U.S. Department
of Transportation
National Highway
Traffic Safety
Administration

NHTSA

DOT HS 813 027

November 2020

Evaluation of FMVSS No. 216a, Roof Crush Resistance, Upgraded Standard

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Suggested APA Citation Format:

Kweon, Y.-J. (2020, November). *Evaluation of FMVSS No. 216a, roof crush resistance, upgraded standard* (Report No. DOT HS 813 027). National Highway Traffic Safety Administration.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
DOT HS 813 027		
4. Title and Subtitle Evaluation of FMVSS No. 216a, Roof Crush Resistance, Upgraded Standard		5. Report Date November 2020 6. Performing Organization Code NSA-310
7. Author(s) Young-Jun Kweon		8. Performing Organization Report No.
9. Performing Organization Name and Address Evaluation Division (NSA-310) National Center for Statistics and Analysis National Highway Traffic Safety Administration 1200 New Jersey Avenue SE Washington, DC 20590		10. Work Unit No. (TRAIS) 11. Contract or Grant No.
12. Sponsoring Agency Name and Address Evaluation Division (NSA-310) National Center for Statistics and Analysis National Highway Traffic Safety Administration 1200 New Jersey Avenue SE Washington, DC 20590		13. Type of Report and Period Covered NHTSA Technical Report 14. Sponsoring Agency Code
15. Supplementary Notes		

Abstract

This study evaluates the safety effect of roof strength of passenger vehicles involved in rollover crashes. To this end, the study develops a regression model relating the probability of an occupant sustaining a severe (fatal or incapacitating) injury to vehicle roof strength measured by the strength-to-weight ratio (SWR). Two essential types of data were acquired, SWR data from roof crush tests and rollover crash data from the State Data System. The data pre-processing procedure was executed to form the study data including 5,153 non-ejected occupants in rolled vehicles at traffic crashes and 36 potential explanatory variables. The binary logit model for severe injury was developed using 1,940 observations where all regression variables have valid values and contain six explanatory variables: occupant gender, age, and belt use, vehicle peak SWR, crash site's surface condition, and crash's time of day. Based on the estimated severe injury logit model, the following conclusions are drawn.

- Stronger vehicle roofs save lives and prevent incapacitating injuries in rollover crashes. An increase in the roof strength by 1 unit of the peak SWR is predicted to reduce the odds of a non-ejected occupant suffering a severe injury by about 14 percent.
- Wearing a seat belt is critical in mitigating a life-threatening crash consequence in a rollover crash. Seat belt use is predicted to lower the odds of a non-ejected occupant sustaining a severe injury by about 38 percent.
- Gender and age affect prospects of sustaining a less serious injury at a rollover crash. A female occupant has a higher probability of suffering a severe injury compared to a male occupant. An older occupant is at a higher risk of getting severely injured compared to a younger occupant.

17. Key Words	18. Distribution Statement		
roof strength, strength-to-weight ratio (SWR) rollover	Document is available to the public through the National Technical Information Service, www.ntis.gov.		
19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	64	

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1. Introduction

1.1. Rollover Crashes

According to national statistics from 2014 to 2018 (National Highway Traffic Safety Administration, 2020), only 2 percent of vehicles in all traffic crashes were involved in rollover crashes, but 24 percent of all fatalities resulted from rollover crashes. In 2017 a total of 23,551 passenger vehicle occupants were killed in traffic crashes and 30 percent of them (7,170 killed occupants) were involved in rollover crashes (National Center for Statistics and Analysis, 2019b). These statistics demonstrate that rollover crashes pose a serious threat to vehicle occupants.

As seen in Figure 1, the past two decades or so (i.e., 2000s and after) have seen higher rollover percentages among fatally injured occupants than their past counterparts in 1980s and 1990s. This implies that improving rollover safety by preventing a vehicle from rolling and/or reducing an injury severity of an occupant during a rollover could play a greater role in reducing rollover fatalities in more recent years.

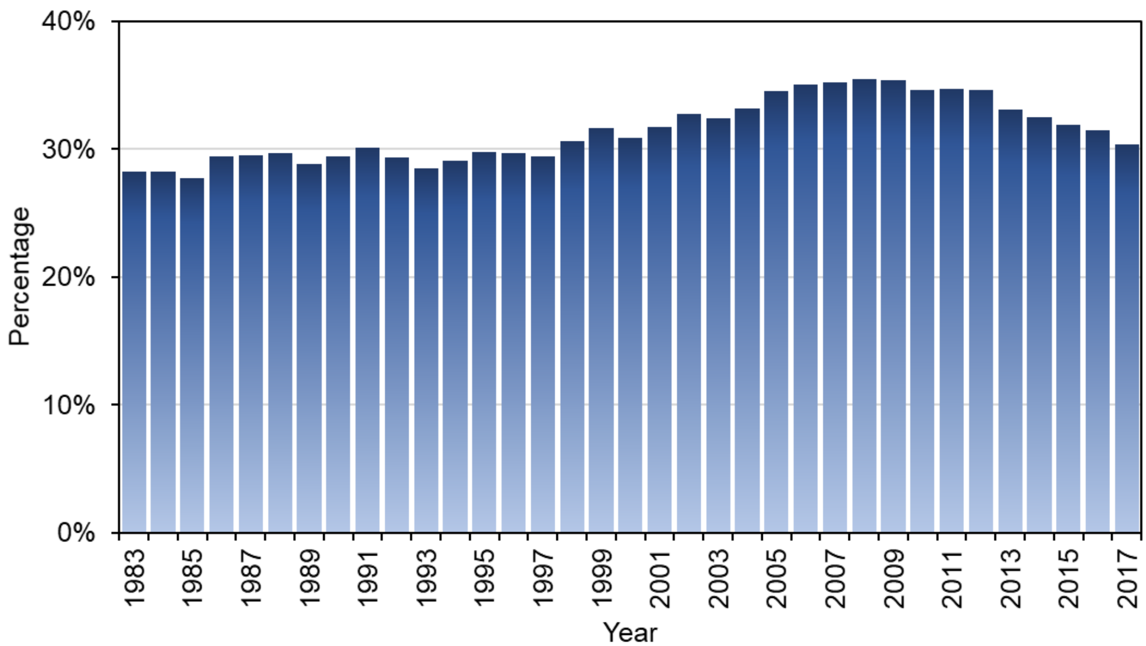

Figure 1. Rollover percentages in killed occupants of passenger cars and light trucks (1983-2017). Figure is created based on Traffic Safety Facts Report (NCSA, 2019c).

Vehicle design and safety features such as a lower center of gravity (CoG), a wider track width, and the electronic stability control (ESC) help prevent rollovers. Other features such as a seat belt, a side curtain air bag, and better interior padding help reduce an injury severity of an occupant when a vehicle rolls. Wearing a seat belt is one of the most effective ways to reduce an injury severity in a rollover crash. Wu et al. (2019) found that an occupant contacted mostly roof, left door, instrumental panel, and seat back support in rollover crashes and a belt use was one of the most important factors to an occupant's injury severity based on National Automotive Sampling System–Crashworthiness Data System (NASS-CDS) data.

However, it should be noted that a seat belt's effectiveness could be diminished if an occupant's survival space is not adequately maintained during a rollover. Thus, higher seat belt use, together with better vehicle design sufficiently protecting the occupant's space, could greatly enhance occupant safety in rollover crashes.

According to the National Occupant Protection Use Survey (NOPUS), driver and right-front occupant seat belt use in passenger vehicles has been increasing over the past two decades (Figure 2). This trend should lead to fewer injuries and injuries that are less severe in rollovers, if other factors are held constant. However, the increasing trend of seat belt use among front-seat passengers in NOPUS contrasts with the declining trend among fatally injured passengers 21 and older in the Fatality Analysis Reporting System (FARS). Moreover, the seat belt use found in fatal crashes is much lower than the general seat belt use. In 2017, for example, only 48 percent of occupants killed in crashes were reported using seat belts while 90 percent of the front-seat occupants in the NOPUS seat belt surveys were observed wearing seat belts.

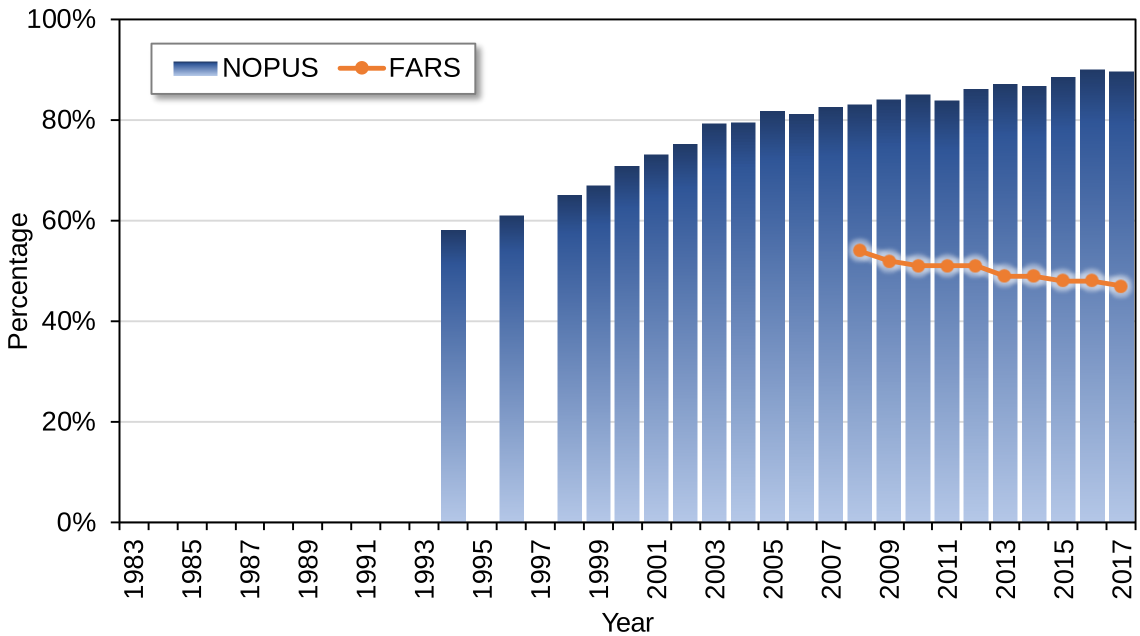

Figure 2. Percentages of Seat Belt Use of Front-Row Occupants in NOPUS and Fatal Occupants in FARS (1994-2017).

This seat belt use plot of NOPUS survey results is created using Traffic Safety Facts Research Notes by Enriquez and Pickrell (2019), and Pickrell and Ye (2019. The seat belt use plot of FARS is created using Quick Facts 2017 (NCSA, 2019a), Quick Facts 2014 (NCSA, 2016), Quick Facts 2013 (NCSA, 2015), and Quick Facts 2010 (NCSA, 2012). The seat belt use percentages of NOPUS are for front-seat passengers in passenger vehicles while the percentages for FARS are for fatally injured occupants 21 and older in traffic crashes. The time period is extended to 1983 to coincide with Figure 1 for easier comparison although the seat belt use percentages in earlier years are not presented due to lack of data.

Increasing seat belt use for vehicle occupants involved in traffic crashes is imperative to reduce fatalities and injuries, especially involving rollovers. However, even if all passengers properly fasten seat belts, their chances of surviving or sustaining less severe injury in rollover crashes would be improved if their vehicles properly maintain occupant compartment integrity. In this study, we examine whether design changes made in response to Federal Motor Vehicle Safety Standard (FMVSS) No. 216a were effective in improving occupant survivability in rollover crashes.

1.2. Vehicle Roof Strength

Two of the principal causes of injuriy during rollovers are occupant ejection and roof crush. Occupant ejection in rollover crashes would be prevented by seat belt use and other ejection mitigation features such as improved side curtain air bags and advanced window glazing. Crushing of a vehicle roof into an occupant compartment during a rollover could be mitigated by a stronger roof structure.

The need for stronger vehicle roof structure led to creation of the vehicle safety standard for roof crush resistance, FMVSS 216, in the early 1970s. The standard has been upgraded several times since its inception. The most noteworthy recent upgrade occurred in 2009, resulting in FMVSS No. 216a. One of the important requirements specified in the standard involves roof strength measured in the strength-to-weight ratio (SWR)—The SWR is a unitless metric measuring a vehicle's roof strength by its own weight. For example, a 3.0 SWR means that a vehicle's roof structure is capable of withstanding 3.0 times the vehicle's unloaded weight under the test conditions specified in FMVSS No. 216a.

1.3. Purpose and Scope

This study aims to evaluate the safety effect of passenger vehicle roof strength in rollover crashes. Specifically, it is to quantify the change in the probability of a severe injury (i.e., fatal or incapacitating) sustained by an occupant of a rolled vehicle in a traffic crash in response to a change in a vehicle's roof crush resistance. To this end, the study develops a statistical model representing a relationship between a probability of being fatally or seriously injured in a rolled vehicle and the vehicle's roof strength measured in the SWR.

The relationship to be developed by the statistical model should be established while controlling for as many potentially influential factors as possible. Such control factors include occupant demographic characteristics (e.g., gender and age), occupant in-vehicle characteristics (e.g., seating position and seat belt use), vehicle characteristics (e.g., vehicle age and safety features), and environment characteristics (e.g., road surface condition and light condition). By properly controlling for these factors, the safety effect of roof strength would be isolated.

The scope of this study is limited to cases where appropriate rollover crash data exists and SWR values corresponding to vehicles involved in those crashes are available. Since traffic crash data itself does not contain SWR values and SWR values are found in the limited number of vehicles that were roof-crush-tested in a laboratory, linking vehicles involved in traffic crashes to vehicles crush-tested is necessary. This linking task was challenging and limited the scope of the data available for this study.

2. Roof Crush Resistance

2.1. Roof Strength

One measure of vehicle roof strength is the SWR, calculated from results of a laboratory roof crush test. The roof crush test pushes a metal plate against a side of the forward edge of a vehicle's roof at a constant rate to a certain distance and the force applied to the metal plate is continuously recorded throughout the test. An SWR value is calculated by dividing an applied force by an unloaded vehicle weight as follows,

$$SWR = \frac{Applied\ Force}{Unloaded\ Vehicle\ Weight} \qquad \text{Eq. (1)}$$

where applied force and unloaded vehicle weight are measured in the same unit such as Newton (N), or pounds-force (lbf) and, thus. a calculated SWR is unitless.

The SWR is devised to represent how much a vehicle's roof structure could withstand its own weight reflecting a rollover event in a crash. A larger SWR value indicates a stronger roof and less occupant compartment intrusion. A vehicle with a larger SWR is more likely to maintain an occupant's survival space when a vehicle rolls, resulting in a higher survivability and occupant injuries that are less serious.

At each crush test continuously pushing the plate, many SWR values can be calculated from the tested vehicle using Equation 1, one for each applied force being recorded. Among those SWR values, the maximum SWR value corresponding to the largest applied force occurring within the *5 inches* of platen travel distance is the peak SWR (see Equation 2). The peak SWR corresponds to the maximum resistance capacity of a vehicle's roof structure against crushing and thus represents the strength of a vehicle's roof.

$$Peak\ SWR = \frac{Maximum\ Applied\ Force}{Unloaded\ Vehicle\ Weight} \qquad \text{Eq. (2)}$$

where the maximum applied force is obtained within 5 inches of the platen displacement.

The peak SWR is the officially designated test result for any vehicle. Throughout this report, the peak SWR refers to the roof strength measured under the test conditions specified in FMVSS No. 216a.

2.2. Roof Crush Resistance Standard and Rating

Efforts to improve occupant safety in rollovers have been initiated by both Federal and private institutions. FMVSS No. 216a regulates minimal roof strength design in vehicles. In addition, the insurance industry has introduced a rating system based on a test similar to FMVSS No. 216a to encourage manufacturers to improve roof designs. These are summarized here to provide relevant information to this study.

2.2.1. FMVSS No. 216a

FMVSS No. 216, roof crush resistance, went into effect on September 1, 1973. It established strength requirements of a roof structure of a passenger car with a gross vehicle weight rating (GVWR) of 2,722 kg (6,000 lb) or less and the SWR threshold specified in FMVSS No. 216 was 1.5, meaning that a passenger car roof should withstand a load of at least 1.5 times the vehicle unloaded weight. The standard has been amended several times since its inception, such as extending to multipurpose passenger vehicles (MPV) and modifying the quasi-static testing procedure. The most recent and substantial amendment occurred in 2009, upgrading the standard to FMVSS No. 216a. Some of the major changes in the 2009 upgrade include raising the SWR threshold of 1.5 to 3.0 for passenger cars, changing from a one-sided to a two-sided test, expanding to heavier passenger vehicles (GVWR greater than 6,000 lb to 10,000 lb or less) with the SWR threshold of 1.5, and introducing headroom maintenance criteria. FMVSS No. 216a became final on April 30, 2009, and laid out a multi-year phase-in compliance requirement beginning in 2012 through 2015, implying that aull compliance should be satisfied for all noted vehicle fleets with the model year of 2016.

2.2.2. Non-Federal Safety Rating

The Insurance Institute for Highway Safety (IIHS) introduced a rating system for vehicle roof strength in 2009, based on the peak SWR from a roof crush test similar to what FMVSS No. 216a specifies. There are several differences between the IIHS and FMVSS No. 216a tests, such as the number of sides to be tested (i.e., one side for IIHS and both sides for FMVSS No. 216a) and no headroom maintenance criterion in IIHS's test. The roof strength rating of IIHS falls into one of the four levels based on the peak SWR (good, acceptable, marginal, and poor) and the highest rating, "Good," requires at least an SWR of 4.0 (IIHS, 2016). IIHS has been testing about 20 to 30 new vehicles for roof strength and other safety characteristics each year to promote safer vehicle designs.

3. Data

The two types of data essential for this study include roof strength data and traffic crash data, described in separate sections.

3.1. Roof Strength Data

Since the study focuses on a safety effect of the strength of vehicle roof structure, it is crucial to include a measure of roof strength in the study data. However, roof strength measures are not found in any traffic crash data. The roof strength in terms of SWR is acquired from a quasi-static roof crush test conducted in a laboratory setting. This study identified two sources of SWR data, NHTSA and IIHS, and these data sources are described separately. The SWR data is presented in Appendix A for reference.

3.1.1. NHTSA

To certify compliance with FMVSS No. 216a, a vehicle manufacturer performs a roof crush test on its vehicle through a third party following the test procedures of FMVSS No. 216a and submits a roof crush compliance report to NHTSA. However, the test serving the compliance purpose may not produce SWR values acceptable for this study's purpose since it could stop before reaching 5 inches in the platen travel distance, soon after meeting the minimum SWR requirement. For example, many of passenger vehicles crush-tested by IIHS produce SWR values well above 3.0 before the plate travels 5 inches. This means if the tests were performed specifically to comply with FMVSS No. 216a, the peak SWRs would not have been found because the test would have stopped when reaching the SWR of 3.0 before their peak SWRs. Thus, a maximum SWR value that could be acquired from the compliance test reports would be inappropriate for this study since it would unlikely represent the strength of a vehicle's roof.

Meanwhile, NHTSA performed roof crush tests on a total of 76 vehicles to support upgrading the roof crush resistance standard resulting in FMVSS No. 216a in 2009, and in those tests the crushing metal plates traveled at least 5 inches. Thus, a peak SWR value, a maximum SWR within 5 inches of the platen travel distance, was obtained from each of the 76 crushed vehicles, and that peak SWR data was deemed proper for this study. Those vehicles crush-tested by NHTSA range from 1997 to 2008 in their model years, implying they include used vehicles at the time of testing. These vehicles were up to 10 years old, but over 80 percent of them were less than 5 years old. Since there is no reason to believe that a vehicle's roof strength would substantially change when the vehicle gets older in a reasonable range of years, the SWR data from the all 76 vehicles was included in the study.

Among the 76 vehicles, 32 vehicles were crush-tested on both sides of their roofs, producing two peak SWRs for each vehicle, one on each side, while the other 44 vehicles were crushed only on one side. Meanwhile, all IIHS tests were one-sided, meaning one peak SWR was found for each vehicle. The sides to be crushed in a one-side test at NHTSA and at IIHS were chosen randomly. The first side to be crushed in a two-side test was chosen randomly and then, the crushing test proceeded to the second side. Since all 358 vehicles from both data sources have peak SWRs on their first sides while 32 of them have the second-side peak SWRs as well, the first-side peak SWRs were determined for use in this study.

There was, however, a concern about using the first-side peak SWR for the study because the SWR thresholds of FMVSS No. 216a apply to a smaller value of the two peak SWRs of a vehicle, typically corresponding to the second-side peak SWR. To address this concern, an analysis was performed to investigate how strongly the two peak SWRs of the same vehicle are correlated. Based on analysis of the 32 vehicles crush-tested on both sides, the two peak SWRs of the same vehicle were found to be statistically close to each other. This finding implies that a peak SWR of either side of a roof can be used for the study as long as SWR values from the same side, first or second side, for all vehicles are used for analysis. Analysis results on the two peak SWRs are provided in Appendix B.

3.1.2. IIHS

IIHS has performed roof crush tests on about 20 to 30 vehicles annually, and crushed a vehicle at least 5 inches, meaning that a peak SWR is always obtained for each tested vehicle. Roof crush test reports are available at the IIHS TechData website[1] for download and reports of 282 vehicles with model years 2008 to 2016 were obtained for this study. Table 1 shows all 358 vehicles with peak SWRs included in this study, 76 vehicles tested by NHTSA and 282 vehicles tested by IIHS. Please note that NHTSA performed the roof crush tests in support of the roof crush resistance standard upgrade enacted in 2009 and IIHS started its tests in 2009, which explains the range of the model years of the tested vehicles by data source.

Table 1. Count of Roof Crush Tested Vehicles by Data Source and Model Year

Model Year	Data Source	
	NHTSA[a]	IIHS[b]
1997	1	0
1998	1	0
1999	1	0
2001	5	0
2002	6	0
2003	16	0
2004	9	0
2005	1	0
2006	16	0
2007	18	0
2008	2	4
2009	0	34
2010	0	57
2011	0	58
2012	0	34
2013	0	25
2014	0	23
2015	0	21
2016	0	26
Total	76	282

[a] NHTSA performed tests in support of upgrading the roof crush resistance standard resulting in FMVSS No. 216a in 2009.
[b] IIHS started roof crush tests in 2008.

[1] Roof crush test reports are accessible at IIHS's TechData website, https://techdata.iihs.org/ after registration.

Figure 3 shows a histogram of the 358 peak SWR values by data source. The peak SWR values of the vehicles tested by NHTSA are generally lower than those of IIHS counterparts primarily because of difference in vehicle model years. All the NHTSA tested vehicles were manufactured before the 2009 standard upgrade while most of the IIHS tested vehicles were produced after the upgrade. It should be noted that the standard upgrade, FMVSS No. 216a, increased the SWR minimum requirement for a passenger vehicle with a GVWR of 6,000 lb or less from 1.5 to 3.0 and introduced the SWR threshold of 1.5 for a passenger vehicle with a GVWR greater than 6,000 lb yet less than or equal to 10,000 lb. Although full compliance with FMVSS No. 216a was mandated by model year 2016, passenger vehicles manufactured after 2009 were anticipated to have stronger roofs compared to their past counterparts.

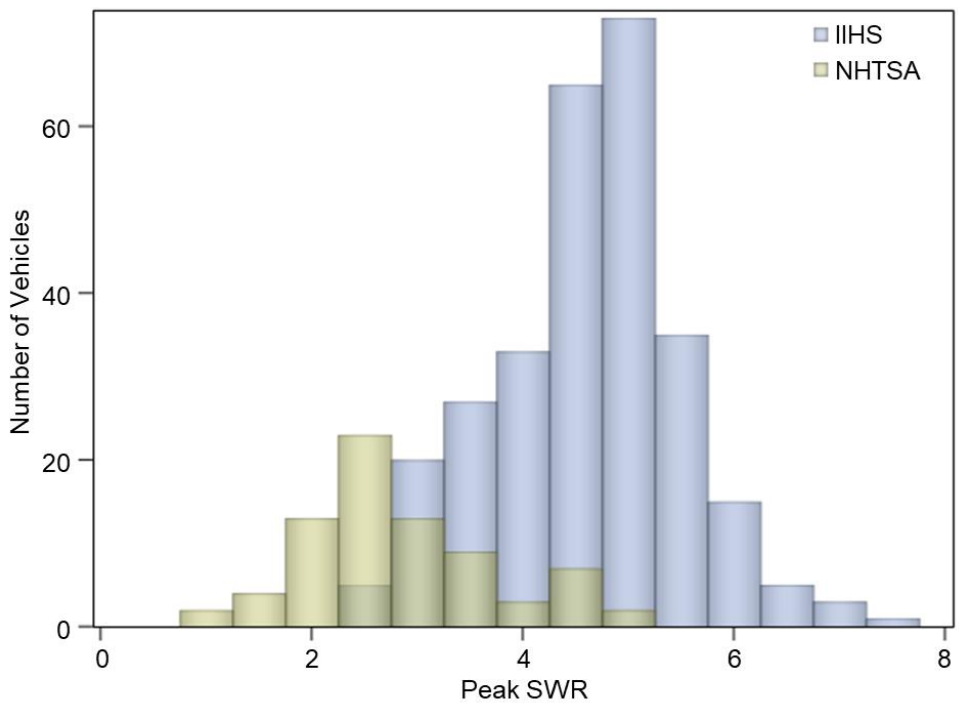

Figure 3. Histogram of peak SWRs by data source.
NHTSA's peak strength-to-weight ratio (SWR) data are for the vehicles with model years 1997 to 2008 while IIHS's are for the vehicles with model years 2008 to 2016. The roof crush resistance standard was upgraded in 2009.

3.2. Traffic Crash Data

There are several sources of traffic crash data potentially useful for this study and the four commonly used data sources were initially considered: FARS, the General Estimates System (GES)/Crash Reporting Sampling System (CRSS), the Crash Investigation Sampling System (CISS)/Crashworthiness Data System (CDS), and State Data System (SDS). Each has its own merits and shortcomings. For example, FARS is a census of police-reported crashes yet is limited to a crash where at least one fatality occurs. CISS/CDS contains detailed crash and vehicle characteristics collected by trained crash researchers but include only about 5,000 crashes a year; CISS started collecting event data recorder (EDR) data in 2017. GES/CRSS encompasses all severity levels contains about 50,000 sampled crashes each year and Vehicle Identification Numbers (VINs) in its vehicle files. SDS is a census of police-reported crashes with all severity levels collected from 32 participating States and a majority of these States include VINs in their vehicle files.

VINs turned out to be critical in preparing the study data, specifically integrating[2] the roof strength data with traffic crash data. Thus, traffic crash data containing VINs are indispensable for the study. In addition, such data should contain a large number of crashes so that a sufficiently large number of rollover crashes can be extracted and integrated with the roof strength data for reliable analysis. In this respect, the CISS/CDS was deemed unsuitable because of a lack of VINs and the small sample size, and GES/CRSS was deemed unsuitable because the number of rollovers that would be included in the final study data was not expected to be large enough for reliable analysis. The study should include crashes sustaining all severity levels, so that a safety effect of the vehicle's roof strength could be investigated on rollover crashes with an entire range of injury severities, not just those with a specific severity outcome. In this aspect, FARS falls short in that it contains only fatal crashes. SDS, meanwhile, looks suitable and promising since it has VINs in its vehicle files for many States and contains all reported traffic crashes ranging from property damage only to fatal crashes.

3.2.1. SDS

Thirty-two States participated in SDS by voluntarily providing their police-reported crash data for NHTSA's internal research purposes. Among the 32 participating States, 21 were found to contain partial VINs, 10 to 12 out of the full 17 digits, in their vehicle files. Among 21 States, one State has VINs only for commercial vehicles, which was deemed unsuitable for this study. The most recent year where crash data is ready to use varies across States. For example, one State has 2017 as the most recent year of data ready for use while one State has 2010 as the most recent year. Most States have their most recent data years of 2014 or 2015 at the time of the study.

Data files for the 20 States storing partial VINs for all crash vehicles were included in the study. Crash data from 1997 to 2017 were used for this study since those were the available years that would contain model years 1997 to 2016, which make up the 358 vehicles in the roof strength data. Since SDS contains all reported crashes, not samples of those, the size of the data to be processed was large. For example, Florida has over 3 million people involved in traffic crashes from 1997 to 2015 (the most recent data year at the time of this study). A single data file for Florida was prepared by merging person, vehicle, and crash files each year and stacking over 19 years; its size was about 7.5 gigabytes. Partly due to the file size and mainly due to formats and/or coding practices varying over the years within the same State and across the 20 States, merging crash, vehicle, and person files was carried out by year for each State before further processing. A few past studies used SDS rollover data to study safety effects of roof strengths. For example, Brumbelow et al. (2009) and Brumbelow and Teoh (2009) studied the relationship between roof strength and injury risk based on roof crush test results of 11 midsize SUV and 12 small passenger cars, respectively. These studies obtained single-vehicle rollover crash data in 14 States from SDS.

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[2] The term "integrating" is used, as opposed to "merging," because merging links the same entities between two data sets and integrating links entities that may not be the same but have similar characteristics. This study links vehicles in roof crush test data to vehicles in traffic crash data. Since a roof-crush tested vehicle was not among vehicles involved in traffic crashes, merging the two sets of the vehicles was inconceivable.

4. Methodology

Methodology employed to process and analyze data is described separately.

4.1. Data Processing

The essential data for the study, SWR and SDS, have been processed separately and later combined using information extracted from VIN. Processing and integrating the two data sets are described in the order that data processing was performed. Chapter 5 presents details of the data processing results including numbers of observations being processed at several milestones in data processing and challenges encountered during the process.

4.1.1. SWR Data

NHTSA's SWR data of 76 vehicles was obtained in a spreadsheet file from its own Office of Vehicle Safety Research. Austin (2010) used the same SWR data for analyzing a relationship between the peak SWR and the maximum vertical roof intrusion based on CDS data. For the IIHS SWR data, individual roof crush test reports of 282 vehicles were taken from the IIHS TechData website. Information found on an individual report such as peak applied force, unloaded vehicle weight, and peak SWR was then manually transported to a spreadsheet file. The two SWR data files, NHTSA's and IIHS's, were then combined to a single SWR data file.

VINs in the combined SWR data were verified and, if needed, corrected using available resources such as the National Insurance Crime Bureau's (NICB) VIN Manual. Then, VIN decoding was performed to extract vehicle information such as the equipping status of ESC and the number of doors. For VIN decoding, two computer programs were used: (1) NHTSA's Product Information Catalog and its Vehicle Listing (vPIC)[3] web-based application (hereinafter vPIC VIN decoder), and (2) the Evaluation Division's internal SAS program[4] (hereinafter ED VIN decoder). Each produced some similar (e.g., vehicle types) and some different vehicle characteristics (e.g., the number of doors by vPIC VIN decoder and ESC by ED VIN decoder).

4.1.2. SDS Crash Data

For each of 20 States, all the relevant data files (person files, vehicle files, crash files, vehicle event files, etc.) stored in SDS database were merged using case number, vehicle number, and person number for each year. Thus, the merged data is person-based, meaning each record corresponds to a person involved in a crash. After yearly merged-data files were prepared, one for each year, they were stacked over all available data years, creating a single multi-year data file for each State.

Combining yearly data files over the multi-year data period required unifying variable formats and coding rules varying over the data period. For example, Florida coded a vehicle event variable "31" for "Overturned" until 2010, and changed to "1" for the same event starting in

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[3] The vPIC is a consolidated platform presenting information collected from manufacturer-reported data and offers a web-based application tool for decoding VINs, https://vpic.nhtsa.dot.gov/.

[4] A set of SAS codes deciphering VINs to populate vehicle information were developed in Evaluation Division in the Office of Regulatory Analysis and Evaluation at National Center for Statistics and Analysis. The program has been updated regularly and the study used the 2016 version of the program, the most recent one at the time of the study.

2011. To prepare the multi-year data rightful for analysis, code values carrying the same information were first matched over the entire data period, and, if not matched, code values were modified in a consistent manner so that the modified values correspond to the same information throughout the data period.

Furthermore, variables having been removed or added over years were found in many States. Some variables discontinued and merged into other variables, some variables discontinued yet reappeared several years later, new variables appeared, and so on. For example, Florida had 22 person file variables and 30 vehicle file variables in 1997, respectively, but increased to 46 and 45 variables in 2014. Several variables discontinued while many new variables had been populated over the years. For instance, the first and second crash events were recorded in Florida's crash files until 2001, and only first event remained after then. Depending on a variable's discontinuation status, some variables remained in the data while others were excluded from further consideration.

Once a single multi-year crash data file with variable format and coding consistent over the data period was prepared for each State, multi-State data was prepared by combining the multi-year crash data files across the 20 States. Similar issues to those encountered in combining yearly data files over the data period for an individual State were noted. Since each State has developed and been practicing its own coding rules in reporting crash information, variation existed in what and how information is reported. For example, Florida reported a restraint use in 11 categories[5] while New York reported a restraint use in 16 categories.[6] For another example, North Dakota recorded up to three harmful events for a vehicle while Missouri was found to record up 15 vehicle events.

4.1.3. SDS Rollover Data

According to the FARS User's Manual (NCSA, 2018), rollover is defined as any vehicle rotation of 90 degrees or more about any true longitudinal or lateral axis and the rollover status of a vehicle is determined by a FARS data analyst after reviewing all available information such as coded values in data files and description and drawing on police crash reports. However, a vehicle's rollover status in SDS crash data was not possibly determined in the same way as was done for FARS due to the number of crash records to be processed. Alternatively, a rollover status was determined in an automated way using coded values in SDS data. This led to developing various algorithms intended to systematically identify a rollover status for each of the millions of vehicles included in the SDS crash data using data elements consistent across as many States as possible.

There were found to be various ways to determine rollover based on coded values. For example, 19 States recorded the first harmful vehicle event for each vehicle involved in a crash and the first vehicle event can be used to determine if the vehicle rolled, which is typically coded as "Overturn" or "Rollover." There are other data fields that can be used for determining rollover. For example, the vehicle's first point of damage being roof, typically coded as "Roof" or

[5] Eleven categories include: None Used, Shoulder and Lap Belt Used, Shoulder Belt Only Used, Lap Belt Only Used, Child Restraint System-Forward Facing, Child Restraint System-Rear Facing, Booster Seat, and so on.
[6] Sixteen categories include: None, Lap Belt, Harness, Lap Belt/Harness, Child Restraint Only, Air Bag Deployed, Air Bag Deployed/Lap Belt, Air Bag Deployed/Harness, Air Bag Deployed/Lap Belt/Harness, Air Bag Deployed/Child Restraint, and so on.

“Rooftop,” could be used to determine the rollover status of the vehicle. However, using the initial area of impact as the sole basis for determining rollover assumes that roof damage occurs only in a rollover, which would introduce inaccuracy because a roof damage could occur in a non-rollover event such as an object falling on the roof. More than one data element can also be used for rollover determination. For example, the crash event being rollover in conjunction with the number of the involved vehicles equaling 1 could be used. However, this excludes rolled vehicles involved in a multi-vehicle crash and a vehicle determined to have rolled by this definition might have experienced a more harmful event at a vehicle’s level than the rollover event, meaning the rollover may not have played a major role in causing its occupant’s injury.

Many algorithms based on several data elements and their combinations were devised and tested to determine a vehicle’s rollover status. Some were found inadequate due to an unacceptable level of accuracy (e.g., a vehicle’s rollover determined by the crash event being rollover where not all vehicles involved in a rollover crash necessarily overturned) while some were deemed very accurate yet resulted in an inadequately small number of identified rollover cases (e.g., a vehicle’s rollover determined by the first vehicle event being rollover, any subsequent events not being any impacting event such as colliding with tree, culvert, or ditch, the number of involved vehicles being one, and the most harmful impact area being roof).

To include as many States and identified rollover cases as possible while maintaining an adequate level of accuracy, two rollover definitions were selected for identifying rolled vehicles in the 20-State SDS crash data: (1) the first harmful vehicle event including rollover, and (2) any of the first four vehicle events including rollover. To isolate the safety effect of the roof strength, multi-vehicle cases were decided to be excluded for analysis. It is noteworthy that not all 20 States have reported rollover event at a vehicle level, resulting in exclusion of a few States not providing vehicle event elements. The identified rollover cases are to be further screened to narrow down to rollover cases fitting the study purpose focusing on roof crush resistance. Out of 20 States included in the study, 19 States provided at least the first vehicle event and 13 provided up to the fourth vehicle event.

After two data sets were filtered out of the SDS crash data by the two rollover definitions, VIN decoding was performed using the two VIN decoders, and decoded vehicle variables were added to the SDS rollover data. Resulting SWR and SDS rollover data with decoded vehicle information were prepared separately thus far. The data integration process that established linkage between the crush-tested vehicles in the SWR data and the crash-involved vehicles in the SDS rollover data is described in the next section.

4.1.4. Integrating SWR and SDS Rollover Data

The VIN-decoded SWR and SDS rollover data were required to be integrated to form the study data suitable for analysis. However, linking these two distinct data sets is far from straightforward. The SWR data include vehicles crush-tested in a laboratory while the SDS rollover data include vehicles rolled in traffic crashes, meaning the vehicles in the two data are not the same vehicles. This is why the term “merging” is avoided in this report and instead, a more general term “integrating” is used.[7] To link the two different sets of the vehicles, various ways of integrating the data were devised and tested based on a combination of vehicle information obtained from VINs. Two approaches were proposed for vehicle linking, (1) a VIN digit-based approach, and (2) a VIN decoder-based approach. In each approach, many specific integration methods or algorithms were formulated and tested.

VIN Digit-Based Approach

This approach uses actual digits of a VIN and the specific methods initially proposed ranges from using the partial VIN such as the first 12 digits to only few digits taken out of the VIN. A handful of the VIN digit-based integration methods remained after a preliminary testing and a logical consideration based on anatomy of a 17-digit VIN[8] is shown in Figure 4.

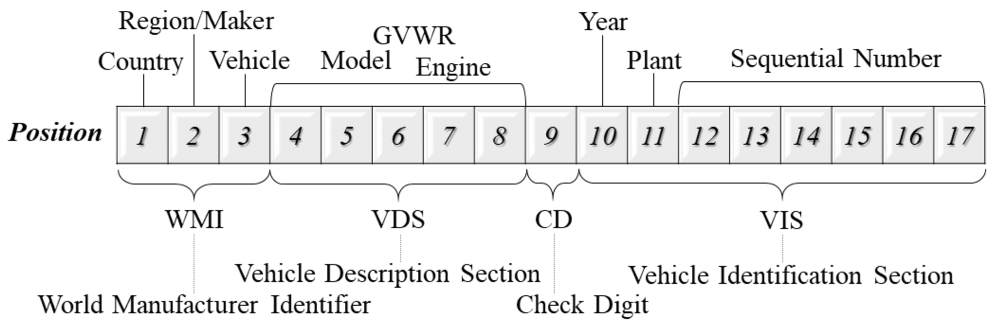

Figure 4. Components of 17-Digit Full Vehicle Identification Number.
This figure is recreated based on a VIN anatomy graphic on NHTSA’s vPIC webpage, *https://vpic.nhtsa.dot.gov/.*

The first three digits correspond to the world manufacturer identifier uniquely identifying the manufacturer of the vehicle. For some manufacturers, the third digit is used to indicate a vehicle category and/or a division of the manufacturer. The vehicle descriptor section (VDS) corresponding to the fourth to the eighth digit is deemed critical for this study since it identifies vehicle characteristics closely related to a roof strength such as vehicle type, model, engine size, and body style. This means the VDS contains core information for linking vehicles for this study. The ninth digit, known as a check digit, is to validate a VIN. Thus, it was determined to be excluded from consideration for vehicle linking. The 10th digit, indicating a vehicle model year, is crucial for this study because roof strength of the same vehicle is likely to change over years, especially over the study data period including the 2009 upgrade and the phase-in period of 2012-2015 for FMVSS No. 216a.

The 11th digit indicates the plant where the corresponding vehicle is manufactured. In theory, where a vehicle is manufactured does not affect a roof structure of the vehicle as long as the same vehicle design and materials are applied, inferred by the same VDS. There might be a possibility that some difference exists in manufacturing practices across different plants within

[7] Integrating data is here referred to a process of combining data from different sources where entities would be disparate and may not be matched between the sources.
[8] A full VIN is a unique 17-digit code identifying an individual motor vehicle manufactured around the world and available in the United States, and its first 11 digits contain vehicle-related information such as manufacturer, vehicle characteristics, and model year.

the same manufacturer and might affect a roof strength of a vehicle with the identical design. However, the 11th digit was decided not to be used for data integration in that the possibility was deemed slight enough to disregard. Moreover, preliminary testing of linking vehicles by a combination of VIN digits containing the 11th digit was found to be too limiting in terms of the number of cases in the resulting integrated data. The last six digits, the 12th to 17th, are the serial number identifying the individual vehicle. They carry no meaningful information for this study and were found only in the SWR data, not in the SDS data. Thus, any of the six digits was determined not appropriate for linking vehicles.

After testing many devised VIN digit-based integration methods, a combination of six digits comprising the first 10 digits of a VIN excluding the first through the third digits and the ninth digit was determined to be appropriate, and is stored in a variable, called V10X4 in this report, to be used for linking vehicles. For an example of a 11-digit VIN, `5J6YH18398L`, the V10X4 contains `YH1838` after excluding the first (`5`), second (`J`), third (`6`), ninth (`9`), and 11th (`L`) digits. V10X4 successfully distinguished most of the 358 vehicles in the SWR data. Integrating data using V10X4 implies that a vehicle in the SDS rollover data has a roof strength (i.e., SWR value) identical to that of a vehicle in the SWR data when the two vehicles have the identical value in their V10X4 variables.

VIN Decoder-Based Approach

The ED VIN decoder generated many variables[9] carrying vehicle characteristics such as BOD2, HYBRID, ROLLCURT, and AWD4X4. A combination of these VIN-decoded variables was explored for linking vehicles between the SWR and SDS data. A number of combinations were formulated and tested ranging from a combination of 5 variables to 11 variables. The combination with the 5 variables (MM2, CG, MY, BOD2, and ESC), called VED05 hereinafter, was assessed to be appropriate based on testing results. VED05 successfully distinguished most of the 358 vehicles in the SWR data and adding more variables to VED05 found no improvement in the differentiating capability. Integrating data using VED05 implies that a vehicle in the SDS rollover data has a roof strength (i.e., SWR value) identical to that of a vehicle in the SWR data when the two vehicles have the identical values in all the 5 variables composing VED05.

4.1.5. Joining the Data Sets

The V10X4 integration method is considered to more accurately link the vehicles in the SWR data to the vehicles in the SDS rollover data, as compared to the VED05 method, meaning that the SWR values mapped to the crash vehicles by V10X4 more accurately represent the roof strength of these vehicles. The resulting integrated data set obtained from the V10X4 integration method was found to be much smaller than the data set obtained by the VED05 integration method. Although the numbers of cases included in the data by V10X4 seem large enough for reliable analysis, the numbers of fatal cases included in those data sets were found to be inadequately small. Furthermore, when main analysis begins, cases where important variables

[9] The ED VIN decoder produces many variables such as BOD2, HYBRID, ROLLCURT, AWD4X4, MM2, CG, MY, and ESC. They are created based on known vehicle information such as manufacturer, model, trim, wheelbase, etc. Some correspond to specific vehicle features such as ROLLCURT being a vehicle's status for equipping rollover air bags while others are for analysis purpose such as CG assigning vehicles into various vehicle groups based on several pieces of vehicle information (e.g., manufacturer, mode, trim, and wheelbase).

contain missing values should inevitably be removed, which would further reduce the amount of data available for analysis.

To include as many cases as possible while not compromising the accuracy of linking the SWR values to the crash vehicles, joining the two integrated data sets was proposed. Specifically, data sets integrated by the two methods (V10X4 and VED05) were first merged based on a combination of the variables that are commonly found across the data sets, serving as a primary key. Since each data set contains peak SWR values, the merged data could have two different peak SWR values for the same vehicle. In such cases, a peak SWR value coming from the integrated data by V10X4 became an accepted value in that the linking accuracy by V10X4 is regarded higher than that by VED05. In non-matching cases, only one SWR value was found for each vehicle, which mostly came from the integrated data by VED05, and was accepted to represent the vehicle’s roof strength.

The two joined data sets were prepared, called DATA1 and DATA2, corresponding to a joined data set where vehicle’s rollover was determined by the first vehicle event and the other by the first four vehicle events, respectively. Accordingly, DATA1 are expected to be smaller than DATA2. After all variables in the two data sets were cleaned and recoded suitably for statistical analysis, they were ready to be analyzed. It should be noted that DATA1 is primary for main analysis while DATA2 is secondary, chiefly because the former is anticipated to isolate the safety effect of a vehicle’s roof strength from that of other vehicle events at a higher degree while the latter would likely exert the isolation at a lesser degree. This means DATA2 could play a meaningful role in analysis only when DATA1 is found unsuitable for some reasons such as its data size being inadequately small for reliable analysis. Otherwise, DATA2 may play a supporting role to reinforce findings from analyzing DATA1 if it were used for the study.

4.2. Data Analysis

Controlling for potential factors affecting an injury severity of an occupant in a rolled vehicle is important to isolate the safety effect of the roof strength of the vehicle from effects of other factors, to the maximum extent possible. One frequently used statistical analysis for that purpose is multiple regression which for each variable included in the model controls for the presence of other variables which might affect occupant injury severity.

4.2.1. Binary Logit Model

There are many types of regression models and, among them, a model type for a categorical outcome was deemed appropriate because the injury severity of an occupant is recorded in a categorical response ranging from no injury to fatal injury, specifically in the KABCO[10] scale reported by the police. Within the model type for a categorical outcome, several specific models such as binary and multinomial response models exist and selecting the best suited model relies chiefly on a distribution of categorical outcomes, the occupant injury severity for this study. Exploratory analysis of DATA1, the primary study data, revealed that there are less than 30 fatal

[10] The KABCO injury scale allows a non-medically trained person to make an injury assessment at a crash scene based on visual examination: K (Killed), A (Incapacitating Injury), B (Non-Incapacitating Injury), C (Possible Injury), and O (No Apparent Injury).

cases among about 5,100 cases. This means separating fatal cases from the other severity levels may not lead to reliable analysis due to the small number fatal cases.

There has been noted variation in reporting an appropriate injury level between non-incapacitating (B) and possible (C) injury severities by the police through visual examination. Such variation raises concerns in distinguishing explicitly these two severity levels for statistical analysis. These considerations led to a decision to collapsing 5-level KABCO scale to 2-level binary response: (1) a severe injury combining killed (K) and incapacitating injury (A) and (2) a non-severe injury combining non-incapacitating injury (B), possible injury (C), and no apparent injury (O). Thus, a binary response model was determined appropriate for analyzing the study data with the binary injury severity outcome (i.e., severe vs. non-severe injury), and a logit specification was employed for the model. The binary logit model is written as follows:

$$\pi_i = Pr(Y_i = 1 | x_{i1}, \ldots, x_{ik}) \text{ and}$$
$$logit(\pi_i) = log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad \text{Eq. (3)}$$

where i = index for an occupant in a rolled vehicle at a crash;

Y_i = binary response variable of an occupant i: Y_i = 1 if an occupant i sustains a severe injury and Y_i = 0 otherwise;

π_i = probability of an occupant i sustaining a severe injury;

$\beta_0, \beta_1, \ldots, \beta_k$ = regression coefficients to be estimated; and

$x_{i1}, \ldots, x_{ik}$ = explanatory variables for an occupant i (e.g., occupant's age and gender, peak SWR of an occupant's vehicle, and time of day for a crash).

When the binary logit model is estimated, estimates of regression coefficients are obtained and used to interpret model results. For example, $\hat{\beta}_k$, an estimate of a slope coefficient for variable x_{ik} is a change in log of odds for one unit increase in x_{ik}. Interpreting an estimated slope coefficient is typically done using odds ratio, which is mathematically expressed as below:

$$Odds\ Ratio(x_{ik}) = \frac{Odds(x_{ik}=c+1)}{Odds(x_{ik}=c)} = \frac{\frac{\pi(x_{ik}=c+1)}{1-\pi(x_{ik}=c+1)}}{\frac{\pi(x_{ik}=c)}{1-\pi(x_{ik}=c)}} = \exp(\beta_k) \qquad \text{Eq. (4)}$$

where c = constant.

Suppose x_{ik} is an indicator variable for the i^{th} occupant's gender, equaling 1 if male and 0 if female and the corresponding slope estimate, $\hat{\beta}_k$ = −0.29. A negative sign of the estimate means that being a male is associated with lower odds of sustaining a severe injury (fatal or incapacitating). To interpret it quantitatively, an estimated odds ratio is calculated as exp(−0.29) = 0.7483 ≈ 0.75. Thus, a male occupant in a rolled vehicle is associated with the odds of sustaining a severe injury being lower by 25 percent compared to a female counterpart if all other conditions being equal. This is loosely translated that a male occupant is less likely to sustain a severe injury than a female occupant by 25 percent in probability.

Predicted probabilities can also be calculated to interpret the model results and they can be calculated using the following equation:

$$\pi_i = \frac{exp(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik})}{1+exp(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik})} = \frac{1}{1+exp[-(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik})]} \qquad \text{Eq. (5)}$$

With model results (i.e., estimated coefficients, $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$) and explanatory variables $(x_{i1}, \ldots, x_{ik})$ set at specific values, a predicted probability, $\hat{\pi}_i$, can be calculated. A series of predicted probabilities can be calculated by varying values for a specific variable of interest while the other variables are fixed at certain values and often visualized in a graph for easier interpretation.

4.2.2. Regression Variables

More than 100 data elements were acquired from traffic crash records in SDS data, roof crush test results in SWR data, and two VIN decoders. Through the data processing described in the previous section, those data elements were transformed to variables suitable for regression analysis. The dependent variable for a regression model is a binary injury outcome transformed from the 5-level KABCO injury severity scale noted earlier. Among the explanatory variables transformed from the data elements, a subset of the variables was selected for potential regression variables based on literature review, logical consideration, and availability across the States included in the study data. Table 2 shows a total of 37 variables potentially entering a binary logit model including one dependent variable. The 36 explanatory variables are classified into three groups; (1) person characteristics, (2) vehicle characteristics, and (3) crash environment characteristics. All person and crash variables came from SDS crash data while all vehicle variables except the vehicle age were derived from the other two sources, SWR data, and the VIN decoders.

Table 2. Potential Variables for A Binary Logit Model

Variable Name	Definition
Dependent Variable	
Severe Injury	1 if a person sustained a severe injury: fatal (K) or incapacitating (A) injury 0 if a person sustained a non-severe injury: non-incapacitating (B), possible (C), or no apparent (O) injury
Explanatory Variables	
Person (Demographic or In-Vehicle) Characteristics	
Male	1 if a person was male; 0 otherwise
Person Age	Person's age (years); Person Age = 98 for 98 years or older
Driver	1 if a person was a driver; 0 otherwise
Belt Use	1 if a person used a restraint; 0 otherwise
Alcohol Use	1 if a person was suspected or found to have consumed alcohol; 0 otherwise
Air bag Deploy	1 if an air bag at a person's seat was deployed; 0 otherwise
Row 1 Left	1 if a person was on left seat on 1st row; 0 otherwise
Row 1 Right	1 if a person was on right seat on 1st row; 0 otherwise
Row 1 All	1 if a person was on any seat on 1st row; 0 otherwise
Row 2 Left	1 if a person was on left seat on 2nd row; 0 otherwise
Row 2 Right	1 if a person was on right seat on 2nd row; 0 otherwise
Row 2 All	1 if a person was on any seat on 2nd row; 0 otherwise

Variable Name	Definition
Vehicle Characteristics	
Peak SWR	Peak strength-to-weight ratio of a vehicle
Vehicle Age	Vehicle's age at the time of crash (years) = crash year – model year
Passenger Car[a]	1 if a vehicle body class is classified passenger car; 0 otherwise
Pickup Truck[a]	1 if a vehicle body class is classified pickup truck; 0 otherwise
Sports Utility Vehicle[a]	1 if a vehicle body class is classified sports utility vehicle; 0 otherwise
GVWR1[a]	1 if a vehicle belongs to GVWR Class 1; 0 otherwise
ESC[b]	Probability of a vehicle being equipped with ESC feature
Curtain Air Bag[b]	Probability of a vehicle being equipped with curtain air bag
Rollover Air Bag[b]	Probability of a vehicle being equipped with rollover air bag
Crash Environment Characteristics	
Speed Limit	Speed limit of a road on which a vehicle was traveling (miles per hour)
Urban	1 if a crash occurred on a road in an urban area
Daylight	1 if a crash occurred in daylight condition; 0 otherwise
Dark	1 if a crash occurred in dark condition; 0 otherwise
Clear Weather	1 if a crash occurred in clear weather condition; 0 otherwise
Rainy Weather	1 if a crash occurred in rainy weather condition; 0 otherwise
Dry Surface	1 if a crash site's surface was dry; 0 otherwise
Wet Surface	1 if a crash site's surface was wet; 0 otherwise
Weekend	1 if a crash occurred during weekend; 0 otherwise
Early AM Hour[c]	1 if a crash occurred in 4 a.m. – 5:59 a.m.; 0 otherwise
AM Peak Hour[c]	1 if a crash occurred in 6 a.m. – 8:59 a.m.; 0 otherwise
Lunch Hour[c]	1 if a crash occurred in 12 p.m. – 12:59 p.m.; 0 otherwise
PM Peak Hour[c]	1 if a crash occurred in 6 p.m. – 7:59 p.m.; 0 otherwise
Early Night Hour[c]	1 if a crash occurred in 8 p.m. – 9:59 p.m.; 0 otherwise
Late Night Hour[c]	1 if a crash occurred in 10 p.m. – 3:59 a.m.; 0 otherwise

[a] Vehicle classification is based on body class information from vPIC VIN decoder and GVWR class was decoded by vPIC VIN decoder.
[b] Proportion of vehicles equipped with the feature in vehicle fleet is calculated by ED VIN decoder since the presence of the feature is not known for an individual vehicle.
[c] Time of day is determined following the definition in NHTSA's report (Eigen, 2010).

Among a total of 12 potential variables reflecting person characteristics, Male, and Person Age variables are an occupant's demographic characteristics while the other 10 variables are an occupant's in-vehicle characteristics in a rollover crash. When occupant's age was not reported or missing but date of birth was available, age was calculated using the date of birth and a crash date. Driver variable is coded to 1 if an occupant was a driver of a vehicle. Belt Use variable is coded to 1 if an occupant was found to wear any type of a seat belt such as lap belt, shoulder belt (also called harness), or both on a police crash report. Alcohol variable is coded to 1 if an occupant was suspected, involved, or detected to have consumed alcohol by a reporting police and it does not necessarily mean being impaired by alcohol. Air bag variable is coded to 1 if any type of air bag (e.g., front air bag, side air bag, curtain air bag, or combination of these) was deployed at the seat of an occupant. Row 1 Left through Row 2 All variable were derived from seat position information. It should be noted that not all States provided such information and some States provided only seat row, not a position within a row.

As for vehicle characteristics, nine explanatory variables were considered being potentially useful for a severe injury binary logit model. peak SWR variable is the focal point of this study and is unitless. It represents the strength of a roof of a vehicle in which an occupant was found to be in a rollover crash and a higher value means a stronger roof. A value of 3.0 for peak SWR variable, for example, means that the vehicle's roof could withstand three times the vehicle's unloaded weight. Vehicle Age variable is calculated by subtracting the vehicle's model year from a crash year. For example, Vehicle Age variable equals to 5 when an involved vehicle's model year was 2010 and a crash occurred in 2015. Vehicle Age variable is set to 0 when a vehicle model year is larger than a crash year (e.g., vehicle model year=2011 and crash year=2010). Three vehicle-type variables were created using vehicle's body class information decoded by vPIC VIN decoder and GVWR classification was directly obtained from vPIC VIN decoder.

ESC, Curtain Air bag, and Rollover Air bag variables were derived from ED VIN decoder. ESC is a safety feature helping a driver maintain a directional control of a vehicle. A curtain air bag is known as a side-impact curtain air bag typically deployed downward from the overhead roof rail, very close to the side windows. Some curtain air bags can also provide protection at a rollover event by a rollover sensing system detecting an imminent rollover and triggering deployment of the air bags and these air bags are known as rollover air bags.[11] Although this information could exist at each vehicle, it was neither found in SDS crash data nor discoverable by the two VIN decoders for an individual vehicle. Meanwhile, the information at a vehicle fleet level could be found using published statistics such as *Ward's Automotive Yearbook* and vehicular regulations such as FMVSSs. ED VIN decoder calculates a fleet-based proportion of vehicles equipped with a certain vehicle feature and assigns a corresponding proportion for each vehicle being decoded. ESC, Curtain Air Bag, and Rollover Air Bag variables, corresponding to three safety features, were generated by ED VIN decoder. Thus, the three variables contain values representing a probability that an individual vehicle is equipped with the corresponding feature and their values range from 0.0 to 1.0. For example, a value of 0.27 for ESC variable indicates that 27 percent of the vehicle fleet corresponding to the vehicle of interest is equipped with ESC and thus the vehicle has 27 percent chance of ESC being equipped.

There are 15 variables reflecting crash environment characteristics. Speed Limit variable records a posted speed limit at a crash site in miles per hour (mph) and Urban variable is coded to 1 if a crash site is located in an urban area. It should be noted that there found variation in defining "urban" in a police crash report across States. For example, Florida defines "urban" to be an area with population greater than or equal to 2,500 while Missouri defining urban for an area with population greater than or equal to 5,000. It is noteworthy that not every State reports this information and some States provided this information only in certain years. Daylight, Dark, Clear Weather, Rainy Weather, Dry Surface, Wet Surface, and Weekend variables are coded to 1 if a crash occurred in daylight condition, dark condition, clear weather, rainy weather, dry

[11] All passenger vehicles with GVWR of 4,536 kg (10,000 lbs) or less must meet FMVSS No. 226; ejection mitigation, by September 1, 2017, with the phase-in compliance starting in 2013. This standard establishes requirements for ejection mitigation systems to reduce the likelihood of ejections of vehicle occupants through side windows during rollovers or side impact events. Since rollover air bags are part of the ejection mitigation systems, more recent vehicles are more likely to have rollover air bags.

surface, wet surface, and weekend, respectively. Time of day (TOD) definitions were adopted from a NHTSA's report (Eigen, 2010) analyzing rollover crashes and six TOD variables were created based on a crash time: Early AM, AM Peak, Lunch, PM Peak, Early Night, and Late Night Hour variables.

Some of the variables appear to be redundant by definition. For example, Dry Surface and Wet Surface variables can be thought to be a complement to each other. However, there are other surface conditions such as surface covered with ice, oil, and sand. In the end, several of the variables in the table were determined to be excluded from development of a logit model due to various reasons such as a high proportion of missing cases and a quasi-separation problem in estimation identified in exploratory analysis. These issues will be discussed in Chapter 5 summarizing analysis results.

4.2.3. Multicollinearity and Variable Selection

Multicollinearity among explanatory variables may not affect prediction accuracy of an entire model but would jeopardize inference on coefficients of individual variables. If a variable is highly related to other variables, its coefficient estimate would be biased—in extreme cases, the sign of the estimate being reversed—and the standard error of the estimate would be inflated. This would result in incorrect inference on the coefficient, leading to an erroneous conclusion about the relationship between the dependent variable and the explanatory variable. For example, if there truly existed a relationship between the variable pair, the presence of multicollinearity could lead to a conclusion of non-existence of the relationship.

There are several diagnostics for helping identify variables causing multicollinearity and the three common ones are employed in this study: (1) a correlation coefficient, (2) a variance inflation factor (VIF), and (3) a condition index in conjunction with a variance proportion. A correlation coefficient being closer to 1 or –1 indicates a higher degree of a linear relationship between two variables. The VIF is an index measuring how much variance of a coefficient estimate is increased due to multicollinearity and has a lower bound of 1. For example, a VIF of 3 means that the variance of a coefficient of interest is three times what would be if the corresponding variable were uncorrelated with all other variables included in a regression model. A rule-of-thumb threshold value of the VIF for determining multicollinearity is 10; a VIF greater than 10 indicates the presence of multicollinearity.

A condition index, also called condition number, is calculated based on eigenvalues of the design matrix, basically a data set containing explanatory variables. When multicollinearity is present, eigenvalues are small causing a corresponding large condition index. A conventional guide on use of the condition index is that the index value greater than 30 indicates moderate to high degree of multicollinearity. Variance proportions in conjunction with the condition index identify specific explanatory variables associated with the identified multicollinearity and are calculated based on eigenvalues. A variance proportion gauges how much of a variance of a coefficient estimate is related with an eigenvalue and a larger proportion implies a higher association with the eigenvalue. Thus, explanatory variables with large variance proportions with respect to a large condition index (i.e., small eigenvalue) cause multicollinearity. A rule-of-thumb cutoff value for the variance proportion is 0.5 implying that a variance proportion greater than 0.5 indicates the corresponding variable is causing multicollinearity.

Variable selection techniques are used to obtain guidance on selecting variables to be included in an initial model specification. Stepwise selection and Least Absolute Shrinkage and Selection Operator (LASSO) selection methods were used with various evaluation criteria such as Akaike Information Criterion (AIC) corrected for small sample (AICc), Bayesian Information Criterion (BIC), Mallow's C_p, and cross-validation with and without model averaging; Other methods such as forward and backward selection were also attempted. Each selection method with specific evaluation criterion produces the best model according to the specified criterion, and a set of variables commonly included in the best models produced by various methods could serve as guidance for choosing an initial set of variables entering a severe injury binary logit model. It should be noted that choosing variables for an initial logit model specification is conducted based on a consultation with logical consideration, results of multicollinearity examination, and results of variable selection methods.

4.2.4. Polynomial Relationship

To examine needs for higher order polynomial terms for a binary logit model, two methods were used, one visual examination and one statistical test. The visual examination is based on a scatter plot between an empirical logit and an explanatory variable. The Box-Tidwell test (Box & Tidwell, 1962) is designed to detect the presence of a non-linear functional relationship, suggesting inclusion of non-linear explanatory variables. While the Box-Cox transformation is applied to the dependent variable for correcting nonlinearity, the Box-Tidwell transformation is applied to the explanatory variables.

Polynomial relationships with interaction terms were also investigated. Interaction terms involving the peak SWR variable and categorical explanatory variables were included in a binary logit model and test statistics for estimated coefficients for the interaction terms were used to determine whether to include the interactions for further model development.

4.2.5. Model Evaluation and Variants

Several goodness-of-fit measures are used for comparing competing models and they include AIC, BIC, and *c* statistics. AIC and BIC are penalized likelihood criteria and can be used to compare non-nested models as long as they use the same data as are being used to develop those models. A model with lower AIC and BIC values is better. The two criteria are mathematically expressed as follow:

$$AIC = 2k - 2LogL \qquad \text{Eq. (6)}$$
$$BIC = k\log(n) - 2LogL \qquad \text{Eq. (7)}$$

where k = number of parameters in the model;
n = number of observations; and
$LogL$ = log-likelihood of the model.

As seen in Equations 6 and 7, the only difference between AIC and BIC is a penalty for the number of parameters in the model, and BIC penalizes more complex models, thus favoring more parsimonious models. AIC and BIC are used for model comparison and their values themselves are not meaningful. *c* statistics is equivalent to the area under the Receiver Operating

Characteristic (ROC) curve (AUC). It ranges from 0.5 to 1 and a model with a higher c value is better.

Two variant models to the binary logit model described in Section 4.2 are employed to add statistical reliability to coefficient estimates of the binary logit model. They are an overdispersion binary logit model and a Bayesian binary logit model. Overdispersion arises when the variance of the binary outcome becomes larger than that of the binomial distribution assumed for the binary logit model. When overdispersion is present in the response data, the estimated standard errors for individual coefficients of the model become smaller than they should be, distorting test statistics and confidence limits. Thus, inference on the statistical significance of the coefficient estimates could be erroneous. For example, with the presence of overdispersion, an explanatory variable truly related to the dependent variable could be erroneously concluded as being not statistically relevant. Thus, the estimates of the standard errors should be adjusted.

This study employed an overdispersed binary logit model proposed by Williams (1982) and the following weight variable was used for estimating the model:

$$Williams'weight = \frac{1}{1+\varphi(m_i-1)} \qquad \text{Eq. (8)}$$

where φ = dispersion parameter to be estimated; and
m_i = the number of trials in i^{th} event.

With the above weight, the variance of the response is larger than the binomial variance.

A Bayesian binary logit model is used with the model specification written in Equation 3 and non-informative priors are assumed for all regression coefficients, $\beta_0, \beta_1, \dots, \beta_k$. A normal non-informative prior was used for the coefficients as below:

$$\beta_i \sim N(0, 10^6) \qquad \text{Eq. (9)}$$

where i = index for a parameter (0,…, k).

5. Results and Discussion

Results in the data processing and data analysis described in Chapter 4 are presented and discussed in separate sections. Since data processing is an important part of this study, it is described in detail, followed by data analysis performed on the processed data.

5.1. Data Processing

5.1.1. Processing SWR Data

A single SWR data set containing 358 vehicles with peak SWRs was prepared as described in Section 4.1.1. Figure 5 shows the distribution of all 358 peak SWR values in the SWR data set. The peak SWRs range from 0.85 to 7.26 with the average of 4.23. The SWR data cover a wide range of the peak SWRs and most of the values are around the average value, 4.2, which looked suitable for analysis.

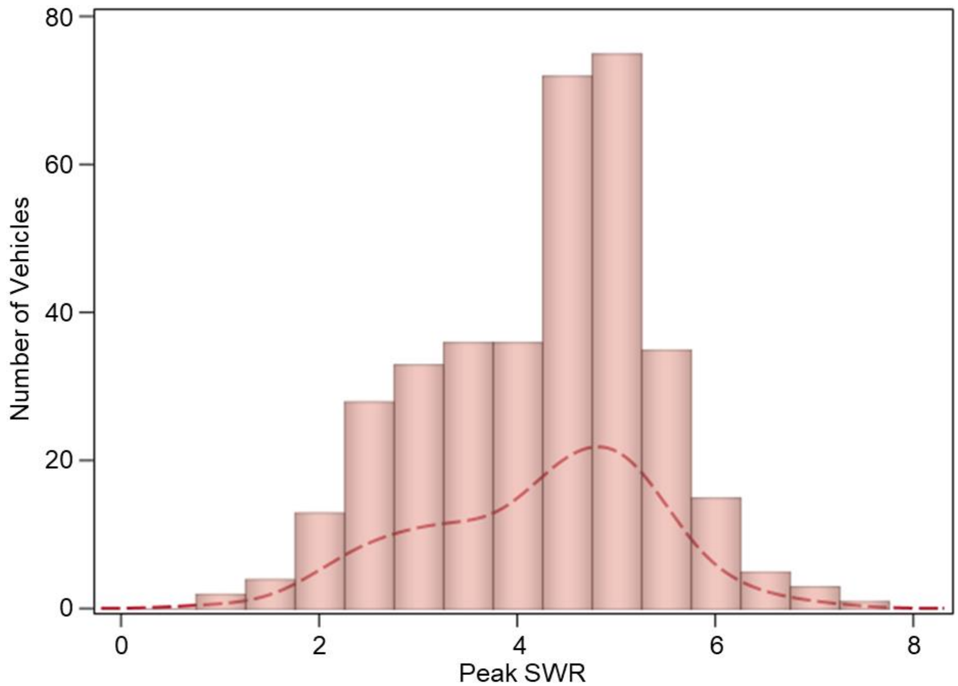

Figure 5. Histogram and Kernel density plot of peak SWRs.
Peak SWR values of 358 vehicles are displayed with a bin width of 0.5 and their model years range from 1997 through 2017.

VINs of the 358 vehicles in the SWR data were examined for their correctness using vPIC VIN decoder[12] and eight of 358 VINs were found invalid. The eight invalid VINs were manually corrected using information generated by vPIC VIN decoder and NICB's VIN Manual. For example, one vehicle was found one digit short of a full 17 VIN digits in the SWR data and which digit is missing was not apparent. Since information on manufacturer, model, and model year of the vehicle were available from the raw data file of the crush tests, a part of NICB's VIN Manual corresponding to the vehicle information was consulted to identify the missing digit and

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[12] The vPIC VIN decoder has a functionality of checking correctness of a VIN, indicating positions of potentially incorrect digits, and offering a suggested correct VIN.

find a correct value for the digit. After all the eight invalid VINs were successfully corrected, VIN decoding was performed on the 358 vehicles using two VIN decoders (vPIC and ED VIN decoders), and decoded vehicle variables were added to the SWR data.

5.1.2. Processing SDS Rollover Data

The 20-State multi-year crash data set was prepared according the process described in Section 4.1.2 and contains 143,007,096 person-based crash cases where crash, vehicle, and person records were matched. Among these cases including all types of crash such as head-on and rear-end crashes, rollover cases were extracted using the two rollover definitions described in Section 4.1.3: (1) the first vehicle event being rollover, and (2) any of the first four vehicle events being rollover. There were 382,632 rollover cases identified by the first vehicle event and 1,567,497 rollover cases by the first four vehicle events. As noted earlier, not all 20 States reported rollover status at a vehicle level. Thus, applying these two rollover definitions, both based on the vehicle events, excluded a few States without vehicle event data elements in their SDS data.

A few things are noteworthy on the identified rollover cases. First, the identified rollover cases include people ejected from their vehicles during rollover. Second, they also include cases involved in multi-vehicle crashes. Third, the rollover cases identified by the first four events include cases where potentially serious impacting events occurred before or after rollover such as a vehicle colliding head-on with tree followed by rollover. These issues could cause bias in analysis outcomes when they are not mitigated appropriately. For example, suppose a vehicle overturns after a head-on collision with another vehicle or a fixed object and its occupant sustains a severe injury. Since it is not possible to determine how much each event contributes to the injury, including such rollover cases in data analysis could lead to a biased result possibly validating or invalidating a hypothesis of this study, a stronger roof reducing injury severity.

The rollover cases identified so far were considered to be valid rolled vehicle cases. However, they were not necessarily appropriate for analysis of the study mainly because of the three issues noted above. Further fine tuning the rollover definitions was deemed necessary. Since two of the principal mechanisms causing injury to occupants during rollover are roof crush and ejection from a vehicle, excluding ejected cases from the identified rollover cases was imperative. Also, to isolate the safety effect of a vehicle's roof strength from that of other events likely causing serious injury, filtering out multi-vehicle cases and cases involving a head-on or angle collision was deemed appropriate. After excluding cases meeting these conditions, 194,272 and 886,765 rollover cases remained from the previously identified rollover cases of 382,632 and 1,567,497, respectively, and they were regarded proper for the study.

Two VIN-decoding programs, vPIC and ED VIN decoders, were then applied on the proper rollover cases to add vehicle information. Although VINs in the SDS data are partial, 10 to 12 digits depending on the State, the two VIN decoders were able to generate vehicle information as long as the partial VINs were valid. Among the 194,272 and 886,765 proper rollover cases, 175,743 and 791,222 were found to be successfully VIN-decoded, respectively, by at least one of the two VIN decoders. The steps of preparing the SWR roof strength data and SDS rollover crash data are illustrated in Figure 6.

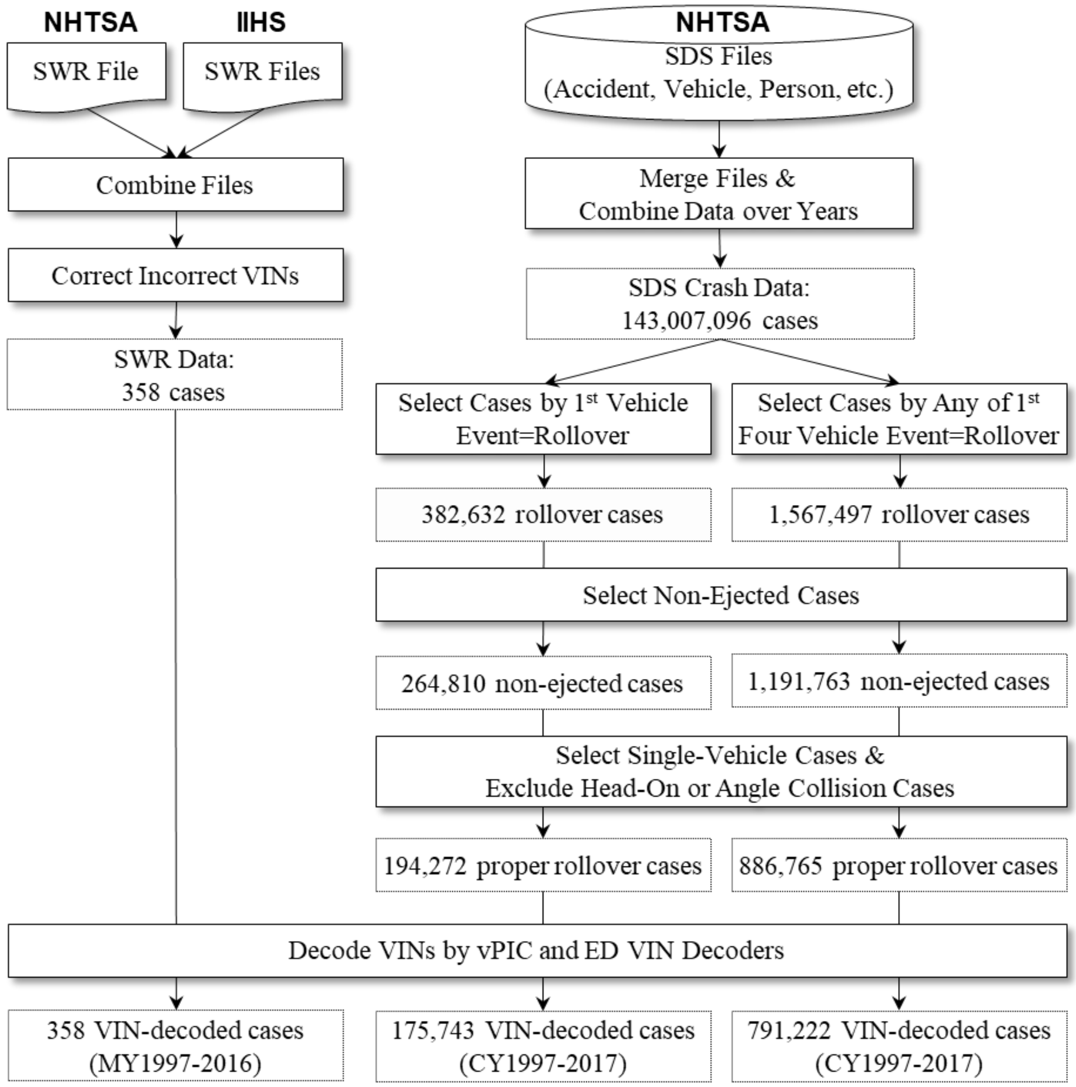

Figure 6. Flowchart of processing SWR and SDS data.
A case in SWR and SDS data corresponds to a vehicle crush-tested in a laboratory and a person involved in a rollover crash, respectively.

As seen in Figure 6, one final SWR data set was prepared while two final SDS proper rollover data sets were prepared in the end and they were ready for integration.

5.1.3. Integrating SWR and SDS Rollover Data

The two data integration methods described in Section 4.1.4, one VIN digit-based method (V10X4) and one VIN decoder-based method (VED05), were applied first to the SWR dataset to identify any duplicate cases by each method. Applying the V10X4 method to the 358 vehicles in the SWR data found eight duplicate cases (i.e., four vehicle-pairs) meaning two vehicles in each pair are identical in terms of their values in V10X4 variable. A duplicate vehicle pair means that the two vehicles would very likely be identical in model year and vehicle design-related characteristics such as vehicle type, model, body style, and engine type. To use V10X4 for integrating the SWR data into the SDS rollover data, it was necessary to aggregate the duplicates and two SWR values in each vehicle pair were averaged. This resulted in 354 cases in the SWR data that are unique in terms of V10X4.

When the VED05 method was applied to the 358 vehicles, 10 duplicate cases (i.e., five vehicle pairs) were identified meaning the two vehicles in each pair are identical in the five vehicle characteristics generated by ED VIN decoder such as car group, body style, and model year. Among the 10 cases, 8 were found duplicate by V10X4 as well. To integrate the data using VED05, two SWR values in each of the 5 vehicle pairs were averaged. This resulted in 353 cases in the SWR data that are unique in terms of VED05.

Austin (2010) integrated SWR data and CDS rollover data by an approach using vehicle analytical groups generated based on VIN. His approach is somewhat similar to the VIN decoder-based approach employed in the current study in that vehicles were classified into homogenous groups based on vehicle characteristics. However, this study's VIN decoder-based method (i.e., VED05) grouping vehicles based on the 5 variables is more stringent than Austin's approach in identifying homogenous vehicles, increasing accuracy of integrating the SWR data and rollover data from a roof strength standpoint. For example, the 2010 study classified 75 vehicles into 50 vehicle groups while the VED05 method classified 358 vehicles into 353 vehicle groups.

After the two SWR aggregate data sets were prepared, integrating data by the two methods was performed between the two SWR data sets and the two SDS rollover data sets. The data integration produced a total of four integrated data sets and its steps are illustrated in Figure 7. The four data sets were generated after the data integration process was completed: (1) 1,412 cases where rollover is defined by the first vehicle event and vehicles are linked by V10X4, (2) 6,364 cases where rollover is defined by the first four vehicle events and vehicles are linked by V10X4, (3) 5,097 cases where rollover is defined by the first vehicle event and vehicles are linked by VED05, and (4) 18,659 cases where rollover is defined by the first four vehicle events and vehicles are linked by VED05. All these data contain proper rollover cases with valid SWR values representing their vehicles' roof strengths. It is noteworthy that the rollover cases identified by the first vehicle event are considered more appropriate for the study than those by the first four vehicle events mainly because the former is anticipated to isolate the effect of the roof strength at a rollover from the effects of other events occurring prior to or after rollover such as running into ditch before or after rollover.

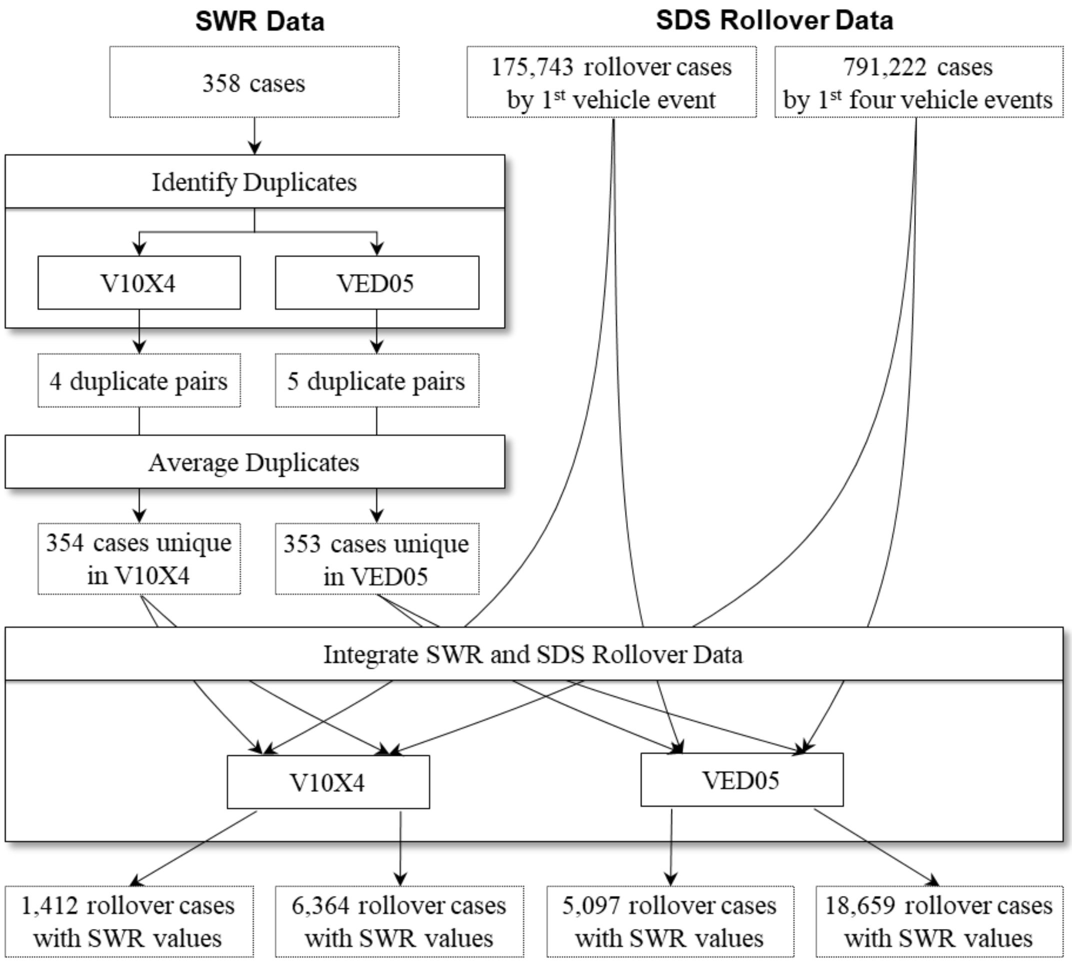

Figure 7. Flowchart of integrating SWR and SDS data.
V10X4 and VED05 are two integration methods for linking the vehicles in the SWR and SDS rollover data sets. V10X4 is to use six digits of a VIN for integration while VED05 is to use five variables decoded by ED VIN decoder.

5.1.4. Joining Integrated Data

Joining the data developed from the two integration methods (V10X4 and VED05) was performed to increase the data size for reliable analysis by including the cases, some of which could have possibly inaccurate SWR values for their vehicles as described in Section 4.1.5. Figure 8 illustrates the process producing the two joined data sets, one with 5,153 cases where their vehicles' rollover was determined by the first vehicle event and the other with 19,167 cases by the first four vehicle events.

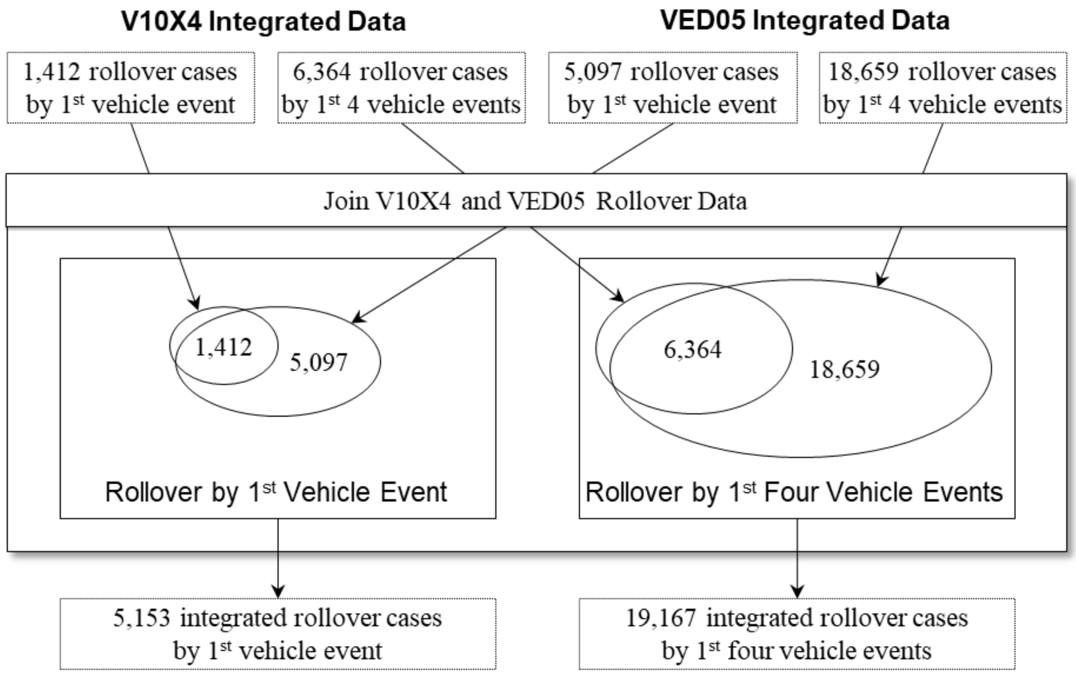

Figure 8. Joining integrated V10X4 and VED05 data.
An intersection area in a Venn diagram represents where two data sets were matched by a combination of variables commonly found in the two data sets, meaning two SWR values exist for the same vehicle. When two SWR values were found in the integrated data, an SWR value from V10X4 data was selected to represent the vehicle.

The resulting two joined data sets served as the final study data for analysis after all the variables were appropriately modified for statistical analysis. They are; DATA1 containing 5,153 non-ejected occupants in vehicles whose rollover status was determined by the vehicle's first event; and DATA2 containing 19,167 non-ejected occupants in vehicles whose rollover was determined by the vehicle's first four events. As noted earlier, DATA1, the primary study data, is analyzed first and if it were found to have inadequate amount of data for developing a severe injury logit model, DATA2, the secondary study data, would serve as the primary data instead. Otherwise, DATA2 may not be used for the study although it could be analyzed in tandem with DATA1.

5.2. Binary Logit Model for Severe Injury at Rollover

5.2.1. Examining Regression Variables

A total of 37 variables including one binary dependent variable (Severe Injury) were identified as potentially useful for developing a binary logit model for a severe injury at a rollover crash (see Table 2 for the variables and their definitions). These variables were examined using the two study data sets, DATA1 and DATA2, since some variables may not be adequate for proceeding to model development. Both data sets were examined and only results on DATA1, the primary study data, are discussed here while those on DATA2 would be occasionally mentioned when needed.

In DATA1 containing 5,153 observations, several variables were found to have many missing cases and they include three person's in-vehicle variables (Belt Use, Alcohol Use, and Air Bag Deploy), three vehicle type variables (Passenger Car, Pickup Truck, and Sports Utility Vehicle) based on vehicle's body class information from vPIC VIN Decoder, three vehicle safety feature variables (ESC, Curtain Air Bag, and Rollover Air Bag) generated by ED VIN decoder, and two crash environment variables (Urban and Speed Limit). Among these variables, some have half or more cases with missing values. For example, Alcohol Use and Urban variables have missing values in 54 percent and 76 percent of the data, respectively. The three safety feature variables include about 50 percent missing cases. Including these variables in a regression analysis means that a regression model would be estimated based on a much smaller data set than the full study data set since the regression analysis only allows observations where valid data values exist in all the variables included in the regression model. This means that the size of the data actually used for estimating a regression model varies depending on variables included in the model.

The dependent variable was found to have 24 missing cases and 5,129 valid cases (468 severe injury cases and 4,661 non-severe injury cases including no injury cases). The number of severe injury cases, 468, appears sufficient for developing a binary logit model for a probability of sustaining a severe (fatal or incapacitating) injury although the number becomes smaller when explanatory variables with missing values enter into the logit model. Two critical explanatory variables for the logit model are peak SWR and Belt Use. Although Belt Use variable has many missing values, about 60 percent, its inclusion in the logit model is strongly desired mainly because seat belts are a known countermeasure for mitigating a severe consequence at a rollover crash.

There were 2,106 cases where all three essential variables for the severe injury logit model, Severe Injury (dependent variable) and peak SWR and Belt Use (explanatory variables) have valid values and 268 of the 2,106 cases sustained a severe injury. This was believed to be adequately large enough for developing a severe injury binary logit model. It should be noted that there was only one peak SWR value, 2.3810, for vehicles classified in GVWR Class 2. This means that GVWR1 variable would be unable to distinguish a differential effect of the two GVWR classes if it were included in a binary logit model. Thus, GVWR Class 2 was excluded from consideration for a binary logit model.

Mainly due to the adequate amount of valid observations on the three essential variables (Severe Injury, Peak SWR, and Belt Use) for a binary logit model, the primary study data (DATA1) was judged to be satisfactory for the study meaning DATA2 would not be needed for the study. As noted earlier, DATA2, the secondary study data, was processed as an alternative data in case DATA1 would contain an insufficient amount of valid observations. Since DATA1 was determined to be the primary data for the study, DATA2 remained as the secondary data and would not be used for the study as long as the final severe injury logit model is successfully developed using DATA1.

5.2.2. Multicollinearity and Variable Selection

To examine multicollinearity among the explanatory variables, three measures explained in Section 4.2.3 were employed: (1) a correlation coefficient, (2) a variance inflation factor (VIF), and (3) a condition index in conjunction with a variance proportion. Several variables were anticipated to be correlated with one another by their definitions and such correlations were confirmed by calculated correlation coefficients. Driver variable is found to be highly correlated with all three first row seat variables, Row 1 Left (0.84), Row 1 Right (-0.59), and Row 1 All

(0.54), with a corresponding Pearson correlation coefficient shown in parenthesis, and the coefficients are statistically significant at 0.01 level. In a similar fashion, Dark variable is highly correlated with Day Light (-0.90) and Late Night (0.62) variables while Clear Weather variable is highly correlated with Rainy Weather (-0.71) and Dry Surface (0.66) variables. All the presented correlation coefficients are highly statistically significant at least 0.05 level. It is worth noting that peak SWR variable is correlated with Curtain Air bag (0.53), Passenger Car (0.51), ESC (0.5), and Vehicle Age (-0.41) variables. Figure 9 displays a heatmap visualizing Pearson correlation coefficients among selected explanatory variables.

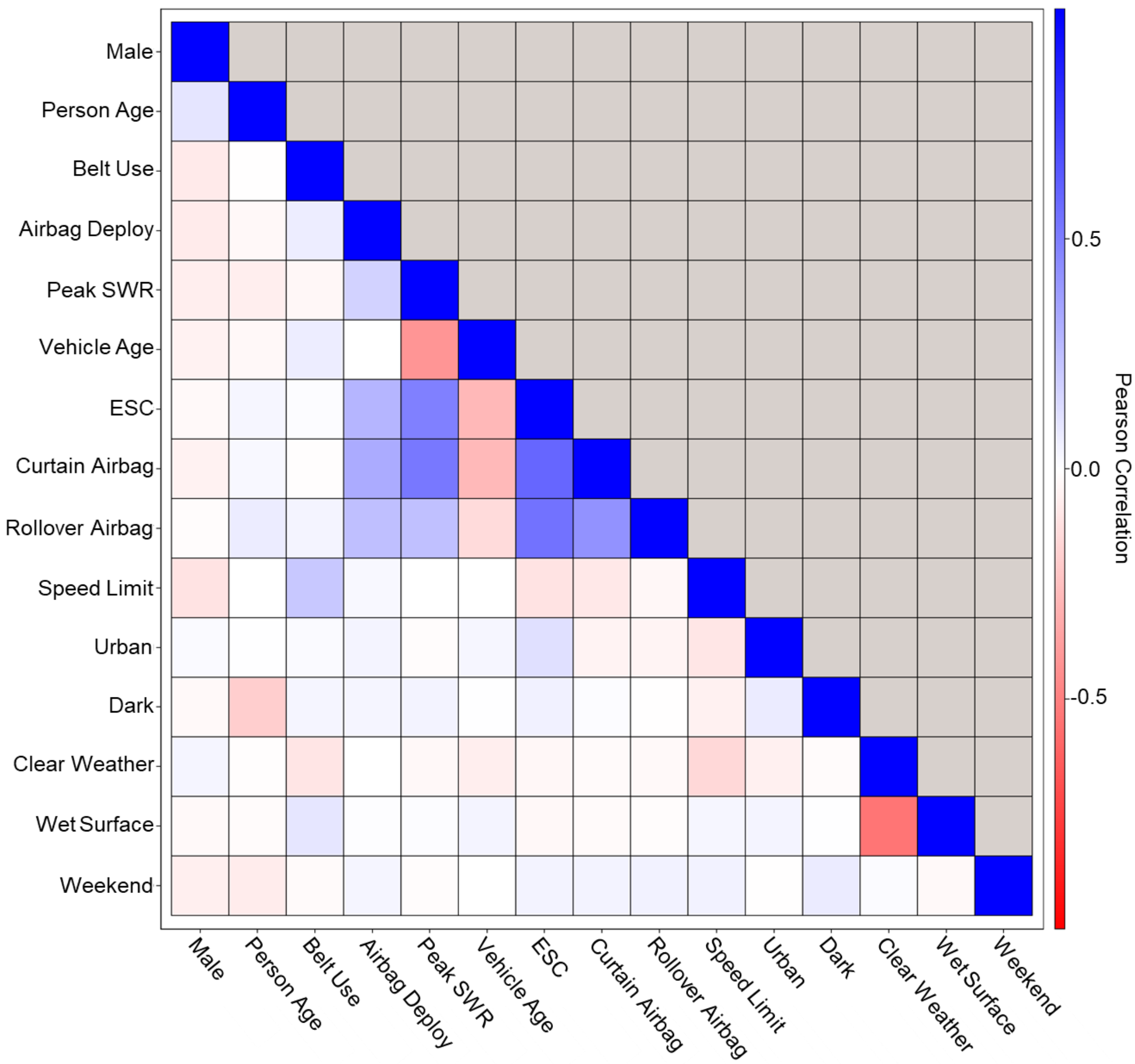

Figure 9. Correlation heatmap for selected variables.
Pearson correlation coefficients are visualized in color for easier indication of the degree of correlation.

The VIF and two sets of condition indices (condition indices without and with adjustment for the intercept) were calculated for a subset of the variables excluding the variables verified for their collinearity by Pearson correlation coefficients—The intercept-adjusted condition index was used when the intercept is found to be involved with collinearity. VIFs for Driver and Air bag variables failed to be calculated due to collinearity. Thus, multicollinearity diagnostic analysis proceeded after these two variables were removed. Since a regression model is used to calculate VIFs and condition indices, including variables with many cases with missing values considerably reduces the number of observations used for the multicollinearity diagnostics. Moreover, a combination of several variables was found to be responsible for about 70 percent of the data being excluded from the diagnostic analysis due to their missing values, and they are Alcohol, Passenger Car, Pickup Truck, SUV, ESC, Curtain Air Bag, Rollover Air Bag, Urban, and Speed Limit. These variables were determined to be excluded from model development due to considerable missing cases. VIFs and condition indices calculated for the remaining 17 variables were found to be below their thresholds, 5 and 30, respectively, meaning no multicollinearity. Thus, analysis continued with these variables.

As seen in Figure 9, Vehicle Age variable is negatively correlated with peak SWR variable in a moderate degree and the relationship was examined using a Kernel density plot. Figure 10 shows the bivariate density of the two variables where Severe Injury and Belt Use variables have valid values. A concentration of observations is noted at two areas, one slightly over 2.0 of peak SWR and the other around 5.0 of peak SWR. What poses little concerns is the area near lower peak SWR where relatively old vehicles aged 2 to 5 years old are overrepresented. As noted earlier, a vehicle's roof strength is not expected to change as the vehicle gets older substantially enough to affect a crash consequence. While the final binary logit model is being developed, Vehicle Age variable would be monitored for possible confounding behavior. If suspicious behavior is noticed such as notable change in a coefficient estimate and its standard error of peak SWR variable with and without Vehicle Age variable, removing Vehicle Age variable would be considered.

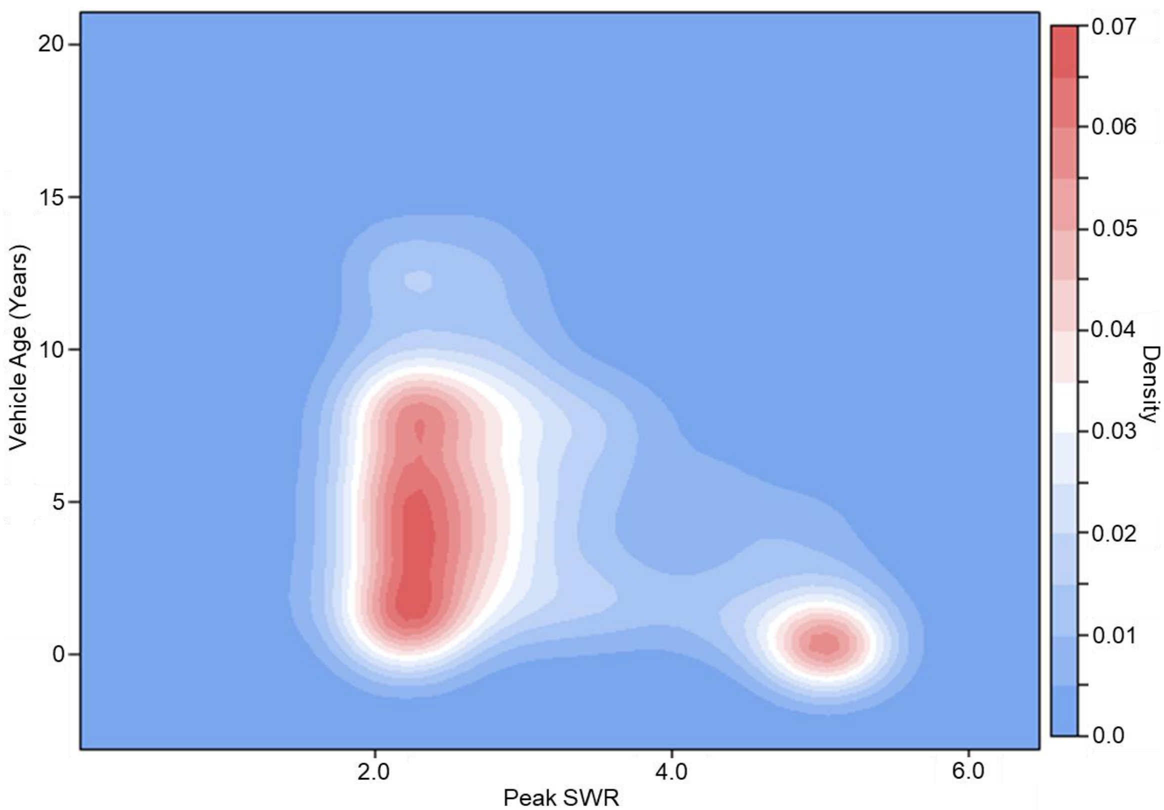

Figure 10. Bivariate density of Peak SWR and Vehicle Age.
Data with valid values in Severe Injury and Belt Use variables are used to create the density plot.

Several model selection methods explained in Section 4.2.3 were adopted to develop insight on variables that could be effective in developing a binary logit model and they include stepwise and LASSO selection methods with various model fit criteria such as AIC, BIC, and predicted residual error sum of squares (PRESS) statistic. Instead of relying on outcomes from a single run of the selection method, random sampling techniques with and without 5-fold cross validation method were adopted to generate outcomes from multiple runs of each model. A total of 100 samples were drawn from the entire study data using two random samplings (with and without replacement) and used to develop the best model for each sample. In the end, 100 best models were developed for each selection method and variables included in these 100 models were tallied to rank them in terms of their selection frequency. Figure 11 shows variables selected in at least 20 out of 100 best models developed by LASSO selection coupled with 5-fold cross-validation using the 100 sample data sets drawn randomly with replacement from the study data.

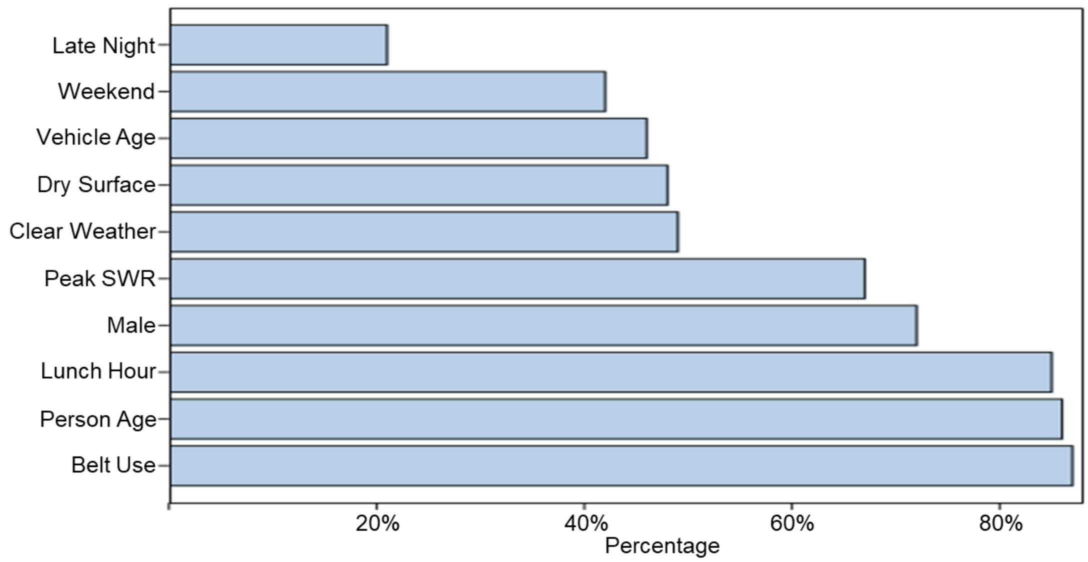

Figure 11. Variables selected by LASSO and 5-fold cross validation method based on 100 random samples.
Variables are ordered by the percentage of corresponding variables included in the 100 best models.

The variables selected are not necessarily in the same model. For example, in Figure 11, Dry Surface and Clear Weather variables were found 48 and 49 models out of 100 best models, respectively. However, the two variables were never found in the same model. It should be noted that a linear regression was used as a basis for variable selection application although the model for this study is a binary logit model. The variables selected through this process offered prospects on variables likely to remain effective when a binary logit model is being developed.

Out of 17 explanatory variables, six variables appeared at least 20 percent of the time for each selection method across all employed methods and they are Male, Person Age, Belt Use, Peak SWR, Dry Surface, and Lunch Hour. All the variables except Lunch Hour were intuitive and expected based on review of relevant literature. Lunch Hour being an explanatory variable in explaining a chance of getting severely injured was unexpected. However, the variable could capture a collective effect of several unobserved factors possibly lending intuitive explanation to a severe injury occurrence.

Based on the results of multicollinearity and variable selection analyses, variables to be included in the initial model specification were determined and are presented in Table 3 with their descriptive statistics. A total of 17 explanatory variables are included for estimating an initial binary logit model with the dependent variable, Severe Injury (fatal or incapacitating injury). In terms of the valid observations, Belt Use variable is the most limiting, meaning that its inclusion in a logit model would reduce the number of observations to be used for estimating the model from 5,153 to 2,108 at the largest. However, as discussed earlier, Belt Use was deemed crucial for this study meaning it is strongly recommended for inclusion in an initial model specification.

Table 3. Descriptive Statistics of Selected Regression Variables

Variable	**Nobs**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Dependent Variable					
Severe Injury	5,129	0.091	0.288	0	1
Explanatory Variables					
Male	5,124	0.710	0.454	0	1
Person Age	5,044	33.73	16.24	0	98
Belt Use	2,108	0.731	0.443	0	1
Row 1 Left	4,951	0.758	0.429	0	1
Row 2 All	4,951	0.044	0.206	0	1
Peak SWR	5,153	3.002	1.111	0.888	6.840
Dark	5,104	0.336	0.472	0	1
Clear Weather	5,136	0.814	0.389	0	1
Rainy Weather	5,136	0.104	0.305	0	1
Dry Surface	5,130	0.713	0.452	0	1
Wet Surface	5,130	0.177	0.382	0	1
Weekend	5,135	0.355	0.479	0	1
AM Peak Hour	4,976	0.111	0.314	0	1
Lunch Hour	4,976	0.055	0.227	0	1
PM Peak Hour	4,976	0.101	0.302	0	1
Early Night Hour	4,976	0.079	0.269	0	1
Late Night Hour	4,976	0.183	0.387	0	1

Note: Definitions of the variables are noted in Table 2.

Many of the variables are a binary indicator variable such as Severe Injury, Male, Belt Use, and Dark. Thus, their mean values represent percentages in decimal. For example, the mean value of 0.710 for Male variable means 71.0 percent of the occupants in the data were male occupants and the mean of 0.336 for Dark variable means 33.6 percent of the occupants were involved in rollover crashes in dark lighting condition. These descriptive statistics are useful for several ways such as checking the presence of erroneous data values and interpreting the final logit model to be estimated by value ranges.

5.2.3. Polynomial Relationship

During the process of developing a logit model, polynomial relationships were examined in two aspects, a higher order term and an interaction term. The polynomial relationship with higher order terms addresses the non-linear relationship between the dependent variable and an explanatory variable and was examined based on two methods, empirical logit plot and Box-Tidwell test described in Section 4.2.4. To create an empirical logit plot, data were first divided into equal-size bins. For each bin, an average of an explanatory variable of interest and a probability for a severe injury were calculated. Logit-transformed probabilities were then plotted against the calculated averages. Figure 12 shows empirical logit plots for Person Age variable in four different bin sizes.

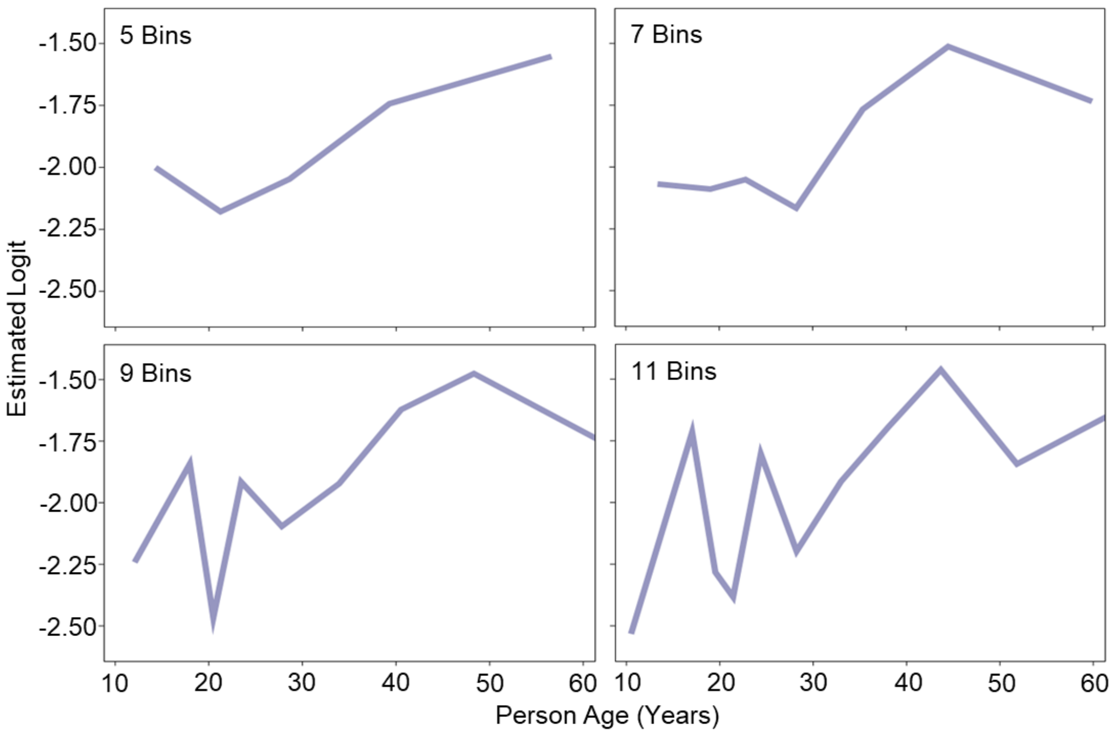

Figure 12. Empirical logit plots for Person Age with four different bin sizes. The plots indicate a possible non-linear relationship between Person Age and Severe Injury variables.

Since a different bin size may generate a plot suggesting a different relationship, a bin size was varied from 5 to 11 with an incremental of 2. Several empirical logit plots were created for the two continuous explanatory variables, Peak SWR and Person Age, to visually examine a possible non-linear relationship and if noted, suggest higher-order terms for corresponding variables to be included in a logit model. In Figure 12, for example, Person Age variable appears to have a positive curvilinear relationship, which merits further examination. In addition to the visual examination, the Box-Tidwell test (Box and Tidwell, 1962) was performed on the two variables to statistically test for the presence of a non-linear relationship. The test results indicated non-linearity for peak SWR variable but linearity for Person Age variable.

Based on the examinations, higher-order polynomial relationships of Person Age and peak SWR variables were further tested by including quadratic and cubic terms in a logit model. A quadratic relationship for peak SWR variable was found statistically significant at 0.05 while Person Age variable was determined to be linear. The logit model with the quadratic peak SWR term was assessed to be slightly better than the logit model without the term in terms of goodness-of-fit measures such as AIC and BIC. The difference in AIC and BIC between the two models are 8.7 and 3.1, respectively.

According to rules of thumb, these differences in AIC and BIC give some preference to the model with the quadratic term. By the BIC-based rule of thumbs proposed by Raftery (1995), a difference of 3.1 between the comparing models means positive evidence of one model being better than the other; differences greater than 6 and 10 indicate strong and very strong evidence, respectively. By contrast, the AIC-based rules of thumb suggested by Burnham and Anderson (2004), a difference of 8.7 in AIC indicates that one model is likely better than the other; a difference greater than 10 is interpreted as one model strongly being better.

Interpreting the estimated binary logit model with the quadratic peak SWR term, however, posed challenges in that the final model to be developed could serve as a basis to calculate safety benefits of FMVSS No. 216a. Specifically, a convex quadratic relationship means a stronger roof raises a risk of getting severely injured until the strength reaches a certain threshold level of strength followed by a reduction in risk after that level, which is not logically explainable. Thus, the quadratic term being found in the study data was conjectured to be an artifact and the model without the quadratic term, which is statistically significant in terms of the overall model test and individual coefficients' tests, was selected for the study. The logit model with the quadratic term of peak SWR variable is provided in Appendix C for reference.

Polynomials with interaction terms were examined by adding interaction terms to a logit model. Although many interaction terms could be formulated, a limited number of interaction terms were tested and interaction with peak SWR variable was the focal point of this examination. For interaction terms to enter to a logit model, three considerations were made. First, a main effect term in the interaction term should be statistically significant before the interaction term enters a logit model. Second, including the interaction term should be logically understandable. Third, a model hierarchy should be maintained. Maintaining a model hierarchy means that main effect variables involving an interaction term should remain even if they are not statistically significant as long as the interaction term is statistically significant.

Suppose an interaction between Dark and peak SWR variables is considered. For the interaction term, Dark×Peak SWR to be included in a logit model, both Dark and Peak SWR variables should be statistically significant at 0.05 level in a model without the interaction term. Also, inclusion of the term should be logical. In this example, Dark×Peak SWR is not believed to be logical for consideration since the interaction term in a severe injury logit model means a potential safety effect of a vehicle's roof strength in terms of peak SWR would change depending on lighting condition at the time of a rollover crash. None of the interaction terms tested was statistically significant using Wald χ^2 statistics. Thus, polynomial with interaction was not considered for a severe injury binary logit model.

5.2.4. Final Binary Logit Model

The estimated final binary logit model for the probability of a non-ejected occupant sustaining severe injury (i.e., fatal or incapacitating injury) in a rolled vehicle is presented in Table 4 and all the estimated coefficients are statistically significant at 0.05 level. A total of 1,940 observations used to estimate the final model have valid data values for the dependent and the six explanatory variables; About 62 percent of the observations in the primary study data set, DATA1, were excluded because values in at least one of the seven variables were missing.

Table 4. Estimated Binary Logit Model for Severe Injury at Rollover

Variable	**Est. Coefficient**	**Std. Error**	**p-value**[a]	**95% PL Confidence Limit**[b]	
Intercept	-1.588	0.328	0.0001	-2.234	-0.947
Male	-0.427	0.142	0.003	-0.704	-0.148
Person Age	0.012	0.004	0.003	0.004	0.021
Belt Use	-0.484	0.145	0.001	-0.766	-0.197
Peak SWR	-0.147	0.072	0.041	-0.292	-0.009
Dry Surface	0.352	0.169	0.037	0.029	0.691
Lunch Hour	0.778	0.253	0.002	0.265	1.261
Dependent Variable	Severe Injury (i.e., Fatal or Incapacitating Injury)				
Num. of Observations	1,940				
Num. of Severe Cases	255				
AIC	1,478				
BIC	1,517				
-2 Log L	1,464				
c statistics	0.610				

[a] Wald χ^2 test
[b] Profile-likelihood (PL) confidence limit
Note: The estimated model is for a non-ejected occupant in a rolled vehicle in a traffic crash.

The final severe injury logit model in Table 4 is expressed in an equation form as below:

$$logit(\hat{\pi}_i) = \begin{pmatrix} -1.588 - 0.427 \times Male_i + 0.012 \times Person\ Age_i \\ -0.484 \times Belt\ Use_i - 0.147 \times Peak\ SWR_i \\ +0.352 \times Dry\ Surface_i + 0.778 \times Lunch\ Hour_i \end{pmatrix} \quad \text{Eq. (10)}$$

where $\hat{\pi}_i$= probability of a non-ejected occupant *i* sustaining severe injury (i.e., fatal or incapacitating injury) in a rolled vehicle.

In addition to the p-value based on Wald χ^2 test statistics, the profile-likelihood (PL) confidence limits (Venzon & Moolgavkar, 1988) are provided to support the statistical significance of the coefficient estimates and verify that all the coefficient estimates are statistically significant since they do not include zero. The PL confidence limit is based on the generalized likelihood ratio test and preferred to the Wald confident limit since an asymmetric coverage could occur when the sampling distribution of the parameter is skewed. An overdispersed binary logit following Williams's method and a Bayesian binary logit model were also estimated using the final model specification shown in Table 4. Both results confirmed the statistical significances of the coefficient estimates at 0.05 level, which provide further reliability to the final model results of Table 4. Their estimated coefficients were found to be practically identical to those of the final logit model. The results of the two variant models are provided in Appendix D for reference.

According to the estimated coefficients, an occupant in a vehicle with a higher peak SWR is less likely to sustain a severe (i.e., fatal or incapacitating) injury when the occupant's vehicle rolls in a traffic crash. This means that a vehicle's stronger roof is associated with a higher survivability and lower chance to sustain an incapacitating injury in a rollover crash, all else being equal. A male occupant is less likely to sustain a severe injury than a female counterpart. An older occupant is more likely to get injured severely than a younger counterpart. An occupant wearing seat belts is less likely to sustain a severe injury.

Being involved in a rollover crash at a site where a surface is dry or during a lunch hour (12:00p.m.–12:59p.m.) is associated with a higher chance of getting a severe injury compared to other surface conditions or hours outside the lunch hour. The effects associated with surface condition and time of day are conjectured to reflect a collective effect of omitted factors related to them. For example, dry surface could be related to a higher driving speed that could potentially put an occupant at a higher risk of getting a severe injury when a rollover crash occurs. Thus, caution should be exercised when attempting to interpret these effects.

It should be noted that the variables included in the final model do not interfere with the safety effect of the peak SWR on the severe injury probability in that all the statistically strongly correlated variables were screened out through the multicollinearity examinations performed in Section 5.2.2. To examine potential influence of the lunch hour variable on the safety effect of the peak SWR, the final logit model was re-estimated after the lunch hour variable was removed and the coefficient estimate of peak SWR variable remains practically identical: -0.147 with Lunch Hour variable and -0.145 without Lunch Hour variable. The re-estimated model is provided in Appendix E.

Odds ratio estimates corresponding to the variables of the final logit model are presented in Table 5 and offer quantitatively understandable interpretations. An increase in a vehicle's peak SWR by 1 unit is predicted to reduce the odds of sustaining a severe injury by about 14 percent, 100%×(1– 0.863). This is loosely translated that a vehicle with a stronger roof by 1-unit higher peak SWR would reduce a severe injury probability for its occupant by 14 percent—Brumbelow et al. (2009) reported 16 percent reduction in a non-ejected driver sustaining fatal or incapacitating injury based on the peak SWRs of 11 midsize SUVs integrated with the single-vehicle rollover crash data from SDS data. The 2009 upgrade in the crush resistance standard (FMVSS No. 216a) raised the peak SWR threshold from 1.5 to 3.0 for passenger vehicles with the GVWR of 6,000 lb or less. Thus, the 2009 upgrade is translated to the reduction in the severe injury probability at a rollover crash by about 20 percent.

Table 5. Odds Ratio Estimates for Severe Injury at Rollover

Variable	Change[a]	Est. Odds Ratio	95% PL Confidence Limit[b]	
Male	Male vs. Female	0.653	0.495	0.863
Person Age	1 Year Older	1.012	1.004	1.021
Belt Use	Belted vs. Unbelted	0.616	0.465	0.821
Peak SWR	1 Unit Higher	0.863	0.747	0.991
Dry Surface	Dry vs. Others	1.422	1.029	1.996
Lunch Hour	Lunch Hour vs. Others	2.178	1.303	3.527

[a] Change in a variable value for calculating a corresponding odds ratio estimate
[b] Profile-likelihood (PL) confidence limit
Note: The odds ratio estimates are based on the model for a non-ejected occupant in a rolled vehicle at a traffic crash.

A male occupant is associated with 35 percent lower odds of getting severely injured at a rollover than a female occupant while all the other conditions (i.e., age, vehicle's roof strength, surface condition, and crash hour) are the same. A belted occupant is associated with 38 percent lower odds of getting severely injured than an unbelted occupant, all else being equal. This could be translated that a male occupant and a belted occupant are less likely to sustain a severe injury than a female occupant and an unbelted occupant by 35 percent and 38 percent in probability, respectively. An occupant being one year older is predicted to increase the odds of getting a severe injury at a rollover crash by slightly over 1 percent. Thus, an occupant expects its odds of being severely injured being higher by 13 percent compared to its a 10-year younger counterpart. A rollover crash occurring during a lunch hour or on a dry surface is associated with 52 percent and 118 percent higher odds of resulting in a severe injury consequence than outside a lunch hour or on a non-dry surface, respectively. As noted earlier, these two effects are likely to capture factors omitted due to data limitations such as a driving speed at the time of a traffic crash that could not be accurately collected by the police even if such information was reported.

A more direct interpretation in terms of a probability compared to the odds-based interpretation is possible by calculating a probability of an occupant being severely injured and the probability can be calculated using Equation 5 with the estimated coefficients as follows:

$$\hat{\pi}_i = \frac{1}{1+exp\left[-\begin{pmatrix}-1.686-0.142\times Peak\ SWR_i-0.418\times Male_i \\ +0.012\times Person\ Age_i-0.451\times Belt\ Use_i \\ +0.430\times Clear\ Weather_i\end{pmatrix}\right]} \qquad \text{Eq. (11)}$$

where $\hat{\pi}_i$= predicted probability of a non-ejected occupant *i* sustaining a severe injury (i.e., fatal or incapacitating injury) in a rolled vehicle.

Various predicted probabilities were calculated using Equation 11 by varying values in the variables of interest. Figure 13 displays predicted probabilities of being severely injured at a rollover crash as the vehicle's roof strength increases. The probabilities were calculated for a 40-year-old male non-ejected occupant whose vehicle has rolled in a crash occurring on a dry surface during hours outside lunch time, separately for wearing and not wearing seat belts.

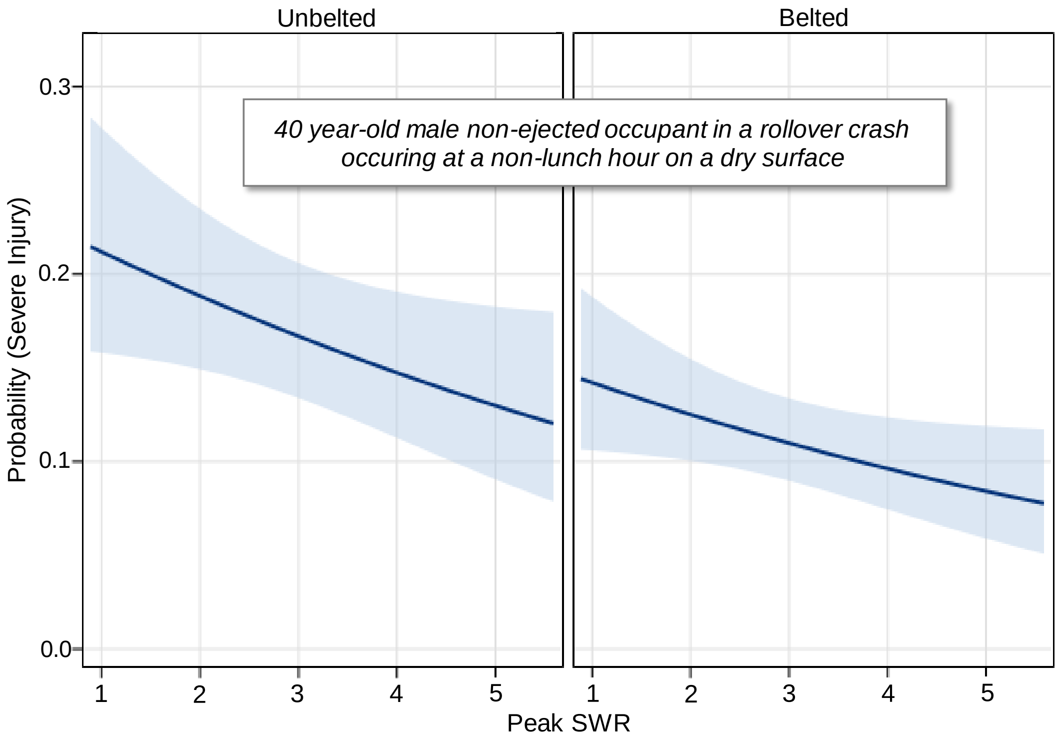

Figure 13. Predicted probabilities for a 40 year-old male non-ejected occupant sustaining a severe injury in a rollover crash occurring at a non-lunch hour on a dry surface by peak SWR. A solid line corresponds to a predicted probability in a varying condition and a shade area encompassing the line corresponds to 95 percent Wald-test-based confidence limit. A severe injury includes a fatal or incapacitating injury.

As seen in the figure, the severe injury probability decreases as a vehicle's peak SWR increases. For an example of an occupant wearing seat belts, his severe injury probability declines from about 0.14 (14%) in a vehicle with the peak SWR of 1.0 to about 0.08 (8%) in a vehicle with the peak SWR of 5.0. It should be noted that the probabilities assume that the vehicle the occupant rides in is identical in all aspects except the roof strength. Under the same conditions, the same occupant not wearing seat belts would face an increased probability of getting a severe injury; For example, in a vehicle with the peak SWR of 3.0, the severe injury probability of its occupant in a rollover crash is predicted to increase from 0.11 (11%) with belt use to 0.17 (17%) without belt use.

Severe injury probabilities for a non-ejected belted occupant were calculated by varying the occupant's age and gender over various roof strengths and Figure 14 was created to visualize the predicted probabilities for an occupant aged 20, 40, and 60 years old. As clearly seen, an occupant at an older age faces a higher probability of getting a severe injury in a rollover crash. For example, a severe injury probability for a female occupant is increased from 0.13 at 20 years old, 0.16 at 40 years old, to 0.20 at 60 years old in a vehicle with a peak SWR of 3.0. The gender effect is also noticeable in the figure. A female occupant is expected to get severely injured more often than her male counterpart in the same vehicle under the same condition (time of day and surface condition). For example, the probability for a 40-year old male occupant in a vehicle with a peak SWR of 3.0 is about 0.11 compared to 0.16 for his female counterpart.

Figure 14. Predicted probabilities for a non-ejected belted occupant sustaining a severe injury in a rollover crash occurring at a non-lunch hour on a dry surface by peak SWR.
A solid line corresponds to a predicted probability in a varying condition and a shade area encompassing the line corresponds to 95 percent Wald-test-based confidence limit. A severe injury includes a fatal or incapacitating injury.

6. Conclusions

In order to secure an adequately large amount of data with an acceptable accuracy on a roof strength measure of vehicles involved in rollover crashes, a complicated and rigorous procedure was employed for data processing including identifying data sources, selecting appropriate data, cleaning selected data, integrating cleaned data, joining integrated data, and transforming joined data suitable for analysis. The final study data has an analysis unit of a person meaning each observation corresponds to an occupant involved in a rollover crash. It includes 5,153 non-ejected occupants in vehicles that were determined by the police to have rolled in crashes as the vehicle's first crash event. Among more than 100 variables prepared, 36 explanatory variables were deemed eligible based on a combination of exploratory analysis, logical consideration, and literature review. After examinations for multicollinearity, potential estimation problems, and the amount of data being used for model estimation, 17 explanatory variables entered an initial logit model specification. The dependent variable was a binary outcome variable indicating that an occupant sustained a severe (i.e., fatal or incapacitating) injury and converted from the 5-level KABCO scale recorded on police crash reports.

The final binary logit model was developed with six explanatory variables: Peak SWR, Male, Person Age, Belt Use, Dry Surface, and Lunch Hour. The model estimation was performed on 1,940 occupants where 255 occupants sustained a severe injury at a rollover crash after about 3,200 observations were removed due to missing or invalid values in at least one of the variables in the final model. All the coefficient estimates (Table 4) are statistically significant at 0.05 level. Based on the estimated logit model for a severe (i.e., fatal or incapacitating) injury, the following three conclusions are drawn:

- *A stronger roof of a vehicle saves lives and prevents incapacitating injuries in a rollover crash.* An increase in the roof strength by 1 unit of the peak SWR is predicted to reduce the odds of a non-ejected occupant suffering a severe injury by about 14 percent when the vehicle rolls in a traffic crash (see Table 5). This implies that the 2009 upgrade in roof crush resistance standard, FMVSS No. 216a, is predicted to have lowered the probability of a non-ejected occupant sustaining a severe injury by 20 percent, as compared to its predecessor, FMVSS No. 216.

- *Wearing seat belts is critical in mitigating a life-threatening crash consequence in a rollover crash*. Seat belt use is predicted to lower the odds of a non-ejected occupant sustaining a severe injury in a rolled vehicle by about 38 percent. This means a stronger vehicle's roof in conjunction with a higher seat belt use rate would offer a considerable safety benefit when the vehicle experiences rollover during a crash.

- *Gender and age affect prospects of sustaining a less serious injury in a rollover crash.* A female occupant is expected to face a higher probability of suffering a severe injury compared to her male counterpart. An older occupant is likely at a higher risk of getting severely injured compared to their younger counterpart in a rollover crash.

Several limitations involving data were noted while conducting the study and two of them are worth mentioning. The primary study data, DATA1, has 1,940 observations with valid values for the variables of the final logit model and the data size is deemed sufficient enough for the model results to be reliable. However, the source of the roof strength, SWR data, includes 358 vehicles, which may not be viewed as convincingly large since roof strength is the focus of the study. Since IIHS performs a roof crush test on 20-30 vehicles each year and makes such data publicly accessible, revisiting analysis of this study in the future could sizably increase the number of crush-tested vehicles with peak SWR values, which would further increase the amount of data available for model development.

There are several variables that were desired for the study but failed to be included due to various reasons such as a large number of cases with missing or invalid values and lack of accurate information on crash conditions. For example, one of the potentially important variables for the study is a traveling speed of a vehicle at the time of a crash. Since the study data included rollover crashes probably with a wide range of traveling speeds, reliably accurate speed data in the study analysis were desired, yet such data were lacking in SDS database. As an alternative, a speed limit of a crash site was attempted for inclusion as a surrogate to a traveling speed and the attempt led to a considerable loss in the available data size due to missing values. In addition, it was also questionable that the speed limit could serve as a reliable surrogate measure for a traveling speed at a rollover crash. Recent advances in reporting crashes such as the EDR included in CISS starting in 2017 could offer an opportunity to extract data elements that were not previously collected and, even if collected, are more reliably recorded than a traditional crash reporting system. Incorporating such data elements in analysis is expected to provide a more holistic picture on the safety effect of the vehicle’s roof strength.

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Appendix A: Peak SWR Data of 358 Roof Crush Tested Vehicles

A total of 358 crush-tested vehicles are the source of the SWR data for this study. IIHS performed one-sided tests on 282 vehicles, resulting in 282 peak SWR values of the first sides. NHTSA performed one-sided tests on 44 vehicles and two-sided tests on 32 vehicles producing two peak SWRs for each vehicle. Table A1 presents the SWR data; Peak SWR1 and Peak SWR2 represent peak SWR values on the first side and second side of the vehicle, respectively.

Table A1. Roof Crush Test Data of 358 Vehicles

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
1	2008 Honda Element	4.31	NA	IIHS
2	2009 Honda CR-V	2.80	NA	IIHS
3	2009 Mitsubishi Outlander	3.32	NA	IIHS
4	2009 Subaru Forester	4.64	NA	IIHS
5	2009 Chevrolet Equinox	3.47	NA	IIHS
6	2009 Jeep Patriot	4.25	NA	IIHS
7	2009 Volkswagen Tiguan	5.82	NA	IIHS
8	2008 Kia Sportage	2.43	NA	IIHS
9	2009 Toyota RAV4	3.46	NA	IIHS
10	2009 Nissan Rogue	3.34	NA	IIHS
11	2008 Suzuki Grand Vitara	2.82	NA	IIHS
12	2009 Ford Escape	2.55	NA	IIHS
13	2009 Volkswagen Tiguan	4.40	NA	IIHS
14	2008 Kia Sportage	2.46	NA	IIHS
15	2009 Suzuki Grand Vitara	3.50	NA	IIHS
16	2009 Subaru Tribeca	4.20	NA	IIHS
17	2009 Subaru Impreza wagon	4.62	NA	IIHS
18	2009 Subaru Impreza sedan	4.50	NA	IIHS
19	2009 Honda Fit	3.42	NA	IIHS
20	2009 Toyota Yaris	3.78	NA	IIHS
21	2009 Chevrolet Aveo	3.09	NA	IIHS
22	2009 Hyundai Accent	3.72	NA	IIHS
23	2009 Mini Cooper	3.44	NA	IIHS
24	2009 Smart Fortwo	5.41	NA	IIHS
25	2009 Mitsubishi Galant	3.81	NA	IIHS
26	2009 Dodge Avenger	4.43	NA	IIHS
27	2010 Dodge Journey	4.55	NA	IIHS
28	2010 Mercedes C class	5.36	NA	IIHS
29	2009 Volvo S40	3.92	NA	IIHS
30	2009 Honda Accord	3.87	NA	IIHS
31	2010 Honda Civic	4.48	NA	IIHS
32	2009 Volkswagen Jetta	5.02	NA	IIHS
33	2009 Volkswagen Passat	4.79	NA	IIHS
34	2009 Audi A3	4.17	NA	IIHS
35	2009 Kia Optima	3.12	NA	IIHS
36	2009 Hyundai Sonata	3.12	NA	IIHS
37	2010 Kia Soul	4.33	NA	IIHS
38	2009 Mazda 6	3.55	NA	IIHS
39	2010 Buick LaCrosse	4.90	NA	IIHS

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
40	2009 Chevrolet Malibu	4.37	NA	IIHS
41	2010 Ford Fusion	3.33	NA	IIHS
42	2010 Ford Taurus	4.22	NA	IIHS
43	2010 Lincoln MKS	4.19	NA	IIHS
44	2009 Nissan Altima	3.79	NA	IIHS
45	2009 Nissan Maxima	3.43	NA	IIHS
46	2009 Nissan Cube	7.26	NA	IIHS
47	2010 Chevrolet Colorado	2.86	NA	IIHS
48	2010 Dodge Dakota	3.23	NA	IIHS
49	2010 Ford Ranger	3.32	NA	IIHS
50	2010 Nissan Frontier	4.11	NA	IIHS
51	2010 Kia Forte	4.58	NA	IIHS
52	2010 Mercedes E class	5.40	NA	IIHS
53	2010 Jeep Liberty	4.96	NA	IIHS
54	2010 Ford Edge	3.50	NA	IIHS
55	2010 Hyundai Genesis	4.92	NA	IIHS
56	2010 Honda Pilot	3.05	NA	IIHS
57	2010 Honda Accord Crosstour	2.82	NA	IIHS
58	2010 Mazda CX-7	3.23	NA	IIHS
59	2010 Mitsubishi Endeavor	3.00	NA	IIHS
60	2010 Chevrolet Equinox	4.17	NA	IIHS
61	2010 Hyundai Tucson	4.43	NA	IIHS
62	2010 Lexus HS 250h	3.60	NA	IIHS
63	2010 Lexus RX 350	4.27	NA	IIHS
64	2010 Audi A4	4.60	NA	IIHS
65	2010 Audi Q5	4.41	NA	IIHS
66	2010 Ford Fusion	4.78	NA	IIHS
67	2010 Lincoln MKT	4.29	NA	IIHS
68	2010 Ford Flex	4.51	NA	IIHS
69	2010 Cadillac SRX	4.14	NA	IIHS
70	2010 Acura RL	2.57	NA	IIHS
71	2010 Audi A6	3.81	NA	IIHS
72	2010 Mitsubishi Lancer	4.31	NA	IIHS
73	2010 Lexus GS 350	3.39	NA	IIHS
74	2010 Mazda CX-9	2.81	NA	IIHS
75	2010 Mercedes-Benz E class coupe	5.58	NA	IIHS
76	2010 Volvo XC90	4.51	NA	IIHS
77	2010 Volvo S80	4.26	NA	IIHS
78	2010 Volvo C30	4.27	NA	IIHS
79	2010 Volvo XC60	5.23	NA	IIHS
80	2010 Subaru Legacy	4.95	NA	IIHS
81	2010 Subaru Outback	4.68	NA	IIHS
82	2010 Volkswagen Golf	5.25	NA	IIHS
83	2010 Toyota Camry	5.31	NA	IIHS
84	2010 Toyota Tacoma	3.08	NA	IIHS
85	2011 Hyundai Sonata	4.89	NA	IIHS
86	2010 Toyota Corolla	5.09	NA	IIHS
87	2010 Scion xB	6.84	NA	IIHS

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
88	2011 Kia Sorento	4.31	NA	IIHS
89	2010 Nissan Murano	3.15	NA	IIHS
90	2010 Toyota Venza	4.70	NA	IIHS
91	2010 Toyota Highlander	4.74	NA	IIHS
92	2011 Jeep Grand Cherokee	4.63	NA	IIHS
93	2011 Toyota Avalon	4.07	NA	IIHS
94	2011 Toyota Sienna	4.12	NA	IIHS
95	2010 Volkswagen Jetta SportWagen	5.13	NA	IIHS
96	2010 Suzuki Kizashi	3.92	NA	IIHS
97	2010 Toyota FJ Cruiser	3.47	NA	IIHS
98	2010 Toyota 4Runner	3.87	NA	IIHS
99	2010 Nissan Pathfinder	3.07	NA	IIHS
100	2010 Nissan Xterra	3.28	NA	IIHS
101	2011 Buick Regal	4.97	NA	IIHS
102	2011 Cadillac CTS	4.12	NA	IIHS
103	2011 BMW 5 series	4.04	NA	IIHS
104	2011 Infiniti M37	4.21	NA	IIHS
105	2011 Ford Fiesta sedan	5.42	NA	IIHS
106	2011 Ford Fiesta hatchback	5.05	NA	IIHS
107	2011 Mercedes-Benz GLK	6.41	NA	IIHS
108	2011 Scion tC	5.68	NA	IIHS
109	2011 Hyundai Santa Fe	4.38	NA	IIHS
110	2011 Chevrolet Cruze	5.07	NA	IIHS
111	2011 Kia Optima	5.12	NA	IIHS
112	2011 Volkswagen Jetta sedan	5.35	NA	IIHS
113	2011 Volkswagen Touareg	4.72	NA	IIHS
114	2011 Mazda 2	4.18	NA	IIHS
115	2011 Ford Explorer	4.58	NA	IIHS
116	2011 Honda CR-Z	3.88	NA	IIHS
117	2011 Honda Insight	3.32	NA	IIHS
118	2011 Dodge Caliber	3.56	NA	IIHS
119	2011 Dodge Charger	5.37	NA	IIHS
120	2011 Nissan Versa	3.69	NA	IIHS
121	2011 Nissan Sentra	3.44	NA	IIHS
122	2011 Nissan Juke	4.46	NA	IIHS
123	2011 Suzuki SX4	3.19	NA	IIHS
124	2011 Mini Countryman	4.97	NA	IIHS
125	2011 Chevrolet Volt	4.23	NA	IIHS
126	2011 Honda Odyssey	5.15	NA	IIHS
127	2012 Volvo S60	4.95	NA	IIHS
128	2011 GMC Acadia	4.00	NA	IIHS
129	2011 Hyundai Elantra	5.07	NA	IIHS
130	2011 Nissan Leaf	5.49	NA	IIHS
131	2011 Mazda 3 sedan	5.32	NA	IIHS
132	2011 Mazda 3 hatchback	5.09	NA	IIHS
133	2011 Lexus CT200h	5.03	NA	IIHS
134	2011 Toyota Prius	4.20	NA	IIHS
135	2011 Scion xD	5.74	NA	IIHS

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
136	2012 Ford Focus	5.38	NA	IIHS
137	2011 Hyundai Equus	4.87	NA	IIHS
138	2011 Ford Edge	4.70	NA	IIHS
139	2011 Ford F-150	4.72	NA	IIHS
140	2011 Chevrolet Silverado	3.13	NA	IIHS
141	2011 Dodge Ram 1500	2.97	NA	IIHS
142	2011 Toyota Tundra	4.49	NA	IIHS
143	2011 Nissan Titan	3.56	NA	IIHS
144	2011 Acura RDX	2.90	NA	IIHS
145	2012 Honda Civic	5.85	NA	IIHS
146	2011 Volkswagen CC	4.40	NA	IIHS
147	2011 BMW 328i	3.91	NA	IIHS
148	2011 Infiniti EX35	4.00	NA	IIHS
149	2011 Infiniti G37	3.98	NA	IIHS
150	2011 Lexus IS 350	3.94	NA	IIHS
151	2011 Lexus ES 350	5.18	NA	IIHS
152	2011 Saab 9-5	5.85	NA	IIHS
153	2011 Chevrolet Impala	3.45	NA	IIHS
154	2012 Hyundai Accent	5.22	NA	IIHS
155	2011 Dodge Durango	4.67	NA	IIHS
156	2012 Audi A6	4.90	NA	IIHS
157	2012 Fiat 500	6.16	NA	IIHS
158	2011 Saab 9-3	3.43	NA	IIHS
159	2012 Chrysler Town & Country	4.51	NA	IIHS
160	2012 Kia Sedona	2.31	NA	IIHS
161	2011 Nissan Quest	3.36	NA	IIHS
162	2012 Volkswagen Passat	6.32	NA	IIHS
163	2012 Chevrolet Sonic	5.37	NA	IIHS
164	2012 Mercedes-Benz ML 350	6.68	NA	IIHS
165	2012 Subaru Impreza	5.20	NA	IIHS
166	2012 Toyota Camry	4.78	NA	IIHS
167	2012 Toyota Yaris	4.47	NA	IIHS
168	2012 Acura MDX	4.46	NA	IIHS
169	2012 Honda CR-V	5.08	NA	IIHS
170	2012 Honda Pilot	4.63	NA	IIHS
171	2012 Acura TL	4.60	NA	IIHS
172	2012 Acura TSX	5.04	NA	IIHS
173	2012 Acura TSX wagon	5.35	NA	IIHS
174	2012 Honda Accord	4.99	NA	IIHS
175	2012 Honda CR-Z	5.92	NA	IIHS
176	2012 Honda Fit	5.02	NA	IIHS
177	2012 Honda Insight	5.03	NA	IIHS
178	2012 Toyota Prius v	4.33	NA	IIHS
179	2012 Honda Ridgeline	4.56	NA	IIHS
180	2012 Nissan Versa	4.95	NA	IIHS
181	2012 Volkswagen Beetle	5.49	NA	IIHS
182	2012 BMW X3	4.69	NA	IIHS
183	2013 Mazda CX-5	5.47	NA	IIHS

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
184	2012 Toyota Prius c	5.28	NA	IIHS
185	2012 Mitsubishi Outlander Sport	4.62	NA	IIHS
186	2013 Lexus GS 350	4.88	NA	IIHS
187	2012 Scion iQ	4.49	NA	IIHS
188	2012 BMW 335i	4.98	NA	IIHS
189	2013 Chevrolet Malibu	5.22	NA	IIHS
190	2012 Hyundai Azera	4.76	NA	IIHS
191	2013 Acura RDX	5.48	NA	IIHS
192	2013 Acura ILX	5.64	NA	IIHS
193	2013 Scion FR-S	5.00	NA	IIHS
194	2013 Ford Escape	5.03	NA	IIHS
195	2013 Lexus ES 350	5.22	NA	IIHS
196	2013 Dodge Dart	4.97	NA	IIHS
197	2013 Hyundai Santa Fe Sport	4.38	NA	IIHS
198	2013 Honda Accord 4-door	4.92	NA	IIHS
199	2013 Honda Accord 2-door	4.64	NA	IIHS
200	2013 Cadillac XTS	4.42	NA	IIHS
201	2013 Ford Fusion	5.14	NA	IIHS
202	2013 Nissan Altima	5.29	NA	IIHS
203	2013 Honda Crosstour	4.62	NA	IIHS
204	2013 Toyota Avalon	5.22	NA	IIHS
205	2013 Toyota 4Runner	4.11	NA	IIHS
206	2013 Honda Civic 2-door	5.21	NA	IIHS
207	2014 Mazda 6	5.21	NA	IIHS
208	2014 Subaru Forester	4.95	NA	IIHS
209	2013 Toyota RAV4	5.00	NA	IIHS
210	2013 BMW X1	5.04	NA	IIHS
211	2013 Buick Encore	4.63	NA	IIHS
212	2013 Lincoln MKZ	4.49	NA	IIHS
213	2013 Nissan Sentra	5.27	NA	IIHS
214	2014 Kia Forte	4.98	NA	IIHS
215	2014 Mitsubishi Outlander	4.95	NA	IIHS
216	2014 Kia Rio	6.30	NA	IIHS
217	2013 Chevrolet Spark	4.43	NA	IIHS
218	2014 Toyota Corolla	5.37	NA	IIHS
219	2014 Honda Odyssey	5.87	NA	IIHS
220	2014 Mazda 3	6.36	NA	IIHS
221	2014 Fiat 500L	5.90	NA	IIHS
222	2014 Jeep Cherokee	5.00	NA	IIHS
223	2014 Kia Soul	5.27	NA	IIHS
224	2014 Maserati Ghibli	5.03	NA	IIHS
225	2014 Acura RLX	5.18	NA	IIHS
226	2014 Acura MDX	5.87	NA	IIHS
227	2014 Mitsubishi Mirage	4.87	NA	IIHS
228	2014 Toyota Highlander	5.40	NA	IIHS
229	2014 Infiniti Q50	5.29	NA	IIHS
230	2014 Nissan Rogue	4.87	NA	IIHS
231	2014 BMW 2 Series	4.98	NA	IIHS

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
232	2015 Audi A3	6.20	NA	IIHS
233	2014 Hyundai Veloster	5.59	NA	IIHS
234	2015 Honda Fit	6.13	NA	IIHS
235	2015 Subaru WRX	5.16	NA	IIHS
236	2015 Hyundai Genesis	4.95	NA	IIHS
237	2014 Ford C-Max Hybrid	6.80	NA	IIHS
238	2014 Volkswagen GTI	5.78	NA	IIHS
239	2014 Mazda 5	4.34	NA	IIHS
240	2015 Hyundai Sonata	5.19	NA	IIHS
241	2015 Chrysler 200	4.74	NA	IIHS
242	2015 Subaru Legacy	5.36	NA	IIHS
243	2015 Kia Sedona SX	4.82	NA	IIHS
244	2015 Acura TLX	5.67	NA	IIHS
245	2015 Nissan Pathfinder	4.68	NA	IIHS
246	2015 Lexus RC	5.18	NA	IIHS
247	2015 Lexus NX	5.13	NA	IIHS
248	2015 Mini Cooper 2D	5.15	NA	IIHS
249	2016 Kia Sorento	4.70	NA	IIHS
250	2015 Nissan Murano	4.54	NA	IIHS
251	2015 Cadillac CTS	4.25	NA	IIHS
252	2015 Ford F-150 Crew Cab	5.85	NA	IIHS
253	2016 Audi Q3	4.13	NA	IIHS
254	2016 Honda Pilot	5.22	NA	IIHS
255	2016 Hyundai Tucson	5.37	NA	IIHS
256	2016 Nissan Maxima	4.52	NA	IIHS
257	2015 Ford Edge	5.11	NA	IIHS
258	2016 Scion iA	6.22	NA	IIHS
259	2016 Honda HR-V	5.14	NA	IIHS
260	2016 Honda Civic	5.78	NA	IIHS
261	2016 Lexus RX 350	4.79	NA	IIHS
262	2015 Ford F-150 Extended Cab	5.34	NA	IIHS
263	2015 Jeep Renegade	5.84	NA	IIHS
264	2016 Fiat 500X	4.26	NA	IIHS
265	2016 Volvo XC90	5.18	NA	IIHS
266	2016 Ram 1500 (Quad Cab)	3.17	NA	IIHS
267	2015 Chevrolet Silverado 1500 (Crew Cab)	4.10	NA	IIHS
268	2015 Chevrolet Silverado 1500 (Double Cab)	4.71	NA	IIHS
269	2016 Toyota Tundra (CrewMax)	3.94	NA	IIHS
270	2016 Toyota Prius	5.67	NA	IIHS
271	2016 BMW X1	5.12	NA	IIHS
272	2016 Chevrolet Camaro	3.70	NA	IIHS
273	2016 Dodge Challenger	3.67	NA	IIHS
274	2016 Lincoln MKX	5.21	NA	IIHS
275	2016 Ford Mustang	4.43	NA	IIHS
276	2016 Honda Civic	4.82	NA	IIHS
277	2016 Mazda CX-3	5.40	NA	IIHS
278	2016 Chevrolet Malibu	5.35	NA	IIHS
279	2016 Mazda CX-9	5.15	NA	IIHS

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
280	2016 Buick Envision	4.65	NA	IIHS
281	2016 Tesla Model S	4.33	NA	IIHS
282	2016 Mercedes-Benz C 300	7.00	NA	IIHS
283	2001 GMC Sierra	1.92	1.90	NHTSA
284	2003 Chevrolet Impala	2.84	2.56	NHTSA
285	2003 Ford Crown Victoria	2.03	1.69	NHTSA
286	2004 Chrysler Pacifica	2.21	2.36	NHTSA
287	2004 Land Rover Freelander	1.72	2.05	NHTSA
288	2004 Lincoln LS	2.58	2.03	NHTSA
289	2004 Lincoln LS (repeat)	2.45	2.24	NHTSA
290	2004 Nissan Quest	2.78	2.69	NHTSA
291	2006 Buick Lacrosse	0.85	0.85	NHTSA
292	2006 Buick Lacrosse (6" beams)	0.92	0.80	NHTSA
293	2006 Chrysler Crossfire	2.87	2.65	NHTSA
294	2006 Subaru Tribeca	1.29	1.19	NHTSA
295	2007 Buick Lucerne	2.35	2.06	NHTSA
296	2007 Chevrolet Colorado	2.17	1.71	NHTSA
297	2007 Chevrolet Express	2.27	1.65	NHTSA
298	2007 Chevrolet Tahoe	2.06	1.72	NHTSA
299	2007 Chrysler 300	2.50	2.54	NHTSA
300	2007 Dodge Caravan	3.04	2.89	NHTSA
301	2007 Ford Edge	3.29	3.17	NHTSA
302	2007 Ford F150	2.31	1.88	NHTSA
303	2007 Honda CRV	2.58	2.45	NHTSA
304	2007 Jeep Cherokee	2.18	1.59	NHTSA
305	2007 Pontiac G6	2.27	1.73	NHTSA
306	2007 Saturn Outlook	2.73	2.17	NHTSA
307	2007 Scion tC	4.62	4.40	NHTSA
308	2007 Toyota Camry	4.31	4.72	NHTSA
309	2007 Toyota Tacoma	4.41	3.90	NHTSA
310	2007 Toyota Tacoma	3.29	3.70	NHTSA
311	2007 Toyota Tundra	3.32	2.74	NHTSA
312	2007 Toyota Yaris	4.04	3.40	NHTSA
313	2008 Honda Accord	3.52	3.97	NHTSA
314	2008 Smart ForTwo	3.51	5.29	NHTSA
315	1997 Dodge Grand Caravan	2.66	NA	NHTSA
316	1998 Chevrolet S-10	2.76	NA	NHTSA
317	2002 Ford Explorer	2.34	NA	NHTSA
318	1999 Ford E150 Van	1.89	NA	NHTSA
319	2001 Ford Crown Victoria	2.09	NA	NHTSA
320	2002 Dodge Ram1500	2.48	NA	NHTSA
321	2002 Toyota Camry	3.12	NA	NHTSA
322	2001 Chevrolet Tahoe	2.92	NA	NHTSA
323	2002 Ford Mustang	2.58	NA	NHTSA
324	2002 Honda CRV	2.67	NA	NHTSA
325	2001 Mitsubishi Montero	2.65	NA	NHTSA
326	2003 Chevrolet Trailblazer	2.16	NA	NHTSA
327	2003 Ford Windstar	2.20	NA	NHTSA

No.	Model Year, Make, Model	Peak SWR1[a]	Peak SWR2[b]	Source
328	2003 Mini Cooper	2.31	NA	NHTSA
329	2003 Kia Sorento	1.96	NA	NHTSA
330	2003 Mazda Mazda6	3.39	NA	NHTSA
331	2001 Ford Taurus	2.03	NA	NHTSA
332	2003 Subaru Forester	4.81	NA	NHTSA
333	2003 Ford Expedition	2.38	NA	NHTSA
334	2002 Nissan Xterra	3.46	NA	NHTSA
335	2003 Chevrolet Impala	3.16	NA	NHTSA
336	2003 Chevrolet Cavalier	2.78	NA	NHTSA
337	2003 Ford Focus	2.77	NA	NHTSA
338	2003 Ford F150 Pickup	2.89	NA	NHTSA
339	2003 Toyota Tacoma	2.69	NA	NHTSA
340	2003 Chevrolet Other	2.05	NA	NHTSA
341	2004 Honda Element	4.31	NA	NHTSA
342	2006 Ford Five Hundred	3.88	NA	NHTSA
343	2006 Hyundai Sonata	3.15	NA	NHTSA
344	2006 Ford Mustang	2.67	NA	NHTSA
345	2006 Mitsubishi Eclipse	3.54	NA	NHTSA
346	2006 Honda Civic	4.48	NA	NHTSA
347	2006 Honda Ridgeline	2.36	NA	NHTSA
348	2006 Mazda Mazda5	4.42	NA	NHTSA
349	2006 Volkswagen Jetta	5.13	NA	NHTSA
350	2006 Dodge Ram 1500	1.67	NA	NHTSA
351	2006 Hummer H3	3.36	NA	NHTSA
352	2006 Dodge Sprinter	2.57	NA	NHTSA
353	2005 Nissan Frontier	3.97	NA	NHTSA
354	2004 Cadillac SRX	2.62	NA	NHTSA
355	2004 Chevrolet Silverado	2.33	NA	NHTSA
356	2006 Volvo XC90	4.55	NA	NHTSA
357	2004 Honda Accord	2.76	NA	NHTSA
358	2003 Ford F250 Pickup	1.72	NA	NHTSA

[a] Peak SWR on the first side of a vehicle's roof
[b] Peak SWR on the second side of a vehicle's roof
Note: NA stands for "not available."

Appendix B: Relationship Between Peak SWRs on First and Second Sides

NHTSA's roof strength data contains SWRs from both one-side and two-side tests while IIHS's data contains SWRs from one-side tests. When the roof strength data files from these two sources were being combined to form a single data file, there was a concern regarding using the peak SWRs from the first-side test of a vehicle's roof for the study because the SWR requirements of FMVSS No. 216a apply to a smaller value of a vehicle's two peak SWRs from a two-side (i.e., driver side and passenger side) roof crush test and the second-side peak SWR is allegedly smaller.

To examine the concern of using the first-side peak SWR for the study, a statistical analysis was performed on the subset of the study data where two peak SWRs exist for the same vehicle, one peak SWR on each side. NHTSA's SWR data contain a total of 32 vehicles with which a two-sided test was performed and two peak SWRs were recorded. On average, the second-side peak SWR was found to be lower than the first-side peak SWR by 6.5 percent.

Regression analysis was performed on the two-side roof crush test data extracted from the entire study data. The purpose of the analysis was to examine how strongly a peak SWR of the first side of a vehicle's roof is correlated to that of the second side. Please note that the first side to be crushed was determined randomly. A linear regression model going through the origin (i.e., no intercept) was developed relating the two peak SWRs. The regression going through the origin is deemed appropriate in this case because the peak SWR on one side should be zero when that on the other side is zero in theory. The estimated models are as follows,

$$Peak\ SWR_1 = 1.01204 \times Peak\ SWR_2\ (R^2 = 0.97) \qquad \text{Eq. (B1)}$$
$$Peak\ SWR_2 = 0.95884 \times Peak\ SWR_1\ (R^2 = 0.97) \qquad \text{Eq. (B2)}$$

where $peak\ SWR_1$= peak SWR on the first side tested and $peak\ SWR_2$ = peak SWR on the second side tested. If the first side tested is a driver side, the second side tested is a passenger side, vice versa.

The estimated slope coefficients are statistically significant at 0.001 level, and the coefficient of determination (0.97) is very high. The analysis results mean that the two peak SWR values are highly correlated meaning, with a peak SWR of one side given, a peak SWR of the other side can be predicted with a high accuracy. For example, the coefficient estimate of 0.95884 in Equation A2 means that the second-side peak SWR is lower than the first-side counterpart by the rate of 0.95884. Thus, given the first-side peak SWR of 3.0, the second-side peak SWR is predicted to be 2.87652, 3.0×0.95884.

Based on the analysis results, it is concluded that either of the two peak SWRs can be used as a roof strength measure of a vehicle for this study purpose, mitigating the concern regarding using the first-side peak SWR values for the study. However, it should be warned that this is not true for purposes of determining vehicle compliance.

Appendix C: Binary Logit Model With a Second-Order Polynomial Term

A binary logit model with a quadratic term of peak SWR variable was developed and Table C1 shows its estimates. If the study were to develop a model mainly for a prediction purpose, the binary logit model with the quadratic term might have been chosen in that AIC and BIC values of the polynomial logit model are slightly lower than those of the logit model without the quadratic term by 8.7 and 3.1, respectively. However, the purpose of this study was to make an inference primarily on peak SWR while controlling for other factors. The logit model without the quadratic term facilitates interpretation of the coefficient estimates from a perspective of evaluating the roof crush resistance standard.

Table C1. Estimated Polynomial Binary Logit Mode for Severe Injury at Rollover

Variable	**Est. Coefficient**	**Std. Error**	**p-value**[a]	**95% PL Confidence Limit**[b]	
Intercept	-4.913	1.098	0.0001	-7.091	-2.793
Male	-0.338	0.144	0.019	-0.620	-0.054
Person Age	0.014	0.004	0.001	0.006	0.022
Belt Use	-0.602	0.151	0.0001	-0.896	-0.305
Peak SWR	1.965	0.666	0.003	0.677	3.284
Peak SWR^2	-0.304	0.096	0.002	-0.494	-0.120
Dry Surface	0.371	0.169	0.029	0.047	0.711
Lunch Hour	0.772	0.254	0.002	0.257	1.256
Dependent Variable	Severe Injury (i.e., Fatal or Incapacitating Injury)				
Num. of Obs.	1,940				
Num. of Severe Cases	255				
AIC	1,469				
BIC	1,514				
-2 Log L	1,453				
c Statistics	0.632				

[a] Wald χ^2 test
[b] Profile-likelihood (PL) confidence limit
Note: The estimated model is for a non-ejected occupant in a rolled vehicle at a traffic crash.

The polynomial logit model is expressed in an equation form as below,

$$logit(\hat{\pi}_i) = \begin{pmatrix} -4.913 - 0.338 \times Male_i + 0.014 \times Person\ Age_i \\ -0.602 \times Belt\ Use_i + 1.965 \times Peak\ SWR_i \\ -0.304 \times Peak\ SWR_i{}^2 + 0.371 \times Dry\ Surface_i \\ +0.772 \times Lunch\ Hour_i \end{pmatrix} \qquad \text{Eq. (C1)}$$

where $\hat{\pi}_i$= probability of a non-ejected occupant *i* sustaining severe injury (i.e., fatal or incapacitating injury) in a rolled vehicle.

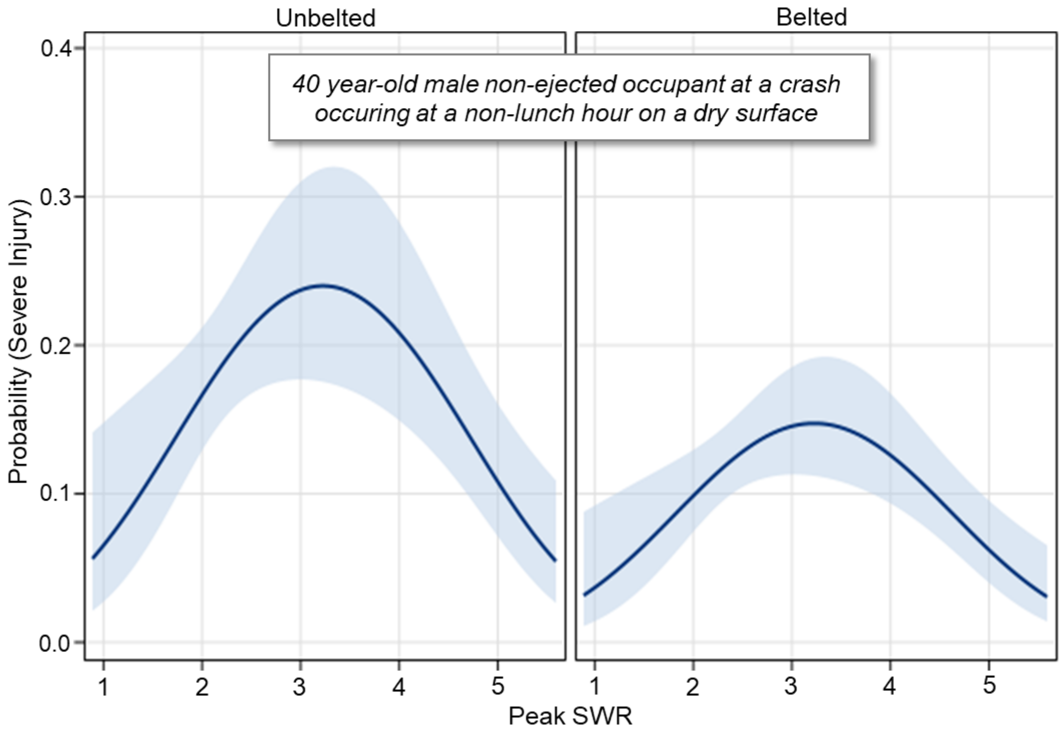

Figure C1. Predicted probabilities for a 40-year-old male non-ejected occupant sustaining a severe injury in a rollover crash occurring at a non-lunch hour on a dry surface by peak SWR based on the polynomial binary logit model.
A solid line corresponds to a predicted probability in a varying condition and a shade area encompassing the line corresponds to 95 percent Wald-test-based confidence limit. A severe injury includes a fatal or incapacitating injury.

Figure C1 shows the quadratic relationship between peak SWR variable and the predicted probability of sustaining a severe injury. This implies that a severe injury probability is predicted to increase until a vehicle's roof strength reaches around lower 3 in its peak SWR and decreases after the reflection point. This relationship failed to offer reasonable explanation and was conjectured to be created as an artifact possibly related to the data limitation.

Appendix D: Two Variant Binary Logit Models

An overdispersed binary logit model and a Bayesian binary logit model were estimated using the same model specification of the final binary logit model shown in Table 4. The overdispersed binary logit model was employed to allow the variance of the response to be greater than the binomial variance and adjusted for the estimates of the standard errors of the regression coefficients in the presence of overdispersion in the response. The overdispersed binary logit model with Williams's (1982) weight was employed and its estimated results are shown in Table D1. All the coefficient estimates are statistically significant at the 0.05 level and their magnitudes are very similar to those of the final logit model in Table 4.

Table D1. Estimated Overdispersed Binary Logit Models for Severe Injury at Rollover

Variable	**Est. Coefficient**	**Std. Error**	**p-value**[a]	**95% PL Confidence Limit**[b]	
Intercept	-2.385	0.305	0.0001	-2.987	-1.790
Male	-0.390	0.131	0.003	-0.646	-0.131
Person Age	0.011	0.004	0.004	0.004	0.019
Belt Use	-0.442	0.134	0.001	-0.703	-0.177
Peak SWR	-0.135	0.067	0.044	-0.270	-0.007
Dry Surface	0.325	0.158	0.040	0.023	0.643
Lunch Hour	0.683	0.226	0.003	0.219	1.108
Weight Variable[c]	$1/(1-0.06)$				
Dependent Variable	Severe Injury (i.e., Fatal or Incapacitating Injury)				
Num. of Obs.	1,940				
Num. of Severe Cases	255				
AIC	1,594				
BIC	1,638				
-2 Log L	1,580				
c Statistics	0.603				

[a] Wald χ^2 test
[b] Profile-likelihood (PL) confidence limit
[c] Williams' weight adjustment using an estimated dispersion of 0.06
Note: The estimated model is for a non-ejected occupant in a rolled vehicle at a traffic crash.

A Bayesian binary logit model with non-informative Normal priors was estimated based on the same model specification and its results are shown in Table D2. A total of 20,000 Markov chain samples were obtained using the Gamerman (1997) algorithm after a 2,000 burn-in period and thinning of 2 was used resulting in 10,000 samples used for posterior statistics on the coefficients. The 95 percent credible interval for any of the variables does not include zero, meaning the posterior mean, corresponding to the coefficient estimate, is statistically significant at 0.05 level. The posterior means for the coefficients are practically identical to the coefficient estimates of the final logit model in Table 4. For example, the estimated coefficient of peak SWR variable in the final logit model (Table 4) is -0.147 while the mean and median (50th percentile) of the estimated coefficients in the corresponding Bayesian logit model are -0.150 and -0.149, respectively.

Table D2. Posterior Distribution for Bayesian Binary Logit Models for Severe Injury at Rollover

Variable	Mean	Std. Deviation	Percentiles		
			2.5%	**50.0%**	**97.5%**
Intercept	-1.592	0.325	-2.236	-1.592	-0.944
Male	-0.428	0.143	-0.705	-0.430	-0.139
Person Age	0.012	0.004	0.004	0.012	0.021
Belt Use	-0.484	0.144	-0.766	-0.483	-0.204
Peak SWR	-0.150	0.072	-0.296	-0.149	-0.013
Dry Surface	0.358	0.167	0.037	0.356	0.696
Lunch Hour	0.768	0.256	0.252	0.771	1.262
Dependent Variable	Severe Injury (i.e., Fatal or Incapacitating Injury)				
Num. of Obs.	1,940				
Num. of Severe Cases	255				
DIC[a]	1,478				
pD[b]	6.922				
Burn-In Size	2,000				
Markov Chain Sample Size	20,000				
Thinning	2				
Sampling Algorithm	Gamerman				
Prior Distribution	$N(0,10^6)$				

[a] Deviance Information Criterion
[b] Effective number of parameters
Note: The estimated model is for a non-ejected occupant in a rolled vehicle at a traffic crash.

Appendix E: Binary Logit Model Without Lunch Hour Variable

The final logit model shown in Table 4 was re-estimated after the Lunch Hour variable was removed to verify that the Lunch Hour variable does not interfere coefficient estimates of the other variables, especially peak SWR. Table E1 shows the estimated binary logit model without Lunch Hour variable. All the coefficient estimates are statistically significant at the 0.05 level and their magnitudes are very similar to those of the final model in Table 4. The estimated coefficients for peak SWR variable are -0.147 and -0.145 with and without the Lunch Hour variable, respectively.

Table E1. Estimated Binary Logit Model for Severe Injury at Rollover Without Lunch Hour

Variable	**Est. Coefficient**	**Std. Error**	**p-value**[a]	**95% PL Confidence Limit**[b]	
Intercept	-1.537	0.327	0.0001	-2.182	-0.898
Male	-0.442	0.141	0.002	-0.718	-0.164
Person Age	0.013	0.004	0.001	0.005	0.022
Belt Use	-0.506	0.144	0.001	-0.787	-0.221
Peak SWR	-0.145	0.072	0.044	-0.289	-0.007
Dry Surface	0.330	0.168	0.049	0.008	0.668
Dependent Variable	Severe Injury (i.e., Fatal or Incapacitating Injury)				
Num. of Observations	1,940				
Num. of Severe Cases	255				
AIC	1,484				
BIC	1,517				
-2 Log L	1,472				
c Statistics	0.612				

[a] Wald χ^2 test

[b] Profile-likelihood (PL) confidence limit

Note: The estimated model is for a non-ejected occupant in a rolled vehicle in a traffic crash.

DOT HS 813 027
November 2020

U.S. Department
of Transportation

National Highway
Traffic Safety
Administration

NHTSA

14982-102320-v2