers. Moreover, our study is of special importance to policy making in China where the market scale of TNCs is huge and where traffic death remains a critical issue. Because of data sensitivity and the limitation of collecting real-time big data, building a centralized supervision platform is very difficult. We believe that, by enriching the understanding of risky driving behavior, our results will contribute to reducing traffic violations in a more cost-efficient, self-motivating and decentralized fashion. Particularly, our results shed light on how to improve the mechanism design on TNC platforms including the design of incentive contract and customer review system.

The rest of this paper is organized as follows. Section 2 describes the experimental design and the violation data. Section 3 raises testable hypotheses and presents the regression results. Section 4 concludes.

2. Experimental design and the data

Compared with famous decentralized TNC platforms like Uber and Didi (the largest decentralized TNC in China), the platform we conduct our experiments on has three distinct features. First, all drivers work full-time as formal employees of the company. Hence, unlike decentralized platforms, this company also pays social security along with other insurance for their drivers. Therefore, any legitimate concern regarding insurance liability that might affect drivers' incentive to commit violations—a common criticism of TNCs—does not exist. Second, all subjects in our experiment drive cars (owned by the company) of the same model with the company's logo on the car body. This fact mitigates a legitimate concern in Chen et al. (2017) that owners of more expensive cars may drive more carefully. Third, the platform works under a centralized mode: It dispatches mandatory orders to drivers according to an exquisite algorithm. These orders cannot be rejected by the designated driver except for verifiable mechanical problems. Because drivers work full-time, and they indicate whether they are ready to serve by pressing a button on an APP, the company can supervise their daily hours of service. This allows the company to consider a driver's consecutive hours of service into account when dispatching orders.

The company offers an incentive contract. Besides the normal commission per order, there is a bonus system which rewards a driver extra money for completing a certain amount of orders on a natural day. At the end of a natural month, the company would classify drivers into four ranks based on their realized turnover in that month, and provide a monthly bonus accordingly. The difference between two adjacent ranks is approximately 120 US dollars. Hence, drivers have incentive to complete more orders especially near the end of a natural month.

2.1. Experimental design

The experiment was conducted on January 28 and 29 in 2018, in the city housing the company's headquarters.[6] All 160 drivers participating in our experiment had served the company for more than one year and had more than five years of driving experience. We randomly divided these drivers into 8 sessions with 20 drivers in each session. We followed Burks et al. (2009) to obtain the economic

[5] For example, in China, the majority of accidents are caused by drunk drinking, which is seldom the case for professional drivers.

[6] This city has a population of 10 million and is one of the most developed metropolitan cities in China.

preference parameters of the drivers, including risk preference, time preference and social preferences. We also gave three non-mandatory questions that were related to cognitive ability at the end of the survey. These questions can measure cognitive reflection, or " the ability or disposition to resist reporting the response that first comes to mind," using the Cognitive Reflection Test (Frederick, 2005). This measure is correlated with numerous standardized tests, such as the SAT, the ACT, and the IQ tests, as well as with time and risk measures (Frederick, 2005). Survey details can be found in the online appendix.

1. Risk preference: Participants answered 4 groups of 6 questions each about their choice between a certainty amount and a lottery. The lottery is the same within each group, while the certainty increases with a stable increment. In the gain-low-stakes group the certainty increases from 5 to 17.5, and the lottery has an equal probability of getting 25 or 5; In the gain-high-stakes group the certainty increases from 10 to 35, and the lottery has an equal probability of getting 50 or 10; in the loss-in-lottery group the certainty increases from 0 to 12.5, and the lottery has an equal probability of getting 25 or − 5; and in the loss-in-certainty-and-lottery group the certainty increases from −12.5 to 0, and the lottery has an equal probability of getting −25 or 5.
2. Time preference: Participants answered 4 groups of 7 questions each about whether they preferred to receive a smaller amount of money on a given earlier day or a larger amount on a given later day. The earlier payment varies from 45 to 75, while the later payment is fixed at 80. The time horizon ranges from 5 days to 9 days, and the earlier day could be the day of the experiment or 5 days after the experiment.
3. Social dilemma: Testing subjects' strategies and beliefs in a sequential prisoner's dilemma game. We randomly assigned the 20 drivers in 10 pairs and gave each driver 30 yuan as the endowment. The identity of the partner was kept anonymous. They then answered the following 6 questions: If they were the first mover, whether they wanted to transfer 30 or 0 to the other player, and their estimate of the number of players transferring 30; if they were the second mover, the amount they would return conditional on the first mover transferring 30 or nothing, and their estimate of the average return of the other drivers in these two scenarios. Any amount that drivers transferred to their partners would be doubled, and they kept the money at the end of the experiment. An extra amount of 5 yuan was awarded for every guess that was accurate (within a radius of 1 to the actual number).

Each session lasted for about one hour. At the end of the experiment, for questions regarding risk preference, we randomly picked one question and determined the risk realization by drawing a ball from a jar with a half-half chance (equal to the probability distribution in all lotteries). For questions regarding time preference, we randomly picked one question. When and how much payment drivers received depended on their answer to that particular question. The average payment to each participant was around 200 yuan, which was comparable to their normal daily earning.

We matched surveys with drivers' employee IDs and obtained 158 effective survey subjects. Following Burks et al. (2009), we obtained four parameters for risk preference by counting the number of times a subject chose the fixed payment over the lottery in each of the four groups of questions about risk attitudes,[7] two parameters to proxy the present bias and the discount rate by running regressions from each subject's choices in the four groups of questions about time preference, and six parameters for subjects' own strategies and beliefs from their answers in the sequential prisoner's dilemma. This procedure left us 150 drivers in the sample.[8] We relegate a more detailed description of drivers' behaviors in answering questions in the risk-preference session in the appendix.

2.2. *Violation types and pattern*

We extracted drivers' traffic violation records from January 1, 2017 to January 31, 2018. Each violation recorded the car plate number, the type of the violation and the punishment. The punishment normally includes a fine and points deduction on the driver's record, except for parking violations and other minor violations for which only a fine is charged. According to the city's traffic law in 2017, the punishment for the most frequent two violations in our data were (1) parking violation: 50 or 150 yuan and no point deduction; (2) direction/sign violation: 100 yuan and 2 or 3 points.[9] We also include two extremely dangerous types of violation: Traffic light violation where the punishment is 150 yuan and 6 points, and speeding where the punishment is 200 yuan and 3 points for exceeding the limit by 10% to 20%, 200 yuan and 6 points for exceeding the limit by 20% to 50%, and 500 yuan and 12 points for exceeding the limit by 50% to 70%.

These four types of violations accounted for 1850 out of the 2313 violations (about 80%). Since a driver's incentive to commit violations may be different with passengers in the car, we also calculate the percentage of such events.[10] Table 1 presents the summary statistics of the violation data at the individual level. Table 2 presents total number of violation data and the number|percentage with passengers on board.

Because these violations can save time for a driver, and because his|her monthly rank is determined at the end of a natural month, we suspect that the incentive for a driver to be aggressive becomes stronger through a natural month. We calculate the average

[7] The scenario for traffic violation is most similar to measure involving loss, where a traffic violation corresponds to a lottery with the risk of accident or punishment. Nevertheless, since risk attitude could vary with stakes and with the payoff being a gain or loss (Markowitz, 1952), we conducted all four measurements in order to obtain a richer assessment of risk attitude.

[8] One driver did not answer one question in the session of the risk preference, and seven other drivers did not answer at least one question in the session of social preference.

[9] The major sub-types of this violation include driving in the wrong lane and making illegal turns.

[10] We have information of the exact starting time and finish time of any order, and the exact time of each violation.

Table 1
Summary statistics: number of violation from each subject.

Variables	N	Mean	Sd	Min	Max
parking	158	6.481	5.338	0	28
Direction|sign	158	3.918	3.567	0	21
traffic light	158	0.728	0.995	0	5
speeding	158	0.582	1.211	0	11

Table 2
Total number of violations.

Variables	Total number of violations	With passengers
Parking	1024	81 (8%)
Direction|sign	619	175 (28%)
Traffic light	115	37 (32%)
Speeding	93	47 (51%)

Table 3
Definitions of variables.

Independent Variables	Description
risk_gain_low	Risk attitude regarding gain in low stakes, measured by number of times a subject chooses the certain amount in questions 19–24.
risk_gain_high	Risk attitude regarding gain in high stakes, measured by number of times a subject chooses the certain amount in questions 1–6.
risk_loss_l	Risk attitude when the lottery incurs loss, measured by number of times a subject chooses the certain amount in questions 7–12.
risk_loss_cl	Risk attitude when both the certainty and the lottery incur loss, measured by number of times a subject chooses the certain amount in questions 13–18.
beta	Present bias
delta	Discount rate
belief	Belief in the proportion of others transferring 30 as the first mover
reciprocity	Conditional kindness (reciprocity), the amount of transfer as the second mover conditional on the first mover transferring 30
uncon	Unconditional kindness, the amount of transfer as the second mover conditional on the first mover transferring 0
hour	Service hours /100

Dependent Variables	Description
parking	Number of parking violations
direction|sign	Number of traffic direction|sign violations
light	Number of traffic light violations
speeding	Number of speeding violations

frequencies of parking violations and direction|sign violations committed in the first seven days, the middle ten days and the final ten days of every month. We get 34.5%, 32.6% and 32.9% for parking violations and 27.4%, 35.4% and 37.2% for direction|sign violations.[11] Hence, the competitive nature of the incentive scheme may create negative externalities for the society through inducing more direction|sign violations.

3. Results

In this section, we examine the relationship between the three sets of drivers' economic preferences and their traffic violations. Among the six parameters derived from the sequential prisoner's dilemma, we focus on three: As the first mover, the belief about the number of other drivers transferring 30, which measures a driver's belief about other players' prosocial inclination; the amount of return conditional on first mover's transfer of 30, which measures the degree of reciprocity or conditional cooperation; and the amount of return conditional on first mover's transfer of 0, which measures the degree of unconditional cooperation. We do not include the other three parameters in our empirical analysis because the first mover's unconditional transfer, which could be explained by both altruism and trust, and the two beliefs about other drivers' transfer as the second mover are not as relevant when analyzing traffic violations.

Table 3 shows the notations and definitions of the variables of interest. We pick total service hours instead of the other three measures for time and distance of driving for two reasons. First, driver fatigue, a critical reason for professional drivers' accidents, is

[11] The number of the other two types of violations is too small for this calculation to be meaningful. The frequencies are 28.4, 37.1 and 34.5% for traffic light violations and 30.4, 25 and 44.6% for speeding violations.

usually measured by the length of time driving instead of the distance driven. Second, since these drivers do not cruise to get orders, their total active hours do not reflect the actual hour worked.[12]

Because the probability of vehicle accidents relates to the total hours and distance of driving, we also extracted this information on drivers over the sample period from the company. We received the total active hours, service hours, total distance and service distance at the individual level. On this platform, a driver indicates that he is active and ready to receive orders, by pressing the "log in" button on the company's app. He can deactivate by pressing the "log out" button. In the data set obtained from the company, a driver's active hours on a certain day are calculated as the sum of hours (in minutes) that he stays online. A driver's service hours on a certain day are calculated as the sum of hours (in minutes) that he is taking an order, starting from the time he is assigned an order until the passenger reaches the destination. The service distance is defined in a similar fashion.

Following Holt and Laury (2002), we measure a driver's four risk preference parameters by counting the number of safe choices chosen.[13] We rule out drivers whose answer for *reciprocity* or *uncon* was strictly larger than 30. This leaves us with 139 drivers for the empirical analysis.

3.1. Hypotheses

In raising testable hypotheses, we start from the conjecture that experienced professional drivers compare the expected gain to the expected loss when deciding whether to commit a violation. Hence, a driver has to estimate the risk of a certain violation (including the risk of being detected by police or electronic police, and the risk of causing, or being involved in accidents), the gain (from the time saved) and the loss (including the punishment, if the violation is detected, and the loss from a possible accident). Since there could be huge heterogeneity across the amount of time saved for different types of violations, and even for the same type of violation in different scenarios, we cannot convincingly estimate a driver's expected gain. Hence, in proposing hypotheses, we focus on the risk and the total loss.

The risk of being detected of a certain violation depends on the frequency of police cruise, the intensity of digital police coverage, and the likelihood of anonymous tips. The risk of an accident increases with its *duration* because of the larger ambiguity involved in the process. The risk also decreases with the attentiveness of other drivers and pedestrians outside the car, which creates a positive externality for the driver.

We rank the four types of violations in the duration and loss as the following, where the loss considers both the punishment and the potential danger. The rank of the loss can explain the difference in the frequencies of violations in Table 2.[14] Speeding has the largest magnitude of ambiguity embedded in risk estimation and potential loss, so it has the lowest frequency despite being punished at a similar level to traffic light violations.

$$\begin{cases} \text{Duration} : \textit{speeding} \simeq \textit{parking} >> \textit{direction} \mid \textit{sign} \simeq \textit{light} \\ \text{Loss} : \textit{speeding} > \textit{light} > \textit{direction} \mid \textit{sign} >> \textit{parking} \end{cases}$$

We raise hypotheses concerning the economic preference parameters. Intuitively, drivers with larger values of any of the four risk-preference parameters have fewer violations, ceteris paribus. Cook, Diamond, Hall, List, and Oyer (2021) also record that risk aversion affects Uber drivers' speed of driving, although they use gender to proxy drivers' risk attitude.

Hypothesis 1. *A more risk-averse driver has fewer violations of all types.*

We next hypothesize how time preference affects a driver's traffic violations. Since β measures impulsiveness, drivers with larger present bias (a smaller β value) may have more violations. More patient drivers (with a larger δ value) value future payoffs more. Because the monthly ranking is determined at the end of a natural month, a violation can be critical if the amount of time it saves helps a driver to complete more orders and achieve a higher rank. Hence, at least part of the gain of a violation is realized in the end of a natural month. However, the expected punishment of a violation is also realized in the future: On average, a driver pays a fine after three month of the violation.[15] If the expected gain from a violation does not vary with δ, a less patient driver has a higher chance of finding a violation worthwhile.[16] We hence raise the second hypothesis.

Hypothesis 2. *Drivers with a larger β or a larger δ have fewer violations.*

[12] According to our interview with the company, drivers usually park at legitimate places when not on an assignment.

[13] The number of drivers exihibiting inconsistency (switching back from certainty to lottery) in question 1–6, 7–12, 13–18 and 19–24 is 54, 60, 69 and 53 respectively. The regressions dropping these drivers show similar results, which are reported in the online appendix.

[14] The WHO designates speeding as the most dangerous factor for traffic injuries. https://www.who.int/newsroom/fact-sheets/detail/road-traffic-injuries.

[15] If a violation is caught by the electronic police instead of a pointsman, the fine is only required to be paid when there are two unpaid tickets on a car plate. Since the sample average number of violations for a driver per month is 0.94, it takes roughly three months for a driver to pay the accumulated bills.

[16] Since on average, the gain of a violation is realized before the punishment, assuming that the reparation payment in the accident triggered by the violation is instantaneous, the expected net gain of violation can be written as $\delta^{\rho}[1-prob(punish)-prob(accident)]\cdot gain-\delta^{\sigma}\cdot prob(punish)\cdot \{payment\ by\ punish\}\ -prob(accident)\cdot\{payment\ in\ accident\}$ where $0<\rho<\sigma$. It is obvious that this expression is more likely to be positive when δ is smaller.

Next, we formulate a hypothesis regarding the relationship between drivers' traffic violations and their behaviors and beliefs in the sequential prisoner's dilemma game. Considering that the subject pool consists of fellow drivers, if player 1 transfers 30, it indicates his|her pro-social inclination or adherence to the social norm.[17] Hence, in the experiment, *belief* can be considered a measure of a driver's belief about the pro-social inclination of fellow TNC drivers. In the context of driving, conceivably, *belief* could also be extend to other people who have interactions with the TNC driver, including all other drivers, pedestrians outside the car, and passengers inside the car.

On the one hand, when *belief* is larger, a driver is more optimistic about the attentiveness of other people outside the car. For example, he believes that other drivers would yield when necessary. This positive externality exists for all dangerous violations, and it may induce the driver to commit more violations. On the other hand, a reverse effect also exists. Unlike taxi drivers with almost no concern for reputation, TNC drivers' business opportunities depend on passengers' reviews, where safety is a critical factor. Hence, a driver with a larger *belief* has an incentive to reduce risky behavior when there is a passenger on board, since a pro-social passenger is likely to leave a negative review. Therefore, the effect of *belief* on the three dangerous violations is ambiguous.

Parking violation is almost the only type of violations where the probability of being detected can be affected by anonymous tips. When people outside the car are more pro-social, having concerns about the inconvenience caused by the parking violation to the general public, the probability of them reporting to the police increases. Hence, we conjecture that drivers commit fewer parking violations when *belief* is larger.

reciprocity and *uncon* have a sequential nature involving possible interactions between the driver and other people including passengers, for which we do not have data. The effect of reciprocity may also come from drivers' gratitude for the company, since this company offers social security and other benefits to drivers which is rare among TNC platforms. When we interpret reciprocity in this way, reciprocal drivers may tend to reward their employer with high-quality service to maintain the company's reputation. Hence, we hypothesize that drivers with higher *reciprocity* or *uncon* have fewer violations.

Hypothesis 3. *Drivers with a larger value of belief have fewer parking violations, but the effect of belief on other violations is ambiguous. Drivers with larger values of reciprocity and uncon have fewer violations of all types.*

Finally, we derive a hypothesis regarding driver fatigue. The Regulations on the Implementation of the Road Traffic Safety Law in China stipulate that drivers must not drive a motor vehicle continuously for over 4 h without taking a break, with the rest period not less than 20 min. According to our calculation, the average number of daily service hours is 5.31 h and the average gap between two orders is 29 min. These data suggest low probability of prolonged driving among these TNC drivers. To further check whether driver fatigue is an issue, we invetigate the relationship between a driver's service hours and the number of violations. If driver fatigue occurs, the number of violations per-service-hour would increase as service hours accumulate.[18] Hence, we advance the following hypothesis.

Hypothesis 4. *The marginal inclination to violate is not affected by service hours.*

3.2. Regression results

The hypotheses concern drivers' *actual* violations, while the data record only the *detected* violations. Since it is not possible to infer the *heterogeneity* across drivers in the accuracy of their estimations of the risk of being detected, we assume for now that they are homogenous in that accuracy.[19] Hence, we can apply the hypotheses to the violation data.

Because the number of violations is discrete, we apply the Poisson model in the following regression specifications.

$$y_i = const + \alpha \times \theta_i + \gamma \times \beta_i + \zeta \times \delta_i + \eta_2 \times s_{2,i} + \eta_3 \times s_{3,i} + \eta_5 \times s_{5,i} + \lambda_1 \times hours_i + \lambda_2 \times hours_i^2 + \varepsilon_i \tag{1}$$

where i is the driver's ID; y_i are $parking$, $direction \mid sign$, $light$ and $speeding$, respectively; θ_i are $risk\_gain\_low$, $risk\_gain\_high$, $risk\_loss\_l$ and $risk\_loss\_cl$. For robustness, we utilize all four risk parameters because an individual's risk attudute could vary based on the stakes involved, potential losses or gains, and context and framing (Kahneman & Tversky, 1979; Pratt, 1978). We add service hours and its square term as covariates to measure average violations and the marginal inclination to commit a violation. Regression results for the other specifications in terms of labor supply (service hours replaced by the number of active hours, driving distance and service distance) are relegated to the online appendix.

We present the regression results in Tables 4 to 7.

We now discuss whether the empirical results support the five hypotheses.

Result 1: For the three dangerous violation types, risk aversion is negatively correlated to violation. However, for parking violations, parameters evaluating higher risk aversion regarding gain in high stakes and loss in both certainty and lottery are positively related to violation.

Coefficients of all four risk parameters are negative in the three types of dangerous violations, and they are all significant in speeding. These results are consistent with hypothesis 1. However, drivers that are tested as more risk averse regarding gain in high

[17] According to our interview with some drivers after the experiment, they consider a player 1's not transfering 30 as a betrayal to fellow drivers.

[18] A possible influencing factor is learning, since greater driving experience, implied by more service hours, may help reduce violations and hence the marginal inclination to violate. However, considering that these drivers had worked in this company for at least one year and had more than five years in this profession, effects from this channel are minimal.

[19] Experience may also affect the accuracy of a driver's estimation. However, all drivers in our data have rich experience.

Table 4
Parking violations.

Risk parameter	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
Risk parameter	−0.046**	0.062***	−0.023	0.047***
	(0.021)	(0.022)	(0.023)	(0.017)
Beta	−0.214	−0.245	−0.24	−0.278
	(0.0.315)	(0.31)	(0.313)	(0.31)
Delta	2.885	2.185	2.7	2.773
	(1.781)	(1.801)	(1.78)	(1.789)
Belief	−0.011*	−0.008	−0.01	−0.009
	(0.007)	(0.007)	(0.007)	(0.007)
Reciprocity	−0.006	−0.012*	−0.01	−0.012*
	(0.0.007)	(0.007)	(0.006)	(0.006)
Uncon	−0.004	−0.004	−0.004	−0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Hours	0.203***	0.212***	0.204***	0.208***
	(0.025)	(0.025)	(0.025)	(0.025)
$Hours^2$	−0.006***	−0.006***	−0.006***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−1.744	−1.238	−2.599	−1.746
	(1.842)	(1.857)	(1.798)	(1.855)
Observations	139	139	139	139
Pseudo R-square	0.147	0.140	0.141	0.142

Standard deviations in parenthesis.*, ** and *** denote significance at 10%, 5%, and 1%, two tailed test.

Table 5
Traffic direction/sign violations.

Risk parameter	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
Risk parameter	−0.047*	0.024	−0.058**	0.001
	(0.027)	(0.029)	(0.03)	(0.023)
Beta	0.463	0.412	0.444	0.417
	(0.39)	(0.385)	(0.388)	(0.387)
Delta	4.527*	4.274*	4.175*	4.48*
	(2.359)	(2.375)	(2.346)	(2.359)
Belief	−0.01	−0.008	−0.008	−0.009
	(0.009)	(0.009)	(0.009)	(0.009)
Reciprocity	−0.013	−0.018**	−0.016**	−0.018**
	(0.009)	(0.008)	(0.008)	(0.008)
Uncon	0.004	0.004	0.005	0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Hours	0.179***	0.184***	0.181***	0.18***
	(0.032)	(0.032)	(0.032)	(0.032)
$Hours^2$	−0.005***	−0.005***	−0.005***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−4.376*	−4.164*	−3.97	−3.268
	(2.46)	(2.469)	(2.445)	(2.348)
Observations	139	139	139	139
Pseudo R-square	0.115	0.110	0.116	0.111

Standard deviations in parenthesis.*, ** and *** denote significance at 10%, 5%, and 1%, two tailed test.

stakes and with loss in both certainty and lottery committed more parking violations. According to Burks et al. (2009), Dohmen et al. (2010) and Benjamin et al. (2013), there is a negative relation between cognitive ability and the magnitude of risk aversion.[20]

The design of the three questions regarding cognitive ability in the experiment followed the spirit of Frederick (2005), which considers not answering questions as an indication of relatively low cognitive ability. Lower cognitive ability could lead to higher probability of detected parking violation. We find that drivers' risk attitude is negatively correlated with whether they gave at least one correct answer in these questions.[21] Hence, more risk averse drivers were more likely to have relatively low cognitive ability. In addition, after deleting drivers who did not answer or gave a wrong answer for any question from the sample, the risk parameters are no longer significantly positive in the regressions regarding parking violations. These results are presented in Table 8 and Table 9 in the

[20] Burks et al. (2009) use three measures, including subjects' scores on a non-verbal IQ test, a quantitative literacy test and the Hit 15 game to measure' cognitive ability. We did attempt to test drivers' cognitive skills by adding three optional math problems to the end of the survey. However, about one third of the drivers skipped this question, and many of those who responded randomly filling in an answer, so we did not include cognitive answers in the main regressions.

[21] We follow Frederick (2005) which treats not answering a question the same as giving a wrong answer for that question.

Table 6
Traffic light violations.

Riskparameter	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
Riskparameter	−0.219***	−0.158**	−0.174**	−0.015
	(0.07)	(0.072)	(0.075)	(0.057)
Beta	0.856	0.602	0.696	0.601
	(0.971)	(0.942)	(0.93)	(0.928)
Delta	6.098	6.717	5.009	6.412
	(5.939)	(5.925)	(5.843)	(5.931)
Belief	0.024	0.023	0.034	0.03
	(0.023)	(0.023)	(0.023)	(0.023)
Reciprocity	−0.027	−0.039**	−0.042**	−0.046**
	(0.019)	(0.018)	(0.018)	(0.019)
Uncon	0.003	0.002	0.004	0.001
	(0.009)	(0.009)	(0.009)	(0.009)
Hours	−0.052	−0.066	−0.044	−0.049
	(0.064)	(0.064)	(0.063)	(0.063)
$Hours^2$	0.003	0.004	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.002)
Constant	−6.447	−6.564	−5.249	−6.548
	(6.204)	(6.162)	(6.094)	(6.193)
Observations	139	139	139	139
PseudoR-square	0.060	0.040	0.042	0.021

Standard deviations in parenthesis.*, ** and *** denote significance at 10%, 5%, and 1%, two tailed test.

Table 7
Speeding violations.

Riskparameter	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
Riskparameter	−0.205***	−0.268***	−0.377***	−0.148**
	(0.072)	(0.078)	(0.086)	(0.061)
Beta	0.553	0.335	0.521	0.544
	(0.978)	(0.963)	(0.942)	(0.946)
Delta	6.232	6.326	2.803	7.107
	(6.256)	(6.179)	(6.075)	(6.137)
Belief	0.059**	0.055**	0.078***	0.059**
	(0.025)	(0.026)	(0.027)	(0.026)
Reciprocity	−0.04**	−0.049***	−0.05***	−0.054***
	(0.02)	(0.019)	(0.019)	(0.019)
Uncon	0.003	0.001	0.004	−0.001
	(0.01)	(0.01)	(0.01)	(0.01)
Hours	0.107	0.084	0.126	0.076
	(0.076)	(0.077)	(0.077)	(0.076)
$Hours^2$	−0.004	−0.003	−0.005	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	−7.098	−6.449	−3.696	−7.448
	(6.599)	(6.476)	(6.371)	(6.439)
Observations	139	139	139	139
PseudoR-square	0.069	0.082	0.102	0.059

Standard deviations in parenthesis.*, ** and *** denote significance at 10%, 5%, and 1%, two tailed test.

Appendix.

Based on these studies, we conjecture that drivers with relatively low cognitive ability could have underestimated the risk of being detected when committing parking violations and could be detected with a higher probability. Interestingly, drivers do not exhibit this reversal in the three types of dangerous violations, indicating that the harsher punishment and potential danger can induce drivers to think more carefully when estimating the risk.

Result 2: Present bias cannot explain any of the violations. More patient drivers (those with larger discount factors) have more direction|sign violations. Patience cannot explain other types of violations.

On average, professional drivers are not impulsive when driving. However, the result regarding the discount factor in direction|sign violations contradicts hypothesis 2. We conjecture that the reversal may have been caused by patient drivers' higher expectation of the gain from a direction|sign violation. Although it is impossible to estimate the exact gain, we find that a more patient driver has higher daily income, excluding the estimated rank bonus (the t-value is 12.86).[22] Hence, when the monthly bonus is also included, this positive relationship will be more significant. A driver's perceived gain from a direction|sign violation may even increase near the end

[22] Because the monthly rank is based on the turnover of all full-time drivers of this company, we do not attempt to estimate a driver's rank.

of a natural month when he attempts to increase his rank.

Result 3: *belief* significantly reduces parking violations but increases speeding. *reciprocity* significantly reduces all types of violations, and its effect is more salient in dangerous violations. *uncon* does not affect any type of violations.

Our hypothesis regarding the effects of *belief* and *reciprocity* is verified. The effect of *belief* on parking violations is only significant in one specification, possibly because most of such violations by TNC drivers do not last long. The salient effect of *belief* on speeding indicates that the positive externality of other drivers' attentiveness is critical only when the duration of the violation is long. Considering that most of direction|sign and traffic light violations are committed without passengers, we may conclude that TNC drivers do not take other drivers' attentiveness into account when the duration of the violation is short.[23] A longer duration of violation implies interactions with possibly more number of drivers and pedestrians during the process, and thus increases the benefit from other people's attentiveness.

Result 4: The coefficients of hour^2 show no sign of driver fatigue. While the number of parking and direction|sign violations increases as a driver's service hours accumulates, the number of the two most dangerous violation types do not change significantly, suggesting that the potential punishment and danger of a violation must have played a key role in professional drivers' decisions. The decreasing marginal inclination in direction|sign violations points to the possibility that the company may have assigned more orders to drivers who drive more attentively, which benefits the society. The usage of driver-specific information in assigning orders, which is not possible for traditional taxi companies, may help to reduce violations.

Remark: We also conduct the regression about parking and direction|sign violations on the sub-samples of violations committed with passengers and without.[24] We find that no economic preference parameter is significantly influential when a driver has passengers (this result is presented in Tables 10 and 11); when there is no passenger, the influential factors are the same as in the full sample. To some extent, drivers' eager to commit violations to save time is mitigated when they have passengers, possibly due to the fear of a poor review.

Overall, our results highlight the advantage and disadvantage of TNCs in regulating drivers' risky driving behavior comparing to traditional taxi companies. The advantages are the customer feedback system, and the possibility to incorporate drivers' various information when dispatching orders. However, the monthly ranking, which is essentially a contest, raises a concern which has been pointed out in Chen, Cramton, List, & Ockenfels (2021): While incentive schemes in workplace can improve workers' performance, their effects on the overall welfare is ambiguous. In the context of over-bidding, Ku, Malhotra, and Murnighan (2005) also point out that in a competitive environment where participants desire to win, competitive arousal and escalation can induce them to behave irrationally.

4. Conclusion

In this paper, we investigate the relationship between the economic preferences of professional TNC drivers and traffic violations. The empirical results exhibit general consistency with our hypotheses. First, all risk parameters negatively affect dangerous violations committed by drivers. Second, drivers' reciprocity helps reduce all dangerous violations. However, only when a dangerous violation lasts a relatively long time, (e.g., speeding violations) drivers are aware of the positive externality generated by other people's attentiveness of driving. Third, we do not find evidence of driver fatigue in the data. Drivers working longer hours have a smaller marginal tendency to commit parking violations and traffic direction|sign violations.

We also have two counter-intuitive results. The first is that drivers with larger parameters of risk aversion with gains in high stakes or loss in both certainty and lottery commit more parking violations. We conjecture that this result is caused by drivers with low cognitive ability who underestimate the risk of being detected when committing these non-dangerous violations. The second is that more patient drivers have more direction|sign violations, which may have been caused more patient drivers' higher expectation of the gain from such violations, especially near the end of a natural month.

Our results are limited due to data availability, since it is not possible to get accurate numbers for actual violations by drivers. Nonetheless, the findings of this study provide several policy implications for reducing risky driving behavior among TNC drivers. TNC platforms could incorporate measures of risk aversion and reciprocity in their driver screening process besides observable demographic features, as drivers with these traits are less likely to commit dangerous violations.[25] The design of incentive schemes should be carefully considered to avoid unintentionally encouraging risky behavior, particularly those near the end of a month. Platforms can also actively influence drivers' social preferences by fostering a sense of reciprocity among them through training programs, peer mentoring, and team-building activities.

Passenger feedback can play a crucial role in regulating risky driving behavior, and TNC platforms should encourage passengers to report dangerous driving. In the context of China, where the TNC market is rapidly growing and traffic safety remains a major concern, implementing these policies could significantly reduce accidents and fatalities. Chinese TNC platforms can improve the safety of their

[23] According to the data, the average value of s_5 is more than 10, which may seem puzzling but is consistent with Burkes et al. (2009). This is possibly caused by the “other-regarding” preference among the cohort of colleague drivers, as in Burkes et al. (2009), which uses truck drivers as subjects.

[24] We do not conduct this exercise on traffic light and speeding violations because the number of these two types of violations with passengers (37 and 47 respectively) is too small to make statistical significance.

[25] Demographic features can also affect people's behavior in the filed, but many studies have found that to some extent, these features infuence people's behavior through economic preferences. For example, women are generally more risk averse, and less over-confident than men.

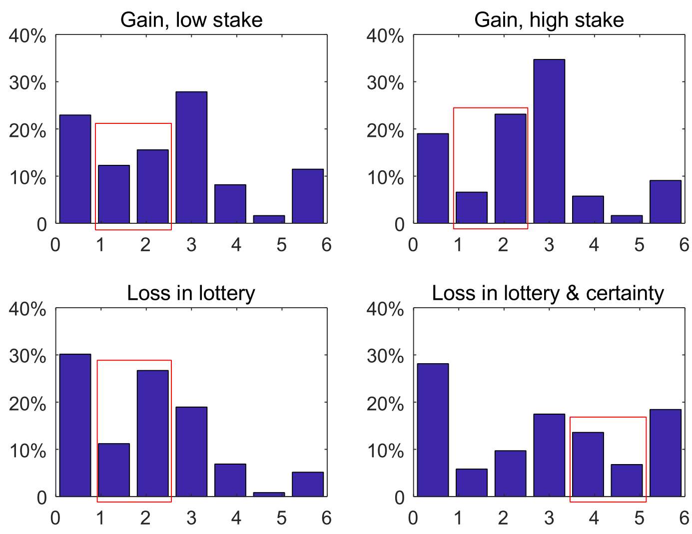

Fig. 1. Proportion of subjects choosing each number of safe choices.

services and contribute to the overall improvement of traffic safety in the country by incorporating these insights into their operations. Adopting safety-oriented policies could also serve as a competitive advantage for platforms in the intense competition among TNC providers in China.

Data availability

Data will be made available on request.

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Appendix A. Appendix

A risk-neutral subject (highlighted by a rectangle) would make one to two safe choices for the *gain-low-stakes, gian-high-stakes and loss-in-lottery* groups of questions (panels (1) to (3)), and four to five safe choices for the *loss–in-certainty-and-lottery* group (panel (4)). Obviously, it is more difficult for drivers to behave consistently when the lottery incurs a loss, especially in the certainty part. Subjects to the right of the rectangle behave as risk averse, and to the left of the rectangle as risk seeking. Fig. 1 suggests that more subjects are measured to be risk averse than risk seeking except in the last set of questions. Specifically, 49%, 51%, 32%, and 18% subjects are measured as risk averse, 28%, 30%, 38%, 7% as risk neutral, and 23%, 19%, 41%, 61% as risk seeking in the four groups of questions. Note that, subjects behaved as slightly more risk averse when the choices involve higher stakes of a positive payoff. When the lottery included a possibility of loss while the certainty choice was a gain in payoff, subjects became less risk averse than in the gain-only questions. Finally, when there existed loss in both certainty choice and lottery, most subjects behaved as risk seeking. This pattern is consistent with Kahneman and Tversky (1979).

Figure 1 characterizes the proportion of subjects with each number of choices of the fixed payment (or loss) in the risk-preference session.

Table 8: Correlation between correctly answering at least one cognitive question and risk preference.

	correct answer	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
correct answer	1.000				
risk_gain_low	−0.054	1.000			
risk_gain_high	−0.002	0.557***	1.000		
risk_loss_l	−0.192**	0.492***	0.400***	1.000	
risk_loss_cl	−0.028	0.170***	0.236***	0.269***	1.000

Table 9: Parking violations: excluding drivers who did not answer cognitive questions.

Risk parameter	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
Risk parameter	−0.04 (0.032)	0.01 (0.034)	−0.027 (0.034)	−0.003 (0.026)
Beta	−0.149 (0.495)	−0.281 (0.487)	−0.287 (0.488)	−0.262 (0.484)
Delta	3.835 (2.757)	3.312 (2.697)	2.707 (2.75)	3.089 (2.768)
Belief	−0.027** (0.012)	−0.022* (0.012)	−0.022** (0.011)	−0.023** (0.011)
Reciprocity	−0.008 (0.013)	−0.015 (0.013)	−0.013 (0.012)	−0.014 (0.012)
Uncon	−0.008* (0.005)	−0.008* (0.005)	−0.008* (0.005)	−0.008* (0.005)
Hours	0.215*** (0.039)	0.205*** (0.038)	0.21*** (0.039)	0.205*** (0.038)
$Hours^2$	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)
Constant	−2.445 (2.829)	−1.631 (2.756)	−1.202 (2.807)	−1.587 (2.829)
Observations	70	70	70	70
Pseudo R-square	0.143	0.140	0.141	0.140

Standard deviations in parenthesis.*, ** and *** denote significance at 10%, 5%, and 1%, two tailed test.

Table 10: Parking violations with passenger presence.

Risk parameter	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
Risk parameter	−0.035 (0.074)	0.123 (0.079)	−0.081 (0.082)	0.06 (0.062)
Beta	−0.802 (1.173)	−0.877 (1.146)	−0.788 (1.183)	−0.886 (1.153)
Delta	1.211 (6.187)	−0.504 (6.304)	0.984 (6.13)	0.914 (6.21)
Belief	−0.015 (0.024)	−0.01 (0.024)	−0.014 (0.024)	−0.012 (0.024)
Reciprocity	−0.026 (0.023)	−0.034 (0.022)	−0.027 (0.021)	−0.033 (0.021)
Uncon	0.013 (0.011)	0.014 (0.011)	0.014 (0.011)	0.014 (0.011)
Hours	0.264*** (0.1)	0.286*** (0.101)	0.265*** (0.1)	0.272*** (0.099)
$Hours^2$	−0.007** (0.004)	−0.008** (0.004)	−0.007** (0.004)	−0.007** (0.004)
Constant	−2.311 (6.359)	−1.001 (6.464)	−2.037 (6.297)	−2.162 (6.4)
Observations	139	139	139	139
Pseudo R-square	0.084	0.092	0.087	0.087

Standard deviations in parenthesis.*, ** and *** denote significance at 10%, 5%, and 1%, two tailed test.

Table 11: Direction/sign violations with passenger presence.

Risk parameter	risk_gain_low	risk_gain_high	risk_loss_l	risk_loss_cl
Risk parameter	−0.026 (0.05)	0.021 (0.55)	−0.045 (0.055)	0.01 (0.043)
Beta	0.343 (4.461)	0.316 (4.499)	0.34 (4.438)	0.307 (4.462)
Delta	0.288 (6.187)	0.09 (6.304)	0.026 (6.13)	0.25 (6.21)
Belief	−0.012 (0.017)	−0.011 (0.017)	−0.011 (0.017)	−0.011 (0.017)
Reciprocity	0.001 (0.017)	0.002 (0.017)	−0.001 (0.016)	−0.002 (0.017)
Uncon	0.01 (0.007)	0.009 (0.007)	0.01 (0.007)	0.009 (0.007)
Hours	0.119** (0.58)	0.124** (0.59)	0.118** (0.58)	0.121** (0.58)
$Hours^2$	−0.002 (0.002)	−0.002 (0.002)	−0.002 (0.002)	−0.002 (0.002)
Constant	−1.644 (4.649)	−1.5 (4.654)	−1.341 (4.621)	−1.612 (4.654)
Observations	139	139	139	139
Pseudo R-square	0.066	0.065	0.067	0.065

Standard deviations in parenthesis.*, ** and *** denote significance at 10%, 5%, and 1%, two tailed test.

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