CrossMark

Traffic fines for road safety programs: could they help?

Multas de tráfico para programas de seguridad vial. podrían ayudar?

Daniel Albalate

Abstract This article tests the role of traffic fines as predictors of crashes suffered by Powered-Two-Wheeler (PTW) riders in Barcelona, the city with the highest number of PTWs per inhabitant in Europe. Results show that traffic fines can work as predictors of road crashes, although not all sanctions have the same importance. Penalties associated with serious offences as running red lights or alcohol violations, are strongly correlated with the number of accidents. Thus, we argue governments are losing a valuable opportunity when using traffic fines only for punitive objectives. Traffic fines offer rich information already collected that can easily serve to identify road users at risk. This result have direct implications on the design of safety campaigns.

Resumen Este artículo contrasta el papel de las multas de tráfico como instrumentos de predicción de los accidentes sufridos por vehículos de dos ruedas a motor (PTW) en Barcelona, la ciudad con el mayor número de estos vehículos por habitante en Europa. Los resultados muestran que las multas de tráfico pueden funcionar como instrumentos de predicción de los accidentes, aunque no todas las sanciones tienen la misma importancia. Las penas asociadas a delitos graves como superar un semáforo en rojo o el consumo de alcohol, están fuertemente correlacionados con los accidentes. Por lo tanto, se sostiene que los gobiernos están perdiendo una oportunidad valiosa cuando utilizan las multas sólo para objetivos punitivos. Las multas ofrecen una rica información ya disponible que pueden servir para identificar a los usuarios en situación de riesgo. Este resultado tiene implicaciones directas para el diseño de las campañas de seguridad vial.

Keywords Road safety · Traffic fines · Behavior · Crime · Motorcycles

D. Albalate (✉)
Department of Enonometrics, Statistics and Applied Economics, Universitat de Barcelona, Av. Diagonal 690, 08034 Barcelona, Spain
e-mail: albalate@ub.edu

URL: http://www.danielalbalate.cat

Introduction

Road safety has become a major challenge for the public health policy of worldwide governments. Efforts devoted to reduce the number of casualties play, nowadays, a major role in achieving road safety objectives. Despite recent encouraging trends of road safety outcomes in Europe, PTW (Powered-Two-Wheelers) driver casualties still present worrying records when comparing with the rest of vehicles (Figura 1). This fact suggests that further efforts must be devoted to understand and prevent their accidents.

Traffic authorities use a variety of measures and a broad range of literature has evaluated their effectiveness in diminishing the number of deaths and accidents. However, the role of traffic tickets as an enforcement tool oriented to prevent repeated violations and affect driving behavior has not been extensively studied. Its effectiveness has been discussed (See [2, 7]) but always

Springer

Figura 1 Motorcycle and moped
fatalities compared with other
modes EU-14, 2001–2010
(2001 = 100)
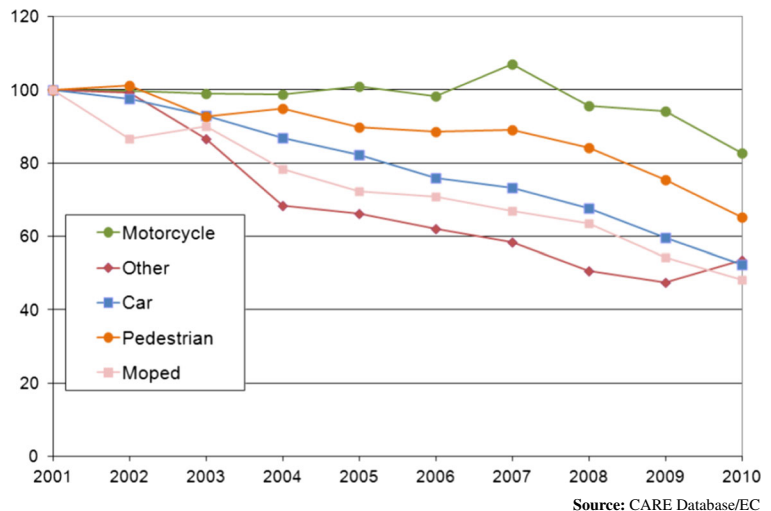
connecting it to a general punitive strategy that seems to provide a faster way of obtaining positive results (See [4] as an evaluation of the penal code reform in Spain). However, less attention has been paid to the potential role of sanctions to identify individuals with higher probabilities of suffering road accidents.

Indeed, traffic fines are understood and used only for punitive objectives, what hinders its effectiveness and brings them into disrepute [6]. Nonetheless, they can also provide rich and useful information to traffic authorities to identify groups at risk. In fact, Elander et al. [5] already found a positive correlation between the willingness to commit traffic violations and crash risk, which was explained by the personality and antisocial motivation. Vereeck and Vrolix [12] also found that willingness to comply matters more than legal specificity on the determination of safety outcomes. If traffic fines act as proofs of an adverse willingness to comply with the law, they can tell traffic authorities what kind of drivers is more prone to suffer an accident.

This study pretends going beyond the traditional punitive approach to traffic tickets by proposing its use for identifying drivers at highest risk. This area of research has received little attention and we only found some efforts in two related aspects. First, studies evaluating the efficient sanctioning according to the degree of seriousness or repeated violations [8, 9] - finding that efficient fines tend to increase more than proportionally with the severity of an offence -. Second, articles focused on the sensitivity to punishment of road users [1, 3] - that estimate how deterrence is affected by fine increases-.

The closest research to our knowledge is Lagarde et al. [10]. These authors used a sample of employees in order to determine their risk taking driving behaviors associated to several factors. Among others, they introduced a variable identifying those individuals that had received at least once a traffic penalty, finding that this situation was associated with a higher probability of bad driving behavior. The rationale behind our approach is based on this result, by considering that traffic penalties are indicators of risk taking behavior. Thus, past traffic fines can be good predictors of the number of accidents given that Lawpoolsri et al. [11] found that traffic citations have limited effects on deterrence.

Aims and hypotheses

The aim of this study is to estimate the impact of a number of PTWs driver characteristics in the city of Barcelona – the city with the highest number of PTW vehicles per inhabitant in Europe - on their records of crashes, paying particular attention to the role played by traffic fines received. Concretely, we propose testing the following hypotheses:

H1. The number of traffic offences has a significant role in predicting the safety outcomes. Our hypothesis is that the acknowledged risky behavior is positively correlated with the historical record of PTW road crashes.

H2. Different types of traffic offences have different predicting power when explaining the safety outcomes. Our hypothesis is that the number of severe violations of traffic law is better predictor than the number of non-severe violations.

H3. Public Health Authorities hardly obtain information regarding risk taking behavior. Nonetheless, our hypothesis is that the number of fines can provide better explanatory power than the declaration of current traffic driving offences.

Data and variables

This work takes advantage of a survey elaborated by the *RACC Foundation* to PTWs' drivers during 2008 in the city of Barcelona. The dataset contains 750 observations on PTWs' drivers regarding their social and demographic characteristics, as well as on their mobility patterns. It also contains information on their current behavior, particularly on traffic violations and risk taking actions. In addition, the database contains the type and number of fines received during their lives as well as the number of accidents suffered by respondents, although it is not possible to acknowledge when these crashes occurred. Giving the low density of these events (fines and accidents), considering information for a long period of time – since respondents became PTWs drivers – avoids problems of representation.

The dataset obtained from the survey is used to construct the following variables:

a) **Dependent variables**

- *Accidents:* binary variable that takes value 1 if the individual has suffered one or more accidents through her life as a PTW, and 0 in other case.
- *N_Accidents:* a continuous variable representing the number of total accidents suffered by the individual through her life as a PTW driver.

b) **Explanatory variables**

　Fines:

- *Fined:* binary variable that takes value 1 if the individual has received one or more fines, and 0 in other case.
- *N_fines:* number of fines received by the individual.
- *Fine_Speed:* binary variable that takes value 1 if the individual has received at least one fine by speed excess and 0 otherwise.

Tabla 1 Logistic and negative binomial estimates. Dependent variable: accidents (binary) and number of accidents (counts)

Covariates	Logistic (1)	Logistic (2)	Neg. Binomial (3)	Neg. Binomial (4)
Number of fines	0.7708***	-	0.5830***	-
	(5.90)		(8.36)	
Fined	-	0.9453***	-	0.7936***
		(6.01)		(7.53)
Experience	0.0207***	0.0204***	0.1429***	0.1396***
	(3.32)	(3.27)	(3.64)	(3.51)
Daily_trips	-0.1698	-0.1484	-0.1543	-0.1209
	(−0.98)	(−0.86)	(−1.31)	(−1.01)
Males	-0.0570	-0.0333	0.3983	0.0855
	(−0.32)	(−0.19)	(0.34)	(0.73)
Ring_trips	-0.1042	-0.1253	0.0068	-0.0265
	(−0.61)	(−0.74)	(0.06)	(−0.24)
Weekend_trips	0.3048*	0.3094*	0.2381**	0.2202**
	(1.82)	(1.85)	(2.18)	(2.00)
Night_trips	0.3171**	0.3251**	0.1419	0.1457
	(2.01)	(2.06)	(1.41)	(1.43)
LR chi2 (7)	63.85***	62.38***	97.33***	86.41***
N. observations	747	747	747	747
Log likelihood	-484.112	-484.850	-872.938	-878.401

T-statistics robust to heteroskedasticidy into parenthesis

*** significance at 1%; ** Significance at 5%; * Significants at 10%

- *Fine_Light:* binary variable that takes value 1 if the individual has been fined at least once for running a red light, and 0 otherwise.
- *Fine_Alcohol:* binary variable that takes value 1 if the individual has been fined at least once for alcohol consumption, and 0 otherwise.

Risk exposure:

- *Experience:* number of years of experience as a motorcycle or moped rider. Because individuals indicate the number of fines and accidents suffered over their live as PTW drivers, the more years of driving become an indicator of risk exposure to the total number of fines and accidents. We expect more accidents and fines with more years of driving.
- *Trips_daily:* number of daily trips with PTW.

Kind of trips:

- *Trips_ringroads:* binary variable that takes value 1 if the individual uses intercity roads usually, particularly ring roads, and 0 if all of her trips are urban.
- *Trips_weekend:* binary variable that takes value 1 if the driver uses the vehicle during weekends, and zero if she uses the vehicle only during week days.
- *Trips_night:* binary variable that takes value 1 if the individual uses the vehicle to do night trips, and zero if she uses it for day trips only.

Gender:

- *Male:* binary variable denoting with 1 male drivers, and 0 female drivers.

Given our interest in studying the link between risk behavior and the number of accidents, we decided to construct two different indexes of risk behavior from the information declared by respondents.

Risk behavior:

- *Absolut_risk_index:* risk index constructed from the acknowledged current traffic offences by individuals in the survey. It is the sum of the

bestowed values in the survey about the degree of recurrence in which some traffic rules are violated. Drivers answered with a 0 to refer those actions that they never did, 1 to refer those actions that they did occasionally, 2 to refer those actions that they did often, and 3 to refer to those actions that they always did. Therefore, this index is based on the summation of all these values for all kind of offences.

- *Variety_risk_index:* risk index constructed from the acknowledged current traffic offences by individuals in the survey. Here we identify those acknowledged infractions and sum the total number of different offences included in their history, beyond the bestowed values in the survey about their degree of recurrence. Therefore, the Variety of Risk Index informs about the total number of typologies of offences.

Tabla 2 Logistic and negative binomial estimates by type of fine. Dependent variable: accidents (binary) and number of accidents (counts)

Covariates	Logistic (5)	Neg. Binomial (6)
Speed_Violation	0.4368 (1.44)	0.3188* (1.78)
Traffic_lights	0.6158** (2.23)	0.4302*** (2.68)
Alcohol	1.1884 (1.47)	0.6161* (1.77)
Experience	0.0220*** (3.57)	0.0157*** (3.84)
Daily_trips	-0.2899* (−1.72)	-0.2617** (−2.16)
Males	0.0259 (0.15)	0.1147 (−0.94)
Ring_trips	-0.1491 (−0.89)	-0.0346 (−0.31)
Weekend_trips	0.2957* (7.80)	0.2117* (1.88)
Night_trips	0.3101** (2.01)	0.1339 (1.28)
LR chi2 (7)	36.15***	44.85***
N. observations	747	747
Log likelihood	-497.964	-899.178

T-statistics robust to heteroskedasticidy into parenthesis

*** significance at 1%; ** Significance at 5%; * Significants at 10%

Methods

We have two endogenous variables on injuries. One of them is a binary variable that takes value 1 if the individual has suffered an injury during her life as a PTW rider, and 0 otherwise. The other, instead, uses the total number of accidents that each individual has suffered during her life.

As a result, we have a binary variable and a count data variable, what shows a concentration of zeros and higher density for responses around the first natural values that decreases dramatically for higher numbers. As a consequence, we choose a logistic regression for the determination of the first dependent variable, while for the second we have chosen the negative binomial regression method.

We expect the number of accidents suffered to be explained by a function that depends on the number and kind of received fines, on the exposure to risk (years of experience and daily trips), on the kind of trips (urban/intercity, day/night, weekday/weekend trips), and on the gender (Eq. 1). This specification will serve to test our first two hypotheses (H1 and H2). Additionally we test the predicting power of the two indexes of risk proposed

(Eq. 2). This specification will allow for a comparison of explanatory power between current driving behavior and the number of fines. This serves to test our last hypothesis (H3).

$$N\_Accidents = f\ (Fines; Risk\ exposure; Kind\ of\ trips; Gender)$$

(1)

$$N\_Accidents = f\ (Risk\ Indexes; Fines; Risk\ exposure; Kind\ of\ trips; Gender)$$

(2)

Results

In Tabla 1 we display results from both the logistic estimation and the negative binomial estimation methods. The number of fines, as well as the fact of being fined, is positively correlated with the number of accidents suffered.

The coefficients associated with the variables of fines are strongly statistically significant (1%) and present a

Tabla 3 Logistic and negative binomial estimates by risk behavior and number of fines. Dependent variable: number of accidents (counts)

Covariates	Neg. Binomial (7)	Neg. Binomial (8)	Neg. Binomial (9)	Neg. Binomial (10)
Absolute Risk Index	0.0617***	-	0.0473***	-
	(5.71)		(4.53)	
Variety Risk Index	-	0.1414***	-	0.1001***
		(6.17)		(4.40)
Number of Fines	-	-	0.5231***	0.6779***
			(7.61)	(5.07)
Experience	0.1714*	0.1812***	0.0157***	0.1634***
	(−1.80)	(4.47)	(4.06)	(4.19)
Daily_trips	-0.2158*	-0.2274*	-0.1081	-0.1325
	(1.36)	(−1.90)	(−0.93)	(−1.14)
Males	0.1614	0.1160	0.0181	-0.0067
	(1.36)	(0.98)	(0.16)	(−0.06)
Ring_trips	-0.0727	-0.677	0.0099	0.0088
	(−0.66)	(−0.61)	(0.09)	(0.08
Weekend_trips	0.2306**	0.2165*	0.2288**	0.2210**
	(2.07)	(1.95)	(2.13)	(2.05)
Night_trips	0.0991	0.0821	0.1041	0.0948
	(0.96)	(0.79)	(1.05)	(0.95)
LR chi2 (7)	62.02***	67.50***	117.28***	116.37***
N. observations	747	747	747	747
Log likelihood	-890.592	-887.857	-862.966	-863.422

T-statistics robust to heteroskedasticidy into parenthesis. *** significance at 1%; ** Significance at 5%; * Significants at 10%

positive sign. Therefore, past fines seem to be good instruments to predict the number of accidents. As a result, we confirm *hypothesis 1*.

In Tabla 2 we show results distinguishing by the kind of fines received. In particular we analyze the impact of penalties related to speed excess, alcohol consumption and traffic lights, compared to the rest of penalties. Penalties related to running over red lights are those with the highest statistical significance, although all three variables report positive and substantial impacts in magnitude respect to the rest of fines. This evidence helps us to identify driver profiles more keen on doing serious offences which involve, in turn, a higher risk. This result confirms *hypothesis 2*.

Tabla 3 shows our results after including our self-constructed risk indexes. Note that both indexes cannot enter together in the same specification due to their 86% of correlation. The coefficients associated with both indexes are statistically significant and positive. The coefficient associated with the variety of fines seems to be larger. More importantly, both indexes seem to have less impact on the number of accidents than the number of fines received. This confirms *hypothesis 3*. It is worth noting that including risk taking variables does not affect the variable *N_fines*, either in terms of its degree of significance nor in its size and sign, what discards colinearity problems with risk indexes.

Conclusions

This paper confirms the main hypotheses proposed. On the one hand, we have shown that the number of received fines can be a good predictor of the number of accidents that a PTW driver can suffer, and thus, the use of this information could allow identifying those users who are potentially at higher risk. Given these results, governments are losing valuable opportunities when using traffic fines only for punishment purposes.

Furthermore, we have seen that not all kind of fines are equally important in terms of their impact on safety. In fact, those drivers who have received fines due to violating traffic lights and alcohol consumption are the ones who suffer more injuries. For this reason it is important to focus the efforts in identifying the profile of drivers who undertake serious traffic violations.

This rich information, already collected by traffic authorities seems to be even more useful than risk taking declarations. Which, in turn, seem more difficult to obtain. For all these reasons, information from fines should be used for improving the design of public health policies and fight the common view of governments using traffic law as a revenue source.

References

1. Bar-Ilan, A., & Sacerdote, B. (2004). The response of criminals and noncriminals to fines. *Journal of Law and Economics, 47*(1), 1–17.
2. Blais, E., & Gagné, M. (2010). The effect on collisions with injuries of a reduction in traffic citations issued by police officers. *Injury Prevention, 16*, 393–397.
3. Castellà, J., & Perez, J. (2004). Sensitivity to punishment and sensitivity to reward and traffic violations. *Accident Analysis and Prevention, 36*(6), 947–952.
4. Castillo-Manzano, J., Castro-Nuñez, M., & Pedregal, D. (2011). Can fear of going to jail reduce the number of road fatalities? The Spanish experience. *Journal of Safety Research, 42*(3), 223–228.
5. Elander, J., West, R., & French, D. (1993). Behavioral correlates of individual differences in road-traffic crash risk: An examination of methods and findings. *Psychological Bulletin, 113*(2), 279–294.
6. Evans, L. (2003). A new traffic safety vision for the United States. *American Journal of Public Health, 93*(9), 1384–1386.
7. Figueiredo, P., Rasslan, S., Bruscagin, V., Cruz, R., & Rocha-Silva, M. (2001). Increases in fines and driver license withdrawal have effectively reduced immediate deaths from trauma on Brazilian roads: First-year report on the new traffic code. *Injury, 32*(2), 91–94.
8. Goerke, L. (2002). Accident law: Efficiency may require an inefficient standard. *German Economic Review, 3*(1), 43–51.
9. Goerke, L. (2003). Road traffic and efficient fines. *European Journal of Law and Economics, 15*, 65–84.
10. Lagarde, E., Chiron, M., & Lafont, S. (2004). Traffic ticket fixing and driving behaviours in a large French working population. *Journal of Epidemiology and Community Health, 58*, 562–568.
11. Lawpoolsri, S., Li, J., & Braver, E. R. (2007). Do speeding tickets reduce the likelihood of receiving subsequent speeding tickets? A longitudinal study of speeding violators in Maryland. *Traffic Injury Prevention, 8*(1), 26–34.
12. Vereeck, L., & Vrolix, K. (2007). The social willingness to comply with the law: The effect of social attitudes on traffic fatalities. *International Review of Law and Economics, 27*, 385–408.