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Time and distance to first accident and driving patterns of young drivers with pay-as-you-drive insurance

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ABSTRACT

We conducted a study of approximately 16,000 drivers under the age of 30 that had purchased a pay-as-you-drive insurance policy, where their risk of being involved in a crash was analyzed from vehicle tracking data using a global positioning system. The comparison of novice vs. experienced young drivers shows that vehicle usage differs significantly between these groups and that the time to the first crash is shorter for those drivers with less experience. Driving at night and a higher proportion of speed limit violations reduces the time to the first crash for both novice and experienced young drivers, while urban driving reduces the distance traveled to the first crash for both groups. Gender differences are also observed in relation to the influence of driving patterns on the risk of accident. Nighttime driving reduces the time to the first accident in the case of women, but not for men. The risk of an accident increases with excessive speed, but the effect of speed is significantly higher for men than it is for women among the more experienced drivers.

1. Introduction

In-vehicle data recording systems can be used to monitor and to provide feedback on driver behavior. These devices provide data that are both more detailed and more reliable than conventional self-report driving data (Blanchard et al., 2010), and so help identify driver maneuvers associated with risky driving and overall trip safety objectively.

To the best of our knowledge, no previous study has undertaken a comparison, within the under-thirty age group, of novice drivers (those driving for less than a year) and their more experienced counterparts in terms of time and distance to the first accident. Employing the usage measurements provided by global positioning systems (GPS) for tracking vehicles, we are able to see how the acquisition of driving experience reduces the risk of being involved in a crash. However, the associated boost in confidence experienced by drivers makes them more likely to drive at high speeds and to exceed speed limits. As such, the risk of being involved in an accident as a result of excess speed increases, thus offsetting the diminishing risk due to accumulated experience. Existing research evidence for the contention that drivers speed after gaining confidence can be found, for instance, in Cestac et al. (2011), but it is still unclear how much experience might be related to an increase in speeding.

In this study we analyze drivers who purchased an insurance policy agreement tied to vehicle usage. A GPS was installed in their vehicles and the drivers were informed that their insurance would be proportional to the number of miles driven. The other metrics tracked included episodes of excessive speed, urban driving and nighttime driving, and these were also taken into consideration in the overall rating system. Here, we analyze the role played by experience and its impact on the risk of being involved in an accident in terms of the time and distance traveled by drivers aged under thirty. As such, our objective is to compare the driving patterns and the respective risks of accident of novice vs. experienced young drivers.

Taking a similar approach, Underwood (2013) also considered newly qualified drivers, finding a difference between younger and older novice drivers. While the average speed of drivers in both groups increased over time, the older novices showed some indications of becoming more cautious with experience. Previously, McCartt et al. (2003) focused on teenage drivers in their first year as license holders and found the risk of crash or traffic citation to be highest during their first 500 miles, but their study is based on retrospective self report. They also find evidence of sociodemographic heterogeneity. Naturalistic driving data has been used to identify high-risk drivers and risk factors (see, Guo and Fang, 2013).

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Bolderdijk et al. (2011) studied a group of young drivers and found that the introduction of a pay-as-you-drive (PAYD) insurance fee significantly reduced their speed violations. While speed enforcement tools can have obvious financial consequences, such as the imposition of penalties, the deterrent effect of a usage based insurance scheme is based on a multitude of risk factors, including driving volume (mileage), driving style (speed, sudden braking, etc.) and other factors (including time of day when driving). In a sample of 228 drivers, the percentage of total distance traveled at a speed that was 6% or more above the local limit (violations of less than 6% being excluded as they can be attributed to involuntary events) was used as an indicator of excessive speed. Bolderdijk et al. (2011) also noted that the PAYD system was less effective on roads on which the speed limit was 30 and 120 km/h than it was on roads with a 50, 80 or 100 km/h limit. The study showed that a financial incentive (i.e., a reduction in the price of insurance coverage) reduced episodes of excessive speed from 20.5 to 17.6% in young adult drivers. A similar positive short-term effect was previously reported by Toledo et al. (2008). An additional advantage of in-vehicle monitoring devices is that drivers are able to obtain a discount on their insurance premium due to low usage or prudent speed patterns.

Speed has been shown to be an important predictor of crash involvement, as have the two dimensions of driver exposure, that is, distance traveled and time traveled. Additionally, spatial (urban, non-urban and off-road) and temporal structures (time of day and day of week) present heterogeneous distributions and can serve as the basis for the construction of risk indices, or numeric measures that can predict a driver's risk of being involved in a car crash in a given period of time. Of course, the more miles one drives the higher the risk of a crash, which is why most studies control for miles/km. 'Crash-involved' drivers tend to drive at higher speeds than 'crash-not-involved' drivers. In this respect, Jun et al. (2011) show that roadway types and trip start times influence the distribution of speed metrics and need to be taken into consideration. Sivak et al. (2007) observed that increased mileage and driving at night on weekends are associated with increased risk of accident.

The concept of 'not speeding' was coined as part of pay-as-you-speed (PAYS) schemes, which promote speed control by granting a premium discount of up to 30% if the speed limit is respected. In an experiment involving 153 drivers, Lahrmann et al. (2012) showed that the proportion of distance driven above the speed limit falls when the driver is monitored using intelligent speed adaptation equipment; however, the effect significantly decreased over time. Thus, we believe that the system can be very effective for novice drivers.

Hultkrantz et al. (2012) argue that PAYS insurance provides the insurance industry with better possibilities of differentiating premiums according to behavior and, therefore, of targeting risk classes more effectively. Here, we obtain a similar result as we find that excessive speed has a significant impact on the risk of being involved in an accident.

Paefgen et al. (2013) have evaluated and aggregated PAYD insurance rate factors; however, they do not consider usage-based information related to excessive speed. More recently, the same authors have evaluated different logistic regression models in a case-control design to analyze the risk of accident involvement as a function of different sets of exposure variables (Paefgen et al., 2014). Here again their application makes use of a dataset made up from PAYD policy holders, but they do not take excessive speed into account. Instead, in both articles they only consider time of day, day of week, road type, average velocity and mileage. It is our contention, however, that driving experience influences driving patterns and that this should also be taken into consideration for rating purposes.

Table 1
Variable description.

Variable	Label
Sex	Binary variable (=1 male, =0 female)
Age	Age of the driver when driving patterns began to be recorded (measured in years)
Age vehicle	Age of the vehicle when driving patterns began to be recorded (measured in years)
Experience	Driving experience, measured by the time elapsed since obtaining license and the point when driving patterns began to be recorded (measured in years)
Urban	% of urban driving (% of the total kilometers traveled in urban areas)
Night	% of nighttime driving (% of the total kilometers traveled at night)
Speed	% of the total kilometers traveled above the mandatory speed limits
km/day	Driving intensity (average number of kilometers traveled per day)

2. Materials and methods

2.1. Data source and follow-up

Our dataset comprises 15,940 young drivers who underwrote a PAYD policy in 2009 with a leading Spanish insurance company. On signing the agreement, their driving patterns began to be registered using a GPS system. The follow-up period was concluded on 31 December 2011. All drivers were under the age of thirty at the time of underwriting the policy.

The information recorded by the GPS system includes the total number of kilometers traveled and a number of other variables capturing elements of the participants' driving patterns. This information was collected for different time periods during each year, as identified by the corresponding beginning/end dates. In Table 1 the variable description is presented.

For each driver in the dataset, we know their gender (binary variable Sex), age (Age), age of the vehicle (Age vehicle) and driving experience (Experience). These variables were recorded when we began monitoring their driving patterns. Urban measures the percentage of total kilometers traveled in urban areas. Similarly, Night measures the percentage of total kilometers traveled at night (between midnight and 6 am). Speed measures the percentage of distance traveled above the mandatory limits. Note that in this definition we do not require the percentage of speed above the local limit to be higher than some threshold value, as Bolderdijk et al. (2011) did. Instead, speed is measured by the percentage of distance traveled at any speed which is above the local limits. Driving intensity, which is measured by the average number of kilometers traveled per day during the period of observation, is also taken into consideration. Finally, note that in some instances we consider "Urban > 25%" representing a binary variable that is equal to one when urban driving is higher than 25%.

Our statistical analysis compares two subsets of drivers:

a) Novice young drivers: individuals that had been in possession of their driving licenses for less than a year when their driving patterns began to be recorded and who were under the age of thirty at that time. The sample includes 2,790 novice drivers (17.5%).
b) Experienced young drivers: individuals that had been in possession of their driving licenses for at least a year when their driving patterns began to be recorded and who were under the age of thirty at that time. The sample includes 13,150 experienced young drivers (82.5%).