Do Young Drivers Become Safer After Being Involved in a Collision?

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Abstract
As drivers age, their risk of being involved in a car collision decreases. The present study investigated if this trend is due, in part, to some risky drivers having a collision early in their driving lives and subsequently reducing their risky driving after that negative experience. Accelerometers and video cameras were installed in the vehicles of 16- to 17-year-old drivers (N = 254), allowing coders to measure the number of g-force events (i.e., events in which a threshold acceleration level was exceeded) per 1,000 miles and the number of collisions. Among the 41 participants who experienced a severe collision, the rate of g-force events dropped significantly in the 1st month after the collision, remained unchanged for the 2nd month, and increased significantly in the 3rd month. There were no changes in the rate of g-force events at comparable time points for the drivers not involved in a collision. Being involved in a collision led to a decrease in risky driving, but this may have been a temporary effect.

Keywords
risky driving, collision, crash, adolescents, g-force events

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Motor-vehicle deaths are a critical public-health problem in the United States and across the world. According to the Centers for Disease Control and Prevention (2017), these deaths led to about 1.2 million years of potential life lost in the United States in 2015 (the most recent year for which the data are available). Motor-vehicle collisions are the leading cause of death among 16- to 24-year-olds in the United States, and drivers in this age group are disproportionately involved in fatal motor collisions (International Traffic Safety Data and Analysis Group, 2014; National Highway Traffic Safety Administration, 2013). Guo et al. (2013) reported that rates of collisions and near collisions among young drivers generally decrease as they get older. Strong evidence suggests that much of the change in collision risk is due to driving experience (Foss, Masten, & Martell, 2014; McKnight & McKnight, 2005).

Little is known about what kinds of experiences drivers learn from during their first months and years of driving. It is possible that some drivers have riskier driving styles than their peers when they begin driving, then experience negative events such as collisions, and subsequently adopt less risky driving styles, implicitly or explicitly. Personal experience of negative events has been found to influence future behavior in the case of risk behaviors such as smoking after a cancer diagnosis (Park et al., 2012), use of contraceptives after an unplanned pregnancy (Pentlicky & Williams, 2010), and use of sunscreen following a melanoma diagnosis (Brännström et al., 2010). However, testing the effect of negative experiences on risky driving has proved difficult. A number of studies have detailed the short- and long-term psychological and physical effects of being in traffic collisions (Ameratunga et al., 2006; Mayou & Bryant, 1994, 2002), but have not looked at actual changes in driving. Additional research has found that people’s seat-belt use does not change markedly after they have been involved in a collision (see Weinstein, 1989). Most of these studies, on driving and other behaviors, have recruited participants who have

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already experienced the negative event. Accordingly, these studies could not determine if participants had changed their behavior; any information about past behavior can only be based on recollection, which itself could be influenced by negative events.

Assessing risky driving poses methodological concerns. Researchers have typically been forced to rely on subjective data, such as self-reported risk behaviors (e.g., Mitchell, Bambach, & Friswell, 2014; Palk, Freeman, Kee, Steinhardt, & Davey, 2011) and police reports (e.g., Schneider, Savolainen, Van Boxtel, & Beverley, 2012; Zhou, Roshandeh, Zhang, & Ma, 2016). The validity of self-reported behavior has been called into serious question (see at Wählberg, 2009), and police reports rely on inferences as to the cause of a collision. Technological advances have enabled naturalistic driving research in which drivers’ behavior during both regular driving situations and collision events can be directly measured. Using this technology, researchers have expanded current understanding of the role that secondary-task engagement plays in collisions (Klauer, Ehsani, McGehee, & Manser, 2015; Klauer et al., 2014), the similarities in driving styles among parents and their children (Ehsani, Simons-Morton, Xie, Klauer, & Albert, 2014), and the relationship between risky driving and collision involvement (Simons-Morton, Zhang, Jackson, & Albert, 2012). Simons-Morton and his colleagues (2012) found that the rate of events in which gravitation force exceeded a certain threshold (henceforth referred to as g-force events) predicted future involvement in collisions and near collisions. This finding supports the use of g forces (which are caused by rapid starts, hard stops, and sharp turns) as a measure of risky driving.

Naturalistic driving measures provide an opportunity to examine changes in driving behavior following a collision. In a study of changes in the rate of acceleration events among bus drivers, af Wählberg (2012) found that all the drivers reduced their rate of g-force events over time, but there was no difference between drivers who were and were not involved in collisions. Although this study provides a clear starting point, its generalizability is limited because af Wählberg observed professional drivers operating large vehicles across 40 routes in a single town in Sweden.

A core question in the literature is why collision risk decreases so much in the first few months and years of driving (Guo et al., 2013). Although learning would presumably result from a variety of experiences, a collision seems likely to be a relatively important learning experience given the possibility of insurance claims, injury, stress, and costly repairs. However, no published studies have investigated changes in driving behavior among young novice drivers in response to involvement in a traffic collision. Because of relatively small sample sizes, previous naturalistic driving studies have observed too few collisions to address this question adequately. In the present study, we were able to use data from a sample of more than 250 young drivers in the Naturalistic Driving Study, part of the Strategic Highway Initiative Program 2 (SHRP 2). This data set contained more collisions within the target age group than any other available data set. The current study is the first investigation of the impact of collision involvement on the driving behavior of young people, and of how long any changes persist. We focused on relatively severe collisions, as it seems reasonable to suppose that if collisions do have an effect on young people’s driving, this effect would be more apparent for severe collisions than for more minor incidents. Our primary hypothesis was that after being involved in a collision severe enough to warrant a police report, young drivers adopt a more cautious driving style.

**Method**

**Participants**

There were 254 participants in the 16- to 17-year-old age group in the Naturalistic Driving Study for SHRP 2. Participants were recruited across six states (Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington) using call centers and advertisements in media such as flyers, mass mailings, and e-mails. Participants received an annual incentive of $500 for remaining in the study. The researchers coordinating recruitment within SHRP 2 did not aim for a specific sample size and instead attempted to recruit approximately equal numbers of participants in different age groups across the 2- to 3-year recruitment period. Of the 254 participants in the 16- to 17-year-old age group, 137 (54%) were female, and the average age of the drivers in this age group at the beginning of the study was 17.1 years (SD = 0.6). One participant did not indicate his or her gender and was assigned to the most common group (females) to avoid exclusion; this had no meaningful impact on any of the results presented here. Participants remained in the study for an average of 16.2 months (SD = 6.4). Of the 254 participants, 41 were involved in a police-reportable or “most severe” collision (see the Measures section for more details). This subgroup did not differ from the full sample of 16- to 17-year-olds in either the proportion of males or the average age. The study was approved by the institutional review board of Virginia Polytechnic Institute and State University.

**Measures**

Participants had a data-acquisition system (DAS) installed on their dashboards. This mini-DAS contained an
accelerometer and processed footage from cameras directed at the driver's face, out the windshield, at the pedals, and over the driver's shoulder (Simons-Morton et al., 2012). Data were archived for later retrieval by trained coders.

**Collision involvement.** For all g-force events (see Lee, Simons-Morton, Klauer, Ouimet, & Dingus, 2011), trained coders viewed images created by custom software that combined the footage from the four cameras on two 23-in. screens; two images were shown on each screen. Each event was coded for a number of characteristics, including whether the event was a near collision (422 events), a low-risk tire strike off a curb (86 events), a minor collision (98 events), a police-reportable collision (26 events), or a most severe collision (16 events). (Note that the coders' instructions referred to "crashes" and "near-crashes," but we have used the word collision to make these instructions consistent with the terminology in the rest of this article.) We focused only on those collisions identified as police reportable or most severe. Table 1 presents the descriptions that coders were given for these two classifications. Coders' classifications of the collisions were based solely on video and accelerometer data and not on medical or property-damage reports. One participant experienced two collisions in these categories, so our final sample consisted of 41 participants even though there were 42 police-reportable and most severe collisions. For the participant with two severe collisions, our analysis included only the first, and data from the point of the second collision onward was excluded. Throughout the text, we refer to those participants who were involved in a police-reportable or most severe collision as collision-involved participants and participants who were not involved in either of these types of collisions as non-collision-involved participants.

**Driving experience at the time of the collision.** Previous driving experience was calculated by subtracting each participant's age at full-time licensure (reported in half years) from his or her age at the beginning of the study (reported in years and months). Five participants (roughly 2% of the sample; 2 in the collision-involved group) had missing data for age at licensure. These participants' age at licensure was set to the mean for the group to which they belonged (collision-involved vs. non-collision-involved). This procedure had no meaningful impact on the results reported. For collision-involved participants, driving experience at the time of collision was calculated as the time elapsed between licensure and the collision (i.e., previous driving experience before the study plus driving experience during the study before the collision). The average driving experience at the time of collision was 1.6 years ($SD = 0.3$).

**Centered month.** We investigated changes in driving behavior over time, and our primary unit of time was a month (28 days). Collision-involved participants experienced their collision at different time points in the study. For each of these participants, the first 28 days after the day of the collision were coded as centered Month 1, the next 28 days were coded as centered Month 2, and so on. The 28 days preceding the collision were coded as centered Month 0 (as this month ended at the center point), the 28 days preceding these were coded as centered Month −1, and so on. The day of collision itself did not contribute to any month, and it was excluded from all analyses.

For non-collision-involved participants, a comparative centered month scale was based on collision-involved participants' average driving experience at the time of collision, that is, 1.6 years. For each non-collision-involved participant, Month 0 was the 28 days preceding the day that marked 1.6 years of driving experience, Month 1 was the 28 days following the day that marked 1.6 years of driving experience, and so on.

**g-force events.** We measured driving-behavior outcomes using the number of g-force events. A g is a measure of acceleration, and 1 g is equal to the acceleration

| Table 1. Instructions Given to the Coders: Classification Criteria for Most Severe and Police-Reportable Collisions |
|---------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Collision severity                                           | Classification criteria                                                                                                                                                                                                                   |
| Most severe collision                                        | Any collision that includes an airbag deployment; any injury of driver, pedal cyclist, or pedestrian; a vehicle roll over; a high Delta V; or that requires vehicle towing. Injury if present should be sufficient to require a doctor's visit, including those self-reported and those apparent from video. A high Delta V is defined as a change in speed of the subject vehicle in any direction during impact greater than 20mph (excluding curb strikes) or acceleration on any axis greater than ±2 g (excluding curb strikes). |
| Police-reportable collision                                 | A police-reportable collision that does not meet the requirements for a Level I [i.e., most severe] collision. Includes sufficient property damage that it is police reportable (minimum of ~$1500 worth of damage, as estimated from video). Also includes collisions that reach an acceleration on any axis greater than ±1.3g (excluding curb strikes). If there is a police report this will be noted. Most large animal strikes and sign strikes are included here. |
of earth's gravity at sea level (−9.8 m/s²). Any driving event that exceeded a threshold acceleration level was classified as a g-force event. The threshold was 0.45 g for hard breaking, 0.35 g for forward acceleration, and 0.5 g for lateral acceleration. These thresholds are based on those developed by Simons-Morton et al. (2012). The number of g-force events for each participant in each centered month was tallied.

**Analysis**

The analysis explored changes in driving behavior after a collision. Collision-involved participants served as their own controls, as we compared their pre- and postcollision driving behaviors; non-collision-involved participants were included in the analysis to provide a benchmark of driving behaviors in this age group. The outcome variable, monthly count of g-force events, was modeled using Poisson regression with random effects for both the intercept and the centered month. The random effects captured the correlations among a given participant's driving behavior at different time points. The random intercept allowed for between-subjects differences in baseline event rates, and the random slope allowed for differences in the effect of time (centered month) on individual event rates. To account for variation in the number of miles a given participant drove in different months, we used the log of the number of thousands of miles driven in that month as an offset term in the Poisson regression (i.e., a covariate with a coefficient forced to be 1). The robust sandwich variance estimator was calculated to deal with potential overdispersion in the Poisson distribution.

Exploratory analyses of the collision-involved participants' data showed an approximately linear trend in the log of the event rate as a function of time prior to the accident, a highly variable period for about 3 months after the accident, and an approximately linear decreasing trend thereafter. Therefore, we used a piecewise linear model that assumed a linear trend before Month 1 (i.e., before the accident in the case of the collision-involved participants), separate change points at Months 1, 2, and 3, and a linear trend following the 3-month mark. An additional reason that we did not model separate change points beyond the 3-month mark is that more than a third of the collision-involved participants exited the study within 3 months of their collision, in accordance with their planned participation. The model adjusted for gender, driving experience at the time of the collision, and collision involvement (yes vs. no). The interaction between collision involvement and piecewise linear time trend was included in the model, which allowed us to model different trajectories for the collision-involved and non-collision-involved groups. The interaction term implies that the same piecewise linear model was fit to the non-collision-involved group. This allowed us to determine whether patterns in the collision-involved group were artifacts of introducing random change points into a complicated longitudinal model, or whether they were actual properties associated with postaccident behavior. Although our approach allowed us to examine patterns in driving behavior across time within each participant group, comparison of the two groups should be interpreted cautiously, as there was no natural event with which to center the data of the non-collision-involved participants. (Interested readers will find the mathematical equation of the model in the Supplemental Material available online.)

The regression coefficients in the Poisson regression are interpreted as the change in the log of the expected number of g-force events per 1,000 miles associated with a 1-unit change in a covariate. Exponentiation of these individual parameters provides the percentage of increase or decrease of the g-force event rate, which we focus on in the Results section. By fixing the covariate values, we were able to estimate the actual event rates at a given time and then examine the trajectory of the event rate over time in a referent population defined with respect to gender and driving experience.

**Results**

Figure 1 illustrates the trajectory of the event rate over time for the collision-involved and non-collision-involved groups by showing the estimated mean number of g-force events per 1,000 miles, with a piecewise linear fit, for the reference group of females with 1.6 years of driving experience. At the 0-month mark (the point at which a collision occurred for the collision-involved participants and the point of 1.6 years of driving experience for the non-collision-involved participants), the rate of g-force events was 69.5% higher (95% confidence interval, CI = [13.7%, 152.6%]) for collision-involved participants (34.7 g-force events per 1,000 miles) than for non-collision-involved participants (20.5 g-force events per 1,000 miles).

For the collision-involved participants, the rate of g-force events increased nonsignificantly by 0.6% per month (95% CI = [−3.1%, 4.4%]) in the precollision months. The event rate dropped significantly, by 34.4% (95% CI = [11.8%, 51.1%]), in the month immediately following the collision; for females with 1.6 years of driving experience, this percentage change corresponded to an expected drop of 11.9 g-force events per 1,000 miles. From Month 1 to Month 2, there was a nonsignificant drop of 17.2% (95% CI = [−48.7%, 33.6%]). From Month 2 to Month 3, the rate of g-force events increased significantly by 43.8% (95% CI = [4.2%, 98.6%]), which corresponded to an expected increase of 17.9 events per 1,000
miles. The rate of g-force events dropped by 21.8% from Month 0 (just before the collision) to Month 3, but this difference was not significant (95% CI = [−41.9%, 5.2%]). From 3 months postcollision onward, the rate of g-force events decreased nonsignificantly by 6.9% per month (95% CI = [−0.8%, 14.0%]).

For the non-collision-involved participants, the rate of g-force events increased by 2.6% per month (95% CI = [0.1%, 5.1%]) in the months preceding Month 0. The event rate did not change significantly in Months 1, 2, and 3. For the months beyond centered Month 3, there was a significant monthly decrease of 6.4% (95% CI = [2.3%, 10.3%]) in the rate of g-force events.

Although the model effectively controlled for the variability in miles driven, it is worth noting that the collision-involved participants significantly reduced the distance they drove in the month following a collision by an average of 220 miles (a 47.8% decrease). The non-collision-involved participants did not reduce their mileage after Month 0, and the interaction between group (collision-involved vs. non-collision-involved participants) and time (Month 0 vs. Month 1) was significant, $F(1, 156) = 16.84, p < .001$.

**Discussion**

Participants who were involved in a collision had a reduced rate of g-force events after the collision, and this difference persisted for at least 2 months. Their rate of g-force events rebounded significantly in the 3rd month following the collision. From Month 3 onward, there was a gradual decrease in the rate of g-force events for all participants. These results broadly support our initial hypothesis that risky driving decreases following an accident. The collision-involved participants' event rate increased in Month 3 to a rate that was still lower than before the collision. However, the difference was not significant. This could be interpreted as evidence that the collision-involved participants returned to their previous driving behavior, but it is worth noting that 8 of these participants (~20%) had exited the study by 3 months postcollision, so the lack of a significant difference between Month 3 and Month 0 may also be explained by a reduction in power.

On average, the participants who experienced collisions did so after 1.6 years of driving. However, the rate of g-force events did not change at this time point among participants who were not involved in a police-reportable or most severe collision. This suggests that the change observed in the collision-involved participants was not due to time or experience alone. The rate of g-force events differed significantly between collision-involved participants and non-collision-involved participants at Month 0. This offers support to the idea that the high collision rate among young drivers may be due, in part, to a high-risk group within this age cohort (Harré, 2000). Both groups of drivers displayed gradual decreases in the rate of g-force events from Month 3 onward, perhaps because of increasing maturity, improvement through experience, or loss of enthusiasm for risky driving.
Unlike the drivers in some other naturalistic studies of teen driving (see Simons-Morton et al., 2011), the drivers in the current study, although relatively young, had variable levels of driving exposure before taking part. This preexisting difference in experience was taken into account in the analysis, but we do not know whether participants were involved in any collisions before their enrollment in the study.

Future research can address these limitations by using an increased sample size and longer sampling periods beginning at the time of licensure. These requirements are difficult considering financial constraints, but recent advances in the use of smartphones for measuring g-force events may provide researchers with a more abundant source of data in the near future. The interpretation of our findings as indicating changes in driving behavior is predicated on the assumption that the rate of g-force events is a valid measure of risky driving. The justification for this assumption comes predominantly from the study by Simons-Morton et al. (2012), and additional research is needed to further understand the nuances of what g-force measures say about driving. The data in this study relate solely to young novice drivers, and future research could compare the outcomes for this group with the outcomes for older, more experienced drivers. Additionally, the current study examined only collisions that were police reportable or most severe, and it is unclear what effect less severe collisions or near misses may have on driving behavior. However, a longitudinal investigation of such relatively frequent events presents a number of nontrivial analytic issues. For example, does the potential effect of a collision event differ depending on the number of negative driving events that have occurred before it?

Adolescence is a period in which many individuals are first exposed to a number of behaviors that present health risks, yet very little research has examined the role of personal negative experience in affecting later behaviors without relying solely on recall. Educational programs focusing on informing young people of the health risks of some behaviors have had limited success (e.g., Ennett, Tobler, Ringwalt, & Flewelling, 1994; Vernick et al., 1999). Although the results of the current study alone do not offer immediate ideas for driver education or education about other health-risk behaviors, they do point to possible directions for research that may inform future interventions. Drivers who were involved in a collision had significantly higher rates of g-force events before the collision compared with drivers who were not involved in a collision, so the rate of g-force events may be of use in identifying high-risk groups of young drivers. Additionally, researchers could seek a greater understanding of what kinds of personal experiences most affect future behavior. For example, does attribution of fault influence learning from an accident? The long-term goal will be to determine the psychological or situational mechanisms through which personal experience influences behavior. An understanding of these mechanisms is the best hope for determining how, if at all, the current findings could be applied to an educational or training initiative that would not actually require a young driver to experience a severe collision. Even if the change in behavior found in the current study is revealed to be short-lived, our results suggest that there may be a period of time immediately following a negative experience when young people are especially open to an intervention. This could be particularly important given that we found that collision-involved drivers may revert back to their precollision levels of g-force events only 3 months after the collision.

In popular media, young drivers are often portrayed as being unaware of the dangers of their risky driving. The results of this study suggest that young drivers alter their driving behavior in a very short space of time following a severe, but non-life-threatening, collision.

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Author Contributions
F. O’Brien was the primary author for this article. He conceived the theoretical idea and coordinated all stages of the project. J. Bible was the primary statistician on this project. He also helped with drafting the manuscript. D. Liu was involved in all statistical analyses, helped with the development of the theoretical questions that we addressed, and helped with drafting the manuscript. B. G. Simons-Morton was involved in the conception of the project and made substantial suggestions regarding the manuscript.

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Declaration of Conflicting Interests
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Supplemental Material
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References


Mayou, R., & Bryant, B. (2002). Outcome 3 years after a road traffic accident. Psychological Medicine, 32, 671–675. doi:10.1017/s0033291702004570


