Automated Vehicle Crash Rate Comparison Using Naturalistic Data

Final Report Delivered by the Virginia Tech Transportation Institute

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Summary

Self-driving cars are quickly moving from prototype to everyday reality. During this transition, the question that is first and foremost on the mind of the public and policy makers is whether or not self-driving cars are more prone to crashes. This would seem to be an easy question to answer: simply compare current published crash rates with the data on self-driving cars. A deeper look at the available data and collection methodologies, however, reveals that such a simple comparison is problematic.

Two factors complicate the national crash data. First, states have different requirements concerning what incidents are reported as crashes. Second, many crashes go unreported. Estimates of unreported rates of crashes have ranged from as little as 15.4 percent to as much as 59.7 percent (Blincoe et al., 2015; M. Davis & Co, 2015). The result is that the current national crash rate is essentially a low estimate of the actual crash rate.

Legal requirements for self-driving cars further complicate matters. In California (arguably the jurisdiction covering most automated vehicles), *every* crash involving a self-driving car, regardless of how minor, must be reported. Thus, we have a situation in which we are attempting to analyze self-driving car data, which has a full record of all crashes, relative to the current vehicle fleet, which has an incomplete record of crashes. The comparison is, as the old saying goes, apples to oranges.

The research in this report, "Automated Vehicle Crash Rate Comparison Using Naturalistic Data," which was performed by the Virginia Tech Transportation Institute (VTTI) and commissioned by Google, sheds light on these issues. It examines both national crash data and data from naturalistic driving studies to better estimate existing crash rates, and then compares the results to data from Google's Self-Driving Car program, which included written reports, video, and vehicle kinematic data.

This study assessed driving risk for the United States nationally and for the Google Self-Driving Car project. Driving safety on public roads was examined in three ways. The total crash rates for the Self-Driving Car and the national population were compared to (1) rates reported to the police, (2) crash rates for different types of roadways, and (3) scenarios that give rise to unreported

crashes. First, crash rates from the Google Self-Driving Car project per million miles driven, broken down by severity level were calculated. The Self-Driving Car rates were compared to rates developed using national databases which draw upon police-reported crashes and rates estimated from the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS). Second, SHRP 2 NDS data were used to calculate crash rates for three levels of crash severity on different types of roads, broken down by the speed limit and geographic classification (termed "locality" in the study; e.g., urban road, interstate). Third, SHRP 2 NDS data were again used to describe various scenarios related to crashes with no known police report. This analysis considered whether such factors as driver distraction or impairment were involved, or whether these crashes involved rear-end collisions or road departures.

Crashes within the SHRP 2 NDS dataset were ranked according to severity for the referenced event/incident type(s) based on the magnitude of vehicle dynamics (e.g., high Delta-V or acceleration), the presumed amount of property damage (less than or greater than $1,500, airbag deployment), knowledge of human injuries (often unknown in this dataset), and the level of risk posed to the drivers and other road users (Antin, et al., 2015; Table 1). Google Self-Driving Car crashes were also analyzed using the methods developed for the SHRP 2 NDS in order to determine crash severity levels and fault (using these methods, none of the vehicles operating in autonomous mode were deemed at fault in crashes).

Table 1. SHRP 2 NDS Crash Severity Classifications

SHRP 2 NDS Crash Severity Level	SHRP 2 NDS Classifications
Level 1	Crashes with airbag deployment, injury, rollover, a high Delta-V, or that require towing. Injury, if present, should be sufficient to require a doctor's visit, including those self-reported and those from apparent video. A high Delta-V is defined as a change in speed of the subject vehicle in any direction during impact greater than 20 mph (excluding curb strikes) or acceleration on any axis greater than ±2 g (excluding curb strikes).
Level 2	Crashes that do not meet the requirements for a Level 1 crash. Includes sufficient property damage that one would anticipate is reported to authorities (minimum of $1,500 worth of damage, as estimated from video). Also includes crashes that reach an acceleration on any axis greater than ±1.3 g (excluding curb strikes). Most large animal strikes and sign strikes are considered Level 2.
Level 3	Crashes involving physical conflict with another object (but with minimal damage) that do not meet the requirements for a Level 1 or Level 2 crash. Includes most road departures (unless criteria for a more severe crash are met), small animal strikes, all curb and tire strikes potentially in conflict with oncoming traffic, and other curb strikes with an increased risk element (e.g., would have resulted in a worse crash had the curb not been there, usually related to some kind of driver behavior or state, for example, hitting a guardrail at low speeds).
Level 4	Tire strike only with little or no risk element (e.g., clipping a curb during a tight turn). Distraction may or may not also be present. Note, the distinction between Level 3 and Level 4 crashes is that Level 3 crashes would have resulted in a worse crash had the curb not been there while Level 4 crashes would not have due to the limited risk involved with the curb strike. Level 4 crashes are considered to be of such minimal risk that most drivers would not consider these incidents to be crashes; therefore, they have been excluded from this analysis.

When compared to national crash rate estimates that control for unreported crashes (4.2 per million miles), the crash rates for the Self-Driving Car operating in autonomous mode when adjusted for crash severity (3.2 per million miles; Level 1 and Level 2 crashes) are lower. These findings reverse an initial assumption that the national crash rate (1.9 per million miles) would be lower than the Self-Driving Car crash rate in autonomous mode (8.7 per million miles) as they do not control for severity of crash or reporting requirements. Additionally, the observed crash rates in the SHRP 2 NDS, at all levels of severity, were higher than the Self-Driving Car rates. Estimated crash rates from SHRP 2 (age-adjusted) and Self-Driving Car are displayed in Figure 1.

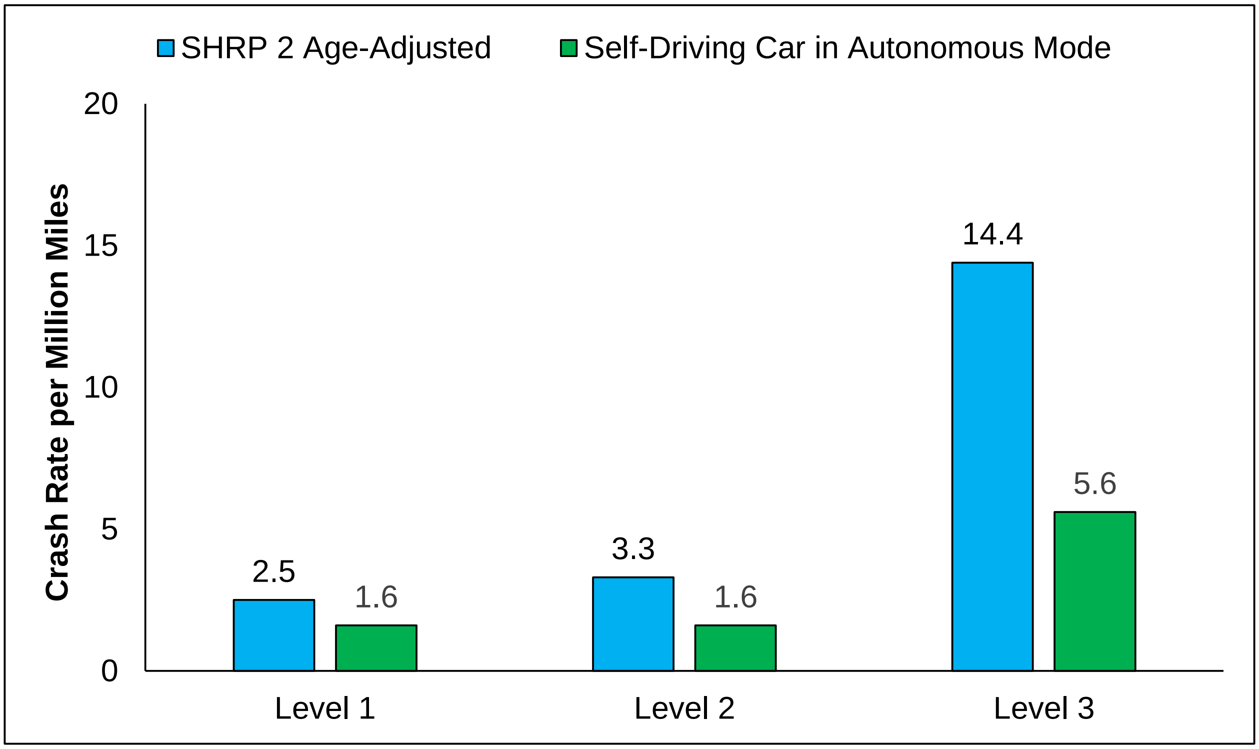

Figure 1. SHRP 2 NDS and Self-Driving Car Crash Rates per Million Miles

Low exposure for self-driving vehicles (about 1.3 million miles in this study) increases the uncertainty in Self-Driving Car crash rates compared to the SHRP 2 NDS (over 34 million miles) and nearly 3 trillion vehicle miles driven nationally in 2013 (2,965,600,000,000).

As self-driving cars continue to be tested and increase their exposure, the uncertainty in their event rates will decrease. Current data suggest that self-driving cars may have low rates of more-severe crashes (Level 1 and Level 2 crashes) when compared to national rates or to rates from naturalistic data sets, but there is currently too much uncertainty in self-driving rates to draw this conclusion with strong confidence. However, the data also suggest that less-severe events (i.e., Level 3 crashes) may happen at a significantly lower rate for self-driving cars than in naturalistic settings. Additionally, when the Self-Driving Car events were analyzed using methods developed for SHRP 2, none of the vehicles operating in autonomous mode were deemed at fault. This fact, together with the reduced crash rate for less-severe events (Level 3 crashes), represents a powerful finding. This is particularly appropriate to vehicles intended for lower-speed use where less-severe events are the most likely to be encountered by the newer generation of the Self-Driving Car fleet.

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List of Acronyms and Abbreviations

CA	California
CAVS	Center for Automated Vehicle Systems
CHP	California Highway Patrol
DAS	Data Acquisition System
DOT	Department of Transportation
DMV	Department of Motor Vehicles
FARS	Fatality Analysis Reporting System
FL	Florida
GES	General Estimates System
IN	Indiana
LOS	Level of Service
NC	North Carolina
NDS	Naturalistic Driving Study
NPR	Non-Police Reported; those crashes within the InSight database for which the research team does not have a confirmed PAR
NY	New York
PA	Pennsylvania
PAR	Police Accident Report
PDO	Property Damage Only
PR	Police Reported Crashes; those crashes within the InSight database for which the research team has a confirmed PAR
PPR	Possibly Police Reported; those crashes within the InSight database for which the research team does have a confirmed PAR as well as those that may have been reported based on crash characteristics; those crashes categorized as Level I and Level II severity
SHRP 2	The Second Strategic Highway Research Program (2006-2015)
VA	Virginia
VTTI	Virginia Tech Transportation Institute
WA	Washington

Chapter 1. Introduction

Objective

The fundamental objectives of the research described in this report are (1) to improve the quality of the available data involving self-driving cars and (2) to analyze existing data to better understand the relative crash rate of self-driving cars. Five research questions guided this analysis:

- Research Questions 1 and 2: How many crashes go unreported to police or insurance? Do unreported crash rates vary by location?
- Research Question 3: How is the comparison between crash rates for the Self-Driving Car and national crash rates affected by the percentage of unreported crashes and severity level?
- Research Question 4: How do crash rates vary based on street type and speed limit?
- Research Question 5: What are the factors contributing to unreported crashes?

Report Overview

This report is structured as follows:

1. A review of the data used for this analysis.
2. A discussion of reported versus unreported crash rates.
3. An analysis of variation in crash rates based on street type and roadway speed limits.
4. An examination of the characteristics of unreported crashes and contributing factors in those crashes.
5. Conclusions and key takeaways.

It should be emphasized that the Virginia Tech Transportation Institute (VTTI) project team was asked to focus on research efforts that would improve the quality of data and to improve understanding regarding the number and nature of crashes. The team was not tasked with evaluating technical aspects of Google's Self-Driving Car project.

Chapter 2. Data Sources

This report draws upon existing published and proprietary research, naturalistic driving data analysis, and new primary research. Data from the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS), state and national crash data, and data from the Self-Driving Car project were used in the analysis. A brief discussion of these resources follows.

The SHRP 2 NDS Dataset

Police accident reports, while an important factor of investigations and research endeavors, have limited accuracy for determining contributing factors to crashes, especially if vehicles were moved from the scene and/or the persons involved miss or forget the details of the event due to fatality, injury, stress, or the passage of time. The use of naturalistic driving studies provides researchers with opportunities to gain a more accurate understanding of driver error, distraction, fatigue, and impairment. In naturalistic driving studies, voluntary participants drive their own vehicles, which have been instrumented with sensors and cameras that record driver behavior, the immediate context, and vehicle kinematics. The resulting data allow researchers to observe and analyze everyday driving environments with real consequences, all with the ultimate goal of ensuring the safety of the traveling public.

For this effort, researchers drew data from the SHRP 2 InSight database. The SHRP 2 NDS covered more than 34 million vehicle miles traveled and produced 2 petabytes of video, kinematic, and audio data during a three-year period for:

- More than 3,500 participants, aged 16 to 98, in Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington;[1]
- An approximately equal mix of male and female drivers;
- More than 3,300 vehicles;
- Approximately 4,000 data years;
- More than 1,000 crashes;
- Nearly 3,000 near-crashes.

When aggregated, the SHRP 2 data represents diverse locations that include a wide range of geographical features, roadways, and climates (Antin, Stulce, Eichelberger, and Hankey, 2015). Additionally, although biased toward recent model years, the SHRP 2 vehicle fleet includes all of the national fleet's light vehicle types and most of its light vehicle makes. It should be noted,

[1] Specific site locations included Tampa, Florida; Indianapolis, Indiana; Buffalo, New York; Durham, North Carolina; State College, Pennsylvania; and Seattle, Washington.

however, that the SHRP 2 NDS deliberately oversampled younger and older drivers. As such, analyses conducted for this effort have weighted the SHRP 2 data to match the national distribution of drivers' ages. (For additional information regarding the SHRP 2 NDS, see Antin et al., 2015).

SHRP 2 Data Reduction

The use of a researcher dictionary allows for reliable and replicable analysis of an NDS using consistently defined variables for a wide range of geographic locations and situations. VTTI has developed a data dictionary for use in the reduction of video related to NDS participants.[2] This dictionary, which has been updated and refined over time, has been used to provide guidance in the analysis of many cases of crash and near-crash events, including those associated with the 100-Car Naturalistic Study (Dingus et al., 2006) and the 40-Teen Naturalistic Driving Study (Lee et al., 2011; Klauer et al., 2011). The data dictionary used for this project was the same version dictionary (version 3.4) that was used for the SHRP 2 NDS. In addition to analyzing video, naturalistic data reduction incorporates corresponding time series data from vehicle sensors, such as forward radar, lateral and longitudinal accelerometers, gyroscope, a Global Positioning System (GPS) unit, and other internal vehicle network data such as speed. In developing the *Researcher Dictionary*, researchers sought the input of experts in the field of human factors research and used the General Estimates System (GES) database compiled by the National Highway Traffic Safety Administration (NHTSA) as a starting point for the development of modified definitions (VTTI, 2015).

SHRP 2 NDS Crash Severity Classifications

Crashes within the SHRP 2 NDS dataset were ranked according to severity for the referenced event/incident type(s) based on the magnitude of vehicle dynamics (e.g., high Delta-V or acceleration), the presumed amount of property damage (less than or greater than $1,500, airbag deployment), knowledge of human injuries (often unknown in this dataset), and the level of risk posed to the drivers and other road users (Antin, et al., 2015). The following schema was used:

- **Level 1:** Crashes with airbag deployment, injury, rollover, a high Delta-V, or that require towing. Injury, if present, should be sufficient to require a doctor's visit, including those self-reported and those from apparent video. A high Delta-V is defined as a change in speed of the subject vehicle in any direction during impact greater than 20 mph (excluding curb strikes) or acceleration on any axis greater than ±2 g (excluding curb strikes).

- **Level 2:** Crashes that do not meet the requirements for a Level 1 crash. Includes sufficient property damage that one would anticipate is reported to authorities (minimum of $1,500

[2] Additional information regarding the SHRP 2 classifications and variables referenced within this report may be found in Appendix A and also in the *SHRP 2 Researcher Dictionary for Video Reduction Data (Version 3.4)*.

worth of damage, as estimated from video). Also includes crashes that reach an acceleration on any axis greater than ±1.3 g (excluding curb strikes). Most large animal strikes and sign strikes are considered Level 2.

- **Level 3:** Crashes involving physical conflict with another object (but with minimal damage) that do not meet the requirements for a Level 1 or Level 2 crash. Includes most road departures (unless criteria for a more severe crash are met), small animal strikes, all curb and tire strikes potentially in conflict with oncoming traffic, and other curb strikes with an increased risk element (e.g., would have resulted in a worse crash had the curb not been there, usually related to some kind of driver behavior or state, for example, hitting a guardrail at low speeds).
- **Level 4:** Tire strike only with little or no risk element (e.g., clipping a curb during a tight turn). Distraction may or may not also be present. The distinction between Level 3 and Level 4 crashes is that Level 3 crashes would have resulted in a worse crash had the curb not been there while Level 4 crashes would not have due to the limited risk involved with the curb strike.

Level 4 crashes are considered to be of such minimal risk that most drivers would not consider these incidents to be crashes. Additionally, these incidents would never meet the threshold required to file a crash report with law enforcement or other government agency. As the focus of this report was on police-reported and unreported crashes, Level 4 crashes have been excluded from this analysis. Instead, this analysis includes only those crashes categorized as Level 1, Level 2, or Level 3 that involve increased risk and could trigger a decision by a driver regarding whether or not to report a crash.

Police Reported SHRP 2 NDS Crashes

If involved in a crash, SHRP 2 NDS participants were instructed to seek emergency help in the manner they normally would, use an incident button to describe the incident, call the research team as soon as it was safe to do so, allow the research team to interview them about the crash in more detail, and provide the research team with access to the police accident report (PAR). When informed of a crash, sites either submitted a PAR to the oversight team or informed the oversight team of a crash (with no PAR ever submitted). Even though SHRP 2 NDS participants were asked to inform the research team when a crash occurred, there were no financial incentives for participants to report crashes, and privacy options permit participants to restrict access to the police report beyond its initial review.[3]

As a result, identifying the true number of PAR crashes within the SHRP 2 NDS dataset is challenging. The dataset is, and always will be, dynamic. As of November 2015, the SHRP 2 NDS InSight database contained 46 crashes that had been associated with a PAR and are, therefore, considered **police reported** (PR). Although Antin et al. (2015) noted 74 crash-associated PARs, these incidents have not all been located in the data and, therefore, are not yet confirmed as part of the SHRP 2 dataset. It may be possible that some of these crashes were not captured by the data acquisition system (DAS)[4], that the crash was located in the video but deemed unsuitable for InSight release (e.g., due to an inability to confirm a consented driver or the identifying nature of the crash), or that the crash was found to have occurred outside the consent period. As a result, the number of PAR-related crashes associated with the SHRP 2 NDS may evolve over time as more researchers work with the dataset and analyze it using alternative methods.

Because it is not always clear in the SHRP 2 database whether a particular crash was reported to the police, the absence of a PAR should not be interpreted as a non-PR crash. Crashes were considered **possibly** police reported (PPR)[5] if it was known to have been reported or if any of the following took place:

- Notable injury;
- Air bag deployment;
- Vehicle rollover;
- Significant property damage (minimum of ~$1,500 worth of damage, as estimated from video);
- Vehicle towed;
- Delta-V of greater than 20 mph or an acceleration on any axis greater than 1.3 g (excluding curb strikes);
- Large animal strike; or
- Sign or roadway furniture strike.

For purposes of this analysis, the following descriptions have been used:

- **Police Reported (PR):** Those crashes within the InSight database for which the research team has a confirmed PAR.

[3] A copy of the full Driver Informed Consent Forms may be found in Appendices J and K of Dingus et al. (2015), which is available online at http://onlinepubs.trb.org/onlinepubs/shrp2/SHRP2_S2-S06-RW-1.pdf.

[4] The crash may have occurred prior to the DAS being active. In rare cases, the crash may have corrupted the data file and rendered all or a critical end of a trip unusable.

[5] This terminology is consistent with Antin et al. (2015).

- **Non-Police Reported (NPR):** Those crashes within the InSight database for which the research team does not have a confirmed PAR.

- **Possibly Police Reported (PPR):** Those crashes within the InSight database for which the research team does have a confirmed PAR and also those that may have been reported based on crash characteristics; that is, those crashes categorized as Level 1 or Level 2 in severity.

- **Level 3:** Those crashes within the InSight database that the research team would not anticipate being reported based upon crash severity level.

Table 2 provides a breakdown of crashes in each of these categories by crash severity level. In addition to the 46 where a PAR was provided, an additional 233 crashes had severe enough characteristics to be potentially reported. Therefore, of the 912 crashes within the InSight database categorized as Level 1, 2, or 3, we would only expect 279 to have been reported to law enforcement.

Table 2. Summary of SHRP 2 Crashes

SHRP 2 Crash Severity Level	Total SHRP 2 Crashes	PR SHRP 2 Crashes	NPR SHRP 2 Crashes	PPR SHRP 2 Crashes
Level 1	120	34	86	120
Level 2	159	12	147	159
Level 3	633	0	633	0
Total	**912**	**46**	**866**	**279**

Select State Reporting Requirements

Crash reporting requirements vary by state. Table 3 summarizes the reporting requirements for the six SHRP 2 states as well as California and Virginia as presented to potential drivers in each state's drivers' education manual and associated websites. As noted, the use of the SHRP 2 crash classification schema provides a consistent and uniform proxy by which crash severity across geographic boundaries may be compared. For example, property damage only (PDO) reporting requirements associated with the states in the SHRP 2 study, California, and Virginia vary from \$500 to \$1,500; the use of the \$1,500 estimated property damage amount provides a conservative basis for analysis.

Table 3. Death, Injury, and Property Damage Reporting Requirements

State	Law Enforcement Reporting Requirements		Additional Requirements
	Death or Injury	PDO	
CA	✓		If someone is killed or injured, California Highway Patrol must be notified within 24 hours. In cases of death or injury or when property damage exceeds $750, a Report of Traffic Accident Occurring in California (SR 1) form must be filed with the Department of Motor Vehicles within 10 days.
FL	✓	If towing required	If the crash involves a charge of driving under the influence (DUI) or results in death, injury, or property damage to the extent a wrecker must tow a vehicle, the officer will fill out a report. If the crash is investigated by an officer, the driver need not make a written report. If property damage appears to be over $500 and no report is written by an officer, a Driver Report of Traffic Crash must be filed with the Department of Highway Safety within 10 days.
IN	✓	$1,000	After an accident and upon request from the Bureau of Motor Vehicles, individuals will be required to file proof of financial responsibility in the form of a Certificate of Compliance (COC) covering the date of the accident in the vehicles involved.
NC	✓	$1,000	Additionally, North Carolina law also requires the driver of a vehicle involved in a reportable crash to provide proof of financial responsibility (liability insurance) on forms provided by the Division of Motor Vehicles. These forms must be completed and filed with Division of Motor Vehicles.
NY	✓		Any accident occurring in New York State causing a fatality, personal injury or damage over $1,000 to the property of any one person must be reported to the NY State Department of Motor Vehicles within 10 days using the MV-104.
PA	✓	If towing required	In these cases, if police do not investigate, drivers must file a Driver's Accident Report with the PA Department of Transportation's Bureau of Highway Safety and Traffic Engineering within 5 days.
VA	✓	$1,500	Drivers are instructed to notify their insurance companies immediately. Law enforcement officers are required to forward a written crash report to Department of Motor Vehicles (DMV) when a traffic crash results in injury or the death of any person or total property damage is in excess of $1,500.
WA[6]	✓	$1,000	If the collision results in an injury, death, or property damage of $1,000 or more to one person's property and a report is not made by a law enforcement officer, a Collision Report form must be completed within four days.

[6] The *Washington Driver Guide* notes a $700 threshold for reporting. As of January 1, 2015, this threshold was increased to $1,000 per WAC 446-85-010. See also the Washington State Department of Licensing's Collision Reporting Web page.

Additional National and State Crash Data

Whenever possible, data were obtained and verified using multiple sources (e.g., comparing NHTSA-reported crashes with state reports) for the years 2009 to 2014. National crash data were obtained from NHTSA, the Federal Highway Administration (FHWA), and the U.S. Census Bureau. State crash summary data were obtained from each of the six SHRP 2 states (Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington) as well as California. State-related data were obtained from a variety of departments, depending on the administrative division of oversight and reporting requirements within each state.[7] To further explore regional crash rate variations, data were also obtained on the county level for each of the SHRP 2 research sites and key locations within the state of California. These locations included:

- Hillsboro County, FL
- Monroe County, IN
- Erie County, NY
- Durham County, NC
- Centre County, PA
- King County, WA
- Los Angeles County, CA
- Santa Clara County, CA

Self-Driving Car Project Data

Several states have also passed specific regulations regarding the operation and testing of self-driving vehicles. These regulations may impose additional reporting requirements on the operators of autonomous vehicles. For example, California requires the documentation of **any crash** involving an autonomous vehicle, regardless of mode (either autonomous or manual; California Department of Motor Vehicles, 2015a). To date,[8] the Google Self-Driving Car has driven over 2.3 million miles (1,266,611 miles in autonomous mode) and has been involved in 16 crashes, 11 in autonomous mode and 5 in manual mode. For purposes of this analysis, crashes that occurred when the vehicle was transitioning from autonomous mode and/or when the human driver of the automated vehicle (AV) was regaining manual control were considered autonomous mode. Because AV drivers would not have been required to react to a transition (or make the decision to transition) in a "traditional" vehicle that was not equipped with autonomous capabilities, these crashes are considered to have occurred in autonomous mode.

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[7] For example, in Washington, driver's license oversight falls under the Department of Licensing, whereas in New York this responsibility is designated to the Department of Motor Vehicles.

[8] As of October 31, 2015.

To further explore the characteristics of these events, researchers were granted access to the Google Self-Driving Car data, including written reports, video, and kinematic data, where available. As video and kinematic data were not available for all crashes, the data reduction was supplemented with discussions with Self-Driving Car project team members. Data were aggregated and analyzed using the SHRP 2 reduction protocol to the extent possible given the available data.[9] The Self-Driving Car data reduction effort was led by the lead SHRP 2 data reductionist who had been involved in the development of the SHRP 2 researcher dictionary. A summary of the reduction of key variables is included as Table 5 and Table 6. Additional narratives for each event are included as Appendix B.

Based upon the reduction completed, Self-Driving Cars have been involved in four Level 1 crashes, four Level 2 crashes, and eight Level 3 crashes. In all crashes, the maneuvers prior to the precipitating event (based on vehicle kinematic data; discussed further in Chapter 5) were judged to be safe and legal. When looking at only crashes in autonomous mode only, there were two Level 1 crashes, two Level 2 crashes, and seven Level 3 crashes (Table 4). If these incidents are considered in light of the California reporting requirements for all vehicles, it is likely that only the Level 1 and 2 crashes would have reached the threshold for a Department of Motor Vehicles (DMV) report. Furthermore, it should be noted that no PARs were filed for any of the Self-Driving Car-involved crashes for which law enforcement were on the scene.

Table 4. Distribution of Self-Driving Car Crashes According to SHRP 2 Severity Levels

SHRP 2 Crash Severity Level	Total Self-Driving Car Crashes	Self-Driving Car Crashes in Autonomous Mode	Self-Driving Car Crashes in Manual Mode
Level 1	4	2	2
Level 2	4	2	2
Level 3	8	7	1
Total	**16**	**11**	**5**

[9] The SHRP 2 NDS analysis relied on a number of camera views afforded by the VTTI DAS. The Self-Driving Car project did not include these camera views, so reduction was not as detailed as the original SHRP 2 NDS reduction. In addition, while written reports (supplemented with discussions with the sponsor) were available for all the crashes, the amount of supplemental data available for analysis varied: 13 crashes were analyzed using video and kinematic data and 1 crash was analyzed using kinematic data but no video data. Analysis of the remaining two crashes relied solely on the written reports and supplemental discussion. However, in all cases, the available data supported the use of the variables included within this report and provided sufficient detail for purposes of the analysis.

Table 5. Self-Driving Car Reduction of Key Variables

Event Date (Month/Year)	Video and Kinematic Data Available[1] (Y/N)	Mode	Pre-Incident Maneuver	Precipitating Events	Incident Type	Fault (Y/N)	SHRP 2 Crash Severity Level	Crash Severity Assessment Summary
5/2010	N	Manual	Decelerating in traffic lane	Subject ahead, but decelerating	Rear-end, struck	N	2	Failed to reach threshold for Level 1. Google autonomous vehicle (AV) sustained damage estimated to meet Level 2 threshold. No injuries reported at the scene. Kinematic data not available; default to AV driver reports.
8/2011	Y	Manual	Going straight, accelerating	Other vehicle ahead, stopped on roadway more than 2 seconds	Rear-end, striking	Y	1	Vehicle not being used for testing purposes. Google AV sustained some damage. No injuries reported at scene. Acceleration X peaked at -5.6 g. The impact pushed V2 into V3, which then pushed into V4 and V5.
10/2012	N	Automated	Stopped in traffic lane	Subject ahead, stopped on roadway more than 2 seconds	Rear-end, struck	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle. Google AV vehicle sustained damage not meeting Level 2 threshold. No injuries reported at the scene. Kinematic data not available; default to AV driver reports.
12/2012	Kinematic only	Manual	Going straight, constant speed	Subject ahead, slowed and stopped 2 seconds or less	Rear-end, struck	N	1	Google AV sustained some damage. No injuries reported at scene. Acceleration X peaked at +3.7 g.
3/2013	Y	Automated w/ takeover	Going straight, constant speed	Other vehicle lane change – right, sideswipe threat	Sideswipe, same direction (left or right)	N	2	Failed to reach threshold for Level 1. Google AV sustained damage estimated to meet Level 2 threshold. No injuries reported at the scene. Acceleration Y reached maximum value at about –0.05 g.

Event Date (Month/Year)	Video and Kinematic Data Available[1] (Y/N)	Mode	Pre-Incident Maneuver	Precipitating Events	Incident Type	Fault (Y/N)	SHRP 2 Crash Severity Level	Crash Severity Assessment Summary
10/2013	Y	Manual	Going straight, constant speed	Subject ahead, slowed and stopped 2 seconds or less	Rear-end, struck	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle. Google AV sustained damage not meeting Level 2 threshold. No injuries reported at the scene. Acceleration X reached maximum value of +0.6 g.
3/2014	Y	Automated	Going straight, constant speed	Subject ahead, stopped on roadway more than 2 seconds	Rear-end, struck	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle (third vehicle hits second vehicle resulting in crash with Google AV). Google AV sustained minor damage not reaching Level 2 threshold. No injuries reported at the scene. Acceleration X reached maximum value of ~1.0 g but it is likely that V2 experienced greater peak when struck by V3.
7/2014	Y	Manual	Turning right	Subject ahead, slowed and stopped 2 seconds or less	Rear-end, struck	N	2	Failed to reach threshold for Level 1. Google AV sustained damage estimated to meet Level 2 threshold. No injuries reported at the scene. The angle of the impact (right front corner of other vehicle hits left rear corner of Google AV) prevents either acceleration direction from exceeding 1.0 g.
2/2015	Y	Automated w/ takeover	Going straight, constant speed	Other vehicle entering intersection – turning same direction	Turn into path (same direction)	N	2	Failed to reach threshold for Level 1. Other vehicle violated a stop sign at near speed, striking the Self-Driving Car. Google AV sustained damage estimated to meet Level 2 threshold. No injuries reported at the scene. Acceleration X reached a peak of about −0.8 g, but this was due to the subject's braking maneuver, not the impact. Acceleration Y peaked about less than 0.5 g, but the angle was not direct.

Event Date (Month/Year)	Video and Kinematic Data Available[1] (Y/N)	Mode	Pre-Incident Maneuver	Precipitating Events	Incident Type	Fault (Y/N)	SHRP 2 Crash Severity Level	Crash Severity Assessment Summary
4/2015 #1	Y	Automated	Turning right	Subject ahead, slowed and stopped 2 seconds or less	Rear-end, struck	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle. Google AV sustained minor damage not meeting Level 2 threshold. No injuries reported at the scene. Acceleration X reached maximum value of +0.4 g.
4/2015 #2	Y	Automated	Decelerating in traffic lane	Other event not attributed to subject vehicle	Sideswipe, same direction (left or right)	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle. No damage or injuries reported at the scene. No peaks in acceleration were observed in the X or Y direction.
5/2015	Y	Automated	Stopped in traffic lane	Subject ahead, stopped on roadway more than 2 seconds	Rear-end, struck	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle. Google AV vehicle sustained minor damage not meeting Level 2 threshold. No injuries reported at the scene. Acceleration X reached maximum value of +0.3 g.
6/2015 #1	Y	Automated	Stopped in traffic lane	Subject ahead, stopped on roadway more than 2 seconds	Rear-end, struck	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle. No damage and no injuries reported at the scene. Acceleration X reached maximum value of +0.56 g.
6/2015 #2	Y	Automated	Stopped in traffic lane	Subject ahead, stopped on roadway more than 2 seconds	Rear-end, struck	N	3	Failed to reach thresholds for Levels 1 or 2. Involved physical contact with another vehicle. Google AV and other vehicle sustained minor damage (scrapes) not meeting Level 2 threshold. No injuries reported at the scene. Acceleration X reached maximum value of +0.8 g.

Event Date (Month/Year)	Video and Kinematic Data Available[1] (Y/N)	Mode	Pre-Incident Maneuver	Precipitating Events	Incident Type	Fault (Y/N)	SHRP 2 Crash Severity Level	Crash Severity Assessment Summary
7/2015	Y	Automated	Going straight, constant speed	Subject ahead, slowed and stopped 2 seconds or less	Rear-end, struck	N	1	Minor damage to the Google AV and significant damage to the other vehicle reported (includes visible deployment of the driver-side front airbag in the following vehicle). At the time of the incident, the driver, co-driver, and rear passenger of the Google AV reported some whiplash. They were driven by other team members to a local hospital, where they were evaluated by medical staff and cleared to return to work. The driver of the other vehicle reported minor neck and back pain. Acceleration X reached a peak of +3.5 g.
8/2015	Y	Automated w/ takeover	Changing lanes	Other vehicle lane change – right behind subject	Rear-end, struck	N	1	The Google AV slowed to yield to a pedestrian in a crosswalk. A vehicle behind and adjacent to the Google AV performed a lane change to travel directly behind the Google AV and failed to decelerate along with traffic in that lane. Following vehicle rear-ended the Google AV just prior to the Google AV coming to a complete stop. Minor damage to Google AV and moderate damage to other vehicle reported. The Google AV test driver reported minor back pain and was taken to a local hospital by Google employees, where he was evaluated and released by medical staff. Acceleration X reached +2.3 g.

[1]Written reports supplemented with discussion with the sponsor were available for all crashes.

Table 6. Additional Self-Driving Car Reduction of Key Variables

Event Date (Month/Year)	Mode	Roadway Speed Limit	Locality	Airbag Deployment (Y/N)	Rollover (Y/N)	Traffic Density
5/2010	Manual	Unknown	Bypass/divided highway with traffic signals	N	N	Unknown
8/2011	Manual	35 mph	Business/Industrial	N	N	Level of Service (LOS) B: Flow with some restrictions
10/2012	Automated	Unknown	Business/Industrial	N	N	Unknown
12/2012	Manual	65 mph	Interstate/bypass/divided highway with no traffic signals	N	N	LOS F: Forced traffic flow condition with low speeds and traffic volumes that are below capacity
3/2013	Automated w/ takeover	65 mph	Interstate/bypass/divided highway with no traffic signals	N	N	LOS B: Flow with some restrictions
10/2013	Manual	Unknown	Playground	N	N	LOS D: Unstable flow, temporary restrictions substantially slow driver
3/2014	Automated	65 mph	Interstate/bypass/divided highway with no traffic signals	N	N	LOS F: Forced traffic flow condition with low speeds and traffic volumes that are below capacity
7/2014	Manual	30 mph and 35 mph	Business/Industrial	N	N	LOS B: Flow with some restrictions
2/2015	Automated w/ takeover	35 mph	Business/Industrial	N	N	LOS B: Flow with some restrictions
4/2015 #1	Automated	35 mph	Business/Industrial	N	N	LOS C: Stable flow, maneuverability and speed are more restricted
4/2015 #2	Automated	35 mph	School[1]	N	N	LOS B: Flow with some restrictions

Event Date (Month/Year)	Mode	Roadway Speed Limit	Locality	Airbag Deployment (Y/N)	Rollover (Y/N)	Traffic Density
5/2015	Automated	35 mph	Business/Industrial	N	N	LOS C: Stable flow, maneuverability and speed are more restricted
6/2015 #1	Automated	35 mph	Urban	N	N	LOS B: Flow with some restrictions
6/2015 #2	Automated	25 mph	Urban	N	N	LOS B: Flow with some restrictions
7/2015	Automated	35 mph	Business/Industrial	N	N	LOS E: Flow is unstable, vehicles are unable to pass, temporary stoppages, etc.
8/2015	Automated w/ takeover	35 mph	Playground	N	N	LOS C: Stable flow, maneuverability and speed are more restricted

[1]Mountain View Academy is on the left, but no access to school is provided on the current road. Locality minus the school is moderate to dense residential.

Chapter 3. Reported Versus Unreported Crashes

One of the key issues confronting the analysis concerned how to account for unreported crashes and how to adjust the rate of known crashes accordingly. This section describes efforts to correct the national rates and to determine rates of unreported crashes based on naturalistic data.

Published crash rates are based on reported accidents (either to police or to state motor vehicle bureaus). However, many crashes go unreported to police and/or insurance companies. This is a known issue with published crash rates, and NHTSA has published two different reports estimating the number of crashes that go unreported. Additionally, the SHRP 2 NDS provides another potential way to estimate unreported crashes.

National Estimates of Reported and Unreported Crashes

NHTSA has published two different estimates for the percentage of crashes that go unreported. First, NHTSA (M. Davis & Co, 2015) used a telephone survey methodology to provide the following estimates regarding motor vehicle crashes that have not been reported to police by drivers:

- 15.4 percent of injury crashes are not reported to police.
- 35.6 percent of PDO crashes are not reported to police.

Second, a NHTSA economic impact report (Blincoe et al., 2015) expands on the unreported estimates published in the previous telephone survey. A driver may have reported a crash to police or other authorities, but this report was never officially filed (e.g., police were called but were unable to respond, or responded but determined that the crash did not meet damage threshold for reporting). This report adjusts unreported rates even further to account for this situation. These increased rates are reported as:

- 24.3 percent of injury crashes are not reported to police.
- 59.7 percent of PDO crashes are not reported to police.

SHRP 2 NDS Estimates of Reported and Unreported Crashes

The SHRP 2 NDS provides another estimate of the percentage of unreported crashes. The SHRP 2 database has 279 identified crashes that are Level 1 or Level 2, and 46 are known to have been reported. Again, the caveat to these totals is that the exact number of crashes that were reported is unknown. The method used relied on self-reports from participants and as such did not capture whether another party reported the incident. Considering this limitation, for the available SHRP 2 data, 16 percent of crashes were PR and 84 percent were NPR. This rate is greater than other published rates but can serve as a basis for an upper bound for unreported crash rates.

Summary

These estimates provide a wide range of rates for unreported crashes. Overall estimates vary based on the methodology (e.g., survey vs. NDS). Still, there appear to be some consistent findings between sources. Higher severity crashes have a higher reported rate. For example, it is assumed that fatal crashes are always reported. Injury crashes have a lower unreported rate than PDO crashes. In the SHRP 2 database, Level 1 crashes were more often reported compared to Level 2 crashes. The percentages for unreported crashes cited the most often are those from the updated economic impact report published by NHTSA (Blincoe et al, 2015).

Unreported Crash Estimate Calculations

In order to estimate the number of unreported crashes, a baseline measure of reported crashes is needed. Where available, reported crash data and vehicle miles traveled (VMT) for the years 2009 to 2014 were averaged at the county level. In the event that yearly data was not reported for all years (2009-2014), the most recent reported estimate for VMT was used for all years. Data for the following SHRP 2 locations were compiled at the county level: Erie County, New York; Durham County, North Carolina; King County, Washington; and Hillborough County, Florida. For the SHRP 2 data collection sites of Monroe County, Indiana, and Centre County, Pennsylvania, a published estimate of VMT was not available. For these two sites, the state totals were used as an estimate. In addition to the SHRP 2 data collection sites, unreported crash estimates were computed for the locations of Santa Clara County, California, and Los Angeles County, California.

The intent of the analysis was to provide a general estimate of unreported crashes in the general population, for comparison with the crash rates of the Self-Driving Car. Again, there is a large difference between estimates of unreported crashes, suggesting that using any one single estimate would not be appropriate. It may also be inappropriate to interpret the percentages too literally, given the differing methodologies and sample sizes used for each. In order to account for these issues, the published percentages and the SHRP 2 estimates were rounded to the nearest 5 percent and three different rates for unreported crash totals were computed for each location: low, moderate, and high. Low estimates were based on the telephone survey rates (rounded to 15 percent for injury crashes and 35 percent for PDO crashes). Moderate estimates were computed using the economic impact report (rounded to 25 percent for injury crashes and 60 percent for PDO crashes). High estimates were based on the economic impact report injury rates (25 percent) and SHRP 2 known reported rates for PDO crashes (rounded to 85 percent). The reported number of crashes and the Total Crash Estimate (Reported + Unreported Estimate) for each site are shown in Table 7.

Table 7. Reported Crashes and Total Crash Estimates

Location	Reported Crashes			Total Crash Estimate		
	Fatal	Injury	PDO	Low Estimate	Moderate Estimate	High Estimate
National Totals	30,057	1,591,000	4,066,000	8,157,206	12,316,390	29,258,057
Santa Clara County, CA	90	6,595	7,807	19,860	28,401	60,929
Los Angeles County, CA	563	50,745	74,843	175,406	255,330	567,174
Monroe County, IN	9	859	3,205	5,950	9,166	22,520
Erie County, NY	51	6,784	9,905	23,270	33,859	75,130
Durham County, NC	20	2,125	5,747	11,210	17,068	41,012
King County, WA	78	11,219	22,696	48,194	71,778	166,345
Centre County, PA	13	594	649	1,721	2,438	5,140
Hillsborough County, FL	155	11,117	9,400	27,850	38,632	77,796

As shown in Table 7, crash totals vary widely by site due to population and driving pattern differences. In order to provide a more even comparison between sites and to the Self-Driving Car data, the Total Crash Estimates were divided by the reported VMT for each location and then multiplied by 1 million. This provides an estimate of Total Crash Rate per million miles traveled that is comparable across all sites and provides a basis to compare with the Self-Driving Car Data. Table 8 shows the computed Total Crash Rates for low, moderate, and high estimates of unreported crashes. Again, note that VMT was not published at the county level for Monroe County, Indiana, and Centre County, Pennsylvania; therefore, the statewide rates were calculated as a surrogate for these two sites. Appendix C contains complete tables for each site.

Table 8. Reported and Unreported Crash Rates per Million Miles Traveled

Location	Reported Rate	Estimate of Total Crash Rate		
		Low	Moderate	High
National Average	1.92	2.75	4.15	9.87
Santa Clara County, CA	0.98	1.34	1.91	4.1
Los Angeles County, CA	1.62	2.25	3.27	7.27
State of Indiana	*2.49*	*3.67*	*5.71*	*14.23*
Erie County, NY	1.81	2.52	3.66	8.12
Durham County, NC	2.29	3.32	5.05	12.14
King County, WA	2.13	3.02	4.5	10.42
State of Pennsylvania	*1.26*	*1.69*	*2.38*	*4.94*
Hillsborough County, FL	1.65	2.2	3.05	6.14

Three locations exceed the national average of 1.9 crashes per million miles traveled: the State of Indiana; Durham County, North Carolina; and King County, Washington. This may be due to reporting thresholds being lower in these locations, as all three have requirements of $1,000 or less.[10] Generally speaking, however, the reported crash rates are similar across sites, suggesting that unreported rates would also be similar.

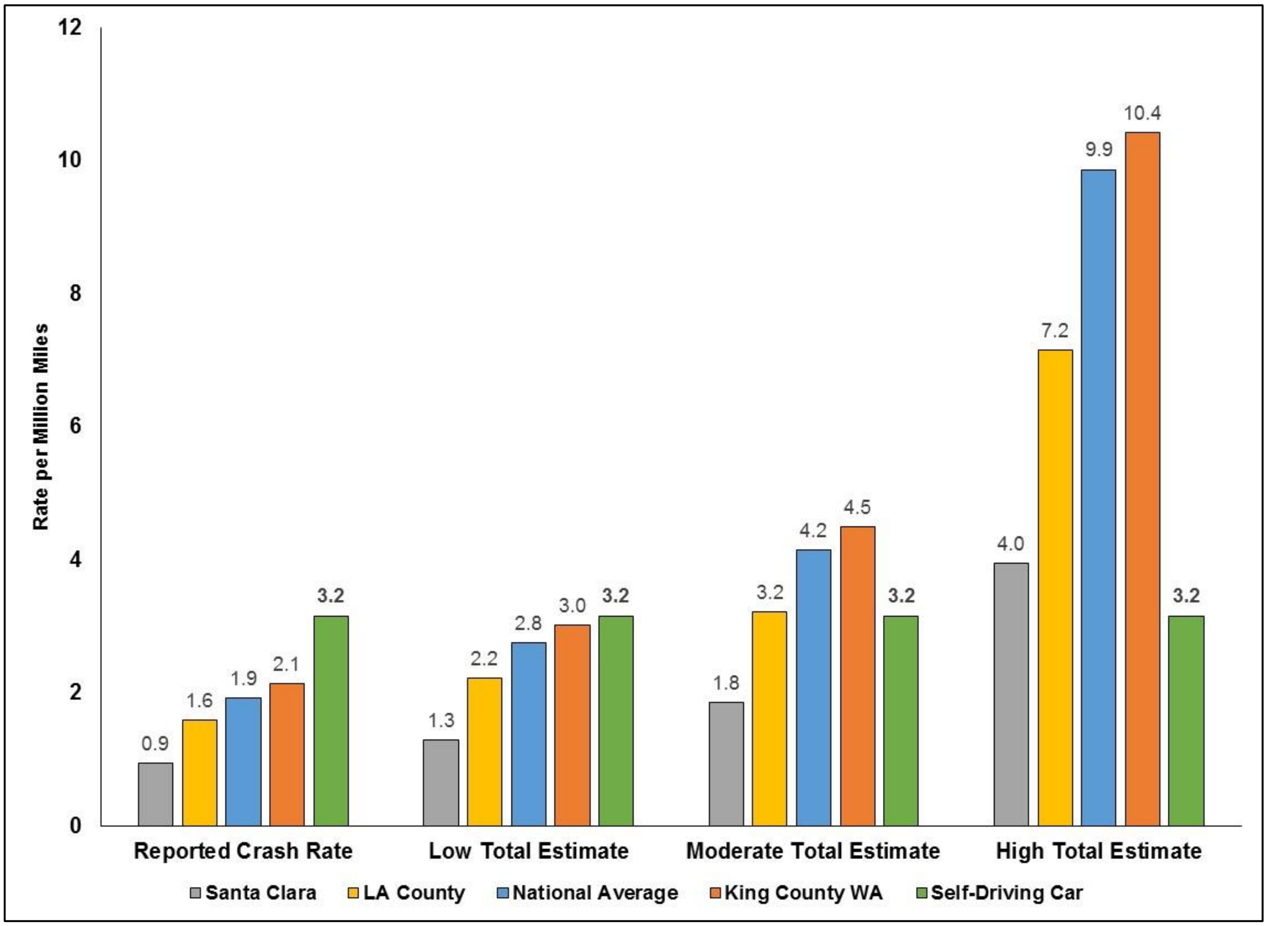

Figure 2. Reported Crash Rates with Low, Mid, and High Total Crash Rate Estimates Compared to Adjusted Self-Driving Car Crash Rates

The initial crash rate of the Self-Driving Car was calculated to be 8.7 per million miles of travel, which is almost four times higher than the national average rate of 1.9 per million miles of travel. However, these two rates are not necessarily comparable without adjustment. First, the Self-Driving Car rate includes seven crashes that were categorized as Level 3 by SHRP 2 definitions. Although these crashes were legally required to be reported to the California DMV, these Level 3 crashes would not be considered severe enough to report to police in any other context or jurisdiction. If these crashes are removed from the Self-Driving Car data and the rate recalculated, the crash rate for the Self-Driving Car is 3.2 per million miles of travel. Second, the reported crash

[10] Prior to January 1, 2015, the reporting threshold in Washington State was $700.

rates for the national average should be adjusted to include unreported crashes. A subset of reported crash rates and Total Crash Rate Estimates are plotted in Figure 2, as is the adjusted Self-Driving Car Data. As shown, the adjusted Self-Driving Car rates compare favorably to the total crash estimates for the national average once unreported crashes are taken into account.

While the Adjusted Self-Driving Car rate is lower than the national average rate, it is higher than the adjusted rate calculated for Santa Clara County, the home location of the project. This may be some cause for concern, since the rate is higher than would be expected for other vehicles operating around it. As calculated in the present analysis, Santa Clara County has a reported crash rate that is close to half the national average. However, it is possible that the present analysis over-estimated the yearly VMT for Santa Clara and Los Angeles Counties. The California Office of Travel Safety reports VMT as a daily estimate. For the present analysis, this daily estimate was multiplied by 365 to extrapolate a yearly estimate. If the daily VMT estimates do not sufficiently correct for low volume travel days (such as weekends) it is possible that this method has systematically overestimated VMT. Overestimation of VMT will, in turn, lead to an under-estimate of crash rates.

Finally, it should be noted that these are not statistical comparisons; statistical comparisons were not calculated due to the small sample of miles driven in automated mode for the Self-Driving Car. At present it is difficult to determine if any true differences exist between the adjusted rates and the Self-Driving Car rates. The following chapter will further explore the crash rates associated with different crash severity levels when compared to SHRP 2 crash events.

Chapter 4. Crash Rate Comparison

As discussed in Chapter 3, estimated national crash rates, while insightful, are limited in that they are based either on police reports or the reliability of surveyed individuals. Naturalistic driving studies, such as SHRP 2, provide a unique opportunity to more reliably assess crash rates by using video to capture a wide range of crashes that otherwise would not see the light of day. These driving studies also allow the assessment of the severity of a crash beyond the reported presence of an injury or fatality. In this section, crash rates from SHRP 2 are computed to provide a comparison with Self-Driving Car rates based on severity level.

Crash rates per million miles of driving were calculated for different severity levels of crashes. Rates were also calculated for NPR crashes, also stratified by crash severity level. Additionally, crash rates of different severity levels were calculated for the Self-Driving Car project. Confidence intervals were calculated for all rates in order to compare the current levels of uncertainty in crash rates between the SHRP 2 NDS and the Self-Driving Car's datasets.

Estimating Crash Rates from the SHRP 2 NDS

Two different procedures were used to estimate crash rates from the SHRP 2 NDS. The first was based on the unweighted SHRP 2 data, and the second was based on weighting by age group, with weighting based on the following age groups: 16-24, 25-39, 40-54, 55-74, and 75+. The unweighted rate allows for a more stable sample size, but the weighted rate accounts for the oversampling of younger drivers (under 25 years old) and older drivers (more than 75 years old) in the SHRP 2 dataset (Antin et al., 2015). Because these two age groups generally have higher crash rates than other drivers (Stutts, Martell, and Staplin, 2008), a crash rate that does not account for the oversampling of these groups will overestimate the crash rate. Therefore, weighted totals for crashes and miles driven were used to calculate age-adjusted rates, with younger and older drivers weighted less, and drivers in the middle age groups weighted more. Weights were based on information from the FHWA (2013, 2014, 2015). Note that ages of 85 drivers in the SHRP 2 study were not known, so their information was not included in the age-adjusted rates. Hence, there were two Level 1, one Level 2, and two Level 3 crashes associated with these 85 drivers that were excluded from the age-adjusted analysis.

Confidence intervals were calculated for crash rates from SHRP 2 based on severity and police-report status using nonparametric bootstrapping procedures. Bootstrapping has the advantage that a specific distribution family does not need to be assumed (Carpenter and Bithell, 2000; Chernick, 2008). For self-driving rates, since all that is known is the total number of events (crashes) and exposure (million miles driven), distributional theory was used to construct confidence intervals. Specifically, exact confidence intervals assuming a Poisson distribution (Ulm,

1990) were calculated using the pois.exact function in R. Note that confidence intervals were calculated only for the time the Self-Driven Car operated in its autonomous mode.

More information on the methods is available in Appendix C.

Comparison of SHRP 2 NDS and Self-Driving Car Crash Rates

When compared to the observed SHRP 2 crash rates per million miles of driving, both overall and age-adjusted, the observed crash rates are lower for self-driving vehicles. With only two Level 1, two Level 2 crashes, and seven Level 3 crashes in about 1.3 million miles of driving, the observed crash rates for the Self-Driving Cars were 1.6, 1.6, and 5.6 per million miles for Level 1, Level 2, and Level 3 crashes, respectively. This compares to SHRP 2 age-adjusted rates of 2.5, 4.7, and 14.4 per million miles for crash Levels 1, 2, and 3, respectively.

Due to the currently limited exposure for the Self-Driving Car project, the observed uncertainty in the Self-Driving Car rates is much greater than in the rates from the SHRP 2 NDS. The confidence intervals for the Self-Driving Car analyses are at least three times wider than the SHRP 2 confidence intervals for all three crash severities. The Self-Driving Car confidence interval lengths are 5.5 for Level 1 and Level 2 crashes, and 9.2 for Level 3 crashes. This compares to confidence interval lengths of 1, 1.3, and 3 for Level 1, 2, and 3 crashes, respectively, from the SHRP 2 NDS data.

Because the 95 percent confidence intervals for the Self-Driving Car data overlap with those in the SHRP 2 NDS for Level 1 and Level 2 crashes, the evidence of any difference in rates of Level 1 and Level 2 crashes between the SHRP 2 NDS and the Self-Driving Car project is inconclusive. However, for Level 3 crashes, the crash rate for the Self-Driving Cars was significantly lower than both the overall and age-adjusted rates observed in SHRP 2, as determined by non-overlapping confidence intervals. Note that non-overlapping 95 percent confidence intervals imply a statistically significant difference, but overlapping confidence intervals do not imply that there is no significant difference (Washington State Department of Health, 2012). However, for crash Levels 1 and 2, the Self-Driving Car confidence intervals completely contain the SHRP 2 confidence intervals (with the exception of the Level 2 age-adjusted PR interval). The estimated crash rates per million miles of driving from the SHRP 2 NDS and the Self-Driving Car project, along with the endpoints of the 95 percent confidence intervals, are graphed in Figure 3.

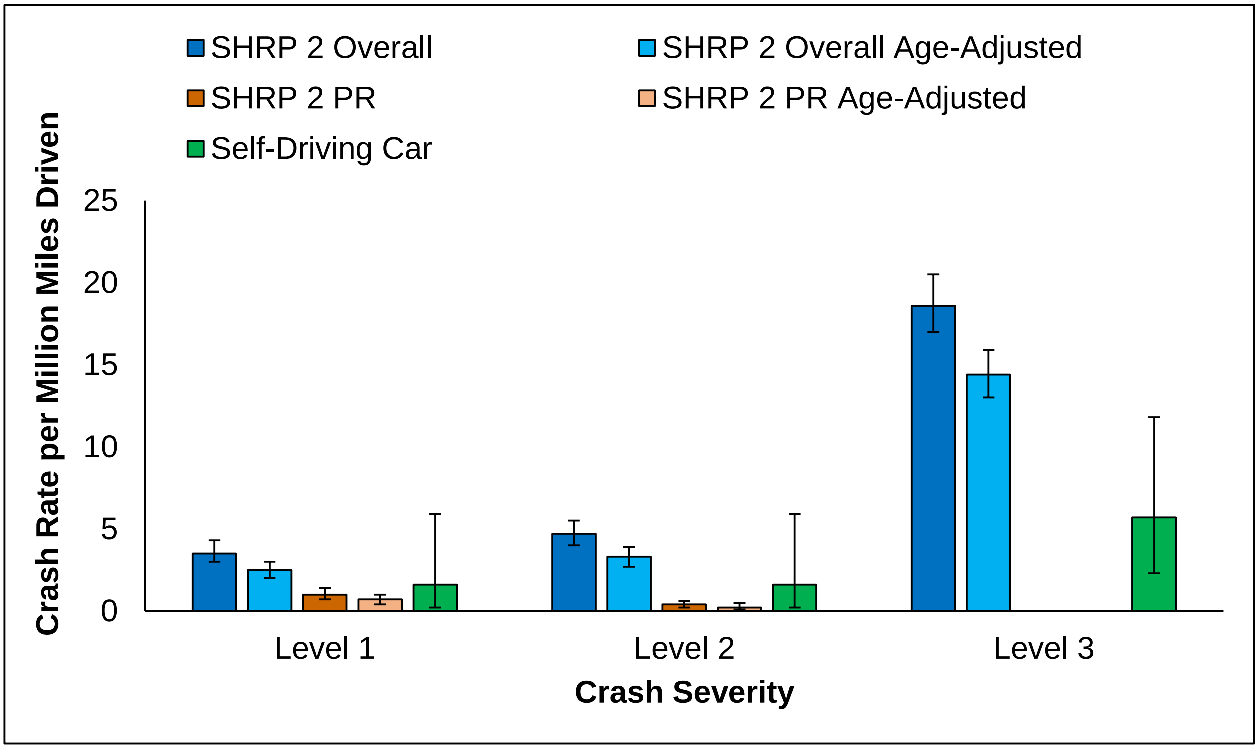

Figure 3. Estimated Crash Rates per Million Miles of Driving with 95 Percent Confidence Intervals

Chapter 5. Variations in Crash Rates Based on Street Type and Roadway Speed Limits

Examining crash rates for different speed zones and types of streets can provide further insight into roadway safety that is not available from standard crash rates. Cities, states, and regions may face different challenges in combating crash risk depending on travel speeds and the types of roads their motorists drive on. In this section, crash rates based on SHRP 2 data are broken down by speed zone and street type (referred to as locality).

Estimate of Total Mileage

SHRP 2 data were used to estimate crash rates per million miles of driving in different speed zones and different localities. It must be noted, however, that the total number of miles driven in different speed zones and localities in SHRP 2 is unknown. Therefore, in order to estimate the rate of crashes per million miles of driving in different speed zones and localities, these total mileages first needed to be estimated. This was done using 20,000 randomly sampled baselines. The following process was used.

1. Speed zones were determined for each baseline using Google Maps Roads API.
2. Distances for each baseline were calculated.
3. Total baseline mileage was determined, along with total baseline mileage for different speed zones and localities.
4. The proportion of baseline distance in different speed zones and localities was estimated by taking the proportion of baseline distance driven in these speed zones and localities.
5. Estimated proportions were applied to the total mileage in SHRP 2, about 34.02 million miles, to create an estimate of total mileage driven in different speed zones and localities.
6. Speed zones were determined for crashes, so that the number of crashes in different speed zones could be calculated.
7. Using the crash totals and estimated mileage in different speed zones and localities, estimated crash rates were then calculated.

As in Chapter 4, age-adjusted rates were also calculated using weighted totals for both total crashes and mileage. Note that there were 31 total crashes (7 Level 1, 6 Level 2, and 18 Level 3) for which the speed zone calculation failed. Hence, only 881 crashes were used in calculating crash rates in different speed zones.

Additional details are provided in Appendix D.

Variations Based on Speed Zones

Crashes tended to happen at a higher rate at slower speeds. The highest rates per million miles of driving occurred at speeds between 26 and 35 mph for Level 1 (4.2 per million miles, age-adjusted) and Level 2 (5.72 per million miles of driving, age-adjusted). For Level 3, the highest rate was for speeds of 25 mph or less, with a rate of 41.48 per million miles (age-adjusted). Meanwhile, the lowest rates were associated with speeds of more than 65 mph for Level 1 (0.8 per million miles, age-adjusted), 56 to 65 mph for Level 2 (0.9 per million miles, age-adjusted), and more than 65 mph for Level 3 (4.9 per million miles, age-adjusted). The rates per million miles of driving for Level 1, Level 2, and Level 3 crashes for different speeds are displayed in Figure 4, Figure 5, and Figure 6, respectively.

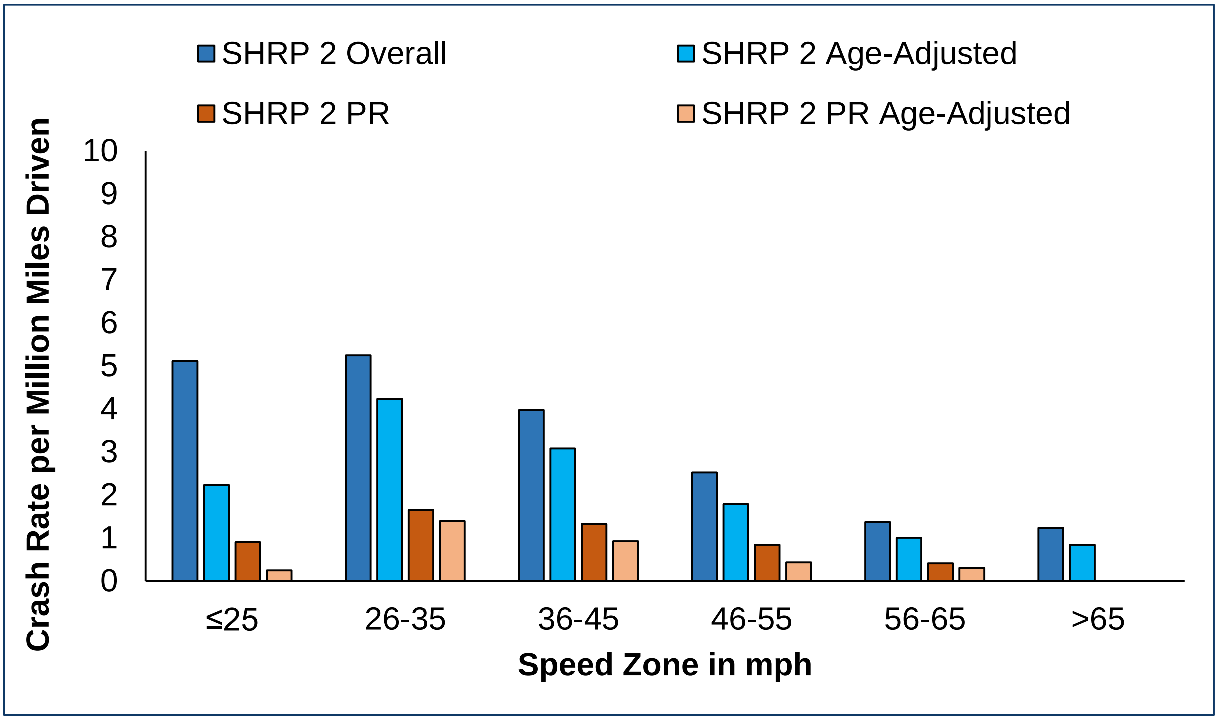

Figure 4. Level 1 Crash Severity Crash Rates per Speed Zone in mph

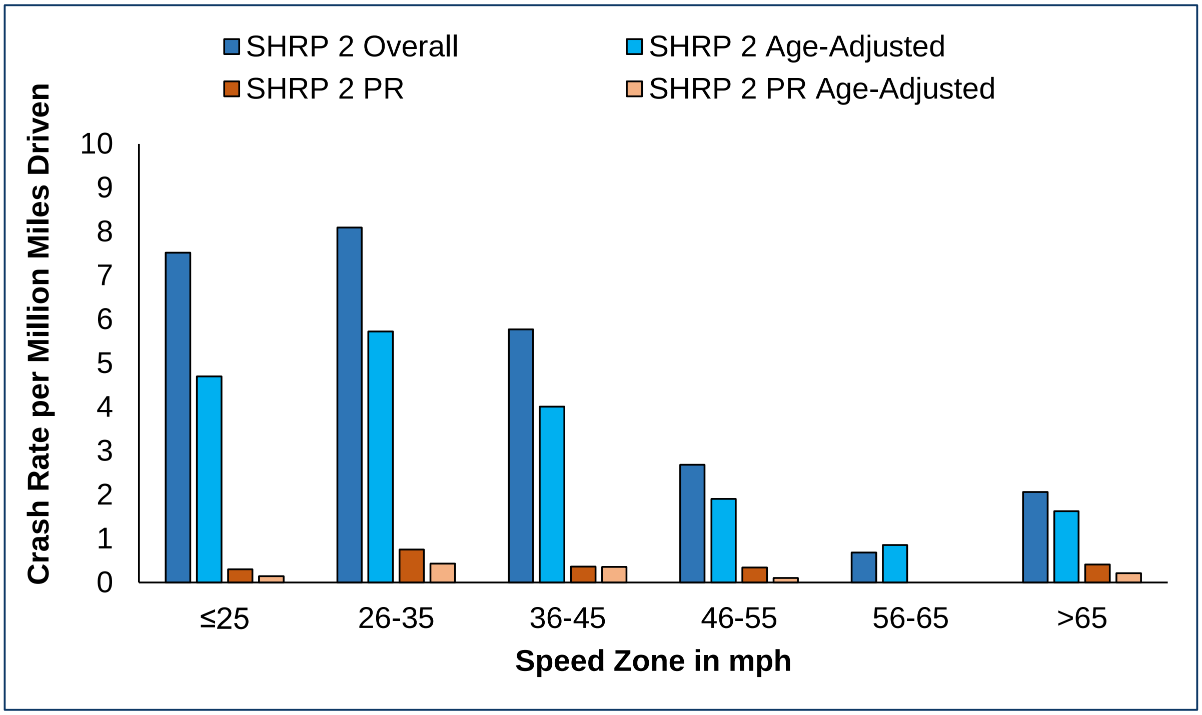

Figure 5. Level 2 Crash Severity Crash Rates per Speed Zone in mph

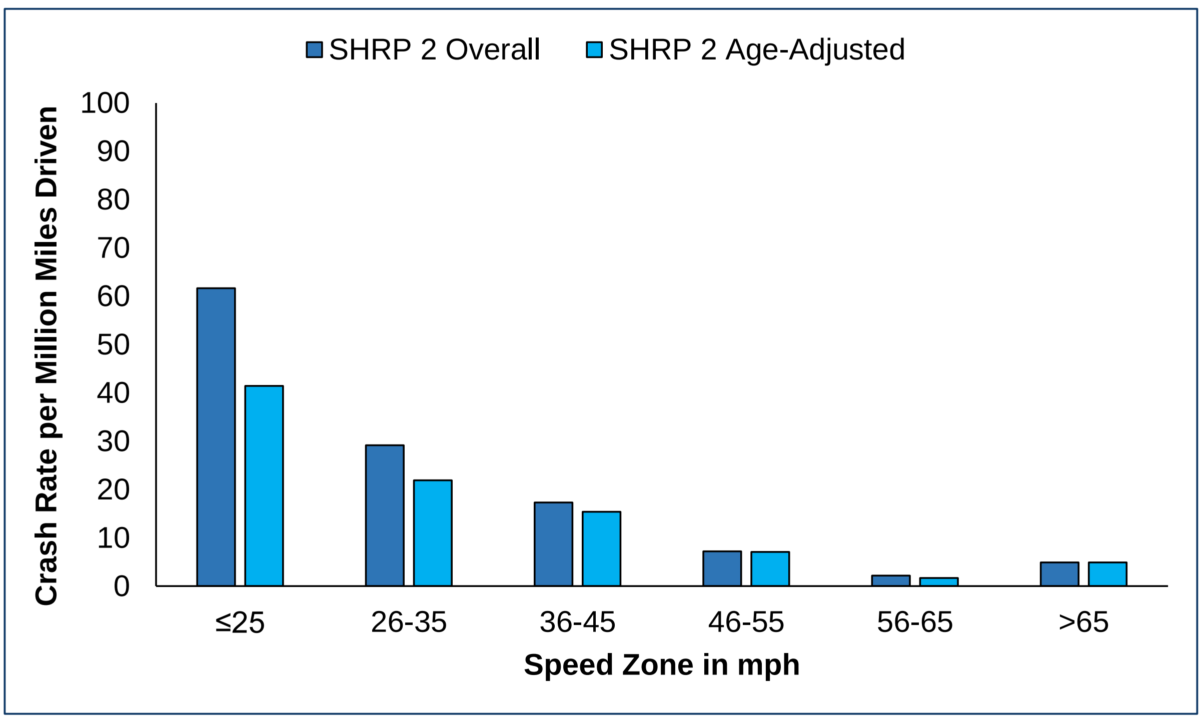

Figure 6. Level 3 Crash Severity Crash Rates per Speed Zone in mph

Variations Based on Locality

For the purpose of this study, locality is a category representing any natural or built surroundings that could influence the flow of traffic at the precipitation of a crash event. Locality classifications were defined as follows (VTTI, 2015):

- **Open Country:** Other than roadway, nothing but vegetation is visible. The road is not an interstate or a bypass/divided highway with traffic signals.
- **Open Residential:** Rural to semi-rural areas where only one or a few houses may be present (e.g., farmland).
- **Moderate Residential:** An area where multiple houses or apartment buildings are present (e.g., residential subdivisions).
- **Business/Industrial:** Any type of business or industrial structure is present, but it is not as dense as an Urban locality. This category takes precedence over residential categories when houses are also present.
- **Church:** One or more involved vehicles pass a church building.
- **Playground:** One or more involved vehicles pass any type of playground or children's playing field (unless the playground/field is on school grounds, in which case it is considered a school).
- **School:** One or more involved vehicles pass any type of school building or are in a school zone. This includes adult learning institutions such as training centers and universities.
- **Urban:** Higher density areas where the blocks are shorter, there is a mix of one- and two-way streets, and traffic can include busses and trams. This category takes precedence over others when either business and/or residences are present.
- **Interstate/Bypass/Divided Highway, Controlled Access:** Vehicles are traveling on an interstate, bypass, or divided highway with no at-grade intersections (regardless of what buildings can be seen) at the time of the precipitating event.
- **Bypass/Divided Highway, Access Not Controlled:** Vehicle is traveling on a bypass or divided highway with at-grade intersections present (either uncontrolled, stop signs, or traffic signals) and no other category fits. The category often appears as Open Country, but with more lanes and/or a divided road.

Note that the Playground locality was not used due to a low estimated exposure (about 132,928 estimated miles driven in SHRP 2).

For all three crash types, the highest crash rates occurred in Urban areas: 6.6 per million miles (age-adjusted) for Level 1, 8.9 per million miles of driving for Level 2 (age-adjusted), and 53.7 per million miles for Level 3 (age-adjusted). The lowest rates occurred in Open Country localities (1.0 per million miles for Level 1 and 0.5 per million miles for Level 2, age-adjusted) and Interstate localities (2.6 per million miles for Level 3, age-adjusted). The crash rates per million miles of driving in different localities for Level 1, Level 2, and Level 3 crashes are displayed in Figure 7, Figure 8, and Figure 9, respectively.

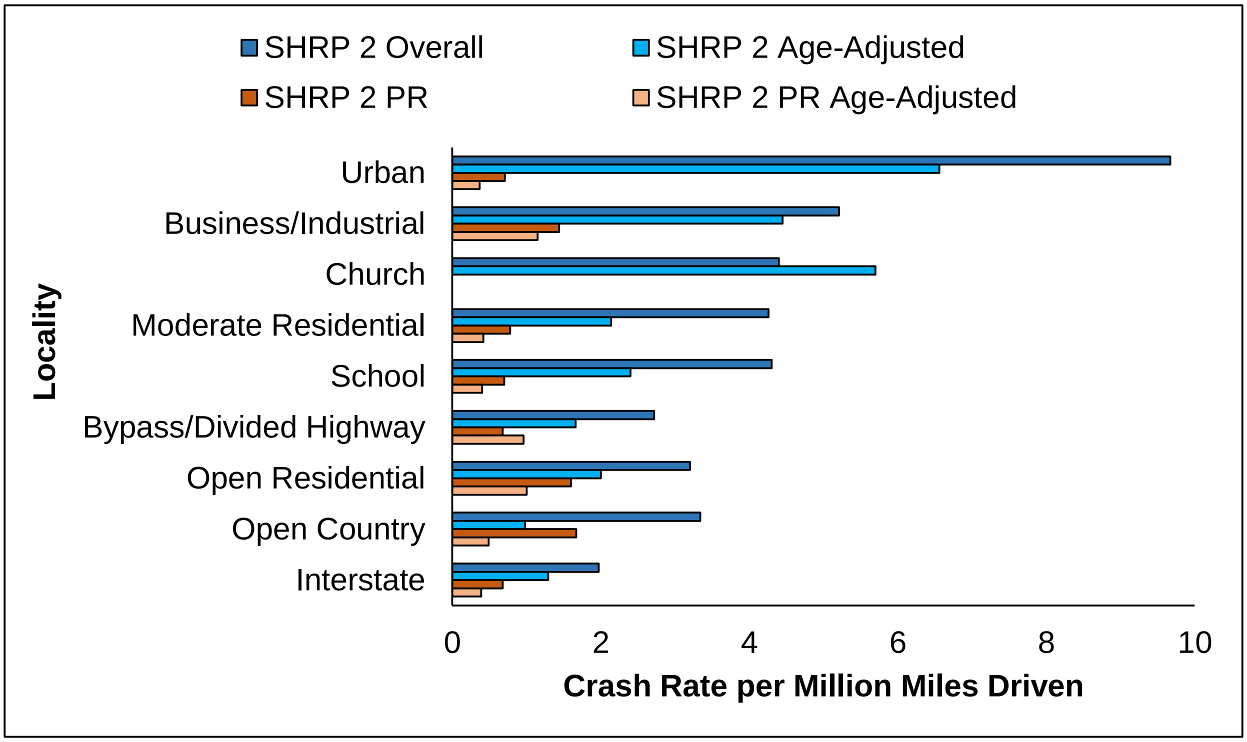

Figure 7. Level 1 Crash Severity Crashes by Locality

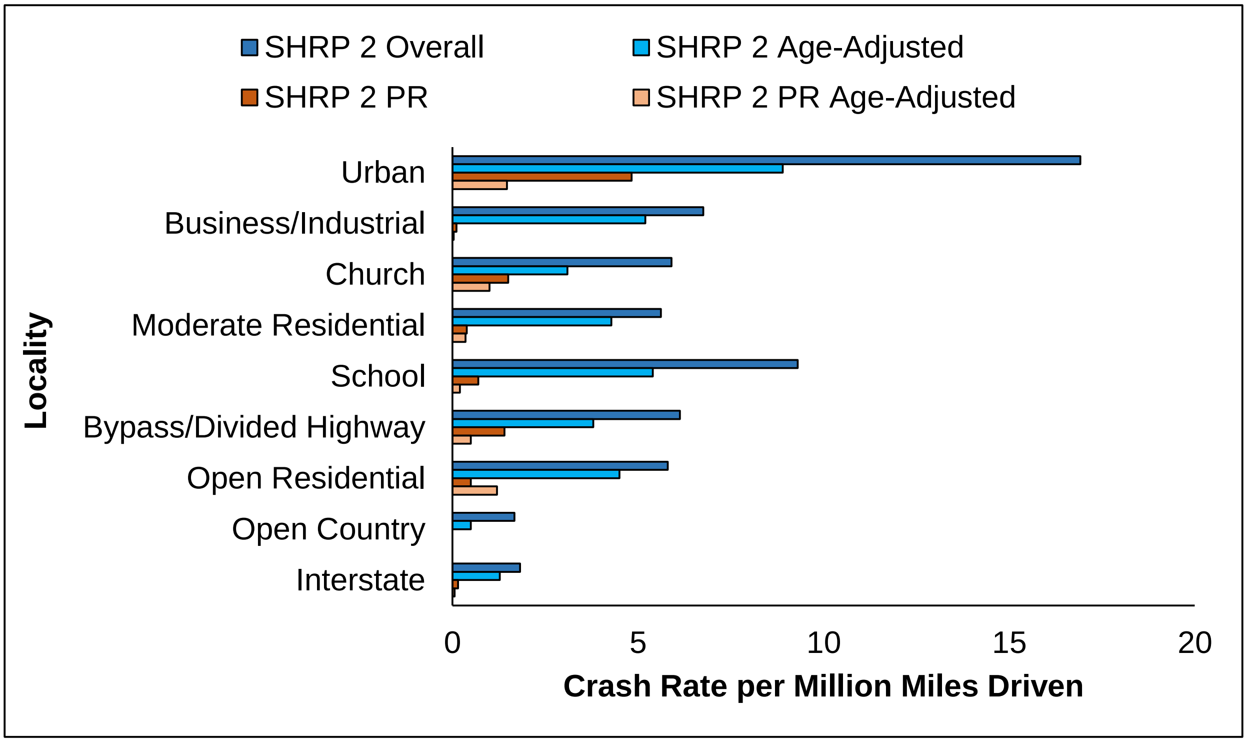

Figure 8. Level 2 Crash Severity Crashes by Locality

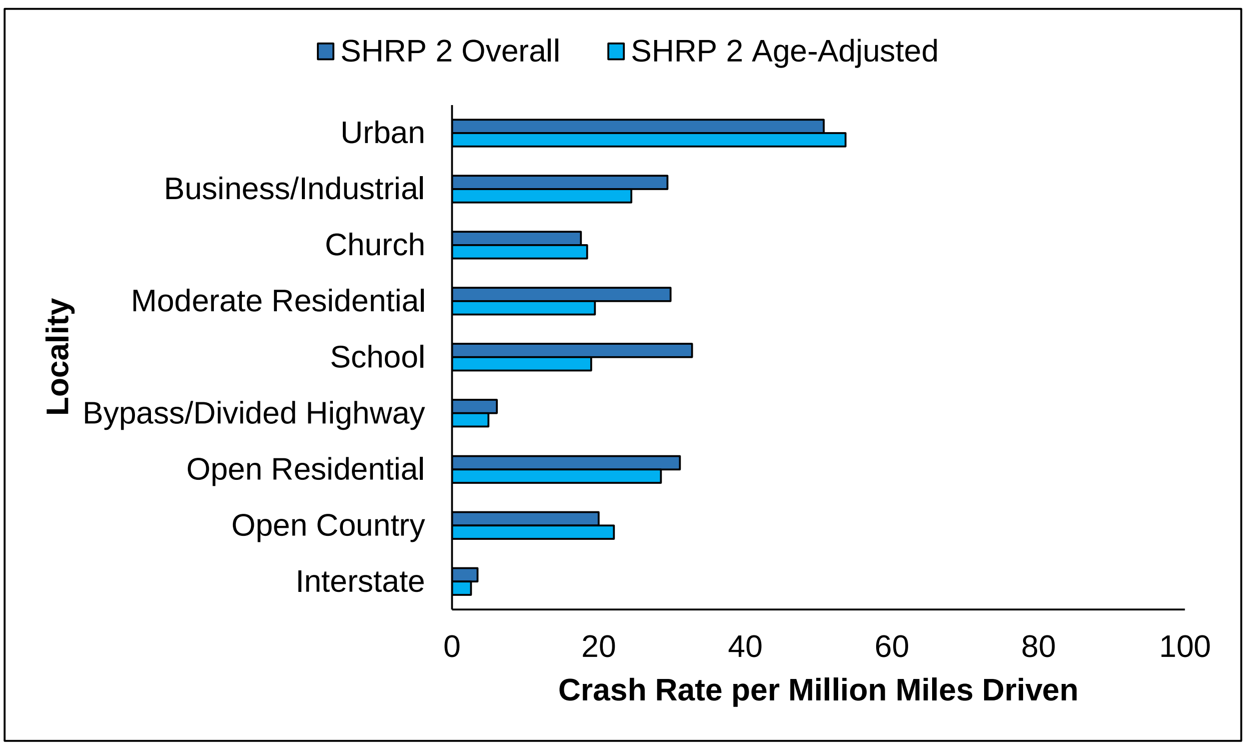

Figure 9. Level 3 Crash Severity Crashes by Locality

Chapter 6. Factors Contributing to Unreported Crashes

In painting a picture of roadway safety, it is important to ask not just how many crashes occur, but why. What are the behavioral and environmental conditions that may contribute to crashes? Moreover, if many crashes are not reported, what are the contributing factors to these crashes? This section examines the nature of the NPR crashes in the SHRP 2 database.

Crash types and crash contributing factors were studied for the NPR crashes in the SHRP 2 NDS in order to explore the scenarios that contribute to unreported crashes. Crash types are determined by the variable incident type in the SHRP 2 NDS *Researcher Dictionary*, while the following variables were examined for contributing factors: fault, traffic density, maneuver judgment, precipitating event, driver behavior, and driver impairment.

This analysis used all crashes in the SHRP 2 database that do not have a known police report. These include all 633 Level 3 crashes, 147 out of 159 Level 2 crashes, and 86 out of 120 Level 1 crashes.

Types of Crashes

NPR crashes have been classified based upon the type of conflict(s) that the subject vehicle has with other vehicles, pedestrians, and objects. If there are multiple conflicts, they are listed sequentially by time. Potential conflict classifications include, but are not limited to:

- Rear-end striking, rear-end struck
- Road departure (left, right, or end)
- Sideswipe, same direction (left or right)
- Opposite direction (head-on or sideswipe)
- Straight crossing path, turn across path, turn into path (same or opposite direction)
- Backing into fixed objects or traffic flow
- Pedestrian, pedal cyclist, or animal-related

A sizeable portion of Level 1 NPR crashes (about 48 percent) and Level 2 NPR crashes (about 46 percent) from SHRP 2 were rear-end collisions, while a majority of Level 3 NPR crashes (about 60 percent) were road departures. During about 28 percent of Level 1 NPR crashes and 30 percent of Level 2 NPR crashes, the subject vehicle rear-ended the lead vehicle; during about 20 percent of Level 1 NPR crashes and 16 percent of Level 2 NPR crashes, the following vehicle rear-ended the subject vehicle. Note that for Level 1 and Level 2 NPR crashes, about 29 percent and about 39 percent, respectively, of rear-end crashes came in speed zones with a speed limit of 35 mph or less. Meanwhile, during Level 3 NPR crashes, about 55 percent of crashes were road departures to the right or left, while about 6 percent of crashes were road departures at the end of the road (i.e., tire leaves end of road). About 68 percent of road departure Level 3 NPR crashes came at speed limits of 35 mph or less. The percentages of incident types for each severity level of NPR crashes are displayed in Figure 10. Note that in this graph, the "other" category includes additional types of crashes. These include pedestrian-related, cyclist-related, backing into traffic or an object, or types that could not be determined via visual reduction.

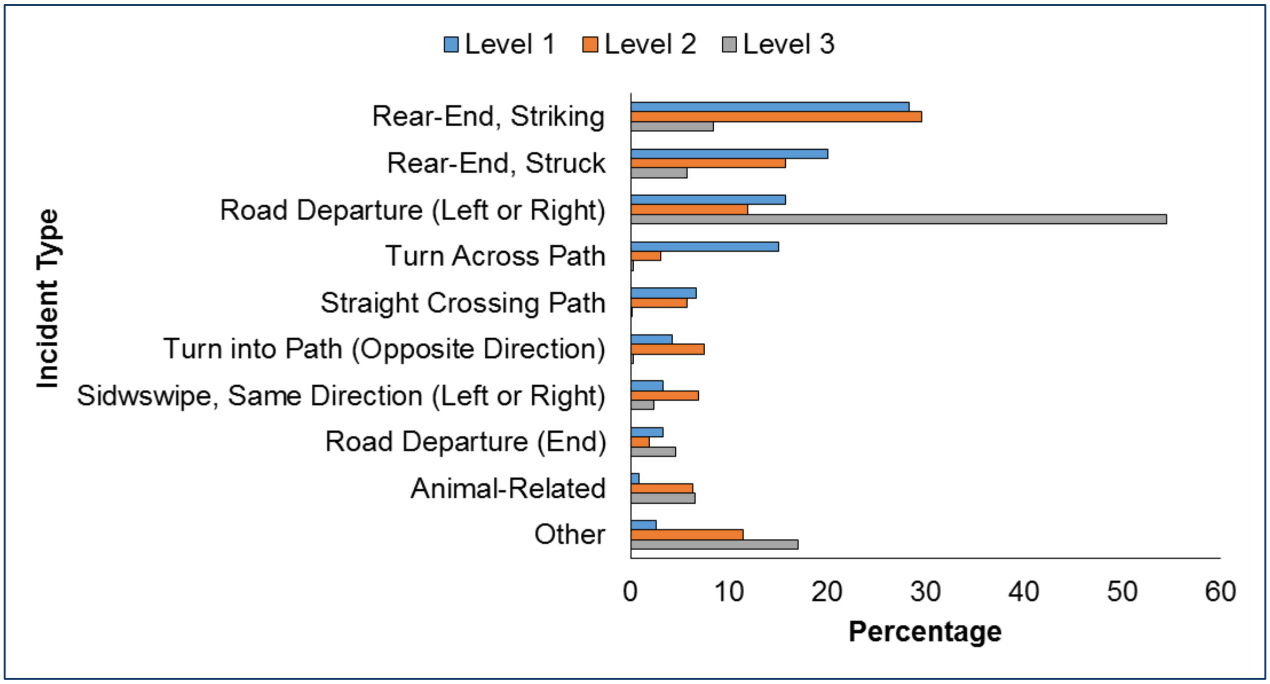

Figure 10. Types of Crashes

Crash Contributing Factors

Traffic Density

Traffic density was evaluated based upon the level of service (LOS) where the NPR crash occurred. Traffic density is based on the number of vehicles present in the subject vehicle's travel lane and other lanes in the subject vehicle's direction of travel, and the ability of the subject vehicle to maneuver between lanes and select the driving speed. In variable speed zones, a reduced speed limit is considered an indicator of traffic density (e.g., a variable speed limit of 30 mph on an interstate should be interpreted as a 50-percent reduction in travel speeds). A summary of the various LOSs are as follows (VTTI, 2015):

- **LOS A1:** Free traffic flow, no leading traffic present
- **LOS A2:** Free traffic flow, leading traffic present
- **LOS B:** Stable traffic flow with some restrictions
- **LOS C:** Stable traffic flow, maneuverability and speed are more restricted
- **LOS D:** Unstable traffic flow, temporary restrictions substantially slow drivers
- **LOS E:** Traffic flow is unstable, vehicles are unable to pass, temporary stoppages, etc.

- **LOS F:** Forced traffic flow condition with low speeds and traffic volumes that are below capacity

For Level 1 and Level 2 NPR crashes, the highest percentage of crashes came in LOS B, the third least-dense traffic scenario. About 40 percent and 31 percent of Level 1 and Level 2 NPR crashes, respectively, occurred within this category, with the next highest occurring in the two lower-density LOSs. Meanwhile, for Level 3 NPR crashes, the highest percentage was in the lowest traffic density, LOS A, and there was a decreasing trend as the traffic density increased. About 56 percent of Level 3 NPR crashes occurred within LOS A1. The percentages of NPR crashes in each category of traffic density, stratified by crash severity, are displayed in Figure 11.

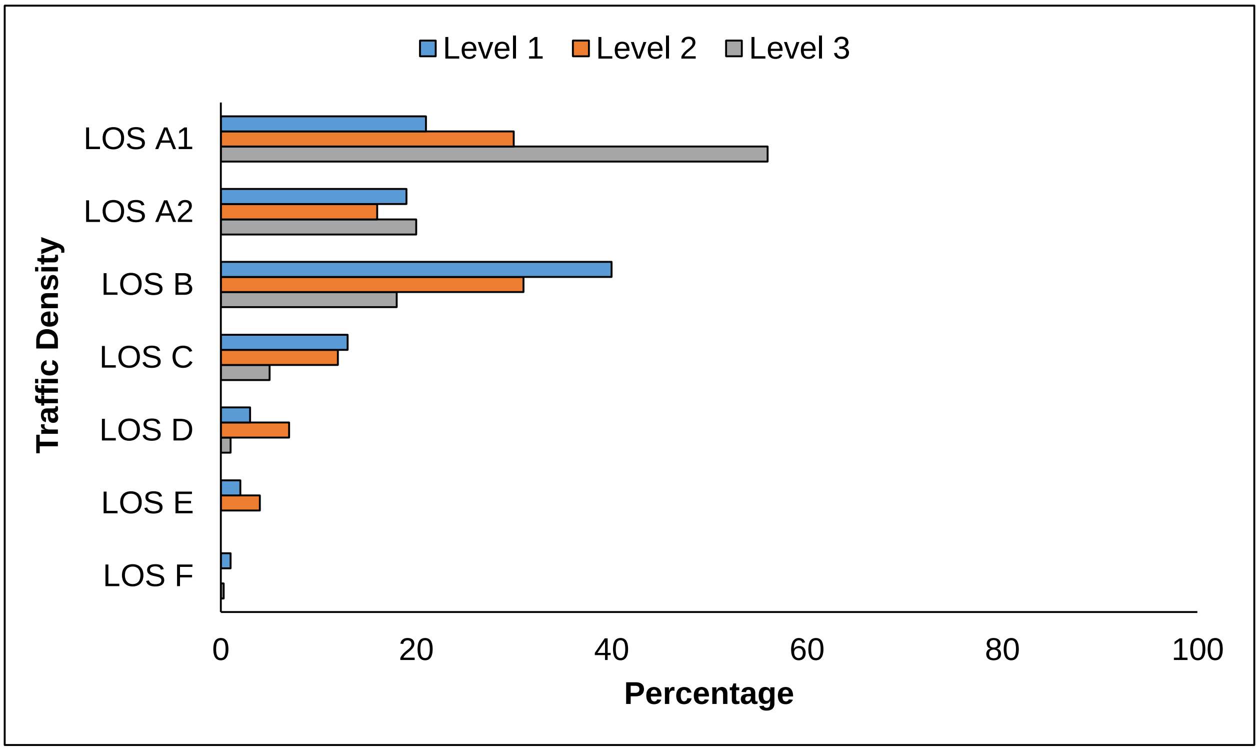

Figure 11. Traffic Density

Maneuver Judgment

Vehicle kinematic data (e.g., the subject vehicle's position and speed and direction of movement) were used to evaluate subjects' maneuvers prior to the precipitating event of a NPR crash. Maneuvers were judged to be safe and legal, unsafe but legal, safe but illegal, or unsafe and illegal. This designation was independent of any secondary tasks or other behaviors that the driver may have been engaged in prior to the precipitating event.

For all three NPR crash severity levels, the subject driver's maneuvering was determined to be safe and legal over 60 percent of the time. For crash Levels 1, 2, and 3, the percentage of NPR crashes in which the maneuvering was determined to be safe and legal was about 62 percent, about 68 percent, and about 67 percent, respectively. Otherwise, the NPR crashes were more likely to have unsafe maneuvering, whether legal or illegal. For crash Level 1, about 19 percent had unsafe and illegal maneuvering, and about 16 percent had unsafe but legal maneuvering. For crash Level 2, about 18 percent had unsafe and illegal maneuvering, while about 13 percent had unsafe but legal maneuvering. For Level 3 crashes, about 16 percent had unsafe but legal maneuvering, while about 14 percent had unsafe and illegal maneuvering. The percentages of NPR crashes in each maneuver judgment category, stratified by crash severity level, are displayed in Figure 12.

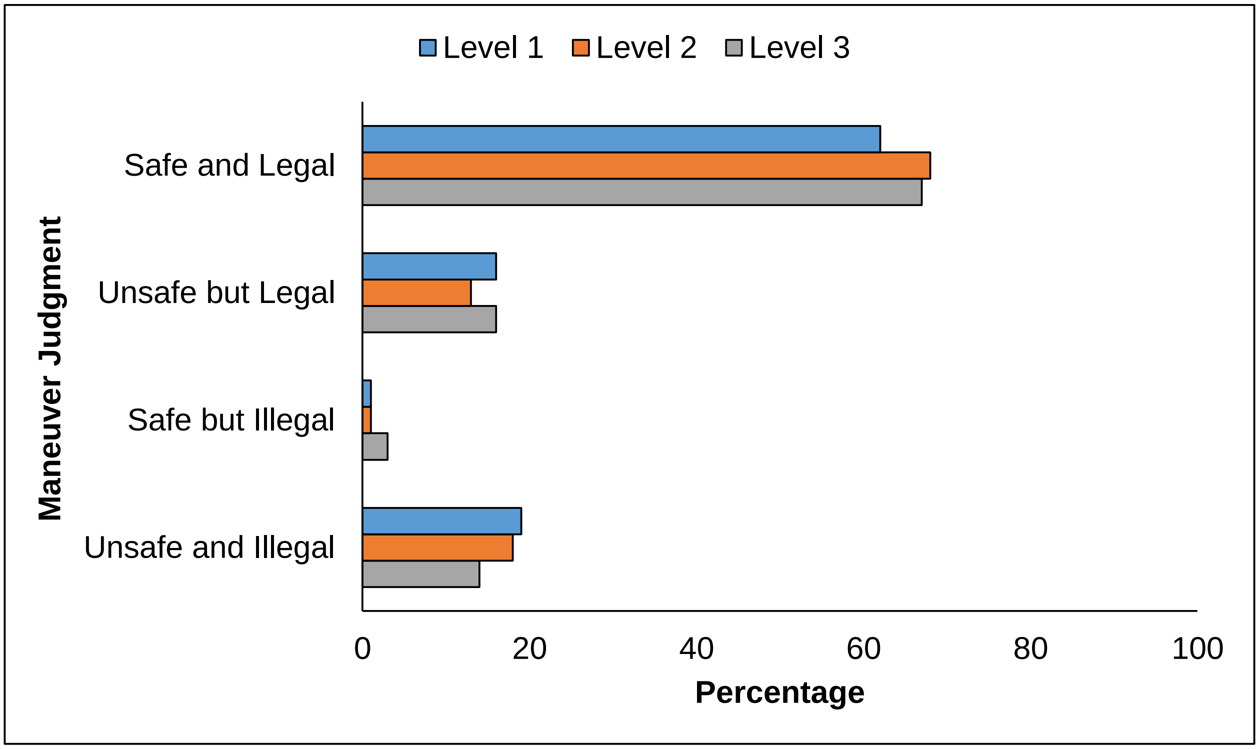

Figure 12. Maneuver Judgement

Fault

Fault indicates which driver or non-motorist (if any) committed the error that led to the event in question. Fault was only assigned if there was observable evidence. For both Level 1 and Level 2 NPR crashes, about 60 percent were determined to be the fault of the subject driver. Meanwhile, for Level 3 NPR crashes, about 79 percent were determined to be the fault of the subject driver. For Level 1 and Level 2 NPR crashes, about 38 percent and about 34 percent of crashes were the fault of another driver, respectively, while for about 2 and about 6 percent of crashes, respectively, the crash was not a conflict with another vehicle. For Level 3 NPR crashes, about 11 percent were the fault of another driver, while about 10 percent were not a conflict with another vehicle. The percentages of at-fault NPR crashes, stratified by crash severity, are displayed in Figure 13.

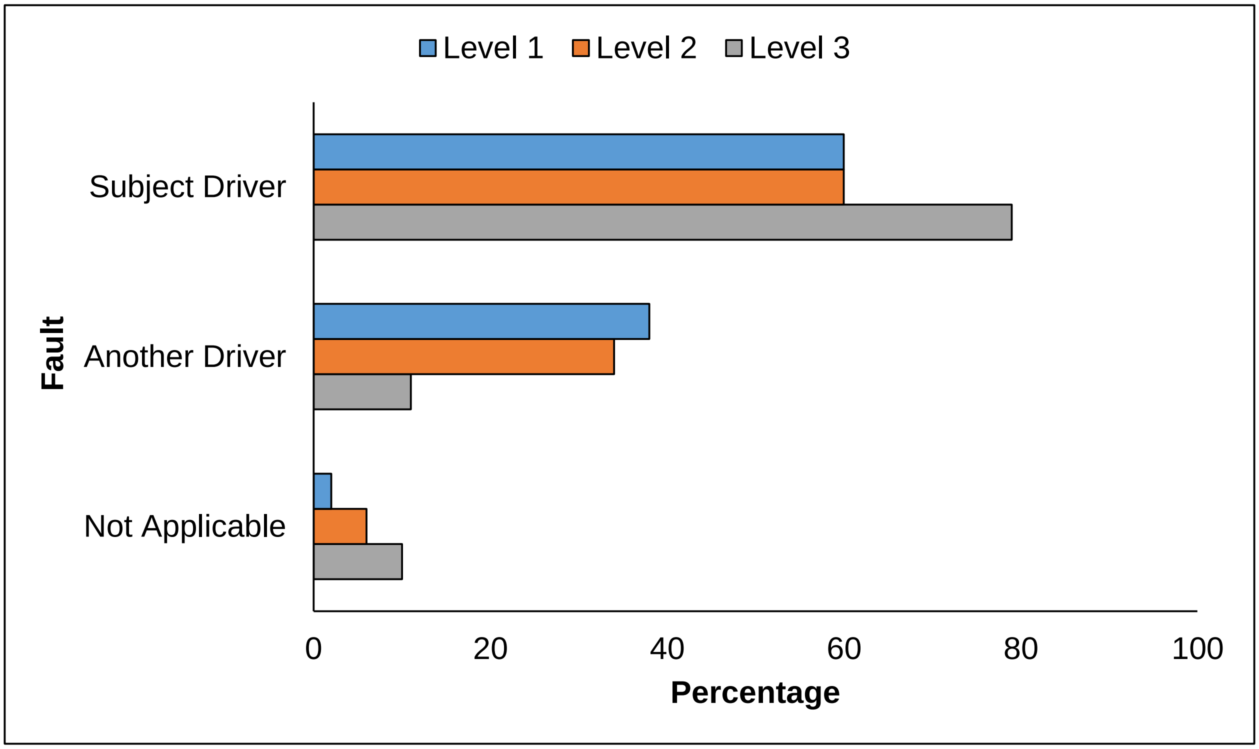

Figure 13. Crash Fault

Precipitating Event

Defined simply, precipitating events are the causes of a crash sequence (VTTI, 2015). More specifically, precipitating events are the environmental conditions (such as poor road conditions) or the actions (such as a deer leaping into the road) that were critical to the vehicle becoming involved in a crash or near-crash. This variable is determined by vehicle kinematic data and is based on what the vehicle does, not a driver's behavior. As such, it does not include factors such as driver distraction, fatigue, or disciplining a child.

Level 1 and Level 2 NPR crashes were more likely to be preceded by deceleration, stopping, or entering an intersection on the part of the subject driver or another vehicle. Level 3 NPR crashes were more likely to be preceded by the subject driver hanging off the edge of the road. For Level 1 and Level 2 NPR crashes, 41 percent and 39 percent, respectively, were preceded by another vehicle decelerating, stopping, or entering an intersection. Additionally, 31 percent of Level 1 NPR crashes and 24 percent of Level 2 NPR crashes were preceded by the subject driver decelerating, stopping, or entering an intersection. Meanwhile, for Level 3 NPR crashes, about 46 percent were preceded by the subject driver hanging off the edge of the road. The percentages of NPR crashes with different precipitating events, stratified by crash severity level, are displayed in Figure 14.

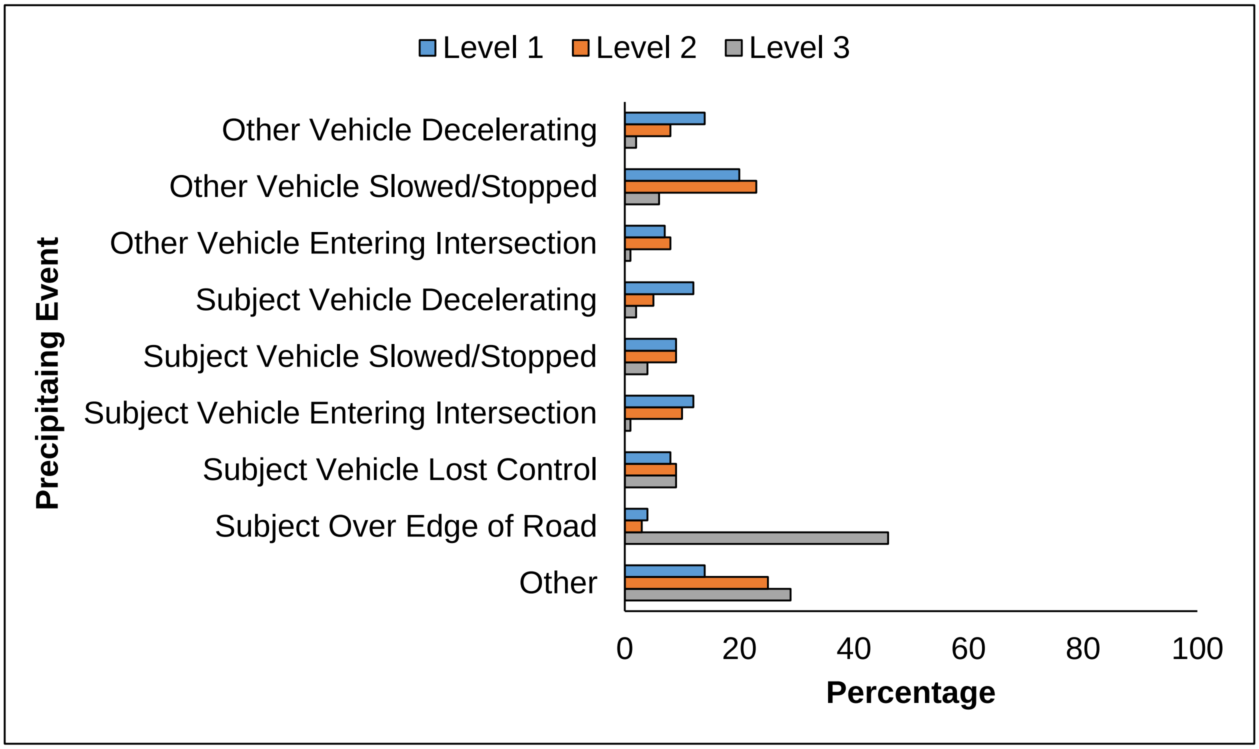

Figure 14. Precipitating Event

Driver Behavior

Driver behavior characterized the behaviors (those that either occurred within seconds prior to the precipitating event or those resulting from the context of the driving environment) that include what the driver did to cause or contribute to the crash or near-crash. Data reductionists coded for over 60 possible driver behaviors, including, but not limited to, distraction, drowsiness, lane drifting, speeding, braking-related errors, improper maneuvers, and aggressive driving.

For each type of NPR crash severity level, most of the drivers were involved in some type of behavior that may have contributed to the crash. For Levels 1 and 2, about 67 percent of the NPR crashes involved some type of driver behavior. For Level 3, about 77 percent involved some driver behavior. The most common behavior for all three was distraction. About 33 percent and about 31 percent of NPR crashes involved driver distraction for Levels 1 and 2, respectively. About 38 percent of NPR Level 3 crashes involved distraction. Percentages of NPR crashes with different types of driver behavior, stratified by crash severity level, are displayed in Figure 15.

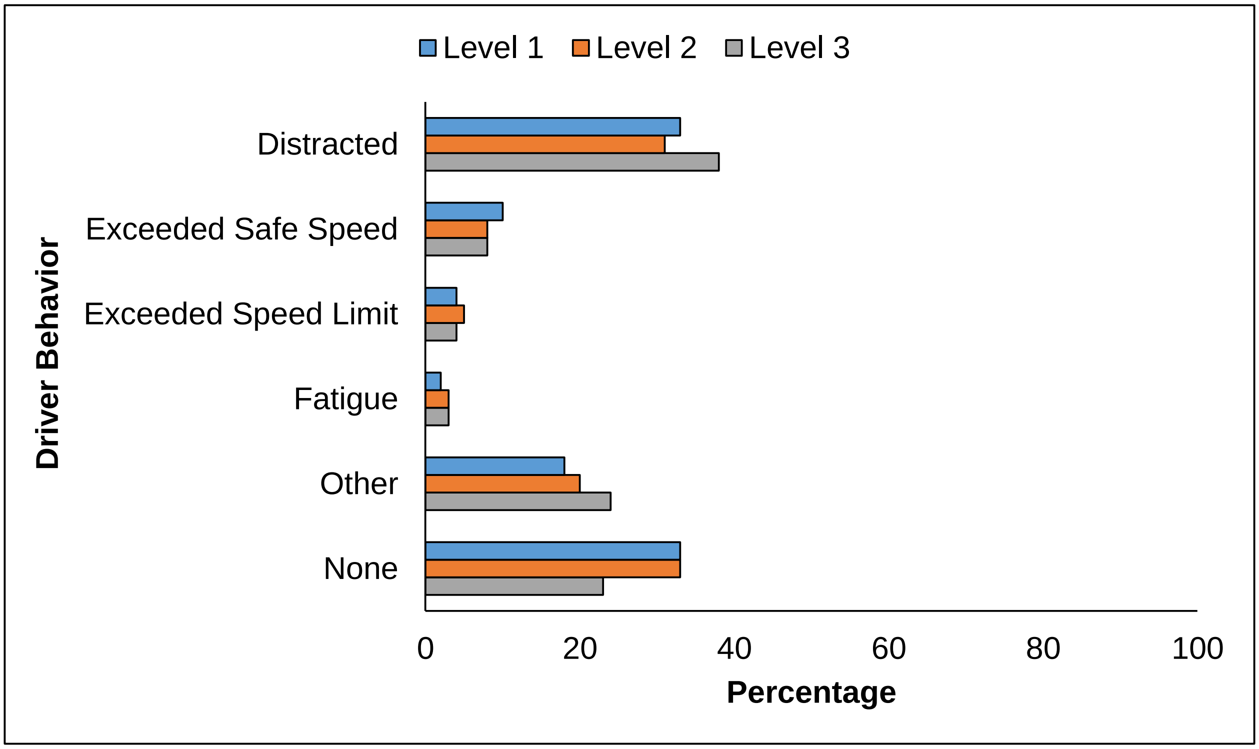

Figure 15. Driver Behavior

Driver Impairment

Driver impairment looks at fatigue, substance use, and other possible driver states that could interfere with safe driving. For all three crash levels for NPR crashes, almost all crashes did not involve driver impairment. For crash Levels 1 and 2, about 93 percent of the NPR crashes did not involve driver impairment. For Level 3 NPR crashes, about 94 percent did not involve driver impairment. For NPR crashes that did involve impairment, fatigue was the most common type for Levels 2 and 3 (about 3 percent for each). For Level 1, the most common impairment was substance abuse (about 4 percent). Percentages of driver impairment categories for NPR crashes, stratified by crash severity level, are displayed in Figure 16.

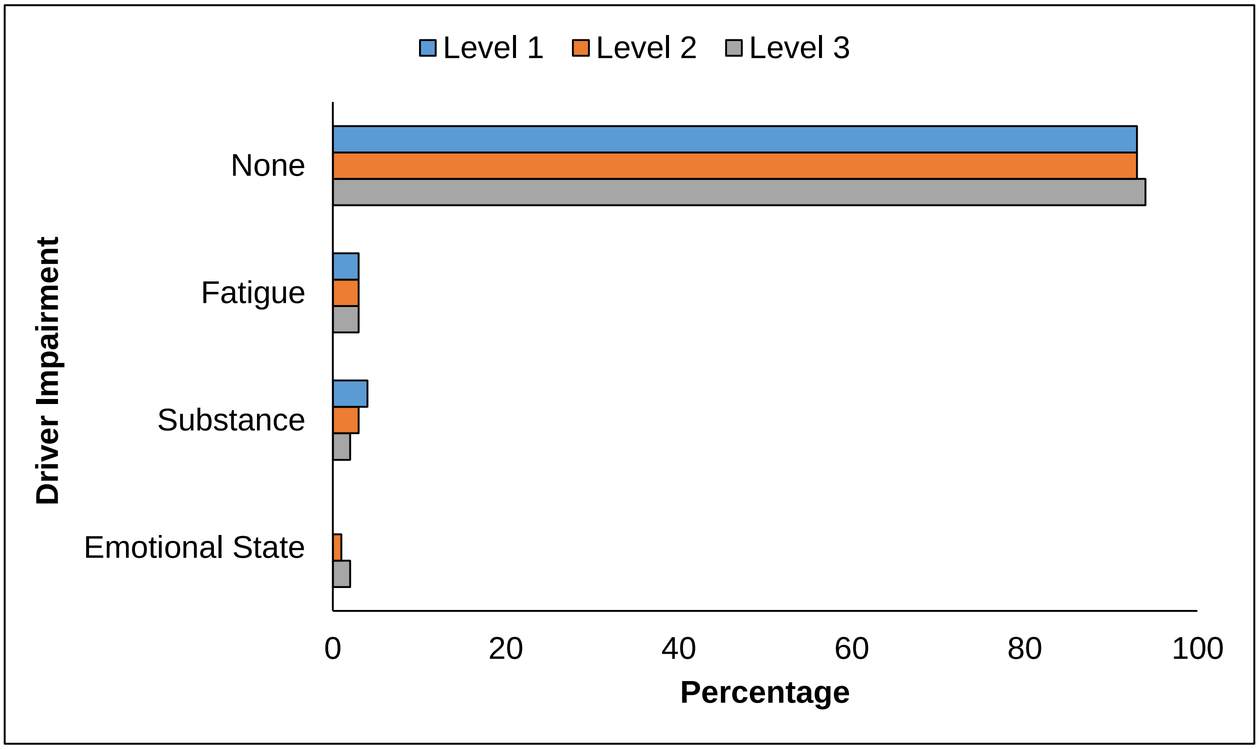

Figure 16. Driver Impairment

Chapter 7. Discussion and Conclusions

Determining the safety impacts of self-driving vehicles will become more important as these vehicles become more common on public roads. In order to assess how self-driving vehicles may alter the overall safety landscape, we need to understand the current risk of crashes and near-crashes better. To that end, this study assessed both the current national driving risk and the driving risk of self-driving cars.

Five research questions guided the study:

- Research Questions 1 and 2: How many crashes go unreported to police or insurance? Do unreported rates vary by location?
- Research Question 3: How is the comparison between crash rates for the Self-Driving Car and national crash rates affected by the percentage of unreported crashes and severity level?
- Research Question 4: How do crash rates vary based on street type and speed limit?
- Research Question 5: What are the factors contributing to unreported crashes?

This study examined these questions from three perspectives: (1) the total crash rate compared to the rate of crashes that are reported to the police, (2) the crash rates for different types of roadways, and (3) the scenarios that give rise to unreported crashes. First, the crash rates from the Google Self-Driving Car project were calculated. Self-Driving Car rates were then compared to rates developed using national databases, which draw upon police-reported crashes, and rates estimated from the SHRP 2 NDS. Second, SHRP 2 NDS data were used to calculate crash rates for different crash levels on different types of roads, broken down by the speed limit and locality (e.g., Urban Road, Interstate). Third, SHRP 2 NDS data were again used to describe various scenarios related to NPR crashes, such as whether driver distraction or impairment was involved, or whether these crashes were rear-end collisions or road departures.

The results of the analyses are summarized and presented below in terms of the research questions that framed the study.

Research Questions 1 and 2

How many crashes go unreported to police or insurance? Do unreported rates vary by location?

The rates of reported crashes across the geographic locations represented in the SHRP 2 database and two counties in California are similar. However, for PDO crashes small differences may exist between locations that have different damage thresholds for their reporting requirement.

Using published estimates and known rates of reported crashes from the SHRP 2 naturalistic driving data, at least 60 percent of PDO and 25 percent of injury crashes go unreported. Applying these percentages to the national average crash rate increases the rate from 1.9 to 4.2 per million miles traveled. It is important to take unreported crashes into consideration when analyses are done in the future. Since all crashes for manually operated vehicles are not reported, a fair comparison with automated vehicles, which must disclose all crashes, can only be made if unreported crashes are included.

Research Question 3

How is the comparison between crash rates for the Self-Driving Car and national crash rates affected by the percentage of unreported crashes and severity level?

Estimated crash rates for the Self-Driving Car project were lower for all three crash levels compared to estimated rates from SHRP 2 NDS data. Additionally, the rate of less-severe crashes (Level 3) for the Self-Driving Car was lower at a statistically significant level. Level 3 crash rates, with 95 percent confidence intervals, are displayed in Figure 17.

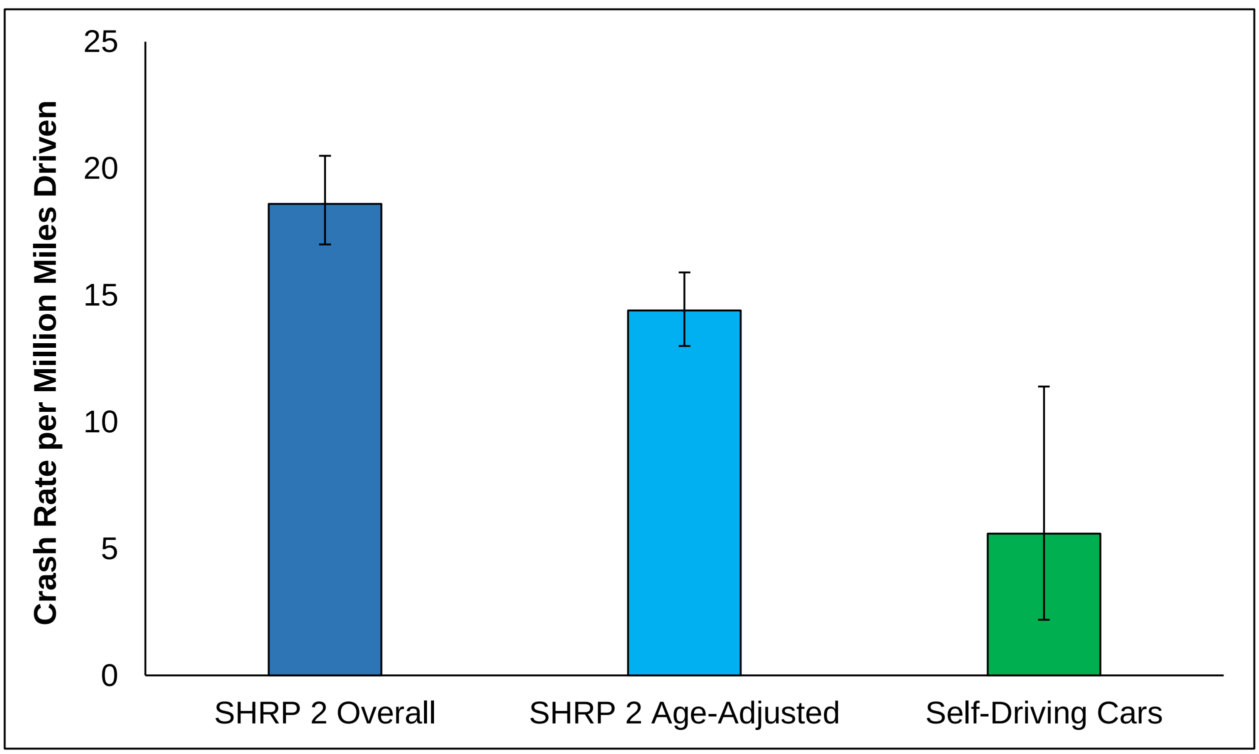

Figure 17. Level 3 Crash Rates

Research Question 4

How do crash rates vary based on speed type and speed limit?

Observed crash rates were highest at slower speeds and in urban areas, while they were lowest at higher speeds and on interstates. The highest crash rates occurred between 26 and 35 mph for Level 1 and Level 2 crashes (rates of 4.2 and 5.7 per million miles, respectively). For Level 3, the highest crash rates happened at speeds of 25 mph or less (crash rate of 41.5 per million miles). Urban areas had the highest crash rates (Table 9).

Table 9. Urban Area Crash Rates

Crash Level	Crash Rate per Million Miles
Level 1	**6.6**
Level 2	**8.9**
Level 3	**53.7**

Research Question 5

What are the factors contributing to unreported crashes?

Almost half of Level 1 and Level 2 NPR crashes (about 48 percent and about 46 percent, respectively) were rear-end collisions. More than half of Level 3 NPR crashes (about 61 percent) were roadway departures. Additionally, most NPR crashes were the fault of the subject driver, with about 60 percent at fault for Levels 1 and 2 and about 79 percent at fault for Level 3. Driver distraction was the most common type of driver behavior associated with NPR crashes. About 33 percent, 31 percent, and 38 percent of Level 1, 2, and 3 NPR crashes involved some level of driver distraction.

Summary

The advent of autonomous vehicles logically raises questions about their safety relative to manually operated vehicles. The answer depends on both the method used for estimating total crash rates and the severity of the crash. When compared to a national crash rate of 1.9 per million miles, Google's Self-Driving Car operating in autonomous mode has a higher crash rate of 8.7 per million miles. However, this statistic alone provides an incomplete representation of the results. Data obtained from sources that include all crashes (current Self-Driving Car project or NDS) must be compared to national crash rate estimates that control for unreported crashes (4.2 per million miles). Naturalistic datasets also offer the opportunity to calculate estimates. Crash rates based on the SHRP 2 NDS suggest that the crash rates for the Self-Driving Car operating in autonomous mode are lower (Table 10).

Table 10. SHRP 2 and Self-Driving Car Calculated Crash Rates per Million Miles Driven

Crash Severity	SHRP 2 Age-Adjusted Estimated Rate per Million Miles	Self-Driving Car Estimated Rate per Million Miles
Level 1	2.5	1.6
Level 2	3.3	1.6
Level 3	14.4	5.6

The limited exposure of the Self-Driving Car project to real-world driving increases statistical uncertainty in its crash rate. That uncertainty will decrease as it receives more on-road, in-traffic testing. Current data suggest that self-driving cars may have low rates of more-severe crashes (Level 1 and Level 2 crashes) when compared to national rates or to rates from naturalistic data sets. However, there is currently too much uncertainty to draw this conclusion with strong confidence. The data also suggest that less-severe events (Level 3 crashes) may happen at a significantly lower rate for self-driving cars. When the Self-Driving Car events were analyzed using methods developed for SHRP 2, none of the vehicles operating in autonomous mode were deemed at fault. This fact, together with the reduced crash rate for less-severe events (Level 3 crashes), represents a powerful finding. This is particularly appropriate for vehicles intended for lower-speed use, where less-severe events are the most likely to be encountered by the newer generation of the Self-Driving Car fleet.

Appendix A. Select SHRP 2 Reduction Dictionary Definitions

This appendix provides SHRP 2 reduction definitions for several of the key variables included as part of this analysis. For additional information regarding the reduction process and variable definitions, see the *SHRP 2 Researcher Dictionary for Video Reduction Data* (Version 3.4).

Table 11. Select SHRP 2 Researcher Dictionary Definitions

Variable # (*Baseline)	Variable Name	Variable Definition	GES Related Variable(s) (modified from GES)
6*	**Pre-Incident Maneuver**	This represents the last type of action or driving maneuver that the subject vehicle driver engaged in or was engaged in just prior to or at the time of the Precipitating Event, beginning anywhere up to 5 seconds before the Precipitating Event (V8). This variable is independent of the driver's engagement in secondary tasks and the Precipitating Event, but should be determined after the precipitating event is defined. It is a vehicle kinematic measure—based on what the vehicle does (movement and position of the vehicle), not on what the driver is doing inside the vehicle. For Baselines, this is the action or driving maneuver that the subject is engaged in for the last 2-6 seconds of the baseline epoch prior to the baseline anchor point (Event Start, V2), which occurs 1 second before the end of the baseline event.	V21 (Vehicle Maneuver/Movement Prior to Critical Event (Precrash 1))
7*	**Maneuver Judgement**	Judgment of the safety and legality of the Pre-Incident Maneuver (V6). This is a vehicle kinematic measure-based on what the vehicle does, independent of the driver's engagement in secondary tasks and the Precipitating Event (V8). (For example, driving while texting on a cell phone may not be safe or legal, but it is not a consideration in this variable.) Although the determination of whether the maneuver is safe or unsafe is situation dependent, the position of the vehicle itself is the main determinant of this factor, and a maneuver may or may not be safe, depending on the vehicle position.	

Variable # (*Baseline)	Variable Name	Variable Definition	GES Related Variable(s) (modified from GES)
8	**Precipitating Events**	The state of environment or action that began the event sequence under analysis. What environmental state or what action by the subject vehicle, another vehicle, person, animal, or non-fixed object was critical to this vehicle becoming involved in the crash or near-crash? This is a vehicle kinematic measure (based on what the vehicle does—an action, not a driver behavior). It does not include factors such as driver distraction, fatigue, or disciplining a child. This is the critical event which made the crash or near-crash possible. It may help to use the "but for" test: "but for this action, would the crash or near-crash have occurred?" This is independent of fault. For example, if Vehicle A is speeding when Vehicle B crosses Vehicle A's path, causing a crash, the Precipitating Event would be Vehicle B crossing Vehicle A's path. If two possible Precipitating Events occur simultaneously, choose the event that imparted the greatest effect on the crash or near-crash. If more than one sequential event contributed to the crash or near-crash, determination of which is the Precipitating Event depends upon whether the driver had enough time or vehicular control to avoid the latter event. If the driver avoids one event and immediately encounters another potentially harmful event (with no time or ability to avoid the latter), then the Precipitating Event is the first obstacle or event that was successfully avoided (this is where the critical envelope begins, and is the reference point for the other variables). If the driver had ample time or vehicular control to avoid the latter event, then that latter event would be coded as the Precipitating Event (the critical envelope would begin here, and all other variables would be coded based on this event). Note that a parking lot is considered a roadway—thus a barrier or light pole in the parking lot would be considered an object in the roadway.	V26 (Critical Event-Precrash 2 (Event))
9, 10,11	**Vehicle 1 (Subject) 2, 3 Configuration**	A numerical designation of the role and configuration of the vehicle or other non-motorists or objects at the time of their first involvement in the sequence of events. Configurations are depicted in Figure 1 in the dictionary and in the Accident Types chart in GES (2014). Vehicle 1 is the subject vehicle, Vehicle 2 is the first other vehicle involved in the study, and Vehicle 3 is the last vehicle to become involved. If more than three vehicles are involved, code the three vehicles at greatest risk.	V23 (Accident Type)

Variable # (*Baseline)	Variable Name	Variable Definition	GES Related Variable(s) (modified from GES)
12, 18	**Event Nature 1, 2**	Identifies the other object(s) of conflict (e.g., lead vehicle, following vehicle) for the crash or near-crash, or safety-related incident that occurred. If multiple Event Natures apply, list them in sequential order by time. If more than two apply, select the two most severe (most harmful or potentially most harmful). Determination of the nature of the event and the envelope surrounding it will lead to the determination of other variables such as pre-incident maneuver (V6) and precipitating event (V8). (Example 1: Subject vehicle that rear-ends a lead vehicle may then be rear-ended by a following vehicle. 1 = Conflict with lead vehicle; 2 = Conflict with following vehicle. Example 2: Subject vehicle avoids rear-ending a lead vehicle (near-crash) by steering off the road into a ditch (a crash). 1 = Conflict with lead vehicle; 2 = Single vehicle conflict. Example 3: Motorcyclist either avoids or fails to avoid rear-ending a lead vehicle by braking hard (near-crash or crash) followed by skidding and the motorcycle going down (crash). 1 = Conflict with lead vehicle; 2 = Single vehicle conflict). Figures 1 and 2 in the *Research Dictionary for Video Reduction Data* should be referenced when coding this variable.	A06 (First Harmful Event), A07 (Manner of Collision), E03 (Point of Impact (This Vehicle)), E05 (Point of Impact (Other Vehicle)), E06 (Action), V20 (Most Harmful Event), V23 (Accident Type (Category))
13, 19	**Incident Type 1, 2**	Identifies the type of conflict(s) that the subject vehicle has with other objects of conflict for the most severe type of crash, near-crash, or safety-related incident that occurred. If multiple Incident Types apply, list them in sequential order by time, correlating with the Event Natures listed in Variables 12 and 18. If more than two apply, select the two most severe (most harmful or potentially most harmful). For categories not involving pedestrians, pedal cyclists, or animals, the orientation of the vehicle(s) is also indicated. However, unless the subject vehicle is specified, "vehicle" may refer to any vehicle involved in the event. (Example 1: A subject vehicle that rear-ends a lead vehicle may then be rear-ended by a following vehicle. 1 = Rear-end, striking; 2 = Rear-end, struck. Example 2: Subject vehicle avoids rear-ending a lead vehicle (near-crash) by steering off the road into a ditch (a crash). 1 = Rear-end, striking (the near-crash); 2 = Run-off-road (the crash). Figures 1 and 2 in the *Research Dictionary for Video Reduction Data* should be referenced when coding this variable.	A07 (Manner of Collision), V23 (Accident Type (Category))
14*, 10	**Event Severity 1, 2**	General term describing the outcome of the event/incident type(s) listed. Denotes the outcome of each event/incident type as a Crash, Near-crash, Crash Relevant, Non-Conflict, or Non-Subject Conflict. For Baselines, only one variable is listed, and it is coded Baseline.	GES codes only crashes—groups them according to type of vehicle(s) involved, vehicle damage, and individual injury type.

Variable # (*Baseline)	Variable Name	Variable Definition	GES Related Variable(s) (modified from GES)
15, 21	**Crash Severity 1, 2**	A ranking of crash severity for the referenced event/incident type(s) based on the magnitude of vehicle dynamics, the presumed amount of property damage, knowledge of human injuries (often unknown in this dataset) and the level of risk posed to the drivers and other road users. This variable is coded only for events that include a Crash. • **Level 1:** Crashes that include airbag deployment, injury, rollover, high Delta-V crashes or towing. High Delta-V is defined as a change in speed of the subject vehicle in any direction during impact greater than 20 mph (excluding curb strikes) or acceleration on any axis greater than ± 2 g (excluding curb strikes) • **Level 2:** Crashes that do not meet the requirements for a Level 1 crash. Includes sufficient property damage that one would anticipate that it is reported to authorities (minimum of $1,500 worth of damage, as estimated from video). Also includes crashes that reach an acceleration on any axis greater than ± 1.3 g (excluding curb strikes). Most large animal strikes and sign strikes are considered Level 2. • **Level 3:** Crashes involving physical conflict with another object (but with minimal damage) that do not meet the requirements for a Level 1 or Level 2 crash. Includes most road departures (unless criteria for a more severe crash are met), small animal strikes, all curb and tires strikes potentially in conflict with oncoming traffic, and other curb strikes with an increased risk element (e.g., would have resulted in worse had curb not been there, usually related to some kind of driver behavior or state, for example, hitting a guardrail at low speeds). • Level 4: Tire strike only with little/no risk element (e.g., clipping a curb during a tight turn).	
24	**Airbag Deployment**	An indication of whether the driver side airbag or any other airbag in the vehicle was deployed during the crash. If Yes, the event is also classified as a Level 1 Crash in Crash Severity.	
25	**Vehicle Rollover**	An indication of whether the subject vehicle rolled over during the crash. If Yes, the event is also classified as a Level 1 Crash in Crash Severity.	
26*, 27*, 28*	**Driver Behavior 1,2,3**	Driver behaviors (those that either occurred within seconds prior to the Precipitating Event or those resulting from the context of the driving environment) that include what the driver did to cause or contribute to the crash or near-crash. Behaviors may be apparent at times other than the time of the Precipitating Event, such as aggressive driving at an earlier moment which led to retaliatory behavior later. If there are more than three behaviors present, select the most critical or those that most directly impact the event as defined by event outcome or proximity in time to the event occurrence. Populate this variable in numerical order. (If there is only one behavior, name it Behavior 1; if there are two, name them Behaviors 1 and 2.) NOTE: The Driver Behavior category “Distracted” is only used for Critical Event analysis in cases where a secondary task (V32, V36, V40)clearly contributed to the event. The Distracted category is omitted from Baseline analysis.	No GES/ VA PAR Variable 17/18

Variable # (*Baseline)	Variable Name	Variable Definition	GES Related Variable(s) (modified from GES)
29*	**Driver Impairments**	Possible reasons for the observed driver behavior(s), judgment, or driving ability. More than one category may be assigned.	P18 (Person's Physical Impairments (Drivers)), P11 (Police-Reported Alcohol Involvement), P17 (Police-Reported Drug Involvement) [NOTE: GES does not account for the conditions "anger" and "other emotional state."]
32*, 36*, 40*	**Secondary Task 1, 2, 3, 4**	Observable driver engagement in any of the listed secondary tasks, beginning at any point during the 5 seconds prior to the Precipitating Event time (Conflict Begin, Variable 2) through the end of the conflict (Conflict End). For Baselines, secondary tasks are coded for the last 6 seconds of the baseline epoch, which includes 5 seconds prior to Event Start through one second after (to the end of the baseline). Distractions include non-driving related glances away from the direction of vehicle movement. Does not include tasks that are critical to the driving task, such as speedometer checks, mirror/blind spot checks, activating wipers/headlights, or shifting gears. Other non-critical tasks are included, including radio adjustments, seatbelt adjustments, window adjustments, and visor and mirror adjustments. Note that there is no lower limit for task duration. If there are more than three secondary tasks present, select the most critical or those that most directly impact the event, as defined by event outcome or proximity in time to the event occurrence. Populate this variable in numerical order. (If there is only one distraction, name it Secondary Task 1; if there are two, name them Secondary Task 1 and 2. Enter "No Additional Secondary Tasks" for remaining Secondary Task variables.)	D07 (Driver Distracted By)
56	**Traffic Density**	The level of traffic density at the time of the start of the Precipitating Event. Based entirely on number of vehicles present in the subject's travel lane and other lanes in the subject's direction of travel, and the ability of the subject vehicle driver to maneuver between lanes and select the driving speed. In Variable Speed zones, consider a reduced speed limit to be an indicator of traffic density (e.g., a variable speed limit of 30 mph on an Interstate should be interpreted as a 50% reduction in travel speeds). Note that this variable is "Not Applicable" in Parking Lot (except for parking lot entrance/exit areas that are still influenced by through traffic) and other non-road situations.	

Variable # (*Baseline)	Variable Name	Variable Definition	GES Related Variable(s) (modified from GES)
62*	**Locality**	Best description of the surroundings that influence or may influence the flow of traffic at the time of the start of the precipitating event. If there are ANY commercial buildings, indicate as business/industrial or urban area as appropriate (these categories take precedence over others except for church, school, and playground). Indicate school, church, or playground if the driver passes one of these areas (or is imminently approaching one) at the same time as the beginning of the Precipitating Event (these categories take precedence over any other categories except urban, and divided highway).	No GES/VA PAR Variable
66	**Fault**	Indicates which driver or non-motorist (if any) committed an error that led to the event. If another motorist or non-motorist (other than the subject) committed the error leading to the event, label that other vehicle or non-motorist as Driver 2 or 3, in accordance with the Vehicle Configurations (V9, V10, V11). Only code a fault if there is observable evidence. Note: Objects and animals cannot be assigned fault.	
95*	**Final Narrative/ Additional Notes**	For critical event reduction, this is a “Final Narrative,” or a short, open-ended description of the event. This variable provides context and descriptions in sufficient detail so as to fill any gaps in reconstructing the event if video were not available. It should always be clear in the written narrative which vehicle is the subject vehicle (SV, Vehicle 1, V1, or “subject vehicle”) and which are the other vehicle(s) (POV or Vehicle 2/3).The narrative includes the following: 1. A description of the most relevant aspects of the environment and traffic dynamics prior to the crash, 2. A description of the sequence of events, focusing in particular on discrepancies between the subject vehicle driver’s activity/state (e.g., driver expectations, eyes off road, impairment) and the environmental context (e.g., the driver looks away while the lead vehicle brakes), and 3. Any other relevant aspects that are not covered by other variables. For Baselines, this variable is “Additional Notes,” only completed when additional information is needed that was not captured in the previous variables.	

Appendix B. Descriptive Narratives of Self-Driving Car Events

Table 12 provides a summary of events involving the Self-Driving Car (Google Self-Driving Car Project, 2015).

Table 12. Descriptive Narratives of Self-Driving Car Events

Event Date	Event Summary
5/2010	A Google Prius model autonomous vehicle (AV) operating in manual mode was involved in an accident on Central Expressway in Mountain View, CA. The Google AV was stopped at a traffic light at Ferguson Drive and was rear-ended by another vehicle. No injuries were reported at the scene. The Google AV sustained some damage.
8/2011	A Google Prius model AV operating in manual mode was involved in an accident on Charleston Road in Mountain View, CA. An employee operating the Google AV to run an errand (i.e., he was not using the vehicle to test our autonomous technology) rear-ended a vehicle that was stopped in traffic. No injuries were reported at the scene. The Google AV sustained some damage.
10/2012	A Google Prius model AV operating in autonomous mode was involved in an accident on Amphitheatre Parkway in Mountain View. The Google AV was stopped at a traffic light and was rear-ended by another vehicle. No injuries were reported at the scene. The Google AV sustained some damage.
12/2012	A Google Lexus model AV operating in manual mode was involved in an accident while driving on Highway 101S in Mountain View near the Moffett exit. The Google AV was driving past a disabled vehicle and emergency vehicles, which were stationary on the shoulder, when it was rear-ended by another vehicle traveling at approximately 20-25 mph. No injuries were reported at the scene. The rear of the Google AV sustained some damage.
3/2013	A Google Lexus model AV operating in autonomous mode was involved in an accident while driving on highway 680S in San Jose. The Google AV was driving at 63 mph when another vehicle traveling in the adjacent right hand lane veered into the side of the Google AV. At the time of impact, the test driver took immediate manual control of the Google AV via the steering wheel. No injuries were reported at the scene. The Google AV sustained some damage.
10/2013	A Google Lexus model AV operating in manual mode on Rengstorff Avenue in Mountain View was involved in an accident. The Google AV was traveling at 2 mph, gradually slowing to a stop at an intersection, when it was rear-ended by another vehicle. No injuries were reported at the scene. The Google AV sustained some damage.
3/2014	A Google Lexus model AV operating in autonomous mode traveling on Highway 101N near Belmont was involved in an accident. The Google AV was stopped in traffic when it was rear-ended by another vehicle. The vehicle that struck the Google AV was initially hit from behind by another vehicle. No injuries were reported at the scene. The Google AV sustained some damage.
7/2014	A Google Lexus model AV operating in manual mode was involved in an accident on Phyllis Avenue in Mountain View. The Google AV was stopped on Phyllis Avenue waiting to make a right turn onto Grant Avenue when another vehicle struck the rear bumper of the Google AV. No injuries were reported at the scene. The Google AV sustained some damage.

Event Date	Event Summary
2/2015	A Google Lexus model AV was traveling northbound on El Camino Real in autonomous mode when another vehicle traveling westbound on View Street failed to come to a stop at the stop sign at the intersection of El Camino and View Street. The other vehicle rolled through the stop sign and struck the right rear quarter panel and right rear wheel of the Google AV. Prior to the collision, the Google AV's autonomous technology began applying the brakes in response to its detection of the other vehicle's speed and trajectory. Just before the collision, the driver of the Google AV disengaged autonomous mode and took manual control of the vehicle in response to the application of the brakes by the Google AV's autonomous technology. The Google AV was in manual mode. No injuries were reported at the scene. The Google AV sustained some damage.
4/2015 #1	A Google Lexus model AV was involved in an accident in Mountain View while travelling northbound on Castro St and making a right turn onto El Camino eastbound. The car was operating in autonomous mode at the time of the accident. The Google AV was travelling northbound in the rightmost lane of Castro St and came to a complete stop for a red light at the intersection of Castro St and El Camino Real. The Google AV then proceeded to make a right turn on red by creeping forward to obtain a better field of view of cross traffic on El Camino Real approaching from the left. While creeping forward, the Google AV detected a vehicle approaching eastbound on El Camino Real and came to a stop in order to yield to the approaching vehicle. The Google AV was just starting to move (<1 mph) when the vehicle following immediately behind it, which was also attempting to make a right turn onto El Camino Real, failed to brake sufficiently and struck the Google AV's bumper at approximately 5 mph. All occupants of both vehicles involved were uninjured in the collision. The Google AV sustained minimal body damage and the other vehicle sustained no visible body damage.
4/2015 #2	A Google Lexus model AV was stopped for a red light at an intersection of California Street and Shoreline Boulevard in Mountain View when another vehicle tried to pass from behind on the right side of the Google AV. The driver of the other vehicle slightly brushed one of the sensors on the Lexus AV with its driver side mirror. The Google AV was in autonomous mode. No injuries were reported at the scene, and there was no damage to either the sensor or either vehicles.
5/2015	A Google Lexus model AV was travelling southbound on Shoreline Boulevard in Mountain View in autonomous mode and was stopped behind traffic at a red light at the intersection of Shoreline Boulevard and El Camino Real. A vehicle approaching from behind collided with the rear bumper and sensor of the Google AV. The approximate speed of the other vehicle at the time of impact was 1 mph. There were no injuries reported at the scene by either party. The Google AV sustained minor damage to its rear sensor and bumper. There was no visible damage to the other vehicle.
6/2015 #1	A Google Lexus model autonomous vehicle ("Google AV") was traveling westbound on California St. in Mountain View in autonomous mode and was stopped behind traffic at a red light at the intersection of California St. and Rengstorff Ave. A vehicle approaching from behind collided with the rear bumper of the Google AV. The Google AV was stopped for approximately 17 seconds prior to the collision. The approximate speed of the other vehicle at the time of impact was <1 mph. There were no injuries reported at the scene by either party. The Google AV sustained no damage and there was no visible damage to the other vehicle.
6/2015 #2	A Google Lexus model autonomous vehicle ("Google AV") was traveling northbound on California St. in Mountain View in autonomous mode and was stopped at a red light in the straight-only lane at the intersection of California St. and Bryant St. The lane to the left of the Google AV was a left-turn-only lane. The vehicle waiting immediately behind the Google AV in the straight-only lane began to move forward when the green arrow left turn signal appeared (despite the signal for the straight-only lane remaining red) and collided with the rear bumper of the Google AV. The Google AV had been stopped for about 11 seconds at the time of impact. The other vehicle was traveling about 5 mph at the time of impact. There were no injuries reported at the scene by either party. The Google AV sustained minor damage (scrapes) to its rear bumper. The other vehicle sustained minor damage (scrapes) to its front bumper.

Event Date	Event Summary
7/2015	A Google Lexus model autonomous vehicle ("Google AV") was traveling northbound on Grant Rd. in Mountain View approaching the intersection of Phyllis Ave. and Martens Ave. in autonomous mode. The two vehicles in front of the Google AV, the Google AV, and the vehicle behind the Google AV were all traveling at a steady speed of ~15 mph. While approaching a green light intersection with stopped traffic on the other side of the intersection, the first vehicle decelerated and came to a stop, keeping clear of the intersection. The vehicle directly in front of the Google AV and the Google AV also decelerated and came to a stop with adequate and similar stopping distances. About 1 second later, the vehicle approaching from the rear struck the Google AV at ~17 mph and did not appear to decelerate prior to the collision. At the time of the incident, the driver, co-driver and rear passenger of the Google AV reported some whiplash. They were driven by other team members to a local hospital, where they were evaluated by medical staff and cleared to return to work. The driver of the other vehicle reported minor neck and back pain. The Google AV sustained minor damage to its rear bumper. The other vehicle sustained significant damage to its front end.
8/2015	A Google Lexus autonomous vehicle ("Google AV") operating in autonomous mode and traveling northbound on Shoreline Blvd. in Mountain View in lane two (the second of three lanes) was involved in an accident. As the Google AV approached the intersection of Shoreline Blvd. and High School Way, a pedestrian began to cross the northbound lanes of Shoreline Blvd. in the crosswalk traveling westbound. The Google AV slowed to yield as it approached the crosswalk, and out of an abundance of caution the Google AV test driver disengaged the autonomous technology and took control of the vehicle. A vehicle in lane three to the immediate right of, and traveling in the same direction as, the Google AV was already stopped and yielding the right of way to the pedestrian. A vehicle in the process of changing lanes from lane one into lane two and approaching from the rear struck the Google AV. The Google AV was traveling 5 mph at the time of impact, and braking to stop for the crosswalk. The other vehicle was traveling approximately 10 mph at the time of impact. The Google AV test driver reported minor back pain and was taken to a local hospital by Google employees, where he was evaluated and released by medical staff. The Google AV co-test driver did not report any injuries. The Google AV sustained minor damage to its rear left bumper. The other vehicle sustained moderate damage to its front end and was towed from the scene. The driver of the other vehicle did not report any injuries at the scene.

Appendix C. Supplemental Crash Rate Calculation Information

Reported and Unreported Crash Tables

The following tables contain the available reported crash data for years 2009-2015 for all locations, including the national average rates. Also included are the reported Vehicle Miles Traveled (VMT), subtotals for unreported crashes, and the estimates for Total Crash Rate. All rates are per million miles traveled.

National Average

Table 13. National Average Crash Rate

Year	Fatal	Injury	PDO	Total	VMT	Overall Reported Rate
2013	30,057	1,591,000	4,066,000	5,687,057	2,965,600,000,000	1.92

Table 14. National Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2013	280,765	530,333	2,189,385	6,099,000	23,040,667	8,157,206	12,316,390	29,258,057

Table 15. National Total Crash Rate

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2013	2.75	4.15	9.87

Santa Clara County, CA

Table 16. Santa Clara Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2009	88	6,464	8,486	15,038	14,857,938,291	1.01
2010	81	6,873	8,543	15,497	14,857,938,291	1.04
2011	91	6,788	7,990	14,869	14,857,938,291	1.00
2012	83	6,640	7,620	14,343	14,857,938,291	0.97
2013	93	6,579	7,447	14,119	14,857,938,291	0.95
2014	103	6,227	6,755	13,085	14,857,938,291	0.88
Average	90	6,595	7,807	14,492	14,857,938,291	0.98

Table 17. Santa Clara Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	1,141	2,155	4,569	12,729	48,087	21,762	29,922	65,280
2010	1,213	2,291	4,600	12,815	48,410	22,388	30,603	66,198
2011	1,198	2,263	4,302	11,985	45,277	21,434	29,117	62,408
2012	1,172	2,213	4,103	11,430	43,180	20,659	27,986	59,736
2013	1,161	2,193	4,010	11,171	42,200	20,322	27,483	58,512
2014	1,099	2,076	3,637	10,133	38,278	18,798	25,293	53,439
Average	1,164	2,198	4,204	11,710	44,239	19,860	28,401	60,929

Table 18. Santa Clara Total Crash Rate

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2009	1.46	2.01	4.39
2010	1.51	2.06	4.46
2011	1.44	1.96	4.20
2012	1.39	1.88	4.02
2013	1.37	1.85	3.94
2014	1.27	1.70	3.60
Average	1.34	1.91	4.10

Los Angeles County, CA

Table 19. Los Angeles County Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2009	554	50,817	77,444	128,815	78,023,686,169	1.65
2010	531	50,204	77,758	128,493	78,023,686,169	1.65
2011	514	50,529	76,970	128,013	78,023,686,169	1.64
2012	585	50,661	73,140	124,386	78,023,686,169	1.59
2013	587	50,965	72,165	123,717	78,023,686,169	1.59
2014	605	51,296	71,579	123,480	78,023,686,169	1.58
Average	563	50,745	74,843	126,151	78,023,686,169	1.62

Table 20. Los Angeles Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	8,968	16,939	41,701	116,166	438,849	187,455	261,920	584,603
2010	8,860	16,735	41,870	116,637	440,629	187,097	261,865	585,856
2011	8,917	16,843	41,445	115,455	436,163	186,301	260,311	581,019
2012	8,940	16,887	39,383	109,710	414,460	180,656	250,983	555,733
2013	8,994	16,988	38,858	108,248	408,935	179,563	248,953	549,640
2014	9,052	17,099	38,543	107,369	405,614	179,121	247,947	546,193
Average	8,955	16,915	40,300	112,264	424,108	175,406	255,330	567,174

Table 21. Los Angeles Total Crash Rates

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2009	2.40	3.36	7.49
2010	2.40	3.36	7.51
2011	2.39	3.34	7.45
2012	2.32	3.22	7.12
2013	2.30	3.19	7.04
2014	2.30	3.18	7.00
Average	2.25	3.27	7.27

Monroe County, IN

Table 22. Monroe County Reported Crashes

Reported Crashes					VMT
Year	Fatal	Injury	PDO	Total	
2009	7	873	3,133	4,013	N/A
2010	13	918	3,122	4,053	N/A
2011	10	824	3,081	3,915	N/A
2012	9	940	3,274	4,223	N/A
2013	5	783	3,276	4,064	N/A
2014	7	817	3,343	4,167	N/A
Average	9	859	3,205	4,073	N/A

Table 23. Monroe County Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	154	291	1,687	4,700	17,754	5,991	9,004	22,058
2010	162	306	1,681	4,683	17,691	6,040	9,042	22,050
2011	145	275	1,659	4,622	17,459	5,849	8,811	21,649
2012	166	313	1,763	4,911	18,553	6,299	9,447	23,089
2013	138	261	1,764	4,914	18,564	6,089	9,239	22,889
2014	144	272	1,800	5,015	18,944	6,239	9,454	23,383
Average	152	286	1,726	4,807	18,161	5,950	9,166	22,520

Indiana State Data

Table 24. Indiana State Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2009	631	33,410	155,620	189,661	76,628,000,000	2.48
2010	700	34,147	158,532	193,379	75,760,000,000	2.56
2011	675	32,789	154,989	188,453	76,485,000,000	2.47
2012	720	34,132	154,308	189,160	78,923,000,000	2.41
2013	710	32,846	159,649	193,205	78,311,000,000	2.48
2014	702	33,823	171,007	205,532	77,221,400,000	2.67
Average	690	33,525	159,018	193,232	77,221,400,000	2.51

Table 25. Indiana State Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	5,896	11,137	83,795	233,430	881,847	285,224	434,859	1,083,275
2010	6,026	11,382	85,363	237,798	898,348	290,825	443,259	1,103,809
2011	5,786	10,930	83,456	232,484	878,271	283,513	432,541	1,078,329
2012	6,023	11,377	83,089	231,462	874,412	284,346	432,719	1,075,669
2013	5,796	10,949	85,965	239,474	904,678	290,829	444,337	1,109,541
2014	5,969	11,274	92,081	256,511	969,040	309,589	474,019	1,186,548
Average	5,916	11,175	85,625	238,526	901,099	285,462	443,622	1,106,195

Table 26. Indiana State Total Crash Rates

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2009	3.72	5.67	14.14
2010	3.84	5.85	14.57
2011	3.71	5.66	14.10
2012	3.60	5.48	13.63
2013	3.71	5.67	14.17
2014	4.01	6.14	15.37
Average	3.70	5.74	14.32

Erie County, NY

Table 27. Erie County Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2009	56	7,096	9,575	16,727	9,248,000,000	1.81
2010	50	7,214	10,125	17,389	9,248,000,000	1.88
2011	44	6,781	10,103	16,928	9,248,000,000	1.83
2012	51	6,422	9,588	16,061	9,248,000,000	1.74
2013	52	6,406	10,135	16,593	9,248,000,000	1.79
Average	51	6,784	9,905	16,740	9,248,000,000	1.81

Table 28. Erie County Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	1,252	2,365	5,156	14,363	54,258	24,248	33,455	73,351
2010	1,273	2,405	5,452	15,188	57,375	25,246	34,981	77,169
2011	1,197	2,260	5,440	15,155	57,250	24,628	34,343	76,439
2012	1,133	2,141	5,163	14,382	54,332	23,364	32,584	72,534
2013	1,130	2,135	5,457	15,203	57,432	24,186	33,931	76,160
Average	1,197	2,261	5,334	14,858	56,129	23,270	33,859	75,130

Table 29. Erie County Total Crash Rates

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2009	2.62	3.62	7.93
2010	2.73	3.78	8.34
2011	2.66	3.71	8.27
2012	2.53	3.52	7.84
2013	2.62	3.67	8.24
Average	2.52	3.66	8.12

Durham County, NC

Table 30. Durham County Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2009	16	2,002	5,406	7,424	3,300,000,000	2.25
2010	21	1,903	5,331	7,255	3,254,000,000	2.23
2011	12	2,027	5,698	7,737	3,222,000,000	2.40
2012	22	2,286	5,753	8,061	3,210,000,000	2.51
2013	24	2,246	5,950	8,220	3,643,000,000	2.26
2014	24	2,287	6,341	8,652	3,643,000,000	2.37
Average	20	2,125	5,747	7,892	3,378,666,667	2.29

Table 31. Durham County Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	353	667	2,911	8,109	30,634	11,002	16,200	38,725
2010	336	634	2,871	7,997	30,209	10,760	15,886	38,098
2011	358	676	3,068	8,547	32,289	11,481	16,960	40,701
2012	403	762	3,098	8,630	32,600	11,921	17,453	41,423
2013	396	749	3,204	8,925	33,717	12,173	17,894	42,685
2014	404	762	3,414	9,512	35,932	4,201	10,298	36,719
Average	375	708	3,094	8,620	32,564	11,210	17,068	41,012

Table 32. Durham County Total Crash Rates

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2009	3.33	4.91	11.73
2010	3.31	4.88	11.71
2011	3.56	5.26	12.63
2012	3.71	5.44	12.90
2013	3.34	4.91	11.72
2014	1.15	2.83	10.08
Average	3.32	5.05	12.14

King County, WA

Table 33. King County Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2010	78	11,114	23,116	34,308	15,959,974,000	2.15
2011	72	11,000	22,744	33,816	15,959,974,000	2.12
2012	85	11,576	22,071	33,732	15,959,974,000	2.11
2013	77	11,187	22,854	34,118	15,959,974,000	2.14
Average	78	11,219	22,696	33,994	15,959,974,000	2.13

Table 34. King County Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2010	1,961	3,705	12,447	34,674	130,991	50,460	72,687	169,003
2011	1,941	3,667	12,247	34,116	128,883	49,729	71,599	166,365
2012	2,043	3,859	11,884	33,107	125,069	49,475	70,697	162,660
2013	1,974	3,729	12,306	34,281	129,506	50,153	72,128	167,353
Average	1,980	3,740	12,221	34,044	128,612	48,194	71,778	166,345

Table 35. King County Total Crash Rates

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2010	3.16	4.55	10.59
2011	3.12	4.49	10.42
2012	3.10	4.43	10.19
2013	3.14	4.52	10.49
Average	3.02	4.50	10.42

Centre County, PA

Table 36. Centre County Reported Crashes

Reported Crashes					VMT
Year	Fatal	Injury	PDO	Total	
2009	12	618	632	1,262	N/A
2010	11	621	576	1,208	N/A
2011	18	618	684	1,320	N/A
2012	13	596	678	1,287	N/A
2013	11	557	674	1,242	N/A
2014	11	552	647	1,210	N/A
Average	13	594	649	1,255	N/A

Table 37. Centre County Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	109	206	340	948	3,581	1,820	2,428	5,061
2010	110	207	310	864	3,264	1,736	2,290	4,690
2011	109	206	368	1,026	3,876	1,912	2,570	5,420
2012	105	199	365	1,017	3,842	1,864	2,516	5,341
2013	98	186	363	1,011	3,819	1,802	2,450	5,258
2014	97	184	348	971	3,666	1,753	2,376	5,071
Average	105	198	349	973	3,675	1,721	2,438	5,140

Pennsylvania State

Table 38. Pennsylvania State Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2009	1,143	61,875	58,224	121,242	103,880,000,000	1.18
2010	1,208	62,666	57,438	121,312	100,329,000,000	1.22
2011	1,191	62,788	61,416	125,395	99,202,000,000	1.28
2012	1,211	62,127	60,754	124,092	98,884,000,000	1.27
2013	1,117	59,917	63,115	124,149	98,600,000,000	1.27
2014	1,107	57,652	62,558	121,317	98,600,000,000	1.24
Average	1,163	61,171	60,584	122,918	99,915,833,333	1.24

Table 39. Pennsylvania State Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2009	10,919	20,625	31,351	87,336	329,936	174,361	230,346	472,946
2010	11,059	20,889	30,928	86,157	325,482	174,337	229,566	468,891
2011	11,080	20,929	33,070	92,124	348,024	180,585	239,639	495,539
2012	10,964	20,709	32,714	91,131	344,273	178,726	237,143	490,285
2013	10,574	19,972	33,985	94,673	357,652	179,223	239,911	502,890
2014	10,174	19,217	33,685	93,837	354,495	175,326	235,478	496,137
Average	10,795	20,390	32,622	90,876	343,310	167,498	235,347	487,781

Table 40. Pennsylvania State Total Crash Rates

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2009	1.68	2.22	4.55
2010	1.74	2.29	4.67
2011	1.82	2.42	5.00
2012	1.81	2.40	4.96
2013	1.82	2.43	5.10
2014	1.78	2.39	5.03
Average	1.68	2.36	4.88

Hillsborough County, FL

Table 41. Hillsborough County Reported Crashes, VMT, and Crash Rate

Reported Crashes					VMT	Overall Reported Rate
Year	Fatal	Injury	PDO	Total		
2011	140	10,477	7,399	18,016	12,538,443,135	1.45
2012	172	10,934	9,119	20,225	12,432,497,505	1.64
2013	166	11,195	10,060	21,421	12,634,318,780	1.71
2014	142	11,863	11,020	23,025	13,035,653,070	1.78
Average	155	11,117	9,400	20,672	12,660,228,123	1.65

Table 42. Hillsborough County Unreported Crash Estimates

Year	Unreported Crashes					Total Crash Estimates		
	15% Injury	25% Injury	35% PDO	60% PDO	85% PDO	Low	Moderate	High
2011	1,849	3,492	3,984	11,099	41,928	25,632	32,747	63,576
2012	1,930	3,645	4,910	13,679	51,674	28,952	37,720	75,716
2013	1,976	3,732	5,417	15,090	57,007	30,736	40,409	82,325
2014	2,093	3,954	5,934	16,530	62,447	33,055	43,651	89,568
Average	1,962	3,706	5,061	14,099	53,264	27,850	38,632	77,796

Table 43. Hillsborough County Total Crash Rates

Year	Estimated Total Crash Rates		
	Low	Moderate	High
2011	2.04	2.61	5.07
2012	2.33	3.03	6.09
2013	2.43	3.20	6.52
2014	2.54	3.35	6.87
Average	2.20	3.05	6.14

Rate Estimation

The method used to estimate various overall crash rates was to take the ratio of the sums of each crash type. Formally, let R be the crash ratio of interest. Then

$$R = \frac{\sum_{i=1}^{n} A_i}{\sum_{i=1}^{n} D_i}$$

where $\sum_{i=1}^{n} A_i$ is the sample sum of crash types A and $\sum_{i=1}^{n} D_i$ is the total sample distance driven, and n is the total sample size in SHRP 2.

The method used to weight crash rates by age group is described in this appendix. The weighting procedure is based on the fact that younger drivers (<25 years) and older drivers (>75 years) are oversampled in the SHRP 2 dataset. Therefore, drivers in the above age groups are overrepresented in SHRP 2, and other drivers underrepresented, compared to the national driving population.

In order to provide more reliable estimated crash rates based on the SHRP 2 data, the rates were computed separately for different age groups, and weighted sums of these computed to arrive at age-weighted estimates. The five age groups used in this study were 16-24, 25-39, 40-54, 55-74, and 75+. The youngest and oldest age groups represent the oversampled age groups, and the three middle age groups each represent a combination of three or four FHWA (2011, 2012, and 2013) age groups. These age groups were combined to strike a balance between separating these ages in a relevant fashion and maintaining adequate sample sizes for more stable estimations. Note that due to sample size constraints, age group was the only demographic variable used to stratify the results, as age group was the most likely variable to bias results based on the sample proportion being unequal to the population proportion.

Sample sizes in SHRP 2 for the uncombined age groups are given in Figure 18, and for the combined age groups in Figure 19. Note that there were 85 SHRP 2 participants whose age group was not known. Note also that these 85 participants of unknown age were involved in five crashes, of which two were Level 1, one was Level 2, and two were Level 3. Also, one of these crashes had a known police report.

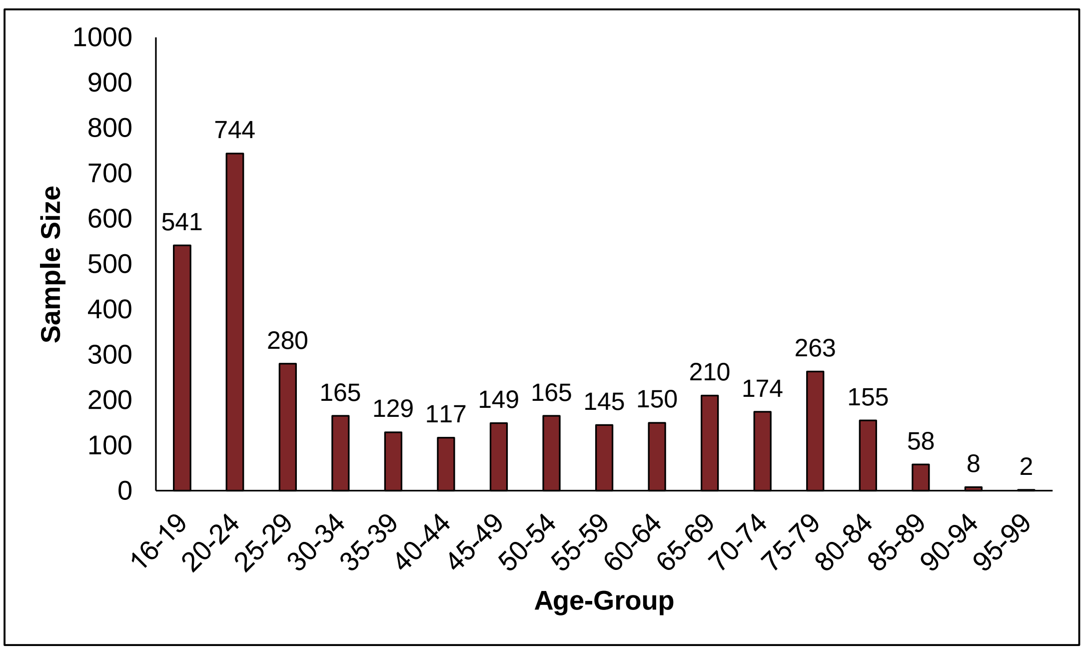

Figure 18. Uncombined SHRP 2 NDS Age Groups

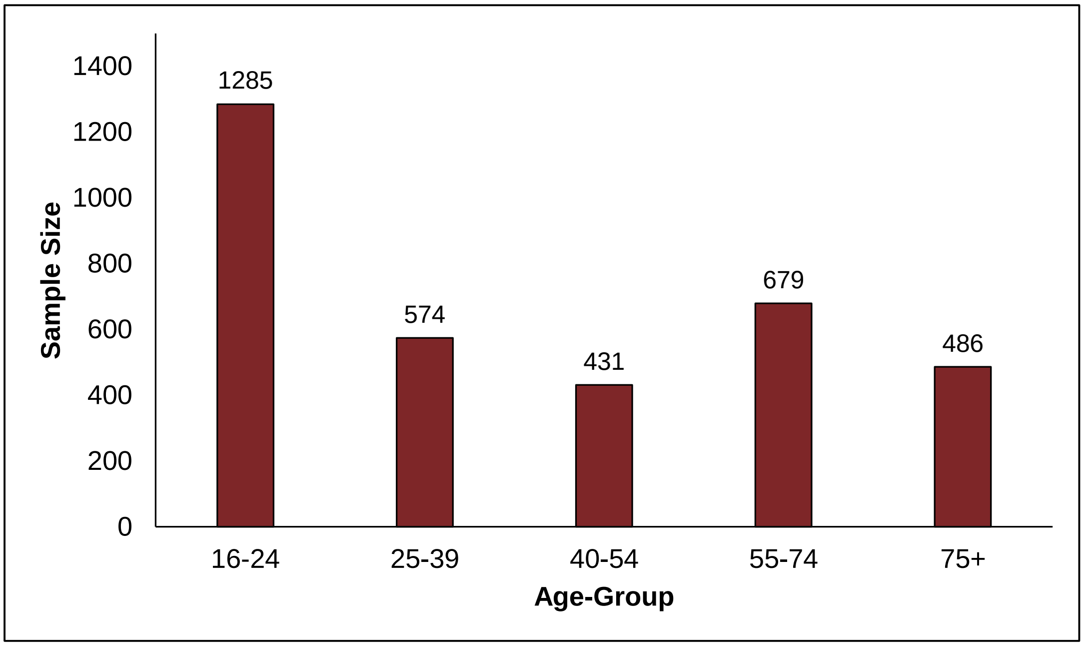

Figure 19. SHRP 2 NDS Combined Age Groups

Figure 20 provides the percentages of representation of each group in SHRP 2, along with the average percentage of U.S. licensed drivers in these age groups from 2011 to 2013, the years in which the SHRP 2 data predominately reside. The source for the U.S. data is the FHWA (2011, 2012, and 2013).

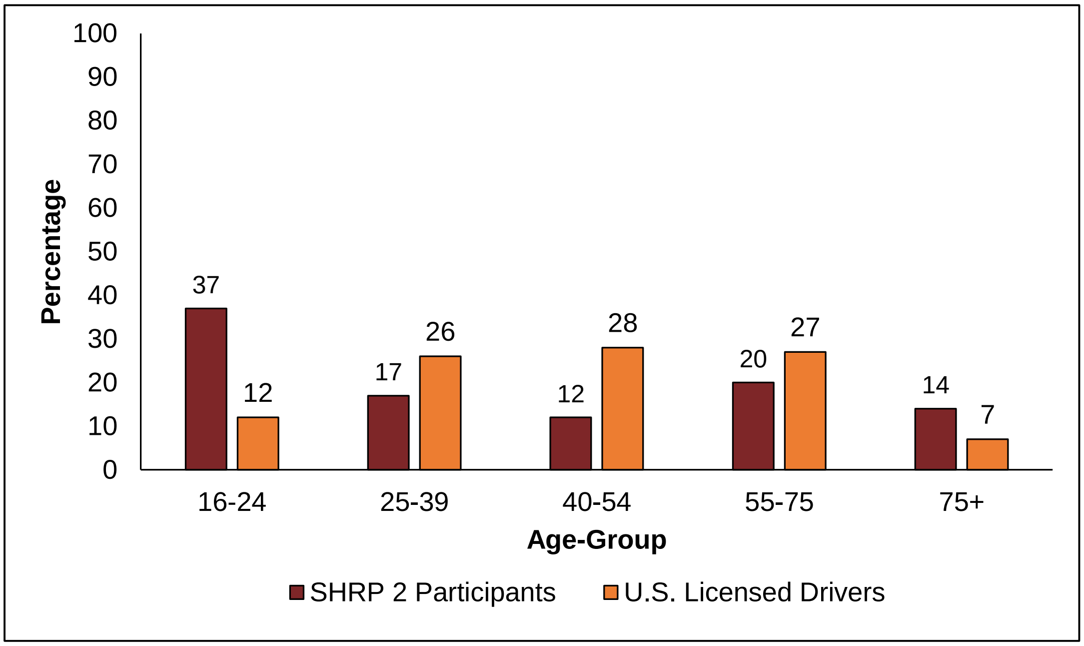

Figure 20. Age Distribution of SHRP 2 NDS and U.S. Licensed Drivers

Data Weighting

The estimated crash ratios and crash rates are weighted using the following steps:

1. Compute each ratio/rate separately within each age group.
2. Multiply the ratio/rate by a weight assigned to each group to create a weighted ratio.
3. Add the weighted sums together to produce an age-weighted ratio/rate.

The weights W_j are computed for each j^{th} age group as

$$W_j = \frac{P_j}{S_j}$$

where P_j is the estimated percentage of the j^{th} age group of U.S. licensed drivers, and S_j is the percentage of the j^{th} age group in SHRP 2. These weights are referred to as post-stratification weights. The weights for each age group, along with the percentages in the sample and U.S. licensed drivers, are displayed in Table 44.

Table 44. Weighted Age Groups

Age Group	Weight	Percentage in SHRP 2 NDS	Percentage of U.S. Licensed Driver
16-24	0.32	37	12
25-39	1.53	17	26
40-54	2.33	12	28
55-74	1.35	20	27
75+	0.5	14	7

Then, the estimated age-adjusted crash rate RAD is then computed as

$$RAD = \frac{\sum_j^L W_j A_j}{\sum_j^L W_j D_j}$$

where A_j is the total number of crashes in the j^{th} age group, D_j is the total distance driven for the j^{th} age group, and L is the total number of age groups.

To illustrate this calculation, consider the rate of Level 1 (most severe) crashes per million miles driven in SHRP 2. There were 120 Level 1 crashes in SHRP 2, and about 34.02 million miles driven (determined by calculating the total distance driven for over 5.7 million trips). Hence, the unweighted rate of Level 1 crashes per million miles driven was

$$R = \frac{120}{34.02} = \mathbf{3.53}$$

Hence, the unweighted rate of level 1 crashes in SHRP 2 was about 3.53 (rounded to 3.5).

Now consider how adjusting for age group affects this ratio. Table 45 gives the number of Level 1 crashes for each age group in SHRP 2.

Table 45. Level 1 Crashes by Age Group and Miles Driven

Age Group	Level 1	Million Miles Driven	Level 1 Crashes per Million Miles
16-24	69	12.9	5.4
25-39	14	6.4	2.2
40-54	7	4.6	1.5
55-74	14	6.3	3.2
75+	14	3.4	4.1

The group crash totals and group weights are combined as in formula 3 to yield the age-adjusted total level 1 crashes as

$$.32 * 69 + 1.53 * 14 + 2.33 * 7 + 1.35 * 14 + .5 * 14 = 85.71$$

and the age-adjusted total million miles driven in SHRP 2 as

$$.32 * 12.9 + 1.53 * 6.4 + 2.33 * 4.6 + 1.35 * 6.3 + .5 * 3.4 = 34.84$$

Hence, the age-adjusted rate of Level 1 crashes per million miles driven is

$$\frac{85.71}{34.84} = \mathbf{2.46}$$

The age-adjusted rate of Level 1 crashes 2.46 per million miles driven (rounded to 2.5) per million miles, which is about 28.6 percent lower than the unadjusted ratio of 3.5 per million miles driven.

Confidence Intervals

SHRP 2 Rates

For the SHRP 2 crash rates, nonparametric bootstrapping procedures were used to calculate the end points of the 95 percent confidence intervals. Bootstrapping is a data resampling procedure in which the data are resampled with replacement (in other words, after a data point is randomly selected from the sample, that data point can still be selected again after that). The advantage of bootstrapping is that it does not assume that the distribution of the rate follows a specific family, such as the Poisson distribution.

In this case, since SHRP 2 consists of a sample of participants who were observed for some amount of time, the participants were randomly sampled with replacement. The basic bootstrap algorithm used in this study was as follows.

1. Resample all participants with replacement, so that a new sample is created with a sample size equivalent to the original sample size *n*. Sample so that each participant has an equal probability of selection.
2. Calculate relevant rate R from the i^{th} sample, so that R_i is the i^{th} bootstrap sample rate.
3. Repeat Steps 1 and 2 10,000 times, producing a sample of 10,000 bootstrapped values of R_i.
4. Use the percentile confidence interval method (in this case, the bias corrected/accelerated method) to find the values within the 10,000 values to be used as the endpoints of the 95 percent confidence intervals.

As mentioned above, the bias corrected and accelerated method was used. The advantage of this method is that it corrects both for any bias in the estimate and skewness in the distribution of the estimator. See Carpenter and Bithell (2000) and Chernick (2008) for more details.

For the unweighted rates, the bootstrap sampling was performed such that all participants had an equal probability of being selected during the process. For the age-adjusted confidence intervals, the bootstrap was performed with the probability of selection varying between the age groups in order to create a bootstrap sample that was more reflective of the national driving population in terms of age group. For example, for the age group 16 to 24, the national population of licensed drivers was about 12 percent, so the probability of selection of a member for that group would be .12. Then, there were 1,281 members used for rate calculations (for 4 participants in this group, the distance calculation failed). Hence, the probability of one member from this age group being selected relative to the whole age group would be 1/1281. Hence, the probability that a particular individual from this age group relative to the entire SHRP 2 sample used would be

$$.12 * \frac{1}{1281} = .000094$$

Table 46 gives the bootstrap age-adjusted probabilities for a member of each age group.

Table 46. Bootstrap Age-Adjusted Probabilities

Age Group	National Proportion	Probability of Selection within Age Group	Probability of Selection within SHRP2 NDS Population
16-24	.12	$\frac{1}{1281}$	.000094
25-39	.26	$\frac{1}{574}$	.00045
40-54	.28	$\frac{1}{430}$	.00065
55-74	.27	$\frac{1}{675}$	.0004
75+	.07	$\frac{1}{486}$	.00014

Self-Driving Car Rates

Bootstrapping was not possible for Self-Driving Car rates, as all that was known was the number of crashes and the exposure. Therefore, a Poisson distribution, which requires only the above two pieces of information, was used to calculate the confidence interval. The interval used is the exact Poisson confidence interval, with the endpoints based on the relationship between the cumulative density functions of the Poisson and Chi-Square Distribution. See Ulm (1990) for details.

Calculated Rates

The crash rates per million miles driven, along with 95 percent confidence intervals, are given in Table 47.

Table 47. Calculated Crash Rates per Million Miles Driven

Crash Severity	Rate Category	Estimated Rate per Million miles	Lower Confidence Limit	Upper Confidence Limit
Level 1	SHRP 2 Overall	3.5	2.9	4.2
Level 1	SHRP 2 Age-Adjusted	2.5	2	3
Level 1	SHRP 2 PR	1	0.7	1.4
Level 1	SHRP 2 PR Age-Adjusted	0.7	0.4	1
Level 1	Self-Driving Car	1.6	0.2	5.7
Level 2	SHRP 2 Overall	4.7	4	5.5
Level 2	SHRP 2 Age-Adjusted	3.3	2.7	4
Level 2	SHRP 2 PR	0.4	0.2	0.6
Level 2	SHRP 2 PR Age-Adjusted	0.2	0.1	0.5
Level 2	Self-Driving Car	1.6	0.2	5.7
Level 3	SHRP 2 Overall	18.6	17	20.4
Level 3	SHRP 2 Age-Adjusted	14.4	13	16
Level 3	Self-Driving Car	5.6	2.2	11.4

Appendix D. Supplemental Crash Rate by Speed and Locality Information

The mileage in different speed zones and localities in SHRP 2 was unknown, and therefore had to be estimated. This was done by estimating the proportion of distance driven in each speed zone and locality during SHRP 2 and applying that proportion to the total mileage calculated in SHRP 2 (about 34,023,947 miles). The steps used for estimating the mileages are described below.

1. Determine the total distance driven in the baselines and the total distance driven in the baselines within different speed zones and localities.
2. Divide the distance driven for each speed zone in the baselines by the total distance in the baselines to estimate the proportion of distance driven in different speed zones.
3. Multiply the total distance driven in SHRP 2 by the estimated proportion of distance driven in different speed zones to get the estimate for total distance driven in different speed zones.

An example of this calculation is as follows:

The total mileage driven in the baselines was 4,552.13 miles (note that for 23 baselines, distance could not be calculated). The total mileage driven in speed zones less than or equal to 25 mph was 444.7. The estimated proportion of driving in this group of speed zones is thus

$$\frac{444.7}{4552.13} = .097$$

Thus, the proportion of driving in speed zones less than or equal to 25 mph is estimated to be .097, or about .1 Applying this to the total distance driven of about 34.02 million miles gives the estimated total distance driven in this group of speed zones as

$$.097 * 34.02\, million = 3.3\, million$$

Hence, the estimated total distance driven in speed zones less than or equal to 25 mph is about 3.3 million miles.

The total mileage driven in the baselines for different speed zones in SHRP 2, their estimated proportion of mileage, and estimated total mileage are displayed in Table 48.

Table 48. Summary of Speed Zone Mileage

Speed Zone	Baseline Mileage	Estimated Proportion of Mileage	Estimated Total Mileage in SHRP 2
≤25	444.7	0.097	3.3 million
26-35	893.5	0.19	6.7 million
36-45	1113.3	0.24	8.3 million
46-55	797.8	0.18	5.9 million
56-65	977.4	0.21	7.3 million
>65	325.3	0.07	2.3 million

Crash rates are calculated as in Appendix C. Using the total crashes in different speed zones. The amount of crashes in each speed zone, stratified by severity, are displayed in Table 49.

Table 49. Summary of Crash Severity by Speed Zone

Speed Zone	Level 1	Level 1 - PR	Level 2	Level 2 - PR	Level 3
≤25	17	3	25	1	205
26-35	35	11	54	5	195
36-45	33	11	48	3	144
46-55	15	5	16	2	43
56-65	10	3	5	0	16
>65	3	0	5	1	12

Locality crash rates are calculated first using estimated mileage driven in different localities, which is calculated as above. Table 50 gives the estimated mileage in each locality, while Table 51 gives the total amount of crashes, stratified by severity, in each locality.

Table 50. Summary of Mileage in Each Locality

Locality	Baseline Mileage	Estimated Proportion of Mileage	Estimated Total Mileage in SHRP 2 NDS
Urban	55.4	0.01	0.4 million
Business/Industrial	1206.4	0.27	9.0 million
Church	91.1	0.02	0.7 million
Moderate Residential	690.5	0.15	5.2 million
School	187.8	0.04	1.4 million
Bypass/Divided Highway	196.4	0.04	1.5 million
Open Residential	253.8	0.06	1.9 million
Open Country	80.1	0.02	0.6 million
Interstate	1767.9	0.39	13.2 million

Table 51. Summary of Crash Severity by Locality

Locality	Level 1	Level 1 - PR	Level 2	Level 2 - PR	Level 3
Urban	4	2	7	2	21
Business/Industrial	47	13	61	1	265
Church	3	0	4	1	12
Moderate Residential	22	4	29	2	154
School	6	1	13	1	46
Bypass/Divided Highway	4	1	9	2	9
Open Residential	6	3	11	1	59
Open Country	2	1	1	0	12
Interstate	26	9	24	2	46

Appendix E. Data Set Limitations

The conclusions of this study are subject to the following limitations.

1. The currently low amount of miles driven from the Self-Driving Car project makes it difficult to draw firm conclusions on the potential safety impact of self-driving cars. With the Self-Driving Car project having only logged about 1.26 million miles (compared to 34.02 million in SHRP 2), the uncertainty in the true crash rates from self-driving vehicles is large, resulting in wide confidence intervals for their observed crash rates. In spite of this, the crash rates for less-severe incidents were found to be significantly lower for self-driving cars than for SHRP 2. However, for more-severe crashes, which are rarer events, it is difficult at this point to say with a high degree of certainty how well self-driving vehicles compare to national and naturalistic rates.

2. Although the SHRP 2 dataset offers a window into driving behavior, the dataset may not be representative of the entire U.S. population. The drivers could only participate voluntarily, and thus could not be selected at random, introducing the possibility of self-selection bias. Therefore, there may be unknown factors that differentiate the SHRP 2 population from the national population. However, the six sites chosen for SHRP 2 reflect a variety of populations and driving conditions that exist in the nation as a whole, which increases the chance that the driving behavior observed in SHRP 2 reflects national driver behavior (Antin et al., 2015). Also, this study used data weighting to compensate for the overrepresentation of younger and older drivers in SHRP 2.

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