The Relationship between Crash Severity and Speeding Tickets: Lessons from a Nation-wide Survey

Murat Anil Mercan*

Gebze Technical University, Kocaeli, Turkey
*Corresponding author: namercan@gtu.edu.tr

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Abstract Although many studies have investigated the relationship between car-crash severity and its determinants, few studies have taken advantage of nationwide datasets. This is especially true for developing countries. This study uses a unique dataset that includes all official police-recorded accidents in a developing country, namely Turkey. With this dataset, we estimate the relationship between the number of speeding tickets and multiple vehicle involvement, applying both Poisson and probit models for our analysis. Our estimates show a negative relationship between the number of speeding tickets issued in the provinces and the severity of deadly crashes; however, when we use the number of injured due to accidents, we find a positive relationship. This suggests that speeding tickets are a good policy to reduce crash severity. In addition, our analysis lets us investigate the determinants of crash severity.

Keywords: speeding, accident, gender, turkey, poisson, probit

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1. Introduction

According to the World Health Organization, about 3,700 people die from traffic accidents every day, and this problem has only grown worse [1]. Therefore, it is evident that societies need to have more effective policies in place to prevent accidents. To reach this goal, the effectiveness of different approaches and accident determinants must be investigated. Although many previous studies have focused on the relationship between traffic accidents and various enforcement policies, few studies have examined the relationship between the number of traffic tickets and their severity [2]. Therefore, estimating both the impact of each risk factor for crash severity and the relationship between the number of speeding tickets and the number of traffic accidents using nationwide datasets should be particularly effective in reducing traffic accidents. As far as we know, our study is the first to use a national dataset to investigate the determinants of crash severity and the effect of speeding tickets in a developing country, namely Turkey.

In Turkey in 2018, according to the Turkish Statistical Institute (TUIK), 1,229,364 traffic accidents resulted in 6,675 deaths (the proportion of the population is about 0.008%) and 307,071 injuries (the proportion of the population is about 0.374%). Moreover, the ratio of accidents to the number of vehicles was 5.38%. In this study, we use a unique dataset provided by the General Directorate of Police to investigate the determinants of traffic accidents in Turkey. The dataset has information for all officially recorded traffic accidents from 2012 to 2017 in which at least one person was injured or died. This data provides us with a unique opportunity to measure speeding tickets’ effect and ascertain the determinants of crash severity. For our analysis, we employed both the Poisson and probit models with a dummy for accidents involving more than two vehicles to account for within-crash correlation.

Traffic accidents occur for both non-human and human-related reasons. In the literature, many articles have looked into the effects of different human-related factors; one study in particular provides an excellent review of these [3]. However, speeding is one of the most critical factors [4]. For instance, a study showed that crash severity increases enormously with increases in vehicle speed—e.g., a frontal impact at 35 mph is one-third more damaging than a similar accident at 30 mph [5].

There have been various studies about different aspects of traffic accidents in Turkey [6-10]; however, we will briefly discuss most related studies with our paper. First of all, a study used a dataset from 2008 to 2013 for Erzurum and Kars provinces. When they applied multinomial logit models in their analyses, contrary to the literature, they found that for accidents involving speeding, the “no injury” level of severity is more likely to occur than the level of “fatal injury” [11]. On the other hand, another paper found that speeding violations increase the probability of accidents with injuries, but not accidents with fatalities [12]. As far as we know, one previous study has employed a nationwide dataset for Turkey. They use the General
Our dataset also has information about the drivers’ characteristics and road characteristics such as their age and the type of road where the accident happened. Our main independent variable is the number of speeding tickets per capita, which states that issue more traffic tickets per capita have fewer accident fatalities than states that issue fewer traffic tickets [15]. Also, another study used a dataset from São Paulo from 2012 to 2017 and found that speed limit reductions result in a significant lowering of road accidents, resulting in a 21.7% decline [16].

In this paper, we will investigate the relationship between speeding tickets’ effect and the determinants of crash severity. In reaching the goal, we also measure the determinants of traffic accidents in Turkey. We believe that investigating these will make an important contribution to the academic literature and help to create better policies; for instance, a well-known study showed that people underestimate the frequency of road accidents [17]; therefore, our study will also raise awareness of the determinants of traffic accidents in Turkey. The paper proceeds as follows. Section II describes the material and methods. The results of the study are described in Section III, and Section IV summarizes and discusses the findings.

2. Material and Methods

In this study, we use a unique dataset taken from the General Directorate of Police in Turkey. The dataset has information for all officially recorded traffic accidents in which at least one person was injured or died in Turkey between 2012 and 2017. Table 1 shows the difference between our sample and the TUIK, which collects data from both the General Directorate of Police and the General Command of Gendarmerie in Turkey, and it shows that our sample includes about 85% of the road accidents for each year from 2012 to 2017. This means that about 15% of the accidents involving death or injury occurred in areas where the gendarmerie is responsible. Our dataset also has information about the drivers’ demographic characteristics such as their age and the type of road where the accident happened.

Even though Table 1 shows that the total number of accidents is 874,764, our dataset would otherwise have 1,342,291 driver-accident cases because some accidents involve more than two vehicles. However, in 48,561 driver-accident cases, the drivers’ age was less than 18 years old, which is when one can obtain a driver’s license. Therefore, we omitted these observations from the sample to be on the safe side. In addition, 191,581 driver-accident cases have missing information in one of the covariates. In the end, we have 1,102,149 driver-accident cases in the sample.

| Year | TUIK     | Our Sample | The Difference |
|------|----------|------------|----------------|
| 2012 | 153,552  | 130,360    | 23,192         |
| 2013 | 161,306  | 136,033    | 25,273         |
| 2014 | 168,512  | 142,372    | 26,140         |
| 2015 | 183,011  | 155,201    | 27,810         |
| 2016 | 185,128  | 156,688    | 28,440         |
| 2017 | 182,669  | 154,110    | 28,559         |
| TOTAL| 1,034,178| 874,764    | 159,414        |

2.1. Statistical Methods

Suppose $Z_i$, which follows a generalized Poisson distribution, is a count response variable. To model accident data, we define $Z_i (i = 1, 2, ..., n)$ as the number of vehicle accidents with injuries/deaths. The probability function of $Z_i$ is given as

$$f_i(z_i; \mu_i, \gamma) = \left( \frac{\mu_i}{1 + \gamma \mu_i} \right) (1 + \gamma \mu_i)^{z_i - 1} \exp \left[ -\mu_i \left( 1 + \gamma z_i \right) \right]$$

where $z_i = 0, 1, 2, ..., \mu_i = \mu(x_i) = \exp(x, \beta)$, $x_i$ is a $(k - 1)$ dimensional vector of covariates, and $\beta$ is a $k$-dimensional vector of regression parameters [18].

We have two different Poisson regression forms for accidents in which there are injuries and deaths. Therefore, our dependent variable is the categories of injuries and fatalities. Our main independent variable is the number of speeding tickets per thousand 18-to-55-year-old residents in the province. Our model includes both drivers’ characteristics and dummies for provinces, years, and the interactions among these as the control variables. For driver characteristics, we use age, the square of their age, and their genders. Moreover, we use a dummy that equals one if the accident involved more than two vehicles.

Table 2 shows the summary statistics for the sample of Poisson models. Throughout the sample period, the average number of people who died in accidents and the average number of people injured in accidents is 0.02 (the standard deviation is 0.17) and 1.74 (the standard deviation is 1.78), respectively. Also, drivers’ average age is around 37 years old, and most of them are men (93%). Finally, the majority of the accidents occurred in boulevards, precisely 60%.

The probit regression models are used to determine the crash severity for drivers. Similar to our Poisson models, we use two different regression forms for injuries and death. In one of these models, the dependent variable equals one if the driver is dead. In another model, the dependent variable equals one if the driver is injured. The probit models also include the same independent variables. In this study, both the Poisson and the probit models are estimated using Stata (version 15.0).
3. Results

3.1. The Poisson Regression Models

In the Poisson models, the dependent variables’ values vary from zero to 127 and from zero to 20 for the analyses of injuries and deaths, respectively. The dependent variable increases with the severity of injuries and fatalities. Therefore, the positive coefficients suggest the likelihood of more severe injuries.

Table 3 shows our estimates from the Poisson regression models. Column A of Table 3 shows the estimates from the model in which the dependent variable is the total number of people injured in accidents. The measure of the goodness of fit is 0.0171. According to Column A of Table 3, when the logarithm of number of speeding tickets per thousand 18–to-55-year-old residents in the province increases, this increases severe injuries as well. Its standard errors are 0.012, which means that the effect is significant at the usual levels. Its incidence rate ratio (IRR) is 1.042, which refers to the likelihood of severe crashes. Furthermore, the IRR of more than two vehicles involvement is 1.264, which means it increases the likelihood of severe injuries in an accident. Moreover, the coefficient for female drivers is -0.026, and the IRR is 0.974. This means that women are less likely to be involved in severe crashes. Our results also suggest that a severe accident is more likely to occur for each one-year increase in age when all other variables are held constant (the IRR is 1.004). Finally, severe crashes are more likely to happen on national roads, village roads, forest roads, provincial roads, and highways than the reference road type, namely, the connector roads. On the other hand, the categories for boulevards, parking lots, service roads, streets, in front of and on a property, and other roads have a statistically significant lower likelihood for severe crashes than connector roads.

Also, Column B of Table 3 shows the estimates from the model in which the dependent variable is the total number of people who died in accidents. In this model, the measure of the goodness of fit is 0.0726. It shows that increasing the number of speeding tickets in the province has a negative impact on crash severity; however, the standard errors are 0.28, which means that the effect is not significant at the usual levels. Moreover, the likelihood for female drivers is similar with a bigger coefficient (the IRR is 0.356). In addition, the estimate for age is also similar to the estimate for injuries. This suggests that an additional year in age increases the likelihood of both injuries and deaths in an accident. Also, national roads and highways have higher probabilities than the reference road, i.e., the connector roads. On the other hand, boulevards, service roads, streets, in front of and on a property, and other roads have a statistically significant lower likelihood of being the location of a deadly crash. The remaining categories do not have any statistically significant estimates. Finally, when more than two vehicles are involved in an accident, the likelihood decreases.

### Table 3. The Results of Poisson Regression Models

| Road Types          | A-INJURY Coefficient | A-INJURY S.E. | B-DEATH Coefficient | B-DEATH S.E. |
|---------------------|----------------------|---------------|---------------------|---------------|
| Connectors          | 0.014***             | 0.012         | -0.029              | 0.028         |
| Boulevards          | 0.234***             | 0.020         | -0.417**            | 0.178         |
| National roads      | 0.004***             | 0.002         | 0.032***            | 0.003         |
| Others              | -0.000***            | 0.000         | -0.000***           | 0.000         |
| Village Roads       | -0.026***            | 0.007         | -1.032***           | 0.039         |
| Forest Roads        | -0.189***            | 0.046         | -0.990***           | 0.132         |
| Streets             | 0.108***             | 0.019         | 0.543***            | 0.149         |
| Others              | -0.158***            | 0.043         | -0.593***           | 0.093         |
| Village Roads       | 0.106                | 0.067         | 0.160               | 0.255         |
| Forest Roads        | 0.247                | 0.065         | -0.514              | 0.916         |
| Highways            | 0.014                | 0.016         | 0.655***            | 0.203         |
| Parking Lots        | -0.363***            | 0.034         | -0.568              | 0.415         |
| Service Roads       | -0.220***            | 0.032         | -0.571***           | 0.054         |
| Streets             | -0.297***            | 0.038         | -1.762***           | 0.205         |
| Front/At A Property | -0.279***            | 0.090         | -0.814***           | 0.291         |
| Province Roads      | 0.156***             | 0.045         | 0.059               | 0.144         |
| Province Dummies    | Yes                  | Yes           | Yes                 | Yes           |
| Year Dummies        | Yes                  | Yes           | Yes                 | Yes           |
| Year x Province     | Yes                  | Yes           | Yes                 | Yes           |
| Pseudo R²           | 0.0171               | 0.0698        |                     |               |

### Table 2. Summary Statistics

| Variable             | Mean   | S.D.   | Min | Max |
|----------------------|--------|--------|-----|-----|
| The Number of Deaths | 0.02   | 0.17   | 0   | 20  |
| The Number of Injured| 1.74   | 1.78   | 0   | 127 |
| Number of Speeding Tickets | 16.73 | 15.12 | 0.01 | 108.76 |
| MoreVehicles | 0.71  | 0.45   | 0.00 | 1.00 |
| Female              | 0.07   | 0.25   | 0   | 1   |
| Driver's Age        | 37.12  | 13.19  | 18  | 99  |
| Road Types          |        |        |     |     |
| Connectors          | 0.01   | 0.11   | 0   | 1   |
| Boulevards          | 0.60   | 0.49   | 0   | 1   |
| National roads      | 0.22   | 0.42   | 0   | 1   |
| Others              | 0.01   | 0.08   | 0   | 1   |
| Village Roads       | 0.00   | 0.07   | 0   | 1   |
| Forest Roads        | 0.00   | 0.01   | 0   | 1   |
| Highways            | 0.03   | 0.17   | 0   | 1   |
| Parking Lots        | 0.00   | 0.03   | 0   | 1   |
| Service Roads       | 0.01   | 0.07   | 0   | 1   |
| Streets             | 0.10   | 0.30   | 0   | 1   |
| Front/At A Property | 0.00   | 0.05   | 0   | 1   |
| Province Roads      | 0.01   | 0.11   | 0   | 1   |
| n                   | 1,102,149 |      |     |     |

1 The number of speeding tickets per thousand 18-55 years old residents
2 It equals to 1, if there are more than two vehicles.
dummy, which is one when the driver is injured. It shows that an injury's likelihood increases when there is a more significant number of speeding tickets. Age reduces but being female increases the possibility of suffering an injury in an accident.

Moreover, Column B of Table 4 shows the estimates when the dependent variable is the dummy, which is equal to one if the driver died in the accident. This indicates that the likelihood of death decreases when there is a more significant number of speeding tickets. In these models, an increase in age increases the likelihood of suffering a fatality, but being female decreases this likelihood. Finally, the involvement of multiple vehicles reduces the possibility of death, but in the analysis of injuries, this increases the likelihood.

| Table 4. The Results of Probit Regression Models |
|------------------------------------------------|
| Speeding Tickets | Coefficient | S.E. | Coefficient | S.E. |
| Speeding Tickets | 2.203*** | 0.010 | -1.493*** | 0.019 |
| More Vehicles  | 0.453*** | 0.053 | -0.248*** | 0.056 |
| Driver's Age   | -0.016*** | 0.001 | 0.013*** | 0.001 |
| Square of Driver's Age | 0.000*** | 0.000 | -0.000*** | 0.000 |
| Female          | 0.454*** | 0.032 | -0.357*** | 0.014 |

| Road Types | Coefficient | S.E. | Coefficient | S.E. |
| Boulevards | 0.331*** | 0.024 | -0.379*** | 0.031 |
| National roads | -0.109* | 0.060 | 0.191*** | 0.068 |
| Others | 0.392*** | 0.123 | -0.364*** | 0.060 |
| Village Roads | 0.302*** | 0.167 | -0.025 | 0.063 |
| Forest Roads | 0.041 | 0.411 | -0.197 | 0.373 |
| Highways | -0.238*** | 0.066 | 0.254*** | 0.092 |
| Parking Lots | 0.256** | 0.104 | -0.306*** | 0.132 |
| Service Roads | 0.092** | 0.033 | -0.280*** | 0.029 |
| Streets | 0.410*** | 0.048 | -0.615*** | 0.047 |
| Front/At A Property | 0.070 | 0.080 | -0.296*** | 0.090 |
| Province Roads | 0.031 | 0.067 | 0.014 | 0.049 |
| Provience Dummies | Yes | Yes | Yes | Yes |
| Year Dummies | Yes | Yes | Yes | Yes |
| Year x Province | Yes | Yes | Yes | Yes |
| Pseudo R² | 0.0750 | 0.0726 | 0.0726 | |
| n | 1,102,149 | 1,102,149 | 1,102,149 | |

*** p<0.01, ** p<0.05, * p<0.10
1 The logarithm of number of speeding tickets per thousand 18-55 years old residents
2 It equals to 1, if there are more than two vehicles.
3 It equals to 1, if the driver is woman.
4 The reference group is Connectors.

4. Discussion

According to TUIK, in 2017, about 1.6% of all deaths occurred at the site of traffic accidents in Turkey. Also, researchers noted that in Turkey between 2000 and 2016, the number of registered vehicles had tripled [19]. Investigating the reasons behind severe crashes is thus of vital concern. Moreover, a study emphasized how traffic accidents place a significant burden on the Turkish population's health [20].

Moreover, our study is the first to use a nationwide dataset to investigate the determinants of crash severity in a developing country when the number of speeding tickets and multiple vehicles' involvement is controlled. Our results show that an increase in the number of speeding tickets does not reduce crash severity for either deaths or injuries; for instance, the coefficient of injury from the Probit model is 2.203 [S.E.: 0.019]. It reduces only the number of deaths; for example, the coefficient of death from the Probit model is -1.493 [S.E.: 0.019]. In addition, we found that female drivers are less likely to be involved in severe crashes that result in injuries. We also found that an increase in age increases the likelihood of being in a severe crash.

Even though our study is the first attempt to estimate crash severity determinants, it has limitations. First, our dataset has only a certain amount of information about the drivers; we do not know their education level. Instead of individual data, we had to use data from the provinces where the accidents occurred. Second, even if we use official police statistics, underreporting of accidents could be a problem for our estimates.

In conclusion, our estimates suggest that increasing the number of speeding tickets is not just a budgetary tool for governments; it is also a tool for reducing the severity of traffic accidents.

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