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16. Abstract

The most urgent issues in crash safety research have typically been identified by searching for high-frequency crash and injury types in retrospective, real-world crash data. However, these retrospective analyses can highlight safety issues that have already been addressed by recent or anticipated safety countermeasures. The objective of this report is to describe methods for using retrospective crash data to project crashes into the future. The resulting projection model uses retrospective passenger-vehicle crash cases and adjusts them to represent the frequency and outcome of similar cases in the future. The retrospective source cases in the model are 2004 to 2015 National Automotive Sampling System Crashworthiness Data System (NASS CDS) occupant cases that have been reweighted with more recent data from 2013 to 2015 National Automotive Sampling System General Estimates System (NASS GES) and Fatality Analysis Reporting System (FARS) crash datasets. The model adjusts each case in the retrospective dataset to represent future crash outcomes using available forecasts of population and transportation trends, as well as estimates of the effects of current and planned safety countermeasures. While it would be unreasonable to expect perfect accuracy in a projection model developed from a large number of individual predictions and forecasts, the goal of the model was to apply the available data as precisely as possible in order to make the best possible projections of passenger vehicle crashes beyond the years for which retrospective data is available and into the future. The results of such projections have the potential to be more useful for identifying the crash, occupant, and injury issues that are expected to remain important in the future than analyses that rely solely on retrospective data. Ultimately, projection model results are anticipated to assist in identifying the most important issues to address in research on passenger vehicle crash occupants. Hypothetical versions of the model could identify combinations of safety interventions with the potential to meet future goals for injury or fatality reduction. A separate report in 2021 will include the initial projections made with these modeling methods for 2020 to 2030 crashes.

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Acronyms and Abbreviations

AAAM	Association for the Advancement of Automotive Medicine
ABS	antilock braking system
ACC	adaptive cruise control
ADS	automated driving systems
AEB	automatic emergency braking
AES	automatic emergency steering
AF	adjustment factor
AIS	abbreviated injury scale
Apps	applications
ATD	anthropomorphic test dummy
BSD	blind spot detection
CACC	cooperative adaptive cruise control
CDC	collision damage classification
CDS	crashworthiness data system
CI	confidence intervals
CIB	crash imminent braking
CIREN	crash injury research & engineering network
CISS	crash investigation sampling system
CMB	cable median barrier
CRSS	crash report sampling system
CUV	car-based sport utility vehicle
delta V	velocity change
E	effectiveness
EDR	event data recorder
EIA	Energy Information Administration
EPA	Environmental Protection Agency
ESC	electric stability control
ESV	enhanced safety of vehicles
FARS	fatality analysis reporting system
FCI	functional capacity index
FCW	forward collision warning
FEA	final economic assessment
FMVSS	Federal Motor Vehicle Safety Standards
FRE	final regulatory evaluation
FRIA	final regulatory impact analysis
GES	general estimates system
GIDAS	German in-depth accident study
GVWR	gross vehicle weight rating
HIC	head injury criterion
HLDI	Highway Loss Data Institute
IIHS	Insurance Institute for Highway Safety
KABCO	injury scale that rates severity from “Killed” to “No injury”
LDW	lane departure warning
LKS	lane keeping support
LTAP/OD	left turn across path/opposite direction

LTV	light trucks and vans
MAD	mean absolute deviation
MAIS	maximum abbreviated injury scale
MDB	moving deformable barrier
MR	mortality rank
MY	model year
NASS	National Automotive Sampling System
NCAP	New Car Assessment Program
NCHRP	National Cooperative Highway Research Program
NCSA	National Center for Statistics and Analysis
NOPUS	National Occupant Protection Use Survey
NSUBS	National Survey of the Use of Booster Seats
NTDB	National Trauma Data Bank
PC	passenger car
PDO	property damage only
PDOF	principal direction of force
PRIA	preliminary regulatory impact analysis
RPMI	risk of permanent medical impairment
SSF	static stability factor
SWR	strength weight ratio
TJA	traffic jam assist
TPMS	tire pressure monitoring system
TY	target year
UMTRI	University of Michigan Transportation Research Institute
UTMOST	Unified Tool for Mapping Opportunities for Safety Technology
V2V	vehicle-to-vehicle
VMT	vehicle miles traveled
VTTI	Virginia Tech Transportation Institute
V2X	vehicle-to-everything communication
WF	weighting factor

Executive Summary

The most urgent issues in crash safety research have typically been identified by searching for high-frequency crash and injury types in retrospective, real-world crash data. However, these retrospective analyses can highlight safety issues that have already been addressed by recent or anticipated safety countermeasures. This report describes methods for using retrospective crash data to project crashes beyond the years for which retrospective data is available and into the future. The model uses available forecasts of population and transportation trends, as well as estimates of the effects of current and planned safety countermeasures. The results of such projections have the potential to be more useful for identifying the crash, occupant, and injury issues that are expected to remain important in the future than analyses that rely solely on retrospective data. These projections are anticipated to assist in identifying the most important issues to address in motor vehicle safety research. Alternative versions of the model can be used to explore how future crash outcomes would change with variation of input parameters and assumptions. Such hypothetical versions of the model could even be used to identify countermeasures or combinations of safety interventions with the potential to meet goals for injury or fatality reduction.

The projection model has been developed using National Highway Traffic Safety Administration crash datasets. The model uses individual crash cases from the past and adjusts them to represent how the frequency or outcome of similar cases would be different in the future. The retrospective source cases in the model are 2004 to 2015 National Automotive Sampling System Crashworthiness Data System occupant cases that have been reweighted with more recent data from the 2013 to 2015 National Automotive Sampling System General Estimates System and Fatality Analysis Reporting System crash datasets. The resulting dataset is consistent with national-level counts of passenger vehicle crash occupants by key parameters during these baseline years. Pedestrians, cyclists, and other non-occupants are not included in the current version of the model because NASS CDS does not contain data for crashes involving these road-users.

The framework for the projection model is based on the concept that a weighted occupant case in the retrospective dataset represents a corresponding number of similar occupant cases in real-world crashes during the retrospective period. The effects of population and transportation trends, and of safety countermeasures that affect the frequency and outcome of crashes, are applied to each individual case in the model to project how the characteristics of those individual modeled cases would change if they occurred in the future. The expected effect of each modeled trend and safety countermeasure on crash frequency is applied to each occupant case in the retrospective dataset by successive adjustments to the case weight of affected cases. The expected effect of each modeled safety countermeasures on the outcome of the crashes that are still expected to occur is applied by manipulating the injuries documented in each case that is in the given countermeasure's target population.

Just as retrospective datasets can be analyzed to explore the characteristics of injury crashes in the past, the modified projected dataset developed using the proposed projection model can be used to analyze the crash, vehicle, occupant, and injury characteristics of crashes expected to remain in the future, given the particular assumptions for that projection.

The model is currently designed to develop full projection datasets for passenger vehicle occupants for the crash years 2020, 2025, and 2030. The model incorporates adjustments to crash projections based on the following forecasted population and transportation trends: population growth by age group, changing driver licensure rates by age group, increased crash exposure with improving economic factors, a continued shift in vehicle types in the fleet toward SUVs, and increasing belt use and age-appropriate child restraint use. Safety countermeasures coded for inclusion in the model to date include several active crash avoidance and mitigation technologies, passive crashworthiness and occupant protection improvements, infrastructure updates, and occupant and behavior interventions and changes that have the potential to affect crash safety.

Estimates of population and transportation trends, and of the effectiveness and implementation or penetration rate of safety countermeasures, were drawn from a wide variety of sources including review of published literature, Federal Motor Vehicle Safety Standards, regulatory impact analyses for those standards, voluntary industry agreements, and insurance data. Some newer countermeasures have not yet been incorporated into the model, but it is anticipated that they can be added later as information about their effectiveness and likely penetration emerges. As such, the projections produced by the model should be considered snapshots of what the future could look like given the current understanding of safety technology and transportation trends.

An evaluation version of the model has been developed for validation purposes. The evaluation model uses retrospective data from 2004 to 2012 to project crash outcomes in 2014. The projected 2014 dataset was compared to annual averages from retrospective real-world crash data from 2013 to 2015 to evaluate the model's potential to predict the crash, occupant, and injury types that will be most frequent in a future year.

This methods report provides a detailed description of the model design and implementation, as well as a comparison of results from the evaluation version of the model to the real-world comparison dataset for 2013 to 2015. Details of the specific countermeasures that are relevant to the evaluation version of the model are included as appendices to this report. Results of 2020 to 2030 projections from the model will be reported separately, in a projection model results report currently in progress (Mallory et al., in press).

1 Introduction

Identification of the highest priority safety issues has typically been accomplished by searching retrospective crash data to identify crash scenarios, occupant types, or injuries that were most frequent or most harmful in the past (Mallory et al., 2017). These real-world database analyses typically involve ten or more years of case data and reflect the safety conditions in the decade (or more) before the search is performed. Few of the vehicles captured in these retrospective cases are equipped with the safety technology that is state-of-the-art at the time of the search. In effect, these retrospective analyses typically identify the most pressing safety issues of the previous decade, some of which may already have been addressed by safety interventions that are already being implemented or are expected to be implemented in the near future.

A predictive look at expected crash frequency and outcomes that incorporates assumptions about recent and emerging countermeasures provides an alternative to a purely retrospective analysis for identifying the crash, occupant, and injury issues that are most urgent for motor vehicle safety research. While previous studies have employed forecasts of individual factors, such as economic conditions or population growth among older occupants to predict changes in the frequency and outcome of future crashes, all available factors expected to affect future crashes must be combined into a single analysis to provide a truly comprehensive projection. NHTSA's methods for calculating benefits of isolated safety technologies and behavioral programs are the gold standard for estimating the number of future crashes or injuries they are expected to prevent. These analyses often account for the expected effects of other individual safety standards, or changes in parameters such as target population, or variables like restraint use on the effectiveness of the technology or program being evaluated. However, to capture a detailed forecast of the crashes and injuries expected to remain after the application of many population trends, transportation trends, and countermeasures, a predictive model would need to ensure that *all* overlapping trends and effects are accounted for and that the benefits for any crash that could be prevented by multiple countermeasures would not be double-counted in the results.

The goal of this project is to develop a projection model that can combine many estimates and assumptions about safety countermeasures and transportation trends to produce comprehensive estimates of potential future crash outcomes. If it is assumed that the best available estimates of variables affecting future crash frequency and safety can be determined through a review of current literature, the resulting projection model could be used to better identify future safety issues. For countermeasures whose effectiveness or likely penetration in the future is uncertain, application of hypothetical ranges of parameter values could also be used to explore best-case and worst-case scenarios for future safety as well as to understand the effects of specific proposed safety programs or technologies.

A modeling strategy has been developed to apply a broad set of predictive estimates to a retrospective case dataset to predict future crash frequency and outcome as comprehensively as possible. This framework allows the incorporation of predictions on diverse safety interventions such as crashworthiness countermeasures, crash avoidance and mitigation countermeasures, driver behavior programs, and infrastructure improvements into a single model. The model is designed so that the effects of these overlapping efforts to improve safety can be predicted simultaneously without double-counting.

This report describes the strategy used to develop this projection model, along with the details of the trends and countermeasures currently included in the model. Although projection results are not included in this report, results from an evaluation version of the model are included in Section 3. The evaluation version of the model was used to project crash outcomes in 2014, and the results were compared with real-world data from 2013 to 2015 as a means of assessing the reliability of the methods. Detailed descriptions of the countermeasures used in the evaluation version of the model are included in the appendices to this report.

While the goal of this project is to create more accurate predictions of crash frequency and outcome in the future, uncertainty is inherent in a predictive model like this one. Every component in the model adds to the uncertainty in the results, starting with the initial retrospective dataset used as the basis for the model and compounded with every predictive adjustment made to the model occupant cases. The projections are highly dependent on the estimates underlying each trend and countermeasure, and if a new trend or countermeasure emerges or proves to have a different effect than initially estimated or is implemented at a different rate than expected, the projections are likely to be less accurate.

Ultimately, the output of the model is intended to be used to try to change future outcomes by targeting research on the most frequent and harmful crash types and injuries in the projections. As such, even more important than the model's absolute accuracy is its usefulness in identifying the most likely safety issues of the future. A single, comprehensive model that combines information from many sources, accounting for simultaneous changes affecting transportation safety, has the potential to provide perspective on how countermeasures and transportation trends may alter crash outcomes in the future and to be more useful than relying on individual estimates of shifts in overall crash rates or isolated benefits estimates for individual technologies and countermeasures.

2 Methods

The projection model described in this report made incremental adjustments to passenger vehicle occupant cases in a weighted retrospective crash dataset. The retrospective dataset was composed of source cases that were drawn from NASS CDS and re-weighted with cases from NASS GES and FARS to represent national-level case counts. In the model, case weights and outcomes for individual occupants in the retrospective dataset were adjusted per the predicted future effects of (1) shifting population and vehicle trends, and (2) recent and future safety countermeasures. These case-by-case adjustments to case weights and outcomes were intended to represent any expected differences in the case outcome that would result from documented or forecasted trends and safety countermeasures introduced between the year of the original crash in the retrospective dataset and the future projection year.

2.1 Overall Model Design

Overall model design is illustrated in Figure 1. Weighted, real-world retrospective cases from 2004 to 2015 were used as a baseline for comparison to projected future crash statistics. These same real-world retrospective cases were also used to develop a foundational "stepping-stone" dataset to use as a basis for the projection model. Changes in the future frequency and outcome of crash cases like the ones represented by the source retrospective cases were predicted by applying the effects of the modeled trends and safety countermeasures to each occupant case in the model.

In this case-by-case method, each case retained many of the crash and occupant characteristics documented in the original version of the source retrospective case, but the weighted frequency and injury outcome was modified in the projected future version of each case. In the model, a case was defined as a single passenger vehicle occupant. Pedestrians, cyclists, and other non-occupants were not included in the current version of the model because NASS CDS does not contain data for crashes involving these road-users. The NASS-assigned weight in each original source case, equivalent to the number of real-world occupants it represents, was incrementally adjusted to a future predicted weight in the projected datasets for 2020, 2025, and 2030. Changes to the outcome of each case in the model were made by deleting or changing the severity of individual injuries in the case, based on the expected effects of the modeled countermeasures.

Details of each stage of this adjustment process are illustrated in Figure 1 and discussed in Sections 2.2 to 2.6. The stages discussed in each section include the initial reweighting of the source dataset; the separate treatment of individual occupants in vehicles in model year 2005 and later; and methods for applying population, vehicle and restraint use trends as well as modeled safety countermeasures. Analysis of model output is discussed in Section 2.7. The intermediate steps involved in developing the baseline retrospective dataset (shown in blue in Figure 1) and the stepping-stone datasets (shown in yellow in Figure 1) are illustrated in Figure 2 and Figure 3. The stepping-stone dataset serves as a foundational dataset for the projection model as described in Section 2.4.

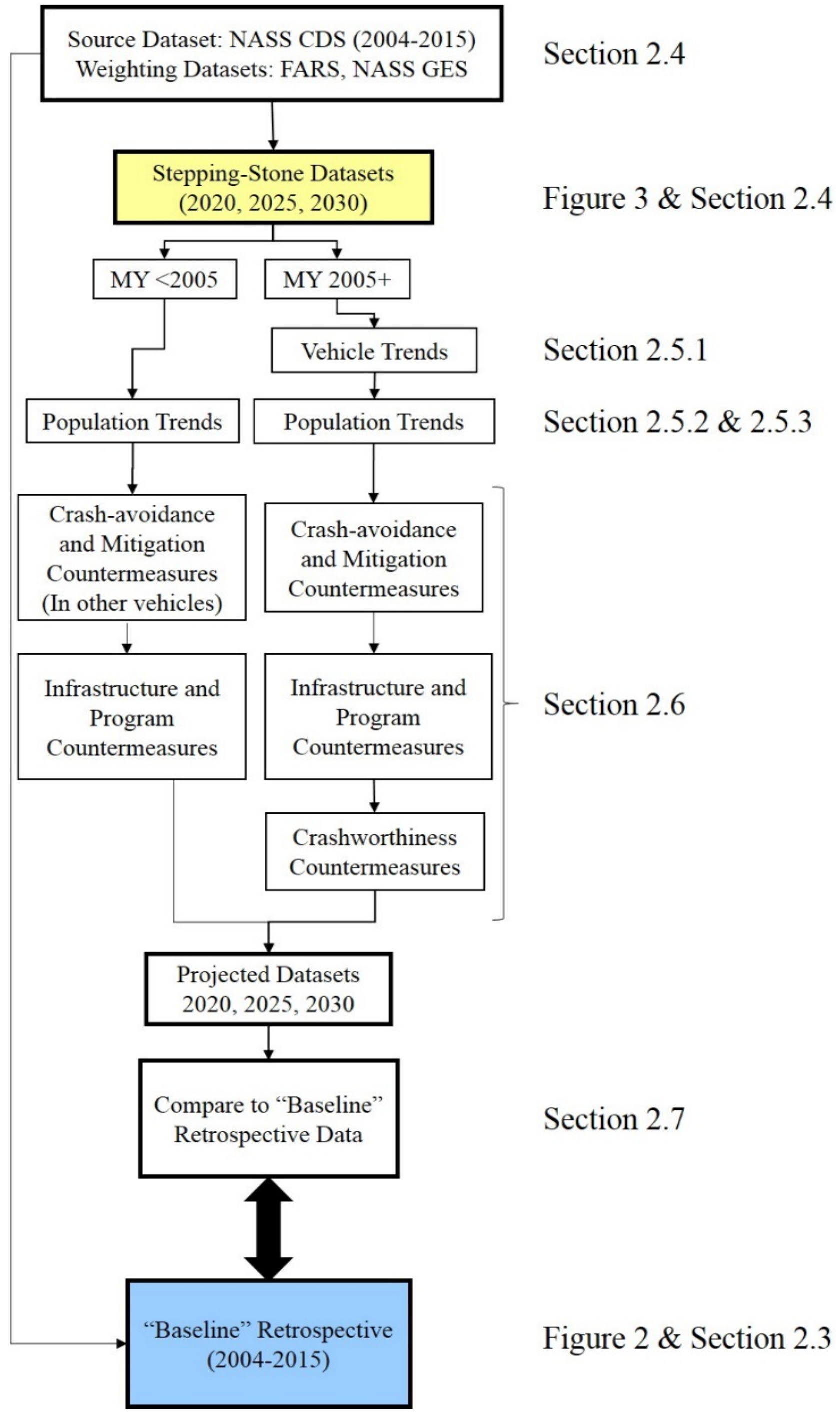

Figure 1. 2020–2030 projection model design with corresponding location of additional information

The projection methods were evaluated by running the model using source retrospective cases from NASS CDS 2004 to 2012 to develop a projection model for the crash year 2014. The reliability of the model was then assessed by comparing the projected 2014 results to real-world case data averaged over the period from 2013 to 2015. Details of this evaluation version of the model can be found in Section 3.

Analysis was performed using SAS data analysis software, Version 9.4 (SAS Institute, Cary NC), with input variables stored in Excel input files. SAS survey analysis procedures were used for all calculations involving weighted case data to account for the structure of the survey-sampled data.

2.2 Source Datasets

The source data used to develop the model were drawn from NHTSA's crash datasets (NASS CDS, NASS GES, and FARS) as described in detail in the following sections. These datasets were used to develop:

- Baseline retrospective datasets, representing real-world crash outcomes in the past, and
- Stepping-stone datasets, the datasets used as the basis for each projection version of the model (2020, 2025, and 2030).

Details of the development of the retrospective datasets and stepping-stone datasets are in Section 2.3 and Section 2.4, respectively.

2.2.1 NASS CDS

Cases that served as the primary source cases for the projection model were drawn from 2004 to 2015 NASS CDS, a survey-sampled NHTSA dataset that included detailed crash information on a national sample of crashes. The NASS CDS datasets are available from NHTSA (NHTSA, 2020c), and details on the structure of the dataset and included variables can be found in the Analytical User's Manual (Radja, 2016) and the Coding and Editing Manual (NHTSA, 2015a). Occupant cases were excluded from the source dataset if any of the following key parameters were unknown:

- Injuries (either unknown if injured, or injured but with injury severity unknown),
- Occupant age,
- Vehicle model year,
- Restraint use, and
- Occupant role (driver/passenger).

Non-crash injuries, such as inhalation and drowning, and occupants who had only these injuries, were also excluded from the analysis. After applying these exclusions, a raw total of 71,954 NASS CDS case occupants remained.

Each NASS CDS case was originally weighted with the CDS Ratio Inflation Factor (variable name RATWGT). As described in the NASS CDS Analytical User's Manual (Radja, 2016), this weight variable is calculated based on the design of the NASS CDS survey-sampled dataset as a function of case parameters and of the estimated total number of crashes in the United States in the year the crash occurred. A single occupant case that was subsequently found to be overly influential on results in several analysis categories was downweighted for use in the projection model, as described in Section 2.3.1. This occupant was identified as a "high leverage" case using procedures developed to find analysis bins that were excessively influenced by a small number of cases. These procedures to check for high leverage cases are explained in detail in

Section 2.8. Subsequently, all CDS-weighted source cases were reweighted using FARS and NASS GES to correct for potential bias resulting from sampling variation and the exclusion of cases with unknown parameters, as discussed in Section 2.3 and Section 2.4.

Case variables, including crash, event, occupant, and injury descriptors were retained for each occupant so that the applicability of every countermeasure could be determined and so that retrospective datasets and projected datasets could be analyzed and compared by a broad set of occupant parameters, crash parameters, and by a variety of measures of harm. See Section 2.7.1 for descriptions of the harm measures used in the analysis of the model, such as costs and numbers/rates of fatalities and injuries.

The Abbreviated Injury Scale is a system for coding and rating the severity of individual injuries. All injuries in NASS CDS 2004 to 2009 were originally coded using NHTSA's AIS coding manual corresponding to the Abbreviated Injury Scale Version 1990/Update 1998 (AAAM, 1998) while all injuries in cases from NASS CDS 2010 and later were originally coded using the NHTSA Injury Coding Manual that was based on AAAM's 2005 AIS/Update 2008 (AAAM, 2008). The injuries from these later cases were mapped in the current project to the corresponding codes in the 1990/98 AIS version as recommended in AAAM's AIS 2005/08 coding manual. The reason that injuries coded in the more recent version of AIS were converted to the earlier version of AIS (instead of translating all codes to the most recent AIS version) was that the majority of the NASS CDS source cases were coded in the earlier 1990/98 AIS version. Converting all coded injuries to the older AIS system reduced the number of cases that needed to be translated, minimizing the potential loss of detail and accuracy that is inherent in conversion of injury codes between coding systems.

Among the new codes introduced in the 2005/08 version of AIS were several specific codes for bilateral injuries that had previously been coded with two separate injury codes in earlier AIS versions. For example, bilateral traumatic amputation of the upper extremities at the elbow would have been coded as two separate AIS 3 injuries (AIS 711000.3) in the AIS 1990/98 version. Using the AIS 2005/08 version, the same occupant would be coded with a single AIS 5 injury code (AIS 711002.5). The code translations provided in the AIS 2005/08 coding manual recommend that the bilateral injury codes (e.g., AIS 2005/08 711002.5) be translated directly to the corresponding single injury codes (e.g., AIS 1990/98 711000.3) when translating from the AIS 2005/08 version to the AIS 1990/98 version. In this model, the translation deviated from this recommendation by translating these bilateral injuries coded in AIS 2005/08 to *two* instances of the corresponding unilateral injury code in AIS 1990/98 to better represent the injuries as they would originally have been coded in AIS 1990/98. Sixteen cases originally coded with bilateral injuries using the AIS 2005/08 codes were subsequently converted to pairs of AIS 1990/98 injuries using this method.

For AIS 2005 codes that did not have a recommended AIS 1990/Update 1998 translation code, the hard-coded AIS 2005 code was used directly to categorize the injury severity of the case by maximum AIS (MAIS) and to categorize the body region, structure, and type of injury.

Note that, starting in crash year 2009 in NASS CDS, only an abbreviated Occupant Assessment record was completed for occupants in vehicles 10 years old or older at the time of the crash.

Since detailed injury data was unavailable for these occupants, they were excluded from the analysis just as were other cases where injury or other key information was unavailable. Implications of this data collection change for this model, and adjustments made to the model to account for this change, are discussed in Section 2.4 and Section 3.

2.2.2 FARS

Fatal occupant cases are under-represented in NASS CDS, based on comparison to FARS, a nationwide census of fatal crashes. Therefore, the fatal NASS CDS cases used in the model were reweighted using FARS. Data from FARS was used to determine the total average annual number of fatalities in NASS CDS-applicable vehicles by seat position, age, and restraint use so that fatal cases from the source NASS CDS dataset could be reweighted accordingly. FARS cases used for this reweighting step were drawn from crash years 2004 to 2015 for the projection models for 2020, 2025, and 2030. FARS datasets are available from NHTSA (NHTSA, 2020a) and details on the structure of the dataset and included variables can be found in the Analytical User's Manual (NHTSA, 2019).

Inclusion criteria for FARS cases used in reweighting were as follows:

- Case occupant is fatality,
- Person type is passenger vehicle occupant,
- Age is known,
- Crashes involving CDS-eligible vehicles, i.e., crashes involving at least one passenger vehicle weighing less than 10,000 pounds (excluding buses unless van-based and motorhomes unless light-truck based), and
- Eligible passenger vehicles were identified using the FARS body type variable (variable name BODY_TYP, included variable values 0-22, 24-49).

No limits were placed on vehicle model year so that annual national totals of passenger vehicle occupant fatalities could be estimated for vehicles of all model years. Case occupants were not excluded based on tow-status of vehicles in the crashes. If the model had excluded crashes that did not meet the CDS criteria of involving at least one passenger vehicle towed due to damage, almost 1000 cases per year would have been excluded from the FARS dataset used in the model. Since FARS is a census dataset, fatal cases from FARS are representative of all fatalities among U.S. passenger vehicle occupants. Therefore, no weighting was used for analysis of FARS data.

Fatal cases in the NASS CDS source dataset were reweighted using FARS data according to the procedures described in Section 2.3 and Section 2.4 for the retrospective dataset and the stepping-stone datasets used in the projection models for 2020, 2025, and 2030.

2.2.3 NASS GES

NASS GES is a survey-sampled NHTSA crash dataset. It includes more cases than NASS CDS, but provides less information about the crashes, occupants and injuries in each case. NASS GES datasets are available from NHTSA (NHTSA, 2020b) and details on the structure of the dataset and included variables can be found in the Analytical User's Manual (NHTSA, 2016a). Data from NASS GES was used to estimate the total average annual number of non-fatally injured occupants in NASS CDS-applicable vehicles by seat position, age, restraint use, and injury severity so that non-fatal cases from the source NASS CDS dataset could be reweighted accordingly. NASS GES cases used for this reweighting step were drawn from crash years 2004 to 2015 for the projection models for 2020, 2025, and 2030.

Inclusion criteria for NASS GES cases used in reweighting were as follows:

- Person type is vehicle occupant,
- Occupant case is non-fatal,
- Occupant is in CDS-eligible vehicle, i.e., a passenger vehicle weighing less than 10,000 pounds (excluding buses unless van-based and motorhomes unless light-truck based), and
- Eligible passenger vehicles were identified using the GES body type variable (variable name BODYTYPE, included variable values 0-22, 24-49).

Imputed variables drawn directly from NASS GES were used where body type, age, and injury severity variables were missing. Thus, estimates of total numbers of injury cases were not underestimated as a result of cases missing data. No limits were placed on vehicle model year so that national annual totals could be estimated for vehicles of all model years. Weighted data was used for all NASS GES analyses.

Injury cases in the NASS CDS source dataset were reweighted for the model's retrospective dataset and stepping-stone datasets using NASS GES data according to the procedures described in Section 2.3 and Section 2.4.

2.3 Baseline Retrospective Dataset 2004-2015

The baseline retrospective dataset represents crashes in the past. It is an annualized "average" dataset of NASS CDS occupants in crashes between 2004 to 2015 and it serves as a real-world baseline or comparison dataset in this model. The baseline retrospective dataset is distinct from the stepping-stone datasets that were each individually reweighted to serve as foundational datasets for the 2020, 2025, and 2030 projection models, as described in Section 2.4. The baseline retrospective dataset is intended to represent actual cases during the 2004 to 2015 period with aggregated weight equal to the annualized average of these years. It is not the basis for projections: it is the "past" data that was used to compare future projected outcomes to average past outcomes.

The baseline retrospective dataset was drawn from the NASS CDS source dataset described in Section 2.2 and reweighted using cases from NASS GES and FARS to:

- Correct for any biases resulting from dropping missing-variable cases,
- Adjust for undercounting of fatal cases in NASS CDS,

- Adjust for under-reporting of low-severity cases in NASS CDS, and
- Get the best estimate of the annual average number of NASS CDS-eligible cases in the U.S. crash population.

Occupant cases used for reweighting the retrospective dataset were drawn from FARS (fatal cases only) and NASS GES (non-fatal cases only) for the entire data range of 2004 to 2015. A model option is also available to provide a baseline retrospective dataset without the adjustment for under-reporting of low-severity cases.

Following reweighting, the dataset was adjusted to correct for belt use over-reporting. The steps in the development of the baseline retrospective dataset are illustrated in Figure 2 and explained in detail in the following sections.

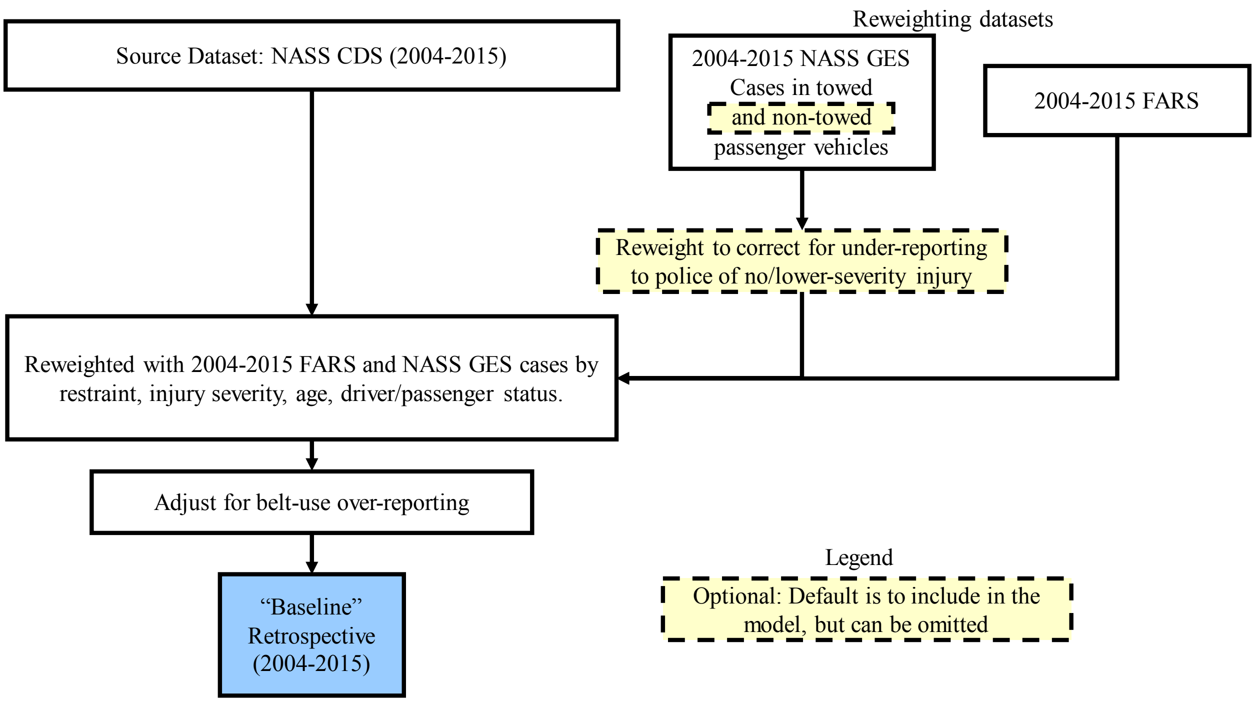

Figure 2. Overview of the development of the baseline retrospective dataset

2.3.1 Retrospective Dataset Case Reweighting Using FARS and GES

Reweighting was performed by grouping all cases in the NASS CDS source dataset, all fatal cases in the FARS reweighting dataset, and all non-fatal cases in the NASS GES reweighting dataset by the occupant characteristic bins shown in Table 1. Binning was performed with weighted case data from NASS CDS and GES and with unweighted data from FARS. As discussed in Section 2.2.1, a single NASS CDS occupant case[1] was identified as having high-leverage effects on multiple analysis categories. Therefore, at this stage before reweighting with NASS GES, that CDS case's weight (CDS variable name RATWGT) was set to the average case weight of all other CDS cases in its corresponding bin in Table 1 (Restrained Passengers, <16

[1] Case year 2015, PSU 43, CASENO 126, VEHNO 2, OCCNO 3.

years old, non-fatal MAIS 3-6). Details of the procedures used to identify high leverage cases are in Section 2.8.

Table 1. Bins used for reweighting cases in source (NASS CDS) dataset using cases from NASS GES and FARS

			Driver by Age			**Passenger by Age**			
			<26	**26-65**	**65+**	**<16**	**16-25**	**26-65**	**66+**
Restrained	Non-fatal MAIS	0-1							
		2							
		3-6							
	Fatal								
Unrestrained	Non-fatal MAIS	0-1							
		2							
		3-6							
	Fatal								

56 Bins

Since NASS GES does not include AIS-coded injury data, binning of NASS GES cases by injury severity for non-fatal cases was based on the KABCO injury scale. KABCO characterizes severity on a scale from "Killed (K)" to "No injury (O)" with A, B, and C representing decreasing severity of injury. It is used in police reports and is typically based on information available at the scene of the crash rather than on medical records. Where this variable was unknown in NASS GES, imputed injury severity data was used (GES variable names INJSEV_H and INJSEV_IM). For each GES case, the individual's KABCO code was converted to a probability of a non-fatal MAIS 0-1, 2, or 3-6 injury using probabilistic conversion tables based on AIS 1990/98 Update injury codes (Blincoe et al., 2015). These tables estimate the probability that the most serious injury in each non-fatal case was equivalent to a given MAIS severity level from 0 to 5 for each level of the KABCO scale. For example, using Table C-1 from the Blincoe et al. report for a GES occupant with a KABCO severity of B ("Non-incapacitating Injury"), the tables estimate a 84.24 percent probability that the occupant would survive with a corresponding MAIS severity code of AIS 0-1, an 11.13 percent probability it would be a non-fatal AIS 2, a 4.47 percent probability that it would be a non-fatal AIS 3-5, and 0 percent probability that it would be a non-fatal AIS 6. The case weight assigned to the original GES case would be proportionally divided among the corresponding bins. For example, if the KABCO=B occupant had a case weight of 100, a case weight of 84.24 would be summed with the corresponding AIS 0-1 bin, a case weight of 11.13 would be summed with the AIS 2 bin, and a case weight of 4.47 would be summed with the AIS 3-6 bin. To estimate the total average annual number of occupants in a given bin, the probability of the given injury severity for each occupant in the bin was summed across all occupants, since probability theory dictates that the sum of the individual probabilities is equal to the expected value of the total.

Restraint status for occupants 8 or older was based on documentation of seat belt or child restraint use as detailed in Section 2.5.5. Occupants younger than age 8 were categorized as restrained, for the purpose of this reweighting step, if they were documented in an age-appropriate child restraint based on the recommendations on NHTSA's safercar.gov website.[2] This categorization allowed binary classification of restraint use for children, without the need to define different categories of restraint use for different age groups. The few cases where children were documented in seats recommended for younger age groups were also categorized as restrained. Children who were unrestrained or in restraint systems inappropriate for their age group were categorized as unrestrained for the purposes of reweighting. This categorization did not account for the potentially substantial proportion of children who were in improperly used but age-appropriate restraints in either GES, FARS or CDS. These children were combined with restrained cases, solely for the purpose of re-weighting.

For each non-fatal bin in Table 1, a weighting factor (WF_b) was calculated, where "b" identified the bin. Each WF_b was a ratio of the weighted number of cases in the bin among the NASS GES cases in the reweighting dataset divided by the weighted number of NASS CDS cases in the bin from the source dataset. Correspondingly for each fatal bin "b" in Table 1, a weighting factor (WF_b) was calculated as a ratio of the number of cases in the bin among the FARS cases in the reweighting dataset divided by the weighted number of NASS CDS cases in the bin from the source dataset.

The NASS-assigned weight (NASS CDS variable name: RATWGT) in each individual case in the NASS CDS source dataset was multiplied by the applicable weighting factor (WF_b) and divided by 12 so that the resulting aggregate dataset represented an annual average over the 12-year period (Equation (1)).

$$Weight_{retro} = \frac{RATWGT \times WF_b}{12} \tag{1}$$

where:
$Weight_{retro}$ is the case's weight in the baseline retrospective dataset,
RATWGT is the NASS CDS-assigned case weight, and
WF_b is the weight factor for the bin assigned to the case.

Thus, the resulting weighted number of occupant cases in each <u>non-fatal</u> bin in the retrospective dataset was equal to the total average annual number of such cases in NASS GES between 2004 to 2015. Similarly, the weighted number of occupant cases in each <u>fatal</u> bin in the retrospective dataset was equal to the average annual number of such cases in each bin in FARS between 2004 and 2015.

It should be noted that there are limitations associated with applying the KABCO-AIS conversion to the GES reweighting dataset that is intended to account for the cases that were excluded from the source NASS CDS dataset because of missing AIS codes. Specifically, applying the conversion method could bias injury severity distribution in the reweighted dataset.

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[2] While child restraint type was available for all crash years in NASS CDS, it was not available in NASS GES and FARS until 2013. Therefore, for the purposes of reweighting, children under age 8 in the FARS and GES cases documented in any child restraint were categorized as restrained prior to crash year 2013.

An exploratory study[3] showed that a shift in injury severity distribution can be introduced as a result of the difference in the severity distribution among the AIS-coded cases used to develop the conversion tables and the severity distribution of cases without AIS codes, even among cases with the same KABCO score. However, based on that exploratory study, the error introduced with this reweighting step is less than the error that would be expected if no adjustment were made to account for exclusion of cases without AIS codes.

2.3.2 Adjustment for Over-Reporting of Belt Use

The final step in the development of the retrospective dataset was to adjust for the over-reporting of belt use in NASS CDS cases that results from police over-reporting belt use. The over-reporting of belt use in police reports has been attributed to reliance on occupant-reported use with negligible use of EDR (event data recorder) data in 2015 and earlier (Kahane, 2018). In the model, no change or adjustment was made to occupant cases where the occupant was coded as unbelted, or to rear-seat occupant cases.[4] Front-seat occupant cases coded as belted were each divided into two pseudo-cases[5]: a belted pseudo-case with all case characteristics identical to the original case and an unbelted pseudo-case with only the belt-use variable modified. The case weight of the original (parent) case was divided between the two pseudo-cases, proportional to the probability that cases coded as belted were indeed belted, based on estimated over-reporting rates for belt use in CDS. Note that this adjustment accounted for under-reporting in the original 2004 to 2015 NASS CDS cases, and does not reflect the likelihood of under-reporting in the projection years 2020 to 2030.

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[3] The KABCO-AIS injury-severity conversion tables were developed by Blincoe et al. based on NASS CDS cases that had both the police-reported KABCO score and NASS-documented AIS codes. An exploratory analysis was performed to confirm for each possible KABCO score that the injury severity among NASS CDS with AIS codes was representative of all NASS CDS cases with that KABCO. The exploratory analysis used the Treatment-Mortality variable (CDS variable name TREATMNT) in NASS CDS cases from 2003-2015. Although the Treatment-Mortality variable provides less detail than AIS codes, it identifies occupants who were transported to the hospital and occupants who received no treatment, which can be used as surrogate variables for estimated injury severity. In cases in the analysis that were coded as KABCO=A (incapacitating) or B (non-incapacitating), injury severity appeared to be worse in cases where AIS was coded, based on higher rates of hospitalization in AIS-coded cases than in cases with missing AIS codes. In contrast, for cases coded with KABCO=C (possible injury) or O (no injury), injury severity appeared to be lower in AIS-coded cases than in cases with missing AIS codes, based on rates of "No Treatment" being higher among cases where AIS was coded. In the context of the model, the KABCO-AIS conversion tables are used to reweight the AIS-coded NASS CDS cases in the model to match the injury-severity distribution in KABCO-coded-NASS GES cases. This reweighting step is intended, in part, to make up for exclusion of cases without AIS codes among the NASS CDS source cases in the model. However, the biases at each KABCO level in the conversion tables could be expected to lead to shifts in the injury severity distribution in the reweighted model datasets. The severity distribution among cases corresponding to KABCO A and B scores may be shifted toward more serious injuries while the severity distribution among cases corresponding to KABCO C and O scores may be shifted toward lower-severity injuries. In other words, there may be an overall tendency to increase the relative weight of the most severe and least severe cases in the model dataset.

[4] In NOPUS, rear seat belt use rates are actually higher than rates in crash data, suggesting that rear seat belt use is not over-reported in crash data (Kahane, 2017).

[5] A pseudo-case is essentially the offspring of a case in the source dataset. Pseudo-cases have many of the same characteristics of the original (parent) case, but the case weight and parameters are adjusted to reflect a modeled prediction about how the case would be different in the future. Typically, a parent case is divided into multiple pseudo-cases, with the parent case's weight divided among the pseudo-cases proportionally to the expected frequency of each possible outcome.

The over-reporting rate for belt use in **non-fatal** cases without EDR data[6] was drawn from a study of 2002 to 2008 NASS CDS driver cases (Kahane, 2018). Using cases where EDR data was available but did not appear to have been used to determine CDS belt use, it was found that 20 percent of MAIS 2+ CDS non-fatal belted cases were coded as unbelted in EDR data. Similarly, 19 percent of MAIS 0-1 CDS coded belted cases were coded as unbelted in EDR data. In the absence of over-reporting data for right front passengers, an estimate of 20 percent over-reporting was applied in the projection model to all belted front-seat occupants. This adjustment was made by applying 80 percent of the parent case weight to the belted pseudo-case, and 20 percent of the parent case weight to the pseudo-case with restraint status adjusted to unbelted.

The over-reporting rate for **fatal** cases was estimated using data from FARS in the same study used for estimating over-reporting in non-fatal cases (Kahane, 2018), which showed that 11 percent of fatal drivers coded as belted were unbelted. Therefore, all belted occupants who were fatally injured in the original retrospective dataset were split into two pseudo-cases: a belted pseudo-case with 89 percent of the weight of the parent case and an unbelted pseudo-case with 11 percent of the weight of the parent case. In the absence of data specific to passengers, these weights were applied to occupants in all front-seat positions.

The decision to adjust cases for belt use over-reporting *after* reweighting with GES was based on the understanding that belt use is also over-reported in GES. Since no data was available to adjust for this over-reporting in GES, the uncorrected CDS data was weighted with uncorrected GES data before applying the belt use adjustment to the reweighted CDS cases. The model and its input files were coded so that the under-reporting rate can be varied, or even set to zero, to explore its effect.

2.3.3 Extrapolation to Include More Minor Cases

NASS CDS has proportionally fewer low-severity occupant cases than occur in real-world crashes. This exclusion of lower-severity crashes from NASS CDS has likely led to an underestimate of the <u>number</u> of low AIS injuries, such as whiplash-associated disorder and mild traumatic brain injury. Undercounting of low-severity cases may also have led to an overestimate of overall injury <u>rates</u> since exclusion of non-injury cases reduces the denominator in injury rate estimates.

Reasons for this under-representation of low-severity cases in NASS CDS include the following:

(1) Exclusion of crashes in non-towed vehicles: CDS was focused on higher-severity crashes as reflected in the case selection criteria, including that at least one CDS vehicle must be towed from the scene. Additionally, occupant injury data were not collected for occupants in passenger vehicles that were coded as not towed from the scene due to damage, so even if these occupants were included in CDS, they were not included in the projection model.

[6] For future applications of this model, EDR data should be evaluated for the cases in the model to determine belt use from available case data where possible.

(2) Under-reporting of low-severity crashes to police: CDS and GES are both limited to police-reported crashes, and lower-severity crashes are less likely to be reported to police than higher-severity crashes.

Procedures for extrapolating from CDS and GES data to upweight lower injury-severity cases to address the two issues above were coded into the model. Although these procedures were coded so that they can be turned off and analysis can be performed only on occupants in CDS-eligible occupant cases, the default was to apply these low-severity upweighting procedures.

The exclusion of occupants in non-towed vehicles was addressed by the reweighting procedures in Section 2.3.1, which reweight the cases in the CDS source dataset using counts of GES case occupants in towed *and* non-towed vehicles. If the optional adjustment of low-severity crashes is turned off, then this reweighting step uses only GES occupants in towed vehicles.

To address the under-reporting of lower-severity cases to police in the projection model, adjustments were made directly to the GES case dataset used for reweighting. This procedure is summarized below and illustrated in Figure 2.

The frequency of under-reporting to police in crashes by injury severity was estimated by Blincoe et al. (2015). Although the motivation for Blincoe's estimate was related to the calculation of crash costs, the results apply to other applications where under-reporting rates by severity are needed. Among PDO crashes, which are crashes with property damage only, it was estimated that 60 percent are not reported to police. In crashes with injuries, the percentage of occupants who were in crashes that were not reported to police was estimated as a function of occupant injury severity (Table 2). It was assumed for the projection model, as it was in Blincoe's study, that GES crashes were representative of police-reported crashes. Therefore, when non-fatal GES cases were binned into the categories in Table 1 using this procedure, case weights were upweighted to account for the under-reporting rates in Table 2.

When binning GES occupants from PDO crashes, the case weights of all occupants in PDO crashes were multiplied by a factor of 2.50 (100/40) to upweight the 40 percent of PDO crashes that are reported to police to correct for the 60 percent of PDO crashes that typically go unreported. For GES injury crashes, i.e., crashes where there was at least one injured occupant, weight multipliers were calculated as a function of MAIS injury severity. As such, the weight multiplier was applied during the conversion of each case's KABCO score to MAIS. For example, without the extrapolation procedures to include more minor cases, the case weight of a non-fatal GES occupant with a given KABCO severity would be distributed in bins proportionally to the probability that the case injury severity was MAIS 0-1, MAIS 2, or MAIS 3-6. Using the extrapolation procedures, the proportional case weight was multiplied by the weight multiplier for the corresponding MAIS level. For example, without the unreported-case correction procedures the case weight of a towed (CDS-eligible) KABCO=A case would have been apportioned so that 61.58 percent of the case weight would be in the non-fatal MAIS=0-1 bin, 19.24 percent in the non-fatal MAIS 2 bin, and 18.74 percent in the non-fatal MAIS 3-6 bin (per Table C-1 in Blincoe's cost study). With the unreported-case correction procedures, 85.49 percent of the case weight would be added to the MAIS 0-1 bin, 24.05 percent to the MAIS 2 bin, and 19.24 percent to the MAIS 3-6 bin.[7] These numbers add up to greater than 100 percent because the proportional distribution of the case weight into bins and the upweighting of the lower-severity cases was done in a single step.

Table 2. Calculation of reweighting value to adjust for under-reporting to police (based on Table 1-3 in Blincoe et al. (2015))

		Unreported to Police (%) (Blincoe et al., 2015)	**Reported to Police (%)**	**Weight Multiplier** $\left(\frac{100}{\%\ Reported\ to\ Police}\right)$
By Crash	**PDO Crashes**	60	40	2.50
By Occupant	MAIS 0[8]	53.1	46.9	2.13
	MAIS 1	25.4	74.6	1.34
	MAIS 2	19.9	80.1	1.25
	MAIS 3	4.3	95.7	1.04
	MAIS 4+	0	100	1.00*
	MAIS 5	0	100	1.00*

** Note that a weight multiplier of 1.00 indicates no adjustment.*

In optional versions of the model that exclude this extrapolation, the upweighting of cases to account for the exclusion of non-towed crashes is also suppressed by using only GES cases in towed vehicles for the reweighting procedures explained in Section 2.3.1.

2.4 Development of the Stepping-Stone Dataset

The case-by-case adjustment of occupant cases from the original source dataset to represent predicted outcome in crashes in the future was accomplished by a sequence of modifications to each case weight and outcome. The first modifications to each case's weight were made in the development of the stepping-stone dataset. The stepping-stone dataset is the foundational dataset to which all population trends and safety countermeasures will later be applied. A separate stepping-stone dataset was developed for the 2020, 2025, and 2030 projections, serving as the first incremental step for each projection model. These stepping-stone datasets do not represent crash counts or outcomes in any time period, historical or predicted. They are simply interim datasets that have undergone the initial adjustments needed to use them to project 2020, 2025, and 2030 crashes. Development of the stepping-stone dataset for each of the projection models is described in the following sections.

In the development of the stepping-stone dataset, cases involving occupants in vehicles of model years earlier than 2005 were treated separately from occupants in newer model-year vehicles. These groups of cases will be referred to as MY<2005 cases and MY2005+ cases throughout this report. The reason for treating occupants in early model vehicles differently in the model was

[7] Using AIS 2 as an example, the 19.24% of KABCO = A cases expected to correspond to MAIS 2 injury severity are multiplied by the 1.25 multiplier from Table 2 to correct for under-reporting of MAIS 2 cases by police. The product (24.05%) is the proportion of the case weight in each KABCO = A case added to the MAIS 2 bin illustrated in Table 1.

[8] In this reweighting procedure, MAIS 0 occupants are uninjured occupants in crashes where at least one occupant was injured.

linked to one of the basic concepts of the model, that each case can be adjusted to reflect how the outcome would vary as a result of vehicle improvements. The model makes adjustments to case outcomes based on every vehicle countermeasure and design change that has been introduced or become more common since the model year of the case occupant's vehicle. That concept requires that even relatively old countermeasures (like electronic stability control) be developed and incorporated in the model to account for the fact that many of the vehicles in the source dataset were not equipped with countermeasures that have since become standard equipment. However, for the earliest-model year vehicles among the source cases, there was simply not enough information available to effectively "adjust" these cases so that outcome would reliably match what would be expected among newer vehicles on the road in 2020 to 2030. The decision to treat cases in older model-year vehicles separately allows these cases to be retained in the model. These cases still represent older model-year vehicles, without needing to apply very old countermeasures, such as the improvements made to frontal air bags in the late 1990's and early 2000's. As result of this 2005 MY cutoff, vehicle-based countermeasures and improvements that were largely implemented by MY 2005 did not need to be included in the model. MY 2005 was selected as a threshold because it retains enough newer-model year cases from the source dataset for making projections, while still ensuring that major earlier vehicle improvements like improved frontal air bags were already fully phased in for the majority of the cases used in those projections.

The MY<2005 occupant cases represent occupants still expected to be in pre-2005 model year vehicles in the projection models, i.e., occupants in vehicles that will be more than 15, 20, or 25 years old in 2020, 2025, and 2030, respectively. As discussed in detail below, these MY<2005 cases will be downweighted to reflect their decreasing prevalence in the fleet and will also be subjected to trends and countermeasures that would affect occupants in these older vehicles. However, vehicle-based countermeasures that would only be expected to be installed in newer vehicles were not applied to the MY<2005 cases, since these occupants still represented occupants in MY<2005 vehicles in the projection datasets. For example, occupants in older MY vehicles would be affected by the increasing prevalence of infrastructure countermeasures, like cable median barriers, but not by vehicle-based countermeasures, such as improved occupant protection or crash avoidance countermeasures.

The adjustments made to cases in the retrospective datasets to produce each stepping-stone dataset were as follows:

1. Cases involving occupants in MY 2005 and newer vehicles were separated from those in earlier-model year vehicles and the two groups of cases were reweighted separately to reflect the distribution of cases by the occupant characteristics in Table 1 (restraint use, injury severity, driver/passenger status, and age) as determined using occupants in NASS GES and FARS cases from 2013 to 2015. The MY<2005 cases were reweighted using GES and FARS cases from older vehicles (16+ y.o. at the time of the crash) and the MY2005+ cases were reweighted using GES and FARS cases from newer vehicles (e.g., 0-15 y.o. at the time of the crash for the 2020 projection).
2. The MY<2005 subset and the MY2005+ subset of occupant cases were each reweighted so that they represented the appropriate proportion of older vehicles (MY<2005) and newer vehicles (MY2005+) expected in the fleet in the targeted projection year (2020, 2025, or

2030). This step upweighted cases in newer model-year vehicles and downweighted cases in older model-year vehicles.

3. As with the retrospective dataset, a model option is available to upweight lower-severity cases to account for under-reporting of lower-severity crashes to police. The default setting in the model is to apply this optional step. In runs of the model when this step is turned "off," the GES cases used for the reweighting in step 1 are limited to occupants in vehicles that were towed from the scene.
4. The weights of belted and unbelted cases were adjusted to address belt use over-reporting in the source NASS CDS and GES datasets.

Figure 3 illustrates the development of the stepping-stone dataset for the 2020 projection. The following section is a discussion of the details and rationale for each step in the development of the 2020, 2025, and 2030 stepping-stone datasets.

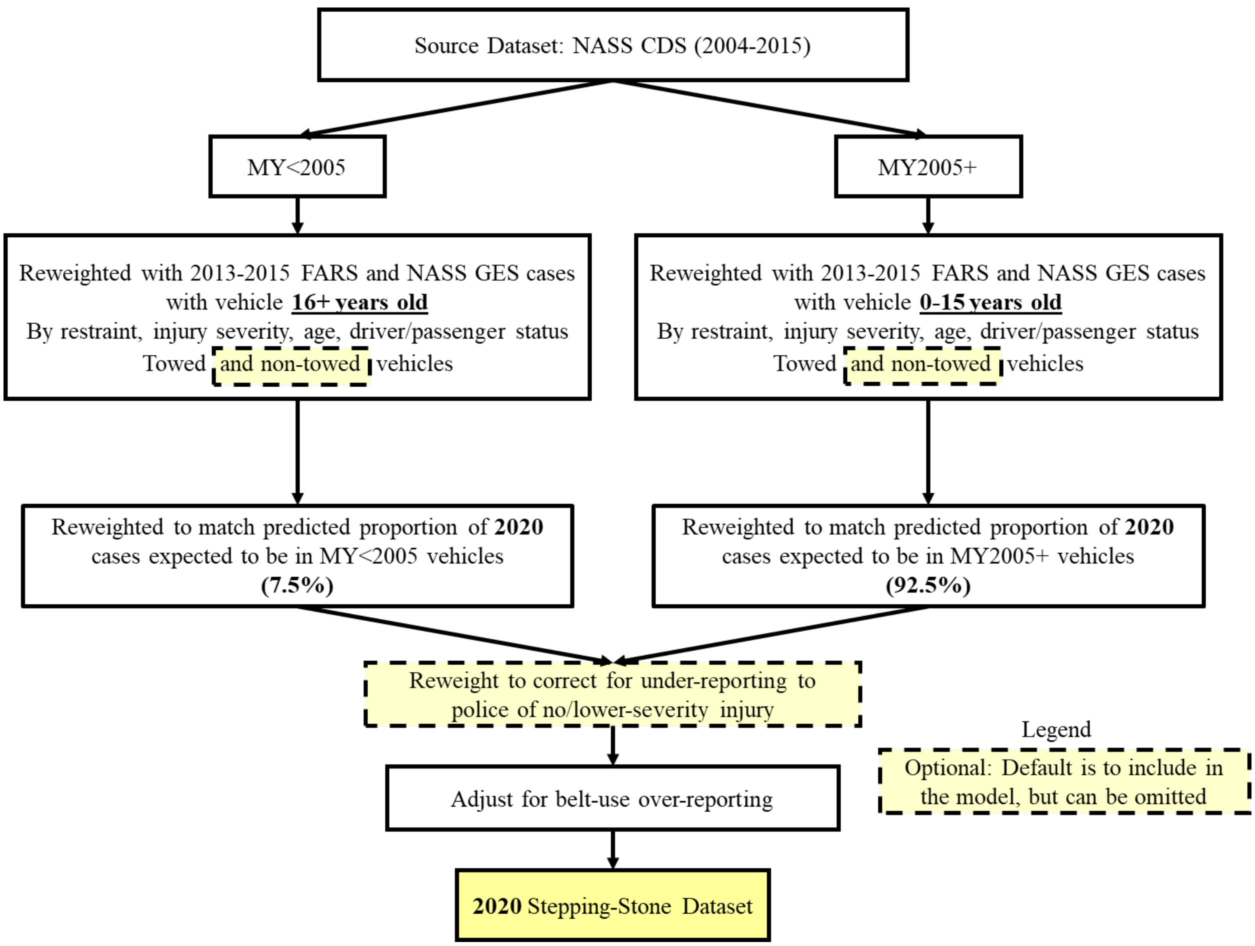


Figure 3. Overview of the development of the stepping-stone dataset for 2020

(**Bold** text indicates values that vary for 2025 and 2030 versions of this flow chart)

2.4.1 Separation of Occupant Cases by Vehicle Model Year

The stepping-stone dataset is a composite of two subsets of cases that were treated separately in the model.

(1) MY2005+: Occupants in MY 2005 and newer vehicles
(2) MY<2005: Occupants in vehicles older than MY 2005

The rationale for this separation, and the selection of MY 2005 as a threshold, is discussed in more detail in Section 2.4.

The MY2005+ dataset was used to build projection datasets representing all occupant crash exposures in MY2005+ vehicles in the future. The MY2005+ subset of occupant cases was subjected to all steps of the projection model, making adjustments for expected improvements in future vehicles as well as for predicted infrastructure improvements and for expected shifts in the population and in vehicle types on the road. After application of the model, the vehicles in MY2005+ cases did not represent vehicles of the model year or vehicle age of the original source cases because these cases had been adjusted to represent vehicles of the model year distributions on the road in the targeted projection year.

In contrast, the MY<2005 subset of occupant cases were used to represent all occupant crash exposures in the future in MY<2005 vehicles. Since vehicles from this era are still expected to be on the road in 2020 to 2030, these cases were retained in the dataset but downweighted to reflect their decreasing frequency on the road and in crashes in the future. A case in a MY<2005 vehicle retained all the characteristics of the vehicle in the source case, including the original model year. However, since these early model year vehicles still on the road in 2020 to 2030 will not be equipped with any additional vehicle technologies that were introduced after MY 2005, these MY<2005 cases were not subjected to any adjustments associated with vehicle-based improvements to the case vehicle. They were, however, adjusted to account for predicted improvements in infrastructure and for trends in population composition and behavior. The MY<2005 cases were also adjusted to account for crash avoidance technology in other vehicles.[9]

These two subsets (MY<2005 and MY2005+) were combined into stepping-stone datasets that served as the foundations for the models predicting 2020, 2025, and 2030 crash outcomes. Separate stepping-stone datasets were developed for each of these projection years since the weighted proportion of occupants in vehicles from model years before and after MY 2005 varied in each of these projection years.

2.4.2 Reweighting the MY2005+ Subset of the Stepping-Stone Dataset

All cases involving occupants in MY2005+ vehicles in the NASS CDS source dataset were reweighted using data from 2013 to 2015 NASS GES and FARS using the weighting bins in Table 1. The weighting procedures were similar to those applied to the retrospective dataset (described in Section 2.3.1) except that 3-year NASS GES and FARS datasets were used instead of the 11-year GES and FARS datasets used for the retrospective analysis. As such, the weight in each case in the NASS CDS source dataset represented a 3-year total after being reweighted

[9] For example, if a MY<2005 vehicle was rear-ended by a MY2005+ vehicle, this crash could potentially be prevented in the future by technology such as automatic emergency braking in the striking vehicle. In that case, the case weight of occupants in the MY<2005 vehicle was adjusted to account for the probability that AEB in the striking vehicle could have prevented the entire crash.

using the applicable weighting factors, and thus was divided by three to represent average annual numbers for 2013 to 2015.

Reweighting using 2013 to 2015 forced the stepping-stone cases to match the distribution of recent U.S. crash occupants in terms of age, restraint use and injury severity. Additionally, more than half of the occupants in the 2013 to 2015 GES reweighting dataset were in MY2005+ vehicles making it more compatible with the MY2005+ source dataset than the 2004 to 2015 FARS/GES dataset used to reweight the retrospective dataset. However, since the crash characteristics of occupants in newer and older vehicles are expected to vary, the GES and FARS cases used for reweighting the MY2005+ CDS cases included only occupant cases in the corresponding vehicle age-range in each projection dataset. The reweighting data for MY2005+ cases in the 2020 projection were therefore limited to GES and FARS occupants in vehicles 0 to 15 years old. Similarly, the reweighting data for the 2025 and 2030 projections were limited to GES and FARS occupants in vehicles 0 to 20 and 0 to 25 years old, respectively, since the MY2005+ cases in the stepping-stone datasets were reweighted and adjusted to represent all crashes in MY2005+ vehicles in those projection years.

2.4.3 Reweighting the MY<2005 Subset of the Stepping-Stone Dataset

As with the MY2005+ subset of the stepping-stone dataset, occupants in vehicles earlier than MY 2005 were also reweighted using data from 2013 to 2015 NASS GES and FARS. Ultimately, these MY<2005 cases represented vehicles greater than 15 years old in projections since a MY 2004 vehicle would be 16 years old in 2020 and 26 years old in 2030. Since case characteristics including restraint use, occupant age, and injury severity likely vary with vehicle age, only crashes involving older vehicles (16 years and older) were included in reweighting cases by these characteristics in this subset of the stepping-stone dataset. Accordingly, the NASS GES and FARS cases used to reweight MY<2005 cases in the source dataset were limited to GES and FARS occupants in vehicles older than 15 years at the time of the crash.

It is noted that the 2009 change in CDS data collection methods that resulted in exclusion of occupants in vehicles 10 years old or older at the time of the crash means that more of these MY<2005 cases came from case years prior to 2009 than from 2009 and later. This bias was not expected to have a major effect on results, given that the distribution of cases by model year was balanced in the projected models as explained in Section 2.4.4.

2.4.4 Combined Stepping-Stone Dataset (MY2005+ and MY<2005)

In the targeted projection years from 2020 to 2030, occupants in vehicles with model year earlier than 2005 will make up a shrinking proportion of cases. The decreasing proportion of MY<2005 cases expected in the future was incorporated by proportionally downweighting cases from the MY<2005 subset and upweighting cases from the MY2005+ subset in each of the stepping-stone datasets for 2020, 2025, and 2030.

The proportion of occupants exposed to potential crashes in 2020, 2025, and 2030 who will be in MY<2005 vehicles was estimated using vehicle age distribution among crash occupants in historical data. Vehicle age at time of crash was determined for all NASS GES occupant cases in

CDS-eligible vehicles between 2006 to 2008[10] to estimate the historical weighted distribution of vehicle age among occupants in passenger vehicle crashes (Appendix A). Based on this historical data, it was estimated that among occupants expected to be exposed to potential crashes in 2020, 7.5 percent would be in vehicles older than 15 years. Therefore, all cases in the MY<2005 subset were reweighted so that they accounted for a total of 7.5 percent of the total number of weighted occupants in the 2020 stepping-stone dataset. Correspondingly, all cases in the MY2005+ subset were reweighted to account for 92.5 percent of the total weighted number of occupants in the 2020 stepping-stone dataset. The 2025 and 2030 stepping-stone datasets were constructed in the same manner, using the estimates that 1.8 percent and 0.6 percent of occupants exposed to potential crashes in 2025 and 2030 would be in vehicles older than MY 2005, respectively. Downweighting the MY<2005 cases was expected to lead to the under-representation in the projected datasets of cases with characteristics associated with occupants of older cars (including age, restraint use, and other socioeconomic and driving behavior factors that are not captured by case codes). This limitation is discussed in Section 4.2.

The next reweighting step for the combined stepping-stone dataset for each of the targeted projection years was an adjustment to account for the under-representation of more minor cases because of crashes that are not reported to police. For model runs with this optional step turned "off" (as described in Section 2.3.3), the upweighting of cases to account for the exclusion of non-towed crashes was also suppressed by using only GES in towed vehicles for the reweighting procedures explained in Section 2.3.1.

The final step in the development of the stepping-stone dataset was to adjust for the over-reporting of belt use in NASS CDS cases. As in the same procedure applied to the retrospective dataset (see Section 2.3.2 for details), no change or adjustment was made to occupant cases where the occupant was documented as unbelted or was a rear-seat occupant. Occupant cases coded as "belted" were divided into two pseudo-cases: a belted pseudo-case with all case characteristics identical to the original case, and an unbelted case with only the belt-use variable modified. The case weight of the original (parent) case was divided between the two pseudo-cases, proportional to the probability that cases coded as belted were indeed belted, based on estimated belt use over-reporting rates in CDS. Non-fatal belted cases were divided into belted and unbelted pseudo-cases with 80 percent and 20 percent of the parent case weight respectively. Fatal cases were divided into belted and unbelted pseudo-cases with 89 percent and 11 percent of the parent case weight respectively. Note that this adjustment accounts for under-reporting in the original 2004 to 2015 NASS CDS cases, and does not reflect the likelihood of under-reporting in the projection years from 2020 to 2030.

The outputs of this step for the three projection years were the stepping-stone datasets, foundational sets of cases to which all components of the projections model would be applied. These stepping-stone datasets do not represent the actual number of crashes expected in the future year, since no adjustments have been made yet to account for expected occupant or vehicle trends or for safety countermeasures implemented since the year of the original case crash. However, the stepping-stone datasets are also not representative of crashes in a past or

[10] This year range was selected because the model-year distribution among vehicles in crashes was affected in subsequent years by economic conditions starting in 2009 that had a substantial effect on the frequency of vehicles of the ages that corresponded to model years 2009 and 2010 in subsequent crash years.

current year, since the proportions of cases by vehicle model year have been manipulated to match future proportions. Therefore, the stepping-stone dataset for each projection model can only be considered as an incremental step to be used as input for the remaining stages of the model.

2.5 Adjustment for Predicted Trends in Population and Vehicle Fleet

After development of the stepping-stone dataset, the next round of adjustments made to case weights in the case-by-case methodology reflected expected shifts in the frequency of crash exposures among different occupant and vehicle groups based on the following predicted trends:

- Shifting vehicle-type distribution in the fleet,
- Shifting age demographics of occupants:
  - Effects of predicted population growth in the U.S. population by age group,
  - Effects of changes in licensure rate among age groups,
- Economic trends, represented in this model by national unemployment rate, and
- Shifting belt use and child restraint use.

Each of these trends, and the information sources used to apply them in the model, will be discussed in the following sections. These anticipated trends were independent of any specific efforts to shift future proportions of factors such as vehicle type or restraint use: they simply represented the expected continued shift in these parameters based on historical data absent any specific additional countermeasures.

The overall strategy for applying these trend projections was to reweight individual cases in order to:

1. **Adjust the *proportion* of occupant cases occurring in different vehicle types or under different restraint conditions**. The case weight for cases involving characteristics that were expected to be more frequent in the future than in the stepping-stone year range (2013 to 2015) was upweighted, while case weight for cases involving characteristics that were expected to be less frequent in the future was downweighted.
2. **Adjust the *absolute number* of occupant cases in driver and passenger age-groups**. This strategy resulted in an increase in the total number of occupants exposed to potential crashes proportional to a function of population growth, licensure rate changes, and economic trends in each age group.

The trends in this section were applied independently, assuming no interactions among them. Specific strategies for application of these trends will be discussed in the following sections.

2.5.1 Vehicle Type Trends

Vehicle type trends were applied only to cases in the MY2005+ subset of each stepping-stone dataset, since these cases were intended to represent occupants in newer model-year vehicles in the future datasets. The proportions of different types of vehicles in MY<2005 cases were not adjusted, since these occupants were assumed in this model to remain in the same older model-year vehicles and would not be affected by subsequent sales patterns.

For the application of predicted vehicle type trends, vehicles were classified using the NASS CDS body type, make, model and model year variables (variable names BODYTYPE, MAKE, MODEL, and MODELYR). Car-based SUVs, referred to in this report as CUVs, were identified based on the make, model, and model-year combinations listed in Appendix B.1.1 because they could not be identified using the body type variable in NASS CDS. The remainder of the vehicle type categories were defined using the body type variable, as shown in Table 3. In other words, if the vehicle fell in one of the make, model, and model-year combinations listed in Table 40 in Appendix B.1.1, then it was classified as a CUV; if it did not, it was classified based on the body type definition in Table 3. Vehicles coded with unknown body type (49) were classified as passenger cars.

When classified for specific countermeasures by the broader categories of passenger cars and light trucks and vans, pickups, vans, and truck-based SUVs were classified as LTVs. Larger vehicles, such as cab-chassis based trucks, truck-based panel trucks, and light-truck based motorhomes were also included in the broader LTV category, but there was insufficient data to apply vehicle type trends to this "other light truck" group, so the proportion of these vehicles relative to other vehicle types was unchanged in the future dataset. The passenger car category included CUVs as well as cars.

Table 3. Vehicle type classifications

	PC/LTV	Body Type (CDS variable name BODYTYPE)
CUVs	PC	Identified by make, model, and model year in Appendix B.1.1
Cars	PC	1:13, 16, 17, 49
Pickups	LTV	30:33, 39
Truck-based SUVs	LTV	14, 15, 19, 45, 48
Vans	LTV	20:22, 24, 25, 28, 29

As explained in detail in Appendix B.1, a projection of the shift in vehicle types exposed to crashes between the stepping-stone dataset and the projection years (2020, 2025, and 2030) was made based on:

- historical year-by-year sales data from the Environmental Protection Agency (EPA, 2015; EPA, 2019) adjusted for SUV sales data from NHTSA (Puckett & Kindelberger, 2016),
- predicted sales data in future years from the Energy Information Administration Annual Energy Outlook (EIA, 2017; EIA, 2018), and
- estimated vehicle age distribution in future crashes.

This calculation was made for vehicles of MY 2005 and later. The results showed that passenger cars were projected to make up 52.8 percent of passenger vehicle crash exposures in the 2013 to 2015 stepping-stone period, but only 49.2 percent of passenger vehicle crash exposures in 2020 and 44.5 percent in 2030.

Adjustment factors for reweighting individual cases to account for shifting vehicle types were calculated to upweight cases that were expected to be more frequent in the future, and downweight cases that were expected to be less frequent. The adjustment factor model variable

AF was a multiplier, unique to each vehicle type in each future projection year, applied to the case weight for every case occupant in a given vehicle type in each stepping-stone dataset.

<u>*Downweighting Adjustment Factors*</u> for vehicle types that were predicted to be <u>*less*</u> frequent in future crashes were calculated as a function of the proportion of potential occupant crash exposures in the given vehicle type in the stepping-stone dataset ($P_{stepping\text{-}stone}$) and in the target projection years (P_{2020}, P_{2025}, P_{2030}). For example, the AF for reweighting all occupant cases in passenger cars in the 2030 projection model is shown in Equation (2).

$$AF(2030)_{PassCar} = \left(\frac{P_{2030}}{P_{stepping-stone}}\right)_{PassCar} \qquad (2)$$

where:
AF is the downweighting adjustment factor for cases involving the given vehicle type, and
P is the proportion of potential crash exposures for the vehicle type in a given year/range.

<u>*Upweighting Adjustment Factors*</u> for vehicle types that were predicted to be <u>*more*</u> frequent in future crashes were calculated to ensure that the adjustment of the dataset for shifting vehicle types changed the proportions of different vehicle types in the dataset without changing the total weighted number of occupant crash exposures in the dataset. In other words, the case weight AF for vehicles expected to be more common in the future datasets was calculated in a manner that ensured that a decrease in the total weighted number of downweighted cases was matched by an increase of the same magnitude in the total weighted number of upweighted cases. Accordingly, the AFs calculated for each vehicle type to be upweighted were a function of results from the stepping-stone dataset, in contrast to the AF for vehicle types that were to be downweighted that were estimated based only on sales predictions and historical data.

Both CUVs and truck-based SUVs are expected to increase in future crash exposures. First, the magnitude of this increase was calculated to ensure that the decrease in the total weighted number of downweighted cases was matched by an increase of the same magnitude in the total weighted number of upweighted cases. Then, the *relative* magnitude of the increase for each of the vehicle types expected to increase in future crash exposures was calculated. These calculations are included in Appendix B.1 for the current model.

Note that for trends involving multiple categories to be upweighted (e.g., CUVs and truck-based SUVs) and multiple categories to be downweighted (e.g., cars, pickups, and vans) the procedure could have been applied in the opposite manner. The AF could have been calculated directly for the categories to be upweighted and then distributed proportionally for the categories to be downweighted. In this study, the decision to calculate the AF directly for the categories to be downweighted was arbitrary. The AFs developed instead based on direct calculation for the categories to be upweighted were only negligibly different.

After application of the vehicle type trend, the number of occupant cases in the stepping-stone datasets was unchanged, but the proportion of occupants in particular vehicle types was adjusted. The absolute number of occupants was adjusted in the application of the next two trends (passenger and driver crash exposure), which were driven by population, licensure, and economic trends.

2.5.2 Passenger Crash Exposure: Population and Economic Trends

It was expected that the future overall growth or reduction in the number of passengers in crashes, i.e., non-driver occupants, would vary with population size and economic trends. Farmer has previously shown a strong relationship between improving economic trends, reflected by falling unemployment rate, and increases in annual motor vehicle crash fatalities and vehicle miles traveled (Farmer, 2017a).

For predicting future crash exposures for this model, the effects of population size and unemployment rate were initially compared with the effects of VMT for crash years 1995, 2001, and 2009, for which population, unemployment, and VMT data were available. This preliminary analysis was limited to these 3 years because VMT data from the National Highway Travel Survey were unavailable for other years in this range. Predictions based on these variables were developed using counts of passenger crash exposures from NASS GES in 1995, 2001, and 2009. That analysis showed that functions of population size and average national unemployment rates were better predictors of the number of passenger crash exposures in each age group than VMT. However, the use of those relationships for prediction of expected exposure rates in the future was limited by the age of the data and the suspicion that unemployment during some of those particular years may have disproportionately affected younger age groups. This potential skew made it questionable to apply the data to individual age groups for predictive purposes.

Based on the results of this preliminary analysis, VMT was dropped from the analysis because it was a less effective predictor of passenger crash exposures. Without VMT, more years of data were available for using the remaining variables as crash exposure predictors. Regression analysis was performed to explore the use of population size, average unemployment rate across the labor force, and age-group-specific unemployment rates to predict the annual number of passenger crash exposures. Data for the regression analysis were drawn from the following sources for 2007 to 2015:

- The number of passenger crash exposures in 2007 to 2015 came from NASS CDS-eligible crashes in weighted NASS GES data. Note that this dataset was not the same one used for reweighting the projection model and did not exclude fatalities.
- Annual population estimates by age group were drawn from census data and estimates (Census Bureau, 2014; Census Bureau, 2019a).
- Historical unemployment rates were obtained from the Bureau of Labor (2018), and predicted future unemployment rates were estimated as in Farmer's work (Farmer, 2017a), applying an annual decline of 1.7 percent annually until 2024 based on estimates attributed to Byun and Nicholson in 2015. Rates were held constant after 2024, in the absence of long-term predictions. The 2020 spike in unemployment associated with the COVID-19 pandemic has not been addressed in the current version of the model. Potential future updates to the model to reflect unemployment and other effects of the pandemic on motor vehicle travel are discussed in Section 4.3.

Regression analysis was performed for individual age groups, with the number of passenger crash exposures in each year (from 2007 to 2015) as the outcome variable. Predictor variables included census-reported population in that age group, and several functions of average U.S. unemployment rate in the workforce and unemployment rates specific to each age group. Since the relationship between crash exposures and unemployment rate was unknown, the mathematical functions explored for each age group included exponential and logarithmic functions of unemployment rate, as well as unemployment rate raised to the power of 0.5 or 2. The following criteria were used to select regression models for the prediction of passenger crash exposures in each age group based on the 2007 to 2015 data:

- The F-test of overall significance must have a p-value of less than 0.05 to conclude that the model was a better fit than an intercept-only model.
- The adjusted R^2 value for each model that adds variables beyond age-group population size must be higher than the adjusted R^2 value for the population-only model.
- The model coefficient for population size must be positive because of the expectation that crash exposures would be expected to increase, rather than decrease, with population growth.
- Where multiple models met these criteria for an age group, the model with the highest adjusted R^2 value was selected.

There were only two age groups where a regression equation including unemployment rate met the criteria above: ages 55-64 and 65-74. The regression equations developed for these age groups are shown in Equation (3). Fit statistics for these regression equations are summarized in Table 4.

$$
\begin{aligned}
Pass.crashes_{55-64} &= -33563 + 0.0028 \times Population_{55-64} - 1127341 \times (UR_{55-64})^2 \\
Pass.crashes_{65-74} &= -27487 + .00195 \times Population_{65-74} - 8823.55 \times ln(UR_{65-74})
\end{aligned}
\qquad (3)
$$

where:
Pass. crashes are the predicted number of passengers exposed to crashes in a given age group,
Population is the number of people in the U.S. population in the given age group, and
UR is the age-group-specific unemployment rate.

Table 4. Fit statistics for regression equations to predict the number of passengers in crashes

	F value	Pr>F	R^2	Adjusted R^2
Age 55-64	13.03	0.0066	0.8129	0.7505
Age 65-74	128.10	<0.001	0.9771	0.9695

The regression equations above were used to predict passenger crash exposures for occupants in the 55-64 and 65-74 age groups in 2020, 2025, and 2030. Predicted population for those projection years were drawn from Census Bureau projections (Census Bureau 2014; Census Bureau 2019a). Predicted unemployment rates in those projection years were estimated based on adjustment of current rates from the Bureau of Labor (2018) assuming an annual decline of 1.7 percent annually until 2024. The decline rate was applied to each age group individually and rates were held constant after 2024.

For all other age groups, not specified in the regression equations above, the number of passengers exposed to potential crashes in target years 2020, 2025, and 2030 was estimated relative to the number of passenger crash exposures in 2013 to 2015, proportional to the change in population in each age group during the same time frame. For these age groups, unemployment rate did not improve the prediction of the number of crash-exposed passengers in the regression analysis of 2007 to 2015 data. An example of this calculation for passenger crash exposures in 2020 is shown in Equation (4).

$$Pass.crashes_{age\ group} = (Crashes\ 2013-15)_{age\ group} \times \frac{Population\ 2020_{age\ group}}{Population\ 2013-15_{age\ group}} \qquad (4)$$

where:

Pass. Crashes are predicted passenger crash exposures in the given age group in 2020,

Crashes 2013–15 is the average annual number of passengers in the age group in CDS-eligible crashes in GES in that year range,

Population 2013-15 is the average annual census-estimated count of people in United States in the age group in that year range, and

Population 2020 is the census-estimated predicted population in the age group in 2020.

Figure 4 shows the historical annual estimates, along with the projected future estimates for all age groups. The resulting estimated number of annual passenger crash exposures in each age group for 2013 to 2015, as well as for each target year, are also tabulated in Table 5.

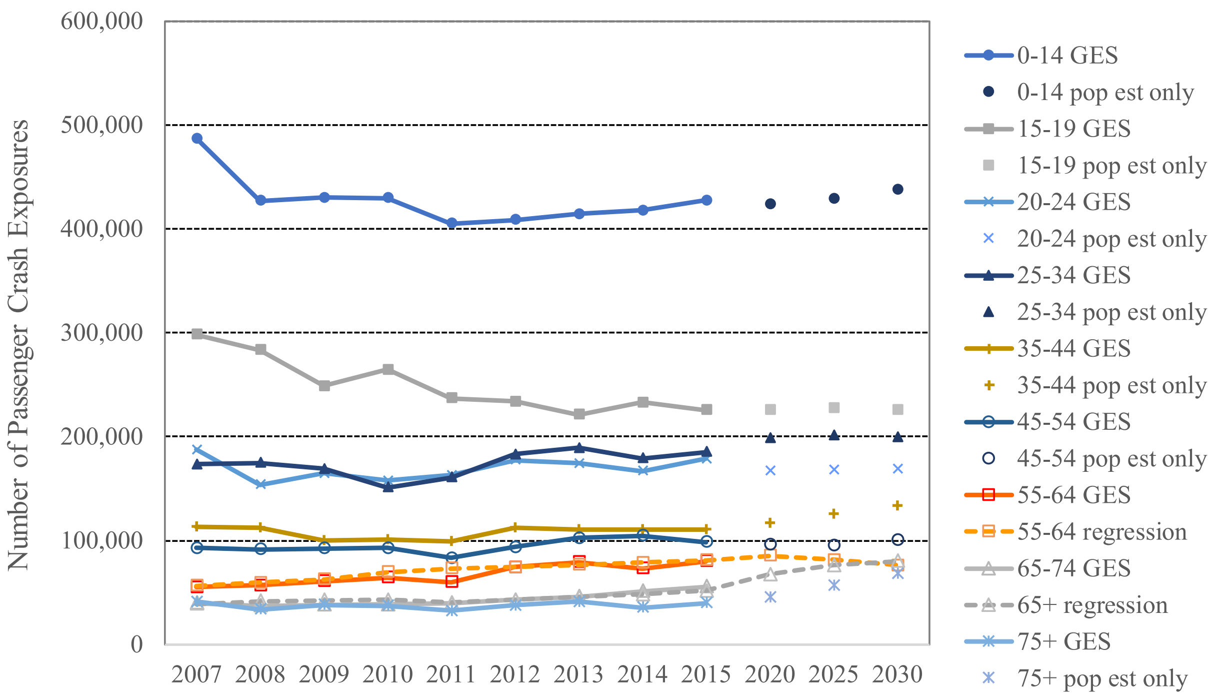


Figure 4. Historical and predicted numbers of passenger crash exposures by age group

Solid lines: historical, from GES
Dotted lines: from regression equations
No line (points only): estimated based on population growth estimates ("pop est only")

Table 5. Estimated annual number of passenger crash exposures

Age	2013-2015	2020	2025	2030
0-14	419,711	423,260	429,289	437,901
15-19	226,559	225,727	227,561	225,856
20-24	173,231	167,333	167,469	169,153
25-34	184,416	198,661	201,470	199,368
35-44	110,684	116,340	125,208	133,016
45-54	101,884	95,661	95,272	100,380
55-64	77,477	85,540	81,622	76,070
65-74	50,949	67,564	76,003	80,164
75+	38,745	45,661	56,335	68,166

The number of passenger crash exposures in the 2020, 2025, and 2030 projection datasets was adjusted to account for population growth and economic trends by multiplying the case weight of each non-driver occupant in the datasets by an adjustment factor, AF. The AF for cases involving passengers (Table 6) were calculated by age group as a ratio of:

- The projected number of passenger crash exposures in the age group in the target projection year (Table 5, columns for 2020, 2025, 2030), over
- The average annual estimated number of passenger crash exposures in the age group between 2013-2015 (Table 5, column for 2013 to 2015).

Table 6. Case weight AF for passenger crash exposures

Age	2020	2025	2030
0-14	1.008	1.023	1.043
15-19	0.996	1.004	0.997
20-24	0.966	0.967	0.976
25-34	1.077	1.092	1.081
35-44	1.051	1.131	1.202
45-54	0.939	0.935	0.985
55-64	1.1041	1.0535	0.9818
65-74	1.3261	1.4918	1.5734
75+	1.178	1.454	1.759

After application of these population and economic trends to passengers in the stepping-stone dataset for each of the three projection models, the stepping-stone datasets had higher total weighted numbers of crash-exposed passengers than they did prior to this step as a result of predicted overall population growth and decreasing unemployment. However, some age groups were expected to have *fewer* passenger crash exposures in the future because the aging population was expected to decrease the size of some age groups. As noted previously, the calculated AF does not account for the effects of the COVID-19 pandemic on crash exposures. Please refer to Section 4.3 for a discussion on plans to incorporate the effects of the pandemic into the model.

2.5.3 *Driver Crash Exposure: Population, Licensing and Economic Trends*

Where expected growth in the number of *passengers* was based on the number of people in the U.S. population in each age group as well as on economic trends, growth in the number of *drivers* was estimated based on the expected number of licensed drivers in each age group along with economic trends. As with passengers, these trends were applied to all drivers in the stepping-stone datasets for 2020, 2025, and 2030, including those in the MY<2005 and MY2005+ subsets of cases.

The application of these trends to the model relied on the premise that the annual number of driver crash exposures for each age group varies with:

- the number of licensed drivers in that age group, where the number of estimated drivers in each age group was estimated from the product of population size and licensure rate, and
- the unemployment rate for that age group.

It was determined for the purposes of the projection model that the number of drivers in crashes in each age group can be best estimated for each year as a function of the number of licensed drivers in each age group and the natural logarithm of the unemployment rate in the given age group and year (Equation (5)). These relationships, developed for each age group using regression analysis of historical data from 2007 to 2015, were found to be better predictors in that regression analysis of the number of driver crash exposures over time by age group than alternative combinations explored.[11] Fit statistics for these regression equations are summarized in Table 7.

The 2007 to 2015 data used to develop these regression equations and the predicted values for projecting to 2020, 2025, and 2030 came from the following sources:

- The number of driver crash exposures in 2007 to 2015 came from CDS-eligible crashes in weighted NASS GES data.
- Historical licensure rates were obtained from Federal Highway Administration data from 2007 to 2015 (FHWA, 2014; FHWA, 2016). Licensure rates for 2020, 2025, and 2030 were estimated by extrapolating a linear best fit trend from the 2007 to 2015 data for each age group. These trends reflected falling rates of youth licensure and increasing rates among some older age groups.
- Population estimates were drawn from census estimates and projections (Census Bureau, 2014; Census Bureau, 2019a).
- Historical unemployment rates were obtained from the Bureau of Labor (2018), and predicted future unemployment rates were estimated as in Farmer's work, estimating an annual decline of 1.7 percent annually until 2024. Rates were held constant after 2024, in

[11] Alternative regression variables explored included year, multiple functions of unemployment and employment rates, including rate, exponential functions of rate, rate squared, and square root of rate in each age group for crash years 2007-2015. Separate empirical analysis of crash years 1996, 2001, and 2009 was also performed to evaluate predictive potential of vehicle miles traveled, the number of licensed drivers in the population, as well as mathematical functions of unemployment rate that included the natural logarithm of unemployment rate, exponential functions of unemployment rate, and unemployment rate raised to powers ranging from 0.1 to 2.

the absence of other predictions. As with passenger crash exposures, no adjustments have been made in the current model to account for the effects of the COVID-19 pandemic on unemployment.

$$
\left.
\begin{aligned}
&Driver\ crashes_{16-19} \\
&\qquad = -395571 + 0.06661 \times Licensed_{16-19} - 212811 \times ln(UR_{16-19}) \\
&Driver\ crashes_{20-24} \\
&\qquad = -294764 + 0.03117 \times Licensed_{20-24} - 147296 \times ln(UR_{20-24}) \\
&Driver\ crashes_{25-34} \\
&\qquad = -918027 + 0.03117 \times Licensed_{25-34} - 179182 \times ln(UR_{25-34}) \\
&Driver\ crashes_{35-44} \\
&\qquad = 314376 - 0.00119 \times Licensed_{35-44} - 103997 \times ln(UR_{35-44}) \\
&Driver\ crashes_{45-54} \\
&\qquad = 667507 - 0.0085 \times Licensed_{45-54} - 60498 \times ln(UR_{45-54}) \\
&Driver\ crashes_{55-64} \\
&\qquad = -381481 + 0.01414 \times Licensed_{55-64} - 81880 \times ln(UR_{55-64}) \\
&Driver\ crashes_{65-74} \\
&\qquad = -96364 + 0.0945 \times Licensed_{65-74} - 27049 \times ln(UR_{65-74}) \\
&Driver\ crashes_{75+} = 5536 + 0.00561 \times Licensed_{75+} - 15081 \times ln(UR_{75+})
\end{aligned}
\right\} \quad (5)
$$

where:
Driver crashes are the predicted number of drivers exposed to crashes in a given age group,
Licensed is the predicted number of licensed drivers in the given age group, and
UR is the predicted unemployment rate in the given age group.

Table 7. Fit statistics for regression equations to predict the number of drivers in crashes

	F value	Pr>F	R^2	Adjusted R^2
Age 16-19	58.33	0.0001	0.9511	0.9348
Age 20-24	9.65	0.0133	0.7629	0.6839
Age 25-34	31.92	0.0006	0.9141	0.8855
Age 35-44	9.08	0.0153	0.7516	0.6688
Age 45-54	17.98	0.0029	0.8570	0.8093
Age 55-64	37.59	0.0004	0.9261	0.9014
Age 65-74	27.63	0.0009	0.9021	0.8694
Age 75+	2.85	0.1352	0.4868	0.3157

Figure 5 shows the annual number of driver crash exposures for 2007 to 2015, as well as the estimated number calculated from the regression relationships for 2007 to 2015 and for the target projection years 2020, 2025, and 2030 for each age group. The values for the average number of driver crash exposures in 2013 to 2015 and the projections are shown in Table 8.

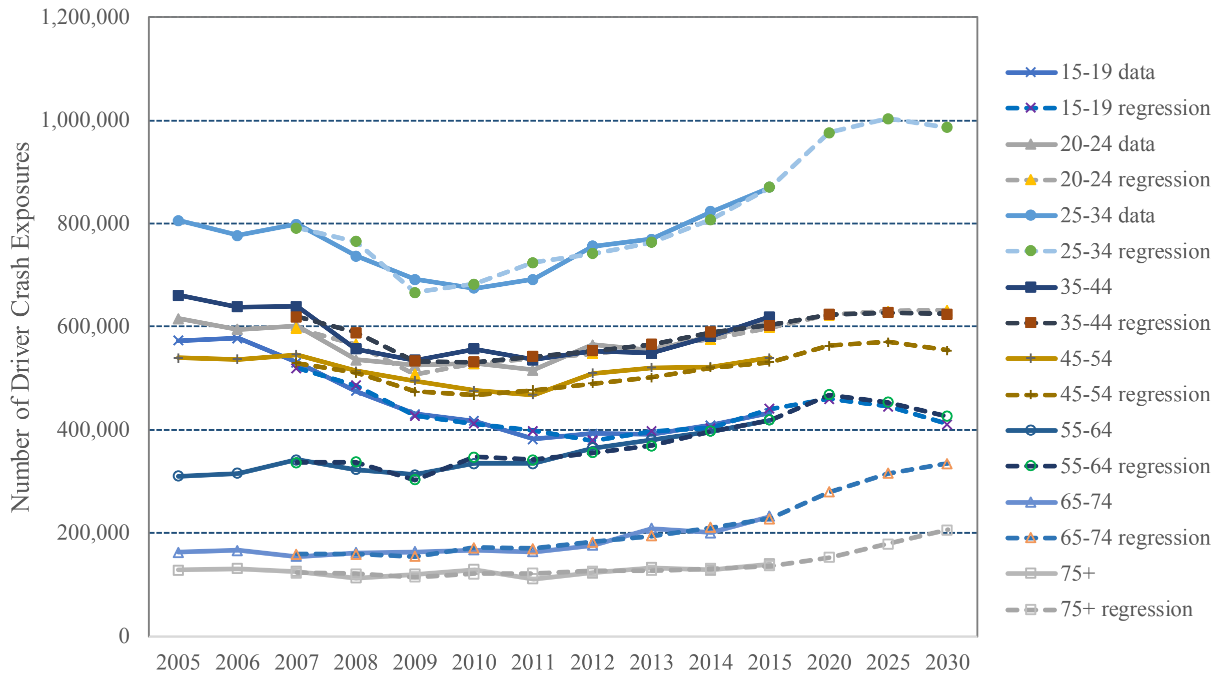


Figure 5. Historical and predicted numbers of driver crash exposures by age group

Solid lines: historical, from GES
Dotted lines: from regression equations

Table 8. Estimated annual number of driver crash exposures

Age	2013-2015	2020	2025	2030
15-19	411,656	459,622	445,571	410,728
20-24	582,738	623,164	630,218	631,972
25-34	821,227	976,027	1,003,884	986,135
35-44	583,251	623,566	627,495	624,724
45-54	527,548	563,676	570,099	554,369
55-64	399,480	468,568	453,760	426,385
65-74	214,297	279,593	316,226	334,612
75+	133,646	152,535	178,938	206,644

Since the stepping-stone dataset had already been reweighted using 2013 to 2015 GES and FARS data, the AF for driver cases projected to 2020, 2025, and 2030 was calculated for each age group as the ratio of:

- The projected number of driver crash exposures for the age group in the target projection year (Table 8, columns for 2020, 2025, or 2030), over
- The average annual estimated number of driver crash exposures in the age group between 2013 to 2015 (Table 8, column for 2013-2015).

The resulting AF by age group are shown in Table 9.

After application of population and licensing trends to drivers in the stepping-stone dataset for each of the three projection models, cases in most age groups in the stepping-stone datasets had higher total weighted numbers of crash-exposed drivers than they did prior to this step as a result of predicted reduction of the unemployment rate and predicted increases in the number of licensed drivers in most age groups in the United States.

Table 9. Case weight AF for driver crash exposures

	Case Weight Adjustment Factors		
Age	**2020**	**2025**	**2030**
16-19	1.1165	1.0824	0.9977
20-24	1.0694	1.0815	1.0845
25-34	1.1885	1.2224	1.2008
35-44	1.0691	1.0759	1.0711
45-54	1.0685	1.0807	1.0508
55-64	1.1729	1.1359	1.0673
65-74	1.3047	1.4756	1.5614
75+	1.1413	1.3389	1.5462

2.5.4 Belt Use Trends

Belt use trends were applied to all occupants eight years and older in the stepping-stone datasets, including those in the MY<2005 and MY2005+ subsets of cases. Since it was difficult to effectively estimate specific changes in injury severity and pattern among occupants who switch from being unbelted to being belted, expected increases in belt use were incorporated by upweighting cases involving belted occupants and downweighting cases involving unbelted occupants. The predicted trends in belt use were applied in a manner that did not change the total weighted number of occupants in the stepping-stone dataset from the number that resulted from applying population-growth, licensing, and economic trends to the dataset: the reduction in the total weighted number of cases from downweighting unbelted cases was equal to the increase in the total weighted number of cases from upweighting belted cases using belt use trends.

Predictions of belt use in the future were made with the “conversion rate” methods summarized below. Calculations are provided in more detail in Appendix B.2. For most occupant groups, year-to-year belt use increases and the annual conversion rate was calculated as the percentage of seat belt non-users who were “converted” to belt users in the subsequent year. When Blincoe and Shankar originally estimated future conversion rates based on historical annual conversion rates from 1998 to 2005, they estimated that the annual average 8 percent conversion rate would continue in the future (Blincoe and Shankar, 2007). However, they also performed estimates on a more conservative future rate of 4 percent, i.e., half of the historical rate. These conversion rate predictions were subsequently evaluated against belt use rates estimated in the following years in the National Occupant Protection Use Survey (Pickrell and Li, 2016). That comparison to NOPUS data showed that the more conservative predicted conversion rate of half the historical conversion rate was closer to the actual average annual conversion rate of 4.3 percent between 2005 to 2015 across all seat positions.

Based on these methods used previously, recent historical conversion rates were estimated (Table 54) from 2008 to 2016, the years for which weighted, disaggregated NOPUS data was available (Table 52). The future annual conversion rate was predicted to be half (50%) of this recent historical rate based on previous trends.

Belt use rates were estimated separately for front- and rear-seat occupants using conversion rate analysis based on observed use rates in NOPUS, with subsequent adjustment to account for lower rates of expected belt use in potentially fatal crashes. These procedures are summarized in this section.

Estimation of belt use rates based on observed use in NOPUS: Future belt use rates were estimated based on historical belt use and conversion rates for front-seat and rear-seat occupants. Front-seat use rates and conversion rates were further disaggregated by vehicle type because belt use rates for front-seat occupants vary more among different vehicle types than by other parameters. Rear-seat use rates varied much more by age than by vehicle type, so use rates and conversion rates for rear seat occupants were disaggregated by age group. These occupant parameters were selected because belt use rates vary substantially among these groups. Absent disaggregation by these characteristics, reweighting cases to reflect increasing overall belt use would unintentionally skew the frequency of other characteristics in the dataset. For example, without disaggregation, global upweighting of all belted cases would artificially inflate the percentages of passenger car occupants and front-seat occupants and reduce the percentages of pickup occupants and rear-seat occupants in the predicted datasets. Historical levels of belt use for the subgroups used in this study were drawn from NOPUS data and disaggregated by seat position, vehicle type, and age group.[12] See Appendix B.2 for a summary of these values and resulting estimates of conversion rates.

The resulting annual predictions of belt non-use are summarized in Table 10 for front-seat occupants (Figure 6) and rear-seat occupants (Figure 7). These predictions reflect the expected reduction in belt non-users for most occupant groups in the future. The only group with a negative average conversion rate, suggesting an expected increase in future non-users, were rear-seat occupants 70 years and older. Review of this sub-group of NOPUS results revealed that historical non-use rates estimated from 2008 to 2016 were based on substantially fewer raw case occupants than in other age groups. Non-use rates for the rear-seat 70+ age group in Table 8 were estimated using an average of only 36 unbelted observations per year, compared to over 200 unbelted observations in all other age groups. Because of the relatively small dataset for 70 or older rear-seat occupants, combined with the unlikely estimate of future increases in belt non-use in this group, it was determined that there was insufficient information to estimate conversion rate accurately for this group. Therefore, the rate of belt non-use for 70 or older rear-seat occupants was coded to remain at 2016 rates in the future, instead of using the rates shown in Table 8. Thus, the conversion rate for this age group of rear-seat occupants was set to 0, and the AF for unrestrained occupants in this category was 1.0. This strategy was equivalent to simply not estimating any subsequent change in belt use rates for this small group of occupants, in the absence of reliable information about conversion rates.

[12] Rajesh Subramanian, chief, Mathematical Analysis Division, National Center for Statistics and Analysis, NHTSA, personal communication. June 6, 2017.

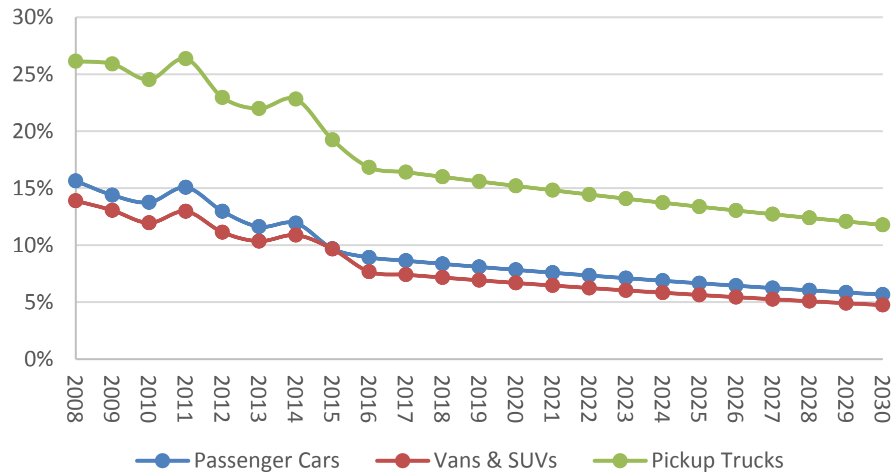


Figure 6. Rates of belt non-use among front-seat occupants

(Based on NOPUS data up to 2016 and predicted subsequently based on 50 percent of historical conversion rates)

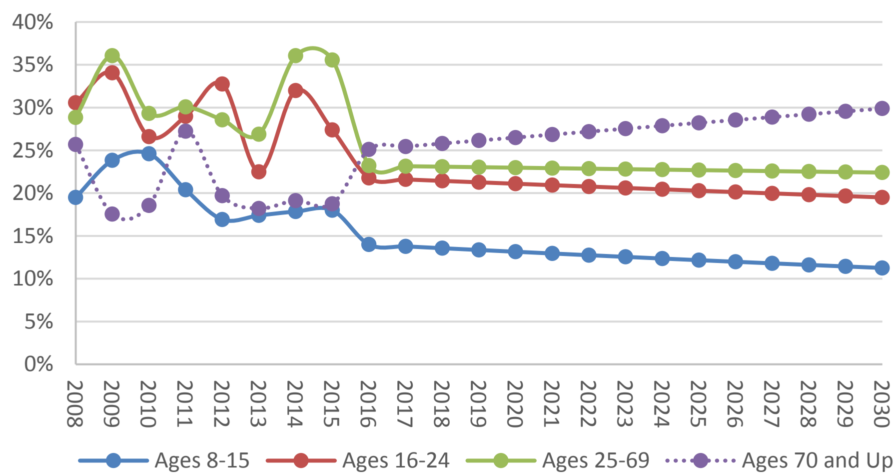


Figure 7. Rates of belt non-use among rear-seat occupants

Data for 70+ not relied on for model

(Based on NOPUS data up to 2016 and predicted subsequently based on 50 percent of historical conversion rates)

Table 10. Historical and predicted future rates of belt non-use based on observation studies

Front Seat					
Age group	**Vehicle type**	**2013-2015 (Average*)**	**2020**	**2025**	**2030**
All ages	Passenger Car	11.1%	7.8%	6.7%	5.7%
	Van/SUV	10.3%	6.7%	5.6%	4.8%
	Pickup Trucks	21.3%	15.2%	13.4%	11.8%
Rear Seat					
Age group	**Vehicle type**	**2013-2015 (Average*)**	**2020**	**2025**	**2030**
Age 8-15	All Vehicle Types	17.8%	13.2%	12.2%	11.3%
Age 16-24		27.3%	21.1%	20.3%	19.5%
Age 25-69		32.8%	23.0%	22.7%	22.4%
Age 70+**		18.7%	26.5%**	28.2%**	29.9%**

**Simple average of three individual annual rates.*

***Estimated conversion rates shown here for rear-seat occupants 70 or older were deemed to be unreliable and not used for the projection model.*

Adjustment for lower rates of expected belt use in potentially fatal crashes: Belt use in potentially fatal crashes has been reported to be lower than observed belt use in studies like NOPUS (Wang & Blincoe, 2003). Therefore, predictions of future belt use in potentially fatal crashes were made by applying Wang and Blincoe's belt use regression model (Equation (6)) to the overall belt use predictions in Table 10. The resulting predicted future rates of belt non-use among potentially fatal crashes are shown in Table 11.

$$BeltUse_{PFC} = 0.47249 * {BeltUse_{Obs}}^2 + 0.43751 * BeltUse_{Obs} \tag{6}$$

where:
$BeltUse_{PFC}$ is the estimated belt use rate in potentially fatal crashes, and
$BeltUse_{Obs}$ is the estimated overall use rate based on observation studies, calculated as (1-(Belt Non-Use Rate)) from Table 10.

Table 11. Historical and predicted future rates of belt non-use in potentially fatal cases

Front Seat					
		2013-2015 (Average*)	**2020**	**2025**	**2030**
All ages	Passenger Car	23.7%	19.5%	18.0%	16.7%
	Van/SUV	22.7%	18.0%	16.6%	15.5%
	Pickup Trucks	36.4%	28.9%	26.7%	24.6%
Rear Seat					
		2013-2015 (Average*)	**2020**	**2025**	**2030**
All vehicle types	Age 8-15	32.1%	26.4%	25.1%	24.0%
	Age 16-24	43.2%	36.1%	35.1%	34.2%
	Age 25-69	49.3%	38.3%	37.9%	37.6%
	Age 70+**	33.2%	42.3%**	44.2%**	46.1%**

**Simple average of three individual annual rates.*

*** Estimated conversion rates shown here for rear-seat occupants 70 or older were deemed to be unreliable and not used for the projection model.*

Reweighting of belted and unbelted cases in the projection model was done separately for occupants categorized as being in potentially fatal crashes and occupants in all other crashes. In previous work (Wang & Blincoe, 2003), the *number* of potentially fatal cases was quantified as a function of the number of actual fatal cases, belt use rates in those cases, and the estimated life-saving effectiveness of belt use. This process essentially estimates how many belted occupants would have been expected to die had they not been belted. To apply the different AF associated with expected belt use rates for potentially fatal crashes versus for all crashes in the projection model, specific cases must be identified as potentially fatal. In the absence of a definitive method for identifying individuals who might have been at risk of fatality had they not been belted, the occurrence of a fatality in a given crash was used as a measure of potential severity for the case occupant. All occupants in a crash with at least one fatality were categorized as being in a potentially fatal crash.

The importance of reweighting cases for belt use in potentially fatal cases separately from other cases was related to two issues:

1. It was expected that the conversion rate among occupants in potentially fatal crashes was lower than for other occupants, so this step prevents overly optimistic estimates of the benefit of belt use increases on the most serious cases.
2. Downweighting of unbelted cases performed to reflect increased belt use was matched by upweighting of belted cases to ensure that reweighting for belt use does not change the total weighted number of occupants. If cases of all severity are reweighted for belt use as a single group, downweighting of unbelted *potentially fatal* cases would be matched by upweighting all cases, including low-severity cases. By reweighting potentially fatal cases separately, downweighting of unbelted potentially fatal cases was matched only by upweighting of

belted *potentially fatal* cases, avoiding an unintentional decrease in the most severe crashes in the projection dataset.

Reweighting of unbelted cases in crashes with no fatalities: Calculation of AF for cases involving unbelted occupants in the stepping-stone dataset required estimates of belt use among the defined NOPUS occupant groups for the stepping-stone year range of 2013 to 2015 and for the projection years 2020, 2025, and 2030. From the data shown in Figure 6 and Figure 7 (and tabulated in Table 10), the AF for each unbelted occupant in a given vehicle type/seat row/age bin was calculated as a ratio of the predicted belt non-use rate in the targeted projection year (2020, 2025, or 2030) divided by the averaged belt non-use rate in 2013 to 2015 for that bin. If, for example, the rate of belt non-use was expected to be 30 percent lower in the targeted projection year than in 2013 to 2015 in a given bin, then each case involving an unbelted occupant in that bin in the stepping-stone dataset would be multiplied by an AF of 0.7, reflecting the expected decreasing frequency of such cases. No AF was applied to case occupants in the 70+ age group in the rear seat, because there was insufficient information to estimate conversion rate for this group as explained on page 44, resulting in no change in the proportion of unbelted individuals in this group in the future. The AF applied to the unbelted cases in each vehicle type/seat row/age bin for the 2020, 2025, and 2030 projections was shown in Table 12. Details on these calculations can be found in Appendix B.2.

Reweighting of belted cases in crashes with no fatalities: The AF for cases involving belted occupants were calculated to ensure that the total weighted number of cases in each vehicle type/seat row/age bin in crashes with no fatalities did not change, but that only the proportion of belted occupants in the bin changed. In other words, the case weight AF for cases involving belted occupants in crashes with no fatalities were determined to guarantee that a decrease in the total weighted number of unbelted cases in these no-fatality crashes was matched by an increase of the same magnitude in the total weighted number of belted cases in no-fatality crashes. Accordingly, the AF calculated for each category of belted cases was a function of results from the stepping-stone dataset, in contrast to the AF for unbelted occupants that were estimated solely on belt use projections in the population.

Table 12. Case weight AF for cases involving unbelted occupants in no-fatality crashes

Front Seat (All Ages)			
Occupants in:	**2020**	**2025**	**2030**
Passenger cars	0.707	0.601	0.511
Vans and SUVs	0.650	0.547	0.461
Pickup trucks	0.712	0.627	0.552

Rear Seat (All Vehicle Types)			
Occupant age:	**2020**	**2025**	**2030**
8-15	0.741	0.685	0.634
16-24	0.773	0.743	0.715
25-69	0.700	0.691	0.682
70+	1.000	1.000	1.000

After application of belt use trends to the stepping-stone dataset for each of the three projection models, each vehicle type/seat row/age bin of the stepping-stone dataset had the same total weighted number of crash occupants in no-fatality crashes as it did before application of this predicted trend. However, the proportion of occupants in each bin who were belted had been shifted to reflect predicted changes in belt use for each category of occupant.

Reweighting of unbelted and belted cases in crashes with at least one fatality: The process above, for reweighting unbelted and belted cases in crashes with no fatalities, was repeated for all occupants in crashes with at least one fatality. The resulting AF are shown in Table 13. The only difference was that instead of using the belt use predictions based on observational studies in Table 10, the AF was based on belt use predictions adjusted for potentially fatal crashes in Table 11. In this way, unbelted cases in crashes with at least one fatality were downweighted at a rate that reflected that conversion to belt use may occur more slowly among occupants in potentially fatal crashes than was reflected in observational studies. This procedure also ensured that the downweighting of unbelted cases in life-threatening crashes was matched by upweighting of belted cases in crashes of corresponding severity.

Table 13. Case weight AF for cases involving unbelted occupants in crashes with at least one fatality

Front Seat (All Ages)			
Occupants in:	**2020**	**2025**	**2030**
Passenger cars	0.823	0.758	0.702
Vans and SUVs	0.793	0.732	0.680
Pickup trucks	0.795	0.733	0.677

Rear Seat (All Vehicle Types)			
Occupant age:	**2020**	**2025**	**2030**
8-15	0.823	0.784	0.748
16-24	0.835	0.812	0.791
25-69	0.776	0.769	0.763
70+	1.000	1.000	1.000

2.5.5 Child Restraint Trends

Child restraint use trends were applied to all occupants 7 or younger in both the MY<2005 and MY2005+ subsets of cases in the stepping-stone datasets.

Child restraint use in the future was predicted based on historical conversion rates, calculated from usage rates documented in the annual National Survey of the Use of Booster Seats (Glassbrenner & Ye, 2007; Glassbrenner & Ye, 2008; Pickrell & Ye, 2010; Pickrell & Ye, 2013; Pickrell & Choi, 2014; Li et al., 2016). NSUBS is an observational survey in which child age is estimated and restraint use documented in one of the following categories:

- Rear-facing child safety seat
- Forward-facing child safety seat
- Booster seat
- Seat belt
- No restraint involved.

The NSUBS results were sorted in the projection model to estimate the proportion of children 7 or younger who were in age-appropriate restraints. Very broadly, children in NSUBS who were documented as using the type of restraint recommended at NHTSA's safercar.gov website for their observed age group were defined in the projection model as appropriately restrained. Children who appeared to have prematurely graduated to restraint systems inappropriate for their estimated age were defined as inappropriately restrained. All unrestrained children were also included in the inappropriate restraint group for the purpose of reweighting. The very few NSUBS cases where children were restrained in a seat recommended for a younger age group (less than 2% of cases for any age group or study year) were binned with the appropriately restrained group. Notably, the classification of child occupants with appropriate or inappropriate restraint reflects only the type of restraint used relative to the recommended restraint for the age group. This binary variable for appropriate restraint use does not capture any other characteristic of restraint use, such as whether the restraint was properly used, because there was insufficient information available to identify misuse in the source cases and reweighting datasets, or to predict how misuse would be likely to change in the future. Therefore, the large percentage of children documented in age-appropriate restraints may not be in ideally installed restraints in spite of the terminology that classified them as appropriately restrained for the purpose of reweighting. However, since the cases were not specifically reweighted according to *proper* restraint use, there should still be a similar proportion of cases in improperly used restraints before and after reweighting for child restraint trends. Additionally, it must be emphasized that grouping together unrestrained children and children who are not in age-appropriate restraints for the purpose of reweighting does not assume that outcomes would be similar for these groups. It simply means that the same reweighting factors were applied to these cases so that the frequency of these cases would be reduced at the same rate in projections made by the model.

As with the application of belt use trends, expected future *increases* in age-appropriate child restraint use were incorporated into the model by upweighting cases involving appropriate restraint and downweighting inappropriate restraint cases in each child age group in the stepping-stone dataset. Similarly, in age groups where analysis suggested future *decreases* in age-appropriate child restraint use compared to the stepping-stone dataset period, cases with appropriate restraint use were downweighted and cases with inappropriate restraint use were upweighted.

Predictions of inappropriate child restraint use rates by age group in the future were made using conversion rate methods. As year-to-year age-appropriate child restraint use increases, the annual conversion rate in each age group was calculated as the percentage of inappropriately restrained children in each age group who were "converted" to appropriate restraint use in the subsequent year. For adults, annual belt use conversion rates have been close to half of historical average annual belt use conversion rates (see Section 2.5.4). In the absence of similar estimates for children, this same estimate was applied to child restraint use, with future annual conversion rates to appropriate child restraint predicted as 50 percent of historical conversion rates from 2006 to 2015 (the years for which NSUBS data was available).

The resulting annual predictions of inappropriate child restraint use (Figure 8) reflect the expected reduction in inappropriate child restraint use in the future.

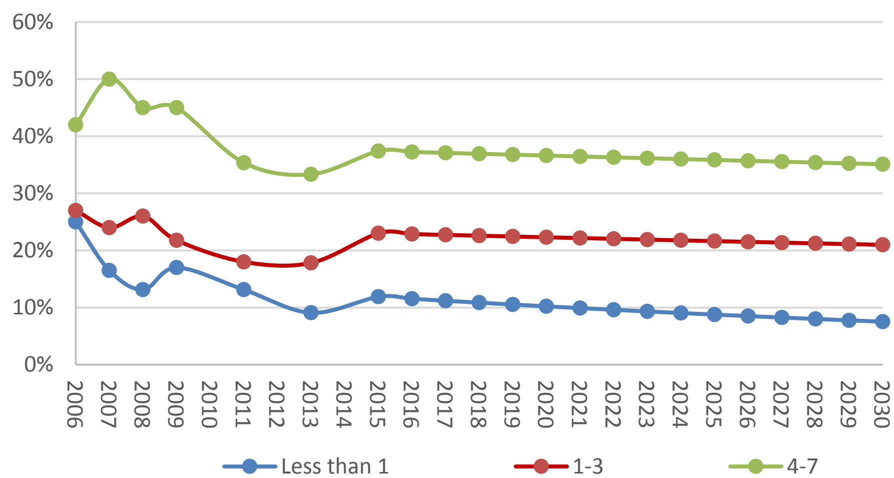


Figure 8. Rates of inappropriate restraint by age group
Based on NSUBS data up to 2015 and predicted subsequently based on 50 percent of historical conversion rates

Reweighting of inappropriate restraint use cases: The AF to be applied to the case weight for each stepping-stone case involving a child who was not in an age-appropriate restraint was calculated as a ratio of the predicted inappropriate-restraint rate in the targeted projection year divided by the inappropriate-restraint rate in 2013 to 2015 for that category. The resulting case-reweighting AF for each age group in the projection years 2020, 2025, and 2030 are shown in Table 14. Source data for the AF calculations can be found in Appendix B.3. For occupants in the two older age groups, the AF was greater than one for some projection years, meaning that inappropriately restrained children in these age groups in the stepping-stone datasets were upweighted in the projection datasets. Although this result was counterintuitive given the overall downward trend in rates of inappropriate use shown in Figure 8, it was consistent with the fact that predicted rates of inappropriate restraint in 2020 (for example) are higher than the *average* documented NSUBS rates from 2013 to 2015.

Table 14. Case weight AF by age group for cases involving inappropriately restrained children

Age Group	2020	2025	2030
Less than 1 year	0.976	0.839	0.720
1-3 years	1.096	1.063	1.031
4-7 years	1.036	1.014	0.993

Reweighting of appropriate restraint use cases: The AF for cases involving children who were documented in age-appropriate restraints were calculated to ensure that the total weighted number of cases in each age group did not change, but that only the proportion of appropriately restrained children in the age group changed. In other words, the case weight AF for cases involving appropriately restrained children in an age group were determined to guarantee that a decrease (or increase) in the total weighted number of inappropriately restrained cases was matched by an increase (or decrease) of the same magnitude in the total weighted number of appropriately restrained cases within that age group. Accordingly, the AF calculated for each category of appropriately restrained cases were a function of results from the stepping-stone dataset, in contrast to the AF for inappropriately restrained children that are estimated solely on the basis of child restraint use projections in the population. The details of those calculations are included in Appendix B.3.

After application of restraint use trends to children in the stepping-stone dataset for each of the three projection models, each age group under age 8 in the stepping-stone dataset had the same total weighted number of crash occupants as before application of this predicted trend. However, the proportion of occupants in each bin who were seated in appropriate restraints for their age group had shifted to reflect predicted increases (or decreases) in restraint use for each age group.

2.6 Application of Safety Countermeasures

While the incorporation of trends (described in Section 2.5) adjusts the number of occupants and vehicles with certain characteristics expected to be *exposed to a potential crash* in the future, the safety countermeasures in the model affect the likelihood that the crash would be prevented or the expected outcome would improve. Additionally, where trends were applied broadly to all cases with a given characteristic (e.g., by age group or vehicle type), countermeasures were applied on a case-by-case basis, with the adjustment depending on variables such as the model year of the occupant's vehicle, the year the crash occurred, or specific characteristics of the crash. Most countermeasures incorporated into the model to date had the potential to prevent the crash (e.g., crash avoidance, infrastructure or program countermeasures), reduce impact speed to mitigate the overall severity of the crash (crash mitigation countermeasures), or to reduce the severity of injuries sustained in the crash (crashworthiness and occupant protection countermeasures). However, the model can also apply the effects of changes expected to lead to increases in crashes or injuries (e.g., increases in maximum speed limits). All of the modeled changes are called countermeasures in the model, even those that reduce safety rather than improve it.

For countermeasures where information was available to identify specific injuries that would be affected (e.g., burn injuries, or head injuries from specific intruding vehicle components), only those specific injuries were deleted or reduced in severity in the future projection versions of the case. For countermeasures where effectiveness was only known in terms of overall injury severity, all injuries at the given severity level in affected cases was modified in the projection versions of the case. For example, if effectiveness was reported for a given countermeasure relative to MAIS 3+ injury, all AIS 3+ injuries in a proportion of cases in the target population could be reduced in severity to AIS 2 injuries.

Countermeasures can include vehicle-based technology and design enhancements, as well as nonvehicle-based infrastructure improvements (e.g., rumble strips) or safety programs (e.g., sobriety checks). While some safety countermeasures have been mandated by Federal Motor Vehicle Safety Standards, others have been encouraged through consumer test programs like the New Car Assessment Program or voluntary industry agreements, initiated through State programs or other agencies, or introduced independently by vehicle manufacturers. In this study, the term "countermeasure" covers all these diverse types of safety innovations, improvements, and interventions.

The effectiveness of a countermeasure is the percentage reduction in the risk of a crash or injury *with* the countermeasure compared to *without* the countermeasure. In the case-by-case methodology, countermeasures were applied to each case in the trend-adjusted dataset (the dataset that remains after all trends have been applied). The estimated effectiveness for each countermeasure was applied to every case in the trend-adjusted dataset that was in the countermeasure's defined target population. If different effectiveness values were available for subpopulations of the target population, these more specific effectiveness values were used. This best estimate of effectiveness for each individual occupant case was defined as the case-specific effectiveness (E).

The effectiveness estimates used in the current projection model were drawn from NHTSA benefit analyses and from studies in the literature estimating the expected difference in outcome between a case with a given countermeasure and a case without the countermeasure. These analyses and studies varied in how effectiveness was reported, e.g., relative to the percentage of target population crashes prevented, relative to the percentage of target injuries or fatalities prevented, or relative to the percentage of injuries expected to trickle down to lower-severity injuries. Thus, the strategy for applying the effectiveness of different countermeasures to the model (e.g., deletion of cases in the projected cases versus modification of injuries in the projected cases) varied depending on the expected effect of each countermeasure. The strategies for applying effectiveness and for estimating injury trickle down are described individually for each countermeasure in Appendices C-F for countermeasures applied in the evaluation model. These appendices also explain how the effectiveness estimates were made from existing data, with references to the source information used. The upcoming projection model results report that includes output for full runs of the model will include details for all additional countermeasures applied (Mallory et al., in press).

Before being applied to cases in the model, case-specific countermeasure effectiveness needed to be adjusted to reflect that some cases in the retrospective dataset already had the countermeasure available and not all cases in the future will have the countermeasure available. This adjusted effectiveness (E_{adj}) was calculated individually for each case in the model based on the overall countermeasure effectiveness for the case's target population and the availability of the countermeasure at the time of the original crash and in the projection year. For vehicle-based countermeasures, the availability of the countermeasure for a given case was estimated by the penetration into the fleet among vehicles exposed to crashes. For nonvehicle-based countermeasures, such as safety programs and infrastructure improvements, the availability of the countermeasure was estimated by its overall implementation rate. For simplicity, this parameter will be called "penetration" for all countermeasures in the model.

The methods used to apply safety countermeasures to cases in the model are described in the following sections. Specifically:

- Section 2.6.1 summarizes the penetration parameters needed for each countermeasure and how these were estimated for countermeasures in the model.
- Section 2.6.2 describes the methods used to adjust the effectiveness estimates for each case based on the penetration of the countermeasure for the original NASS CDS case as well as for the projected future version of the case.
- Section 2.6.3 summarizes the methods used to apply the adjusted effectiveness estimates to each case in the model to predict the frequency and outcome of such cases in the future.

More detailed descriptions of the target population, effectiveness and penetration estimates for each countermeasure applied in the evaluation version of the model are provided in the countermeasure summaries appended to this report.

2.6.1 Estimation of Countermeasure Penetration

Three basic penetration parameters used in the application of each countermeasure to cases in the model are defined as follows:

α: *Penetration of a countermeasure among vehicles of the model year of the relevant vehicle for vehicle-based countermeasures, or in the crash year of the original case for nonvehicle-based countermeasures.*

- This parameter reflects the probability that a countermeasure was available to a crash occupant in the original case crash. For this model, it was typically estimated using penetration among vehicles sold by model year for vehicle-based countermeasures (such as forward collision warning technology or side air bags compliant with

FMVSS No. 214), or by crash year for nonvehicle-based countermeasures (such as red light cameras or changes in speed limits). For vehicle-based countermeasures, the relevant vehicle can be the occupant's vehicle. For example, the occupant's own vehicle would be the relevant vehicle for crash avoidance countermeasures if the occupant were in the striking vehicle in a rear impact. For other situations, the relevant vehicle was a partner vehicle in the crash (for example, if the occupant was in the struck vehicle in a rear impact crash).

α': *Penetration of a countermeasure among cases that involve crashes or injuries that the countermeasure was intended to prevent.*

- This parameter accounts for the overall penetration of the countermeasure (α), but also for the decreased likelihood that an occupant who has the countermeasure available was likely to be involved in the targeted type of crash or sustain the targeted type of injury. For example, a vehicle in a rollover case was less likely to have been equipped with ESC than would be estimated using the ESC penetration rate for the vehicle's model year. Thus, α' was calculated as a function of α and case-specific effectiveness (E) and represents the probability that an occupant in the countermeasure target population in the original retrospective case already had the countermeasure.

β: *Penetration of a countermeasure among all occupants exposed to potential crashes in a target projection crash year.*

- For vehicle-based countermeasures, this parameter was calculated as a function of the penetration of the countermeasure in vehicles in each model year, and the relative frequency of each model year vehicle among occupant crashes in the future crash year. For nonvehicle-based countermeasures, this parameter was estimated using predicted future penetration by crash year.

For all countermeasures in the model, the penetration parameter α must be estimated for the crash year or model years of the relevant vehicle in the original retrospective cases. The penetration parameter β must be estimated for the target projection crash years, including the evaluation year 2014, as well as the projection years 2020, 2025, and 2030.

For a small number of countermeasures (e.g., side curtain air bags or conversion to roundabout intersections), the source case information can be used to determine if the countermeasure was available in a given occupant case so that α' can be set to 0 or to 1. However, since for most countermeasures the presence of the countermeasure in the original crash cannot be determined from the NASS CDS variables, the probability that a countermeasure was present in a retrospective case (α') needs to be estimated instead. Future penetration in target projection years, β, must be estimated for all countermeasures.

Countermeasure penetration estimates were drawn from a variety of sources but were based on real-world data when available. When real-world data was not available, penetration was estimated from regulatory phase-in requirements, voluntary agreement targets, and estimates from literature and industry experts. For countermeasures where both real-world penetration data and regulatory phase-in requirements were known, actual compliance was substantially faster than required since manufacturers typically exceed the minimum phase-in requirements. Therefore, in FMVSS-required countermeasures where minimum regulatory phase-in requirements were known but actual phase-in was unknown, penetration of the countermeasure was estimated assuming similar rates of early compliance as observed for other regulations. Penetration in the future was especially difficult to predict, necessitating use of predictions from multiple sources whenever available. For countermeasures included in the evaluation version of the model in this report, the data sources for penetration estimates are summarized with each countermeasure in its corresponding appendix.

2.6.2 Application of Penetration to Case-by-Case Effectiveness

In the case-by-case methodology, each occupant case in the model was modified for each target projection year to represent the likely change in frequency or outcome if the same potential crash exposure were to occur in the future crash year. This modification was based on the estimated case-specific effectiveness (E) for the countermeasure, but also on the likelihood that the countermeasure was present when the original crash occurred and the likelihood it would be present in the future projection year.

Since effectiveness was a measure of the difference in safety between a crash exposure ***with*** a countermeasure and a crash exposure ***without*** the countermeasure, countermeasure effectiveness was effectively zero in the model for a retrospective case occupant who already had the countermeasure in the original crash since adding the countermeasure would make no change to the crash. Effectiveness was also effectively zero for a future projection case where the case occupant was still not expected to have the countermeasure.

The penetration parameters that correspond to the penetration of the countermeasure among cases in the target population (α') and among cases in the projection target year (β_{TY}) were used to adjust the case-specific effectiveness in each weighted case in the model. This adjustment accounted for the fact that the countermeasure was not effective for the proportion of cases in which the countermeasure was already available in the original case and the proportion of cases which were still not expected to have the countermeasure in the future. Equations (7) and (8) show, in the simplest terms, how adjusted effectiveness (E_{adj}) in each case was calculated based on countermeasure penetration. For vehicle-based countermeasures, penetration in the original case-vehicle model year was needed (α'_{MY}). For nonvehicle-based countermeasures, the penetration in the original crash year was needed (α'_{CY}) instead. All countermeasures required estimated penetration in the target year for the projection (β_{TY}).

Vehicle-Based Countermeasures: $$E_{adj} = E \times (\beta_{TY} - \alpha'_{MY}) \quad (7)$$

Nonvehicle-Based Countermeasures: $$E_{adj} = E \times (\beta_{TY} - \alpha'_{CY}) \quad (8)$$

where:

E_{adj} is the adjusted effectiveness for a countermeasure in a given case,
E is the effectiveness of the countermeasure for that case's target population,
β_{TY} is the penetration in the target year for the projection, and
α' is the penetration in the original vehicle model year or the crash year of the original case.

The model can be used to explore a variety of hypothetical future countermeasure penetration scenarios by varying estimates of β_{TY}. These scenarios can be used to explore the potential effects of future penetration rates that are lower than expected or higher than expected for combinations of countermeasures. In the evaluation version of the model included in this methods report, the most realistic estimates of penetration were used for any countermeasure for which predictions were available. The methods used to estimate these parameters (α' and β_{TY}) are explained below, where β_{TY} for the evaluation model represents countermeasure penetration in 2014. For projection versions of the model, the target year can be set to 2020, 2025, or 2030.

Probability of countermeasure presence in original retrospective case (α'): Estimation of the probability that a case in the target population for a countermeasure *had* the countermeasure available (α') must account for the fact that a vehicle with a crash avoidance countermeasure available was less likely to have been involved in a crash than a vehicle without the countermeasure. Similarly, a case occupant with injuries in the target population for a crashworthiness countermeasure was less likely to have been equipped with the countermeasure. For example, the probability that an occupant with roof-crush injuries was in a vehicle compliant with the FMVSS No. 216 Roof Strength Upgrade (α'), was lower than the overall penetration of that countermeasure in the occupant's vehicle model year (α). Therefore, α', which was defined as the probability that a given countermeasure was present among all occupants exposed to potential crash/injury situations in the target population, was expected to be lower than α.

The penetration of a given technology or countermeasure among cases in a countermeasure's target population (α') was estimated as a function of α, the penetration of the countermeasure among all potential crash exposures, and the effectiveness (E) of the countermeasure for the given case's target population. This calculation relies on Bayes' theorem (Equation (9)) and is shown in Equation (10). The calculation can be expressed in terms of the variables used in this study (Equation (11)). The risk of a given crash or injury *without* the countermeasure of interest is defined as R, so the probability of the given crash or injury *with* the countermeasure was (1-E)R. The resulting relationship can be re-arranged and applied to estimates of penetration by model year for vehicle-based countermeasures (Equation (12)) or by crash year for nonvehicle-based countermeasures (Equation (13)).

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \tag{9}$$

$$\alpha' = \frac{(P(crash\ inj)|CM\ present) \times P(CM\ present)}{(P(crash\ inj)|CM\ present) \times P(CM\ present) + (P(\ crash\ inj)|\emptyset CM\ present) \times P(\emptyset CM\ present)} \tag{10}$$

where:

P(CM present) and P(ØCM present) are probabilities that the countermeasure is present or not present, and

P(crash inj|CM present) and P(crash inj|ØCM present) are probabilities that the given crash or injury would occur given that the countermeasure is present or not present.

$$\alpha' = \frac{(1-E) \times R \times \alpha}{(1-E) \times R \times \alpha + R \times (1-\alpha)} \tag{11}$$

where:

R is the probability of the crash or injury occurring without the countermeasure

Vehicle-based countermeasures:

$$\alpha'_{MY} = \frac{\alpha_{MY} - \alpha_{MY}E}{1 - \alpha_{MY}E} \tag{12}$$

Nonvehicle-based countermeasures:

$$\alpha'_{CY} = \frac{\alpha_{CY} - \alpha_{CY}E}{1 - \alpha_{CY}E} \tag{13}$$

Probability of countermeasure for the future version of case in the target year (β_{TY}): For nonvehicle-based countermeasures, such as infrastructure improvements or programs aimed at occupant behavior, the probability that the future version of a given case in the model would be expected to have the countermeasure was estimated directly from countermeasure penetration estimates for the target crash year (2020, 2025, or 2030). For example, penetration for intersection-specific countermeasures can be estimated as the percentage of intersections in the target population that are likely to be equipped with the given infrastructure feature in the target crash year. Those penetration estimates are needed for each of the target crash years for application of the countermeasure into the model.

For vehicle-based countermeasures, future penetration in the target crash years was calculated from two estimated parameters:

- The expected distribution of vehicle model year for occupants exposed to crashes in the target year (expressed as C_{MY}, which was the percentage of occupants in crashes in the future target year expected to be in vehicles of the given model year), and
- The estimated penetration rate of the countermeasure into the fleet for each model year (α_{MY}).

In theory, the product of those two percentages, summed across all model years up to the projection target year, was an estimate of the percentage of the fleet equipped with a given countermeasure in the projected crash-fleet in the target year. However, applying this concept to the projection model was complicated by the fact that cases involving vehicles of model year earlier than 2005 (MY<2005) were analyzed separately in the model, with no adjustment for countermeasures made in these older-vehicle cases. Therefore, the estimate of the proportion of the future fleet that would have each countermeasure in each projection target year (Overall β_{TY}) was calculated only across model years 2005 and later (MY2005+), as shown in Equation (14). Values for α_{MY} were estimated individually for each vehicle-based countermeasure. Values for C_{MY}, the predicted percentage of all occupant crash exposures in MY2005+ vehicles in each model year, were estimated separately for each projection target year (2020, 2025, 2030) and are tabulated in Appendix A.

$$Overall\ \beta_{TY} = \sum_{MY=2005}^{TY} C_{MY} \times \alpha_{MY} \tag{14}$$

where:
TY is the target year of the projection,
Overall β_{TY} is the proportion of the future fleet that would have the countermeasure in the given target year, and
C_{MY} is the percentage of occupants in crashes in the future target year expected to be in vehicles of the given model year.

However, the equation above could lead to cases where the estimated Overall β_{TY} was less than α', which when applied to Equation (7) and Equation (8) results in a nonsensical estimate of adjusted effectiveness. For example, a 2015 model year vehicle in the trend-adjusted dataset might have an α' near 100 percent if the countermeasure was required by FMVSS. However, by the crash year 2020, penetration of that countermeasure into the on-road fleet could still be substantially lower than 100 percent because of vehicles from model-years predating the introduction of the countermeasure. Therefore, rather than using Overall β_{TY} for each countermeasure for each projection target year, β_{TY} was estimated individually for each case-vehicle model year from 2005 to 2015, for each of the projection target year models. This step provided a customized β_{TY} for cases in the MY2005+ dataset, based on vehicle model year. This method guaranteed for every case in the model that the probability of having the countermeasure in the future was at least as great as the probability of having the countermeasure in the model year of the original case.

For this individual estimation of β_{TY} for each case-vehicle model year, intermediate calculations were performed to estimate the probabilities that a case *with* versus *without* the countermeasure in the original retrospective period (2005 to 2015) would have the countermeasure in the future version of the case in the projected target year. The probability that a case in the retrospective dataset *with* the countermeasure also had the countermeasure in the adjusted version of the case in the projected target year, defined as β^*_{CM}, was assumed to be 100 percent. The probability that cases in the retrospective dataset *without* the given countermeasure had the countermeasure in the projected target year was defined as β^*_{NoCM}. The value of β^*_{NoCM} was calculated so that the average penetration across all cases in the target year was, on aggregate, equal to the Overall β_{TY}. The steps involved in that calculation are shown in Equations (15) and (16).

$$\beta^*_{CM}(Overall\ \alpha_{Retro}) + \beta^*_{NoCM}(1 - Overall\ \alpha_{Retro}) = Overall\ \beta_{TY} \qquad (15)$$

where:

$$Overall\ \alpha_{Retro} = \sum_{MY=2005}^{2015} C_{MY} \times \alpha_{MY} \qquad (16)$$

and where:
β^*_{CM} is the probability that a retrospective case with the countermeasure also had the countermeasure in the adjusted version of the case in the target projection year, and
β^*_{NOCM} is the probability that a retrospective case without the countermeasure had the countermeasure in then adjusted version of the case in the target projection year.

Since β^*_{CM}=100%, β^*_{NoCM} was estimated for each future target year by re-arranging the relationship in Equation (15) as shown in Equation (17).

$$\beta^*_{NoCM} = \frac{Overall\ \beta_{TY} - Overall\ \alpha_{Retro}}{1 - Overall\ \alpha_{Retro}} \qquad (17)$$

Thus, β_{TY} for a given case in the trend-adjusted dataset was calculated as a function of the penetration of a given countermeasure in the vehicle model year in the case and β^*_{NoCM}, which had a unique value for each projection target year (2020, 2025, and 2030). Therefore, every case in the dataset associated with a given model year of vehicle was assigned the same β_{TY} for a countermeasure projected to a given target year (Equation (18)).

$$\beta_{TY} = (\alpha_{MY}) + \beta^*_{NoCM}(1 - \alpha_{MY}) \qquad (18)$$

All vehicle-based countermeasures implemented in the model to date have been implemented using Equations (7) and (18), with the exception of the update to FMVSS No. 214, NHTSA's Side Impact Protection standard. In the case of the FMVSS No. 214 update, it was possible to make a broad assumption regarding whether individual cases in the trend-adjusted dataset were in vehicles compliant with the regulation, i.e., whether they had the countermeasure, using NASS CDS data on air bag deployment in the crash. For occupant cases in the trend-adjusted dataset documented with the countermeasure, case-specific effectiveness for this countermeasure was set to 0 since no improvement would be expected for this case in the projected target years. For occupant cases in the trend-adjusted dataset where side air bags were not present, or where it was unknown if they were present, the method described above in Equations (7) through (18) was modified as described in the appendix corresponding to the FMVSS No. 214 update.

When the relevant vehicle was a partner vehicle rather than the occupant's vehicle: For crashworthiness countermeasures, it was the likelihood that an occupant's own vehicle was equipped with a given countermeasure that was important, i.e., the occupant's vehicle was the relevant vehicle with respect to countermeasure penetration. For crash avoidance and mitigation countermeasures, the likelihood of countermeasure installation on a vehicle other than the occupant's vehicle can be more important, making another vehicle the relevant vehicle for a given occupant. For example, for occupants in the struck or leading vehicle in a rear-impact crash, the likelihood that forward collision technology would prevent the crash was dependent on the model year of the opposing "partner" vehicle rather than on the occupant's own vehicle, since it was the striking vehicle that could potentially prevent the crash. Therefore, for any countermeasure where the effect on an occupant relies on the likelihood that the countermeasure was present on *another* vehicle in the crash, that partner vehicle's characteristics were used to determine expected penetration relative to the case occupant.

For occupant cases where the relevant vehicle was a partner vehicle rather than the occupant's vehicle, procedures for applying penetration estimates were modified since early model-year vehicles were over-represented among partner vehicles in the projection dataset.[13] The primary

[13] In the retrospective dataset (2004-2015), approximately 61 percent of occupants in multi-vehicle crashes were in MY<2005 vehicles. In the projected target datasets, the occupants in these MY<2005 vehicles were downweighted to represent the much smaller proportion of occupants expected to be in these older vehicles in 2020-2030. Correspondingly, occupants in newer-model year vehicles were upweighted. After reweighting, however, the model year in the partner vehicle in each occupant case remained as it was coded in the original case. Thus the distribution of model years hard-coded for partner vehicles in the projection dataset does not reflect the much newer distribution of vehicle model years expected to be on the road in 2020 to 2030.

difference in estimating future penetration among cases where it was the partner vehicle that was the relevant vehicle (rather than the occupant's own vehicle) was that countermeasures are applied to all cases in the dataset, not only those where the model year was 2005 or later. Thus, procedures for estimating future penetration (β parameters) for cases where the relevant vehicle in the original crash was a partner vehicle with model year earlier than 2005 were modified as described below. Procedures for estimating penetration for the original case (α parameters) and future penetration (β parameters) for cases where the partner vehicle in the original case was MY2005+ are the same as for cases where the occupant's vehicle was the relevant vehicle.

For occupant cases where the relevant vehicle was a partner vehicle with model year earlier than 2005 or with model year unknown, $\beta_{TY(PartnerMY<2005)}$ was calculated with the goal of ensuring that the proportion of partner vehicles in the weighted projection dataset that were estimated to have the given countermeasure in the target year matched the expected overall penetration of the countermeasure in the fleet for that target year. Therefore, $\beta_{TY(PartnerMY<2005)}$ for the MY<2005 partner vehicles was calculated in Equation (19) as a function of:

- the expected future penetration of the countermeasure among MY2005+ vehicles (Overall β_{TY} from Equation (14)) in the target projection year,
- the expected penetration of the countermeasure among MY<2005 vehicles ($\beta_{TY(MY<2005)}$) in the target projection year, calculated from penetration estimates by model year for each countermeasure, along with the distribution of vehicles by age estimated in Appendix A,
- the proportion of occupants in the projected target year ($O_{MY2005+(TY)}$) expected to be in MY2005+ vehicles, calculated based on the distribution of vehicles by age estimated in Appendix A and
- the proportion of occupants in the dataset with relevant partner vehicle that was MY2005+, approximated by the proportion of occupants in multi-vehicle crashes in the retrospective dataset who are in MY2005+ vehicles ($O_{MY2005+(Partner)}$). This proportion, drawn for this calculation directly from analysis of the model's retrospective dataset, was 38.7 percent.

$$\beta_{TY(PartnerMY<2005)} = \frac{\left(1 - O_{MY2005+(TY)}\right) \times \beta_{TY(MY<2005)} + \left(O_{MY2005+(TY)} - O_{MY2005+(Partner)}\right) \times Overall\beta_{TY}}{1 - O_{MY2005+(Partner)}} \quad (19)$$

where:

$\beta_{TY(PartnerMY<2005)}$ *is proportion of the future fleet that would have the countermeasure in the given target year when the relevant vehicle is a partner vehicle with MY prior to 2005,*

$\beta_{TY(MY<2005)}$ *is proportion of the future fleet that would have the countermeasure in the given target year among all vehicles with MY prior to 2005,*

$O_{MY2005+(TY)}$ *is proportion of occupants in the projected target year expected to be in MY2005+ vehicles, and*

$O_{MY2005+(Partner)}$ *is proportion of occupants with relevant partner vehicle that was MY2005+ among cases where relevant vehicle is a partner vehicle.*

2.6.3 Case-by-Case Application of Safety Countermeasures

While the application of vehicle and population trends described in Section 2.5 involved reweighting cases in the stepping-stone dataset to reflect how trends would affect the number and proportion of occupants exposed to certain crash conditions, the application of safety countermeasures involved manipulating the case weight and/or case characteristics to reflect how a countermeasure could be expected to change the outcome of a given crash exposure.

Crash avoidance countermeasures: For crash avoidance countermeasures where effectiveness was estimated as a percentage of a target population of crashes that would be *prevented* by a given crash avoidance countermeasure, the adjusted case-specific effectiveness for each crash avoidance countermeasure (E_{CA}) was applied directly to case weight as shown in Equation (20) to reflect the percentage of such cases that would be prevented. Although the application of a crash avoidance countermeasure did not change the number of raw cases in the dataset, the total weighted number of occupants in crashes in the projected dataset was reduced.

$$Weight_{adjusted} = Weight(1 - E_{CA}) \quad (20)$$

where:

E_{CA} *is the penetration-adjusted case-specific effectiveness for a given crash avoidance countermeasure,*

$Weight_{adjusted}$ *is the weight of a case in the model after application of the countermeasure, and*

Weight is the weight of a case in the model prior to application of the countermeasure.

For some countermeasures (e.g., SSF updates to NCAP that changed the criteria for evaluating static stability factor), effectiveness was negative for some cases in the target population. Where positive effectiveness for SSF represented a reduction in the frequency of rollovers with an increase in SSF, some categories of vehicles in the target population were documented with decreased SSF resulting in negative effectiveness. The negative effectiveness reflected that a decrease in SSF could lead to a rollover in cases that had previously only involved a side impact. This countermeasure was implemented by *adding* typical rollover injuries to cases in the target population associated with negative effectiveness. The details of this addition of injuries to the resulting pseudo-cases is discussed in the summary in the appendix corresponding to the NCAP 2004 SSF update.

Crashworthiness countermeasures: For crashworthiness countermeasures, where effectiveness was estimated as a percentage of a target population that would experience a defined improvement in outcome as a result of a given crashworthiness countermeasure, each case in the target population was replaced by two pseudo-cases. One pseudo-case retained all the original case characteristics but was downweighted as shown in Equation (21). The other pseudo-case was altered to reflect the predicted outcome improvement with a weight calculated as shown in Equation (22). The outcome alteration can involve deletion of a specific injury or set of injuries in a case, or adjustment of the severity of case injuries, depending on the predicted effects of the countermeasure. If effectiveness estimates for a given countermeasure predicted the probability that injury severity will be "trickled down" to multiple lower-severity levels, then a pseudo-case was made for each of the possible reduced-severity outcomes with the pseudo-case weights distributed proportionally according to trickle-down probabilities. Since the sum of the weights of the resulting pseudo-cases always equaled the weight of the original case, the total number of occupants was not changed by the application of a crashworthiness countermeasure, but the overall frequency of poor outcome was reduced.

$$Pseudo\text{–}case\ 1\text{:}\ Weight_{adjusted} = Weight(1 - E_{CW}) \tag{21}$$

$$Pseudo\text{–}case\ 2\text{:}\ Weight_{adjusted} = Weight(E_{CW}) \tag{22}$$

where:
E_{CW} is the penetration-adjusted case-specific effectiveness for a given crashworthiness countermeasure,
$Weight_{adjusted}$ is the weight of a case in the model after application of the countermeasure, and
Weight is the weight of a case in the model prior to application of the countermeasure.

Crash mitigation countermeasures: For crash mitigation countermeasures, effectiveness was defined as the percentage of a target population that would be exposed to a *reduced severity crash* by the given countermeasure. As with crashworthiness countermeasures, application of crash mitigation countermeasures results in division of a weighted case into proportionally weighted pseudo-cases, representing the proportion of occupants whose outcome would be unchanged and the proportion of occupants whose outcome would be altered by the reduced severity. The changes in the outcome of the reduced severity pseudo-case were estimated by calculating the average change of injury risk with the expected severity reduction associated with the countermeasure. Thus, as in crashworthiness countermeasures, crash mitigation countermeasures affected the injuries in an occupant case without changing the expected frequency of a case. Examples of crash mitigation countermeasures in the model included crash imminent braking and tire pressure monitoring systems. Details of the adjustment of outcome based on the predicted reduction in severity with specific countermeasures were included in the appendices to this report.

Interactions among the effects of countermeasures: The case-by-case procedures used in this model prevented double-counting the effect of multiple countermeasures since a countermeasure only affected the cases and injuries that remained after other countermeasures had been applied. Countermeasures that potentially affected the same injury in a given case were applied sequentially. Therefore, if two countermeasures affecting head injury were applied to an occupant, application of the first countermeasure resulted in one pseudo-case with the head injury deleted and one pseudo-case that still had the head injury. When the second head-countermeasure was applied to the pseudo-case with no head injury, it would have no effect since any head injuries were already deleted. The second countermeasure would only affect the pseudo-case that still had a head injury, i.e., the head injury cases still expected to remain after application of the first countermeasure. Similarly, if a pair of overlapping countermeasures such as roadside rumble strips and lane departure warning were applied to the same road departure case, the second countermeasure would only be applied to the portion of the case weight that remained after the first countermeasure was applied. In these situations, each case weight adjustment was applied as a multiplier so the result was the same regardless of the order in which countermeasures were applied for most countermeasures.

However, categories of countermeasures have been identified for which interactions between the countermeasures could result in a situation where the order of countermeasure application mattered:

- Countermeasures expected to change the crash delta V,
- Countermeasures expected to modify other case characteristics used to determine the target population or effectiveness of other countermeasures, and
- Countermeasures expected to be redundant with ADS.

Countermeasures expected to change the crash delta V: Crash mitigation countermeasures that change injury severity by reducing crash delta V (such as CIB, or braking vehicles with TPMS) may modify the effect of other countermeasures. Since other countermeasures rely on delta V, the change in delta V expected with these mitigation countermeasures could change whether the case was still in the target population or the effectiveness of these other countermeasures. As a result:

- Countermeasures with the potential to change crash delta V (such as CIB and TPMS) were applied prior to the application of any countermeasures with potentially overlapping target populations that use delta V to identify the target population or estimate effectiveness. Countermeasures that relied on delta V included updates associated with FMVSS No. 208, 214, and 301.
- The reduction in delta V resulting from application of countermeasures that changed delta V was saved in the pseudo-cases that resulted from application of those countermeasures. For example, the reduction in delta V expected after application of TPMS to a given case was saved in the case as a variable called R_{TPMS}.

Thus, for each countermeasure that used case delta V to identify target population or effectiveness, any delta V reduction resulting from previously applied countermeasures was accounted for.

Countermeasures expected to modify other case characteristics used to determine the target population or effectiveness of other cases: The application of some countermeasures produced pseudo-cases that were in the target population of other countermeasures that would not have affected their corresponding original parent cases. For example, application of the SSF updates in the 2004 NCAP enhancement resulted in the addition of rollover injuries to pseudo-cases whose parent cases had not involved a rollover. These resulting pseudo-cases could therefore be included in the target populations for countermeasures such as ejection mitigation (FMVSS No. 226) and roof crush reduction (FMVSS No. 216), while the parent cases without rollover would not have been in these target populations. Interactions such as these were addressed individually for countermeasures, such as SSF, that alter characteristics used to determine the target population of other countermeasures. These interactions were addressed by ensuring, for example, that countermeasures like SSF were applied prior to other countermeasures whose target populations may be affected.

Countermeasures expected to be redundant with automated driving systems: Crash avoidance and crash mitigation countermeasures that duplicated functions accounted for in the modeled ADS countermeasure (such as forward collision warning or crash imminent braking) were not applied to the portion of each case expected to be affected by high-level driving automation in the target future dataset. Additionally, countermeasures that affect driver attention (such as distraction and alcohol-targeted countermeasures) were not applied to the proportion of cases affected by high-level driving automation in the model. It was expected that a vehicle with ADS would outperform these individual safety countermeasures that duplicated functions accounted for in the modeled ADS countermeasure. As a check, all the countermeasures that were dropped for the proportion of cases expected to be ADS-equipped in the future were applied in parallel to the ADS countermeasures. If the benefits of the individual countermeasures were greater than the benefits from ADS for a given case, the individual countermeasures were applied instead of the ADS countermeasures.

2.7 Analysis of Model Output

Weighted crash and injury results for the projected datasets for 2020, 2025, and 2030 can be analyzed in the same way that weighted retrospective data can be analyzed. Since the projected datasets are still full datasets with all the same variables that were available in the original retrospective cases, the future results can be disaggregated by most of the same crash/vehicle/occupant parameters that can be used to analyze retrospective data (Mallory et al., 2017). Similarly, the detailed injury results in the projected datasets can be used to quantify crash harm in the future target years, just as it can be quantified for the period covered by the retrospective cases. Analysis of the weighted pseudo-cases was performed using the same procedures for survey-sampled data that were applied to the weighted retrospective dataset.

In the ultimate output of the projection model summarized in the results report (Mallory et al., in press), results from the projection model for 2020, 2025, and 2030 will be shown along with retrospective results for comparison. In the results of the evaluation model included in this methodology report, results compare only projected data and comparison data from 2013 to 2015. Results for the full projection model will include the frequency of different types of crash scenarios and the injury outcome for different crash, vehicle, and occupant groups. The results for the evaluation model in this report include only a limited sample of the ways the model output can be analyzed.

The following sections provide detail on the several measures of outcome harm (Section 2.7.1) and crash and occupant characteristics (Section 2.7.2) that can be used to analyze projected future cases. These measures of harm were estimated using SURVEYFREQ procedures in SAS for all harm measures except those associated with cost, which were estimated using SURVEYMEANS procedures.

For many of the harm measures in the retrospective dataset, ninety-five percent confidence intervals can be estimated as 1.96 times the standard error calculated using SAS survey analysis procedures. The standard errors calculated by survey analysis procedures estimate the error that results from sampling individual cases from the population. The standard error calculations in this model are a function of case weights. The weights in the retrospective dataset are based on the CDS survey design, and thus account for the original sampling error in CDS. However, the weights have been scaled in the retrospective model using counts of fatalities from FARS and sample-based estimates of non-fatal case counts from GES. Thus, the standard error estimates are thus also adjusted by the survey analysis procedures to account for the upweighting and downweighting of the point estimates using FARS and GES data. Sampling error in GES was not explicitly captured in the confidence interval estimation. Confidence intervals were not estimated for the projection datasets or for attributable fatality, cost, or equivalent lives lost estimates because of the complexity of the adjustments made to individual cases for these calculations.

2.7.1 Measures of Harm

Multiple measures of injury harm were compared in the analysis, to estimate both mean level of harm and total amount of harm in the retrospective and projected future datasets. Included measures of harm in the current model were as follows:

- Fatality and attributable fatality
- Injury by AIS severity
- Cost and attributable cost
- Equivalent lives lost

Early versions of the model have also been used to quantify harm in terms of disability and attributable disability, using FCI, which is a functional capacity index corresponding to AIS (Segui-Gomez, 1996). Preliminary results, however, have shown that FCI was ineffective in capturing the effects of injuries such as whiplash associated disorder or mild traumatic brain injury. Future versions of the model will therefore incorporate alternative measures of disability, such as the revised FCI or the RPMI, which estimates the risk of permanent medical impairment associated with specific injuries (Malm et al., 2008; Gustafsson et al., 2015). No disability results are currently output by the model.

The details of the harm measures available for analysis of the model results are described in the following sections.

2.7.1.1 Fatality & Attributable Fatality

Fatality in retrospective cases: For analysis of retrospective data, which describes the injuries documented in the original NASS CDS case, *fatality* was identified using the CDS treatment/mortality variable which identifies cases with crash-related fatality within 30 days of the crash (NASS CDS variable name: TREATMNT=1). In cases where the treatment/mortality variable was missing, the KABCO variable was used to identify fatal cases. For analysis of projected data, in which the treatment/mortality variable will no longer be valid if there was a possibility that reduced injury severity may have prevented death, harm associated with fatality was estimated using the attributable fatality method. Below, the attributable fatality method is described, along with the application of these methods to the estimation of fatality in the projected datasets.

Attributable fatality method: The attributable fatality method, under ongoing development by Martin and others (Martin & Eppinger, 2003; Hasija et al., 2006; Mallory et al., 2017), was used to estimate the importance of injuries in different body regions with respect to threat to life.

In the attributable fatality method, *the probability of fatality in each adult occupant case* was estimated following the procedure described by Hasija et al. in 2006 (Equation [23]). In that procedure, each AIS-coded injury type was assigned a "mortality rank" (MR) value that corresponds to its relative contribution to fatality risk. The MR values for AIS 2+ injuries and the five function parameters in Equation (23) were drawn from the values re-optimized for the attributable fatality method in 2017 using updated datasets from the Crash Injury Research & Engineering Network (Mallory et al., 2017). The fatality probability function in Equation (23) can be applied to occupants age 15 and older in the projection model because this range corresponds to the dataset used to develop the mortality rank values used in the attributable fatality methodology.

$$\text{Age 15+: } pFatal = \frac{1}{\left(1+e^{-(a0+a1I1+a2I2+a3I3)}\right)^{1/d}} \qquad (23)$$

where:
pFatal is an occupant's probability of fatality,
I1, I2, and I3 are the mortality rank (MR) values corresponding to the three highest-MR injuries respectively, and
a0, a1, a2, a3 and d are function parameters.

In this way, the probability of fatality was calculated based on each adult occupant's most serious three injuries. Given that MAIS 1 and 2 cases are very rarely expected to be fatal and MAIS 6 cases are expected to be fatal more frequently than was reflected in the data used to optimize mortality ranking values,[14] the probability of fatality (pFatal) was set to 0.01 percent (the lowest possible value) for cases where the most serious injury was AIS 1 or 2 and to 99.99 percent (the highest possible value) for cases with an AIS 6 injury. AIS 7 codes corresponding to injuries where the patient "died without further evaluation" were also assigned a pFatal of 99.99 percent.

[14] Since CIREN data comes from trauma center data collection teams, occupants who die at the scene of a crash prior to emergency transport are less likely to be included in the dataset, potentially resulting in a bias toward higher survivability of AIS 6 injuries than would be expected if the dead-at-the-scene cases were included.

Harm, including probability of fatality, was calculated for the future projection datasets as well as for retrospective datasets. However, there are injuries in the dataset with reduced severity compared to originally coded injuries. This severity adjustment can result in combinations of injury type and severity that do not exist, and that therefore have no associated MR estimate. For example, application of countermeasures can reduce the severity of an AIS 5 brainstem injury to an AIS 4 brainstem injury, which does not exist in the AIS coding system and therefore has no associated MR. In such cases, the modified-code injuries were re-grouped to the most similar injury region that did have an associated MR. For example, brainstem injuries reduced to AIS 4 in the projection datasets were assigned MR values associated with other AIS 4 head injuries in the more general head injury/loss of consciousness/other MR category.

In the projection model, *the probability of fatality among occupants younger than age 15* was estimated based on mortality rates among children in the NTDB dataset of trauma center cases. Previously, Doud reported on the NTDB mortality rate among children with specific AIS-coded injuries, where that injury was the MAIS injury (Doud et al., 2015). That study provided MAIS-based mortality rates for the most common AIS-coded injuries, covering 95 percent of the pediatric injuries coded in pediatric motor vehicle crash cases. Data on the mortality rate for individual injuries in Appendix 1 of the Doud study were applied in the projection model to estimate the probability of fatality (pFatal) for pediatric age groups by the body region and AIS injury severity of the MAIS injury (Table 15 to Table 17). For each child occupant in the projection model, pFatal was estimated as the mortality rate for the child's MAIS injury from these tables. For example, a mortality rate of 7.41 percent would be applied to a 3-year old child whose highest-AIS injury was an AIS 4 head injury. In cases with multiple injuries of the severity level of the case MAIS, the highest corresponding mortality rate was used. Mortality rate for body region/severity combinations for which no information was available from the Doud data are left blank (--) in the tables below. If no mortality rate estimate was provided for any of a child's MAIS injuries, pFatal was estimated to be equal to the mortality rate that corresponds to the severity level of the child's MAIS injury across all body regions. For example, a child with MAIS 4 injuries to the neck and abdomen would be assigned a pFatal of 7.59 percent. As with adult occupants, pFatal was set to 0.01 percent for cases where the most serious injury was AIS 1 or 2 and to 99.99 percent for cases with an AIS 6 injury or an AIS 7 injury corresponding to the "died without further evaluation" codes.

Table 15. Mortality rates by MAIS injury region and severity for age 0-4

AIS Injury Region	MAIS 3	MAIS 4	MAIS 5
1 Head	0.0182	0.0741	0.3187
2 Face	0.0000	--	--
3 Neck	--	--	--
4 Thorax	0.0285	0.1250	--
5 Abdomen	0.0000	--	0.1600
6 Spine	0.0000	--	--
7 Upper Extremity	0.0164	--	--
8 Lower Extremity	0.0136	--	--
9 Unspecified	--	--	--
All Body Regions	0.0180	0.0759	0.2924

Table 16. Mortality rates by MAIS injury region and severity for age 5-9

AIS Injury Region	MAIS 3	MAIS 4	MAIS 5
1 Head	0.0207	0.0610	0.3450
2 Face	0.0000	--	--
3 Neck	--	--	--
4 Thorax	0.0118	0.0736	--
5 Abdomen	--	0.0000	0.0000
6 Spine	0.1667	--	--
7 Upper Extremity	0.0162	--	--
8 Lower Extremity	0.0092	--	--
9 Unspecified	--	--	--
All Body Regions	0.0140	0.0614	0.3420

Table 17. Mortality rates by MAIS injury region and severity for age 10-14

AIS Injury Region	MAIS 3	MAIS 4	MAIS 5
1 Head	0.0149	0.0516	0.3005
2 Face	0.0000	--	--
3 Neck	--	--	--
4 Thorax	0.0076	0.0285	--
5 Abdomen	0.0027	0.0305	--
6 Spine	0.0000	--	--
7 Upper Extremity	0.0070	--	--
8 Lower Extremity	0.0058	--	--
9 Unspecified	--	--	--
All Body Regions	0.0079	0.0457	0.3005

Calculation of the fatalities attributable to a particular body region was a three-step process:

1. The expected number of fatalities in an occupant group (e.g., all occupants in a certain crash type) was estimated by summing the probability of fatality (pFatal) for all occupants in the group.
2. Next, all injuries to the body region of interest were deleted, the pFatal recalculated for each case, and a revised expected number of fatalities was estimated for the group by summing the re-calculated probability of fatality (pFatal) for all occupants.
3. The difference between these two totals (the expected number of fatalities minus the revised expected number of fatalities absent injuries to the body region of interest) was the number of fatalities attributable to the given body region.

It should be noted that the sum of attributable fatalities associated with each body region will be less than the total number of expected deaths in an occupant set as a result of occupants who sustain life-threatening injuries to multiple body regions. For example, for an occupant with a life-threatening head injury and a life-threatening thorax injury, elimination of all head injuries *or* elimination of all thorax injuries would each lead to a reduced probability of fatality, but only elimination of all head injuries *and* all thorax injuries would lead to zero probability of fatality for that occupant. Correspondingly, summed over the whole dataset, a fraction of fatalities could be prevented by elimination of head injuries, and a fraction of fatalities could be prevented by elimination of thorax injuries, but there will always be a fraction of fatalities that could only be prevented if both head and thorax injuries were eliminated.

Note also that fatalities associated with injuries not coded with a particular body region (e.g., burns or skin injuries that are coded as body region 9) do not get captured in analyses of attributable fatality by body region.

Fatality in projected future cases: The injuries coded in pseudo-cases in the future projected dataset were modified to reflect injury reduction expected with countermeasures. However, the treatment/mortality variable associated with each original case was not modified to reflect the reduced fatality risk associated with each injury reduction and instead remained at its initial value. Therefore, that variable could not be used to analyze fatality frequency in the future projected dataset for comparison to the fatality frequency in the retrospective dataset. Instead, after application of all countermeasures, the cases in the projected future datasets that were descended from retrospective cases that were originally fatal were each divided into two pseudo-cases: one fatal and one non-fatal. The proportion of each case's weight that was assigned to its fatal and non-fatal pseudo-cases was determined based on the reduced injuries in each projected case in comparison to its corresponding original retrospective case. These proportions were estimated for each occupant using Equations (24) and (25). For adults, the pFatal was estimated by applying Equation (23) to the injuries in the pseudo-case in the projection dataset and in the original parent case in the retrospective dataset. For children, pFatal was estimated in the projected case and the original parent case using Table 15 to Table 17. For any pseudo-case where the corresponding original retrospective or "parent" case was non-fatal, it was assumed that the pseudo-case outcome was also non-fatal.

$$Weight_{pseudo(fatal)} = Weight_{parent} * \frac{pFatal_{pseudo}}{pFatal_{parent}} \tag{24}$$

$$Weight_{\ pseudo(not\ fatal)} = Weight_{parent} * \left(1 - \frac{pFatal_{pseudo}}{pFatal_{parent}}\right) \tag{25}$$

where:

pFatal is the probability of fatality in the countermeasure-modified pseudo-case and the original NASS CDS parent case, calculated as a function of the coded injuries using Equation (23) for adults and Table 15 to Table 17 for children.

For the relatively rare cases where the original parent case was fatal despite being coded with MAIS of 2 or less, the probability of fatality (pFatal) was set to 0.01 percent by the methods described earlier in this section, thus avoiding division by zero. Therefore, in originally fatal parent cases with MAIS<=2, the ratio of $pFatal_{pseudo}$ and $pFatal_{parent}$ was 1 even when injuries were reduced in the countermeasure-modified pseudo-case. In other words, these fatal cases with moderate and minor injuries were still assumed to be fatal even with a reduction in injuries, absent quantifiable information on the reduction of fatality risk.

As in the analysis of retrospective cases, the *attributable fatality method* was used on cases in the projected future datasets to break down the importance of injuries by body regions with respect to threat to life.

2.7.1.2 Injury by AIS Severity

Injuries from NASS CDS cases from 2009 and earlier were coded with AIS codes corresponding to the 2000 NASS Injury Coding Manual, which in turn was based on the 1990 Revision (1998 Update) of the AAAM AIS Coding Manual. Injuries from cases in 2010 and later that were originally coded with the NHTSA Injury Coding Manual that was based on AAAM's 2005 AIS/Update 2008 (AAAM, 2008) were converted for this model to equivalent AIS 1990/98 codes as described in Section 2.2.1. Thus, all injuries in the model, including those in retrospective and projection datasets, were represented by AIS 1990/98 injury codes.

In analyses of injury among vehicle occupants by severity, occupants with MAIS injury at the 2+, 3+, 4+ or 5+ level included any surviving occupants with one or more injuries with at least the given severity level to any body region, as well as all fatally injured occupants (regardless of MAIS). Fatal cases were identified using the methods developed in Section 2.7.1.1, rather than relying on the fatality status of the original parent case.

In analyses of severity by MAIS, each occupant was counted only once. Analyses of injuries by body region and AIS severity counted the number of occupants with at least one injury in the given body region so that occupants with multiple injuries in a body region were only counted once, but occupants could be counted in multiple body regions.

2.7.1.3 Cost and Attributable Cost

The cost associated with injury crashes was estimated using the methods and values reported by Blincoe et al., (2015). Each AIS-coded injury was categorized into the body categories defined by Blincoe et al., based on the REGION90, STRUTYPE, STRUSPEC, and AIS severity digits of the seven-digit AIS code. For cases from 2010 and later, hard-coded in AIS 2005/08, the mapped AIS 1990/98 code was used if available. If no equivalent AIS 1990/98 code was recommended in the AIS 2005/08 manual, the regions, structure type, specific structure and AIS severity digits of the untranslated AIS 2005/Update 2008 code were used. Where injury categories were ambiguous, categorization of AIS-coded injuries into the cost-study injury bins was done in consultation with one of the authors of the original study.[15] Injuries coded as burns with AIS severity 3 or 4 were assigned the cost associated with AIS 2 burns, as there were no costs available for these higher severities.

For non-fatal cases, each coded injury was keyed to a cost that included medical and emergency services, lost household and wage work, and legal and insurance costs in 2010 dollars. This total did not include property damage or values associated with lost quality of life and did not vary by occupant age. A per-occupant cost was then set to each occupant's highest-cost injury. A cost of $1,381,984 was applied to fatal cases. Uninjured occupants were assigned a cost of $0 in the projection model. For cases in the projected dataset, which has no definitive fatality variable, the methods for estimating fatality in projection cases in Section 2.7.1.1 were used to separate each projection case into a fatal pseudo-case (to which the fatal cost estimate was applied) and a nonfatal pseudo-case (for which costs were estimated based on the highest-cost injury).

The estimated cost associated with an individual occupant case did not reflect actual or documented medical costs for that occupant, but rather an estimate of costs expected given the individual's injuries. The occupant cost was set to the costliest of the AIS-coded injuries in the case.

Following a procedure similar to Martin's "attributable fatality" method (Martin & Eppinger, 2003; Hasija et al., 2006), the proportion of cost that can be attributed to specific body regions was estimated for each occupant. This procedure is summarized below. This *attributable cost* represents the *total cost* expected to be saved if injuries to a particular body region were completely eliminated.

[15] Ted R. Miller, Pacific Institute for Research and Evaluation, personal communication, 2015.

Calculating the cost attributable to a particular body region was a three-step process:

1. The expected total cost of injury in a particular analysis subgroup was estimated by summing the expected injury costs of all occupants in the group.
2. Next, all injuries to the body region of interest were deleted, the cost recalculated for each case, and the revised expected total cost was estimated for the group by summing the re-calculated cost for all occupants.
3. The difference between these two totals (the expected total cost to all occupants – the revised expected total cost absent injuries to the body region of interest) was the total injury cost attributable to the given body region.

The magnitude of total estimated cost attributable to individual body regions represents the total cost-savings predicted by eliminating all injuries to the given body region. As with attributable fatality, the sum of attributable costs across body regions would be expected to be less than the total costs predicted to all occupants in the analysis group as a result of individual occupants with injuries to multiple body regions. When comparing costs attributable to different body regions over time, it should be noted that a decrease in injury frequency in one body region can lead to an apparent increase in costs in another body region. This potentially misleading increase occurs because each occupant's cost was linked to the costliest injury. For instance, reduction of head injury in a large number of cases could result in the thorax or extremity injuries becoming the costliest injury in those cases. This shift would increase the cost attributable to thorax or extremity injury without any increase in the frequency of these injuries. Therefore, increases in attributable cost cannot be interpreted as absolute increases in the frequency or severity of injury to particular body regions. Note that costs associated with injuries not coded with a particular body region (e.g., burns or skin injury coded in body region 9) do not get captured in analyses of attributable fatality by body region.

Since harm was calculated for the future projection datasets, as well as for retrospective datasets, there were injuries in the dataset with reduced severity compared to originally coded injuries. This severity adjustment can result in combinations of injury type and severity that do not exist, and that therefore have no associated cost estimate. For example, application of countermeasures can reduce the severity of an AIS 4 cervical spinal cord injury to an AIS 3 cervical spinal cord injury, which does not exist in the AIS coding system and therefore has no associated cost estimate. In such cases, the modified-code injuries were re-grouped to the most similar injury region that did have an associated cost in Blincoe et al. (2015). For example, cervical spinal cord injuries reduced to AIS 3 in the projection datasets were assigned costs associated with other cervical spine injuries in the face/other head/neck cost category.

2.7.1.4 Equivalent Lives Lost

"Equivalent lives lost" is a harm measure developed for this projection model effort, analogous to the "equivalent lives saved" estimation often used in National Center for Statistics and Analysis benefits analyses. In both harm measures, outcomes from non-fatal and fatal cases are combined to provide a single, cost-based estimate of harm, expressed in terms of the estimated cost of associated with one fatality. For example, a non-fatal case with an estimated cost of 10% of the estimated cost of a fatal case, would be weighted as 0.1 equivalent lives lost. This cost-based weight can be summed across groups of crash occupants to estimate the total equivalent number of lives lost expected for the group. Comprehensive costs estimated for fatalities and for MAIS injuries by body region were obtained for the calculation of equivalent lives lost from NHTSA's most recent cost analysis (Blincoe et al., 2015). These cost estimates were used to estimate equivalent lives lost in both the retrospective and projected future datasets, in 2010 dollars without adjustment for inflation or updated value of a statistical life. The discount rate that is typically used in benefits analyses did not apply in the model because the output represents problems remaining at a specific point in time (versus benefits over the lifetime of a vehicle). Therefore, only undiscounted values are presented. While equivalent lives saved is calculated based on the difference between the cost-based estimate of the number of equivalent fatalities before and after a safety improvement, the equivalent lives lost metric in this model was simply a count of the equivalent lives lost estimated in a given dataset.

To calculate equivalent lives lost in the projection model, AIS codes and fatality status were needed for all cases in the dataset. For estimation of this harm measure in the projected datasets, fatality was determined as explained in Section 2.7.1.1 rather than by using the fatality status of the original case.

2.7.2 Analysis Subgroups

The primary groups available to disaggregate results were pre-crash scenario and impact direction. For additional disaggregation of the data, the variables available for each case in the model datasets were the same NASS CDS variables that were coded with the original source cases. Variables available to further analyze by pre-crash scenario included intersection type, roadway type, lighting, surface condition, and road curvature. Variables available for analysis by impact direction included occupant age, restraint use, seat position, and injured body region. These variables are described below in more detail. Results can also be analyzed by vehicle type, which was categorized as explained in Section 2.5.1.

Pre-crash scenario: Cases were classified according to the pre-crash scenario typology developed by Swanson et al., (2016). This draft revised typology defines 36 pre-crash scenarios that are determined by vehicle movements and critical events occurring immediately prior to a crash. To display the results effectively, the number of analysis subgroups was limited as defined in Table 18. The scenario numbers in that table correspond to the numbering system used by Swanson et al. All other crashes that did not fall into the defined scenario sub-groups were included in an "Other" category in the model results. This "Other" category included relatively low frequency scenarios where the NASS CDS case occupant was in a vehicle that impacted an animal, pedestrian, or cyclist.

Table 18. Pre-crash scenario group definitions

Group	Scenario & Scenario #		SAS Coding Definition (NASS CDS Variables)
Control Loss	Control loss/vehicle action	2	For same vehicle: PREEVENT in (5:9) & PREMOVE in (1:4, 6, 8:97) For same vehicle: ACCTYPE in (2, 7) & PREMOVE in (1:4, 6, 8:97) For same vehicle: ACCTYPE in (34, 36, 54, 56) & PREMOVE in (1:4, 6, 8:97)
	Control loss/no vehicle action	3	
Road Departure	Road edge depart/maneuver	4	PREEVENT in (10:14) & PREMOVE^=13 ACCTYPE in (1, 6, 14, 92) & PREMOVE^=13
	Road edge depart/no maneuver	5	
Lane Change	Turning/same direction	14	VEHFORMS=1 & PREEVENT=60, 61 PREEVENT=64 ACCTYPE in (44:49, 70:73) & PREMOVE in (1:12, 14:16) ACCTYPE in (20:43) & Struck vehicle: PREMOVE in (6, 8:12, 15:16) Any combination of vehicles: PREMOVE in (8:12) & PREEVENT in (60:61) Any combination of vehicles: PREMOVE in (6, 15:16) & PREEVENT in (60:61)
	Parking/same direction	15	
	Changing lanes/same direction	16	
	Drifting/same direction	17	
Opposite Direction	Opposite direct/maneuver	18	VEHFORMS=1 & PREEVENT=54, 62:63 VEHFORMS>1 & ACCTYPE in 50:67
	Opposite direct/no maneuver	19	
Rear-End	Striking maneuver	20	PREEVENT in (50:52) ACCTYPE in (20:43) & striking vehicle: PREMOVE in (6, 8:13, 15:97) ACCTYPE in (20:43) & struck vehicle: PREMOVE in (1:5, 7, 14) Same vehicle: PREMOVE in (1:5, 7, 14) & PREEVENT=53 ACCTYPE in (21:23, 25:27, 29:31) ACCTYPE in (20:43) & one vehicle: PREMOVE=1 & other vehicle: PREMOVE=0
	Lead Vehicle Accelerating	21	
	Lead Vehicle Moving	22	
	Lead Vehicle Decelerating	23	
	Lead Vehicle Stopped	24	
Lateral Crossing Paths	Right turn into path	25	VEHFORMS=1 & TRAFCONT^=1 & PREEVENT in (65:68, 70:73) TRAFCONT=1 & ACCTYPE in (78:81) Any combination: TRAFCONT=1 & PREMOVE=10 & PREEVENT in (65:68) TRAFCONT=1 & PREMOVE=10 & ACCTYPE in (74:75, 84:85) TRAFCONT=1 & one vehicle: PREEVENT=16 & other vehicle: PREEVENT in (65:68) TRAFCONT^=1 & ACCTYPE in (74:86) TRAFCONT^=1 & PREEVENT in (65:68, 70:78) ACCTYPE in (76:83, 86:89)
	Right turn across path	26	
	Straight crossing paths	27	
	Left turn across path, lateral direction	28	
	Left turn into path	29	
LTAP/OD	LTAP/OD - Left turn across path, opposite direction	30	ACCTYPE in (68:69) Any combination of vehicles: PREMOVE=11 & PREEVENT in (54, 62:63) One vehicle: PREEVENT=15 & other vehicle: Vy_PREEVENT in (54, 62:63) TRAFCONT=1 & ACCTYPE in (74:75) & one vehicle: PREMOVE=11 & other vehicle: PREMOVE^=10

Intersection type: The relation of each case to an intersection was identified using the variables Relationship to Interchange or Junction (NASS CDS variable name RELINTER) and Traffic Control Device (NASS CDS variable name TRAFCONT) as seen in Table 19. For this projection model, a sign-controlled intersection included stop, yield, warning, school, and other signs. Included in the “Other” category were crashes that occurred at a driveway, an alley, an uncontrolled intersection, or were coded as unknown.

Table 19. Intersection type definitions

Intersection Type	SAS Coding Definition (NASS CDS Variables)
Non-Intersection	RELINTER=0
Interchange	RELINTER=1
Sign Controlled	RELINTER=2 & TRAFCONT in (2:7)
Signal Controlled	RELINTER=2 & TRAFCONT=1
Other	RELINTER ^in (0:2) or TRAFCONT ^in (1:7)

Roadway type: Since urban and rural freeways and highways are not specifically identified in NASS CDS, roadway type was classified using the variables Trafficway Flow (NASS CDS variable name TRAFFLOW) and Posted Speed Limit (NASS CDS variable name SPLIMIT), which was coded in km/h. The Trafficway Flow variable, used to differentiate types of high-speed roadways, indicated if a median or centerline barrier was present. Included in the “Other” category were crashes where the speed limit was unknown, the speed limit did not exist, or it was unknown if a highway was divided.

Table 20. Roadway type definitions

Roadway Type	SAS Coding Definition (NASS CDS Variables)
≥ 45 mph, Divided	72≤SPLIMIT<999 & TRAFFLOW in (1:2)
≥ 45 mph, Not Divided	72≤SPLIMIT<999 & TRAFFLOW in (0, 3:5)
> 25 mph & < 45mph	41<SPLIMIT<72
≤ 25 mph	SPLIMIT≤41
Other	SPLIMIT ^in (1:998) or (SPLIMI≥72 & TRAFFLOW ^in (0:5)

Lighting: Output can be disaggregated using the Lighting Condition variable (NASS CDS variable name LGTCOND) as seen in Table 21. For this projection model, the category of “Day” included dusk and dawn. Included in the “Other” category were crashes that occurred when the light conditions were unknown.

Table 21. Lighting variable definitions

Lighting	SAS Coding Definition (NASS CDS Variables)
Day	LGTCOND in (1, 4:5)
Night	LGTCOND=2
Night With Lights	LGTCOND=3
Other	LGTCOND ^in (1:5)

Surface condition: The roadway surface was defined using the Surface Condition variable (NASS CDS variable name SURCOND) as seen in Table 22. “Dry” roads included surfaces that were dry and those covered with sand, mud, dirt, and gravel. The “Slippery” category included wet, snow, slush, ice, frost, water, and oil. Included in the “Other” category were crashes that occurred when road surface conditions were unknown.

Table 22. Surface condition definition

Surface Condition	SAS Coding Definition (NASS CDS Variables)
Dry	SURCOND in (1, 7:8)
Slippery	SURCOND in (2:6, 9)
Other	SURCOND ^in (1:9)

Road curvature: Road curvature was defined using the Alignment variable (NASS CDS variable name ALIGNMNT) as seen in Table 23. The “Other” category included crashes where the road curvature was coded as unknown.

Table 23. Road curvature definitions

Road Curvature	SAS Coding Definition (NASS CDS Variables)
Straight	ALIGNMNT=1
Curved (right & left)	ALIGNMNT in (2, 3)
Other	ALIGNMNT ^in (1:3)

Impact direction: Rollovers were identified as those with primary damage from overturn (SAS coding definition TDD1=“O”) as shown in Table 24. Other occupant cases analyzed in NASS CDS were sorted by impact direction using the CDC variables that describe damage distribution according to the Collison Damage Classification system (SAE 1980). This classification was based on the area of first contact as well as on principal direction of force and area of greatest deformation or contact (Table 25). The categories used included frontal oblique crashes following previously defined methods (NHTSA, 2015b) as well as frontal, side, and rear crashes, defined on similar principles. Cases with missing CDC variables were classified using the accident type variable (NASS CDS variable name ACCTYPE) when possible, as shown in Table 26. Vehicles that were identified as the rear-impacted vehicle in the “rear end” and “forward impact” configurations were assumed to be rear impacts.

Table 24. Impact direction definition (overturn)

<table>
<tr><th colspan="4">SAS Coding Definition</th><th rowspan="3">Impact Direction</th></tr>
<tr><th rowspan="2">TDD1</th><th colspan="3">CDC Variables</th></tr>
<tr><th>GAD1</th><th>SHL1</th><th>DOF1</th></tr>
<tr><td>O</td><td>Any</td><td>Any</td><td>Any</td><td>Rollover</td></tr>
</table>

Table 25. Impact direction definitions (anything other than overturn)

SAS Coding Definition			Impact Direction
GAD1	SHL1	DOF1	
F	L	11 -12 o'clock	Frontal Oblique
		1-3 o'clock	Other
		9-10 o'clock	Side
		Unknown	Frontal Oblique
	R	9-11 o'clock	Other
		12-1 o'clock	Frontal Oblique
		2-3 o'clock	Side
		Unknown	Frontal Oblique
	Y	12 o'clock	Frontal
		11 o'clock	Frontal Oblique
		1-3 o'clock	Other
		9-10 o'clock	Side
		Unknown	Frontal Oblique
	Z	12 o'clock	Frontal
		1 o'clock	Frontal Oblique
		2-3 o'clock	Side
		9-11 o'clock	Other
		Unknown	Frontal Oblique
	D	12 o'clock	Frontal
		11 o'clock 1 o'clock	Frontal Oblique
		2-3 o'clock 9-10 o'clock	Side
		Unknown	Frontal
	C	12 o'clock	Frontal
		11 o'clock 1 o'clock	Frontal Oblique
		2-3 o'clock 9-10 o'clock	Other
		Unknown	Frontal
	Unknown	12 o'clock	Frontal
		11 o'clock 1 o'clock	Frontal Oblique
		2-3 o'clock 9-10 o'clock	Other
		Unknown	Frontal

SAS Coding Definition			Impact Direction
GAD1	SHL1	DOF1	
L	F, Y	11-12 o'clock	Frontal Oblique
		7-10 o'clock	Side
		1-5 o'clock	Other
	B, Z	8-11 o'clock	Side
		7 o’clock	Rear
		12-5 o'clock	Other
	P, D	7-11 o’clock	Side
		12-5 o’clock	Other
	Any	6 o'clock	Rear
		Unknown	Side
	Unknown	7-10 o'clock	Side
		11-12 o'clock	Frontal Oblique
R	F, Y	12-1 o'clock	Frontal Oblique
		2-5 o'clock	Side
		7-11 o'clock	Other
	B, Z	1-4 o'clock	Side
		5 o’clock	Rear
		7-12 o'clock	Other
	P, D	1-5 o’clock	Side
		7-12 o’clock	Other
	Any	6 o'clock	Rear
		Unknown	Side
	Unknown	2-5 o'clock	Side
		12-1 o'clock	Frontal Oblique
B	Any	4-8 o'clock	Rear
		3 o’clock 9 o’clock	Side
		10-2 o'clock	Other
		Unknown	Rear
T, U	Any	Any	Other

Table 26. Impact direction definition (unknown CDC)

CDC Variables			ACCTYPE	Impact Direction
GAD1	SHL1	DOF1		
Unknown	Any	Unknown	21:23, 25:27, 29:31, 35, 37, 39, 41	Rear

Restraint use: Restrained occupants were those identified with seat belt or child restraint using the following NASS CDS restraint use variables: CHTYPE (1:8), MANUSE (2:8, 12:18), and ABELTUSE (1).

Age group: Three age groups were used for fatality and AIS injury analysis: 0-15, 16-59, and 60+. Analysis by cost and attributable fatality were not disaggregated by age since the parameters for these analyses represented average values across age groups.

Sex: Results can be analyzed by sex (NASS CDS variable name SEX), with males coded with the variable of SEX=1 and females as SEX=2:6.

Seat position: Drivers were identified using the seat position variable (NASS CDS variable name SEATPOS) coded as SEATPOS=11, front-seat passengers as SEATPOS=12:19, and rear row occupants identified as any occupant in a known seat position other than the first row (SEATPOS=21:59).

Impact side: For side and frontal oblique impacts, front and rear seat occupants can be further broken down as near-side or far-side occupants (Table 27).

Table 27. Impact side definition for side or frontal oblique impact

Impact	Impact Side	SAS Coding Definition (NASS CDS Variables)	
		Seat Position (NASS CDS Variable SEATPOS)	CDC Variables
Near-side front	Left	11	GAD1=L or SHL1=L or DOF1 in (9 o'clock to 11 o'clock) or (SHL1=Y & DOF1=Unknown)
	Right	13	GAD1=R or SHL1=R or DOF1 in (1 o'clock to 3 o'clock) or (SHL1=Z & DOF1=Unknown)
Far-side front	Right	11	GAD1=R or SHL1=R or DOF1 in (1 o'clock to 3 o'clock) or (SHL1=Z & DOF1=Unknown)
	Left	13	GAD1=L or SHL1=L or DOF1 in (9 o'clock to 11 o'clock) or (SHL1=Y & DOF1=Unknown)
Near-side rear	Left	21, 31, 41, 51	GAD1=L or SHL1=L or DOF1 in (9 o'clock to 11 o'clock) or (SHL1=Y & DOF1=Unknown)
	Right	23, 33, 43, 53	GAD1=R or SHL1=R or DOF1 in (1 o'clock to 3 o'clock) or (SHL1=Z & DOF1=Unknown)
Far-side rear	Right	21, 31, 41, 51	GAD1=R or SHL1=R or DOF1 in (1 o'clock to 3 o'clock) or (SHL1=Z & DOF1=Unknown)
	Left	23, 33, 43, 53	GAD1=L or SHL1=L or DOF1 in (9 o'clock to 11 o'clock) or (SHL1=Y & DOF1=Unknown)

Injury body region: Body region categories correspond to the AIS-coded body region with the exception of face and neck injuries (which were combined into one bin), and spinal injuries (which were separated by level) as listed in Table 28. For cases from NASS CDS 2010 and later, originally hard-coded with AIS 2005/08, the categorization was based on the body region and specific structure digits in the translated AIS 1990/98 code. For AIS 2005/08 codes without a recommended AIS 1990/98 translation code, the hard-coded AIS 2005/08 body region and specific structure digits were used to bin the injury by body region.

Table 28. Definition of injury region categories

AIS 1990/98 Injury Code		Injury Category in Projection Model
Body Region (REGION90)	**Specific Structure (STRUSPEC)**	
1	All	Head
2 or 3	All	Face/Neck *(includes all non-spinal neck injuries)*
4	All	Thorax
5	All	Abdomen
6	02, 50, 59	Cervical Spine
6	04, 06, 60, 69, 70, 79	Thoracic/Lumbar Spine
7	All	Upper Extremity
8	All	Lower Extremity
9	All	Unspecified

2.8 High Leverage Check

Model results were affected by the original NASS CDS case weights for source cases, as well as by reweighting using NASS GES and FARS cases, and by the subsequent adjustments made to each case to apply trends and countermeasures included in the model. As in retrospective studies, there was potential for individual cases with high weight relative to other cases in a given category, i.e., high leverage cases, to unduly influence projection results. The potential effects of high-weight cases can become even more pronounced as data is disaggregated and analyses become more granular and focused on specific types of crashes. In a conventional retrospective NASS CDS study, analysis categories that could potentially be affected by high leverage cases can be identified by flagging calculations based on fewer than 10 to 20 individual cases in the source dataset, or those that rely on one or more particularly high-weight individual source cases. However, these strategies do not work for the analysis of projection results because the source cases have each been reweighted and divided into many pseudo-cases.

Therefore, the trend-adjusted source cases were reviewed by analysis category to identify individual categories that appeared to be affected by high-leverage cases. This review occurred after trends were applied but before countermeasures were applied. Average case weight was calculated for the trend-adjusted source cases in each of 866 analysis categories that will be used ultimately for analysis of projected results (e.g., MAIS 3+ injured drivers in rollover crashes). As a first step, categories with high average case weight were identified. Next, cases in the identified categories were reviewed in detail to determine if one or more individual high-leverage cases could be unduly influencing the results for each identified category.

The threshold for "high" average case weight varied by injury severity. Analysis categories that included low-severity cases had much higher average case weights than categories that included high-severity cases since lower-severity cases are assigned higher case weights in NASS CDS and they are further upweighted in the projection model to account for under-counting of cases that are not reported to police or do not involve towed vehicles. Therefore, the threshold average case weight for further review of a category for high-weight cases was based on the distribution of case weights at each MAIS level. Figure 9 illustrates the distribution of case weights in the trend-adjusted datasets by MAIS severity. The sizes of the bubbles in the plot are proportional to the number of cases at each weight level. Also marked and listed in Table 29 are the mean weights for all cases at each severity level and the mean weight plus mean absolute deviation (mean + MAD) of the weights in each category.

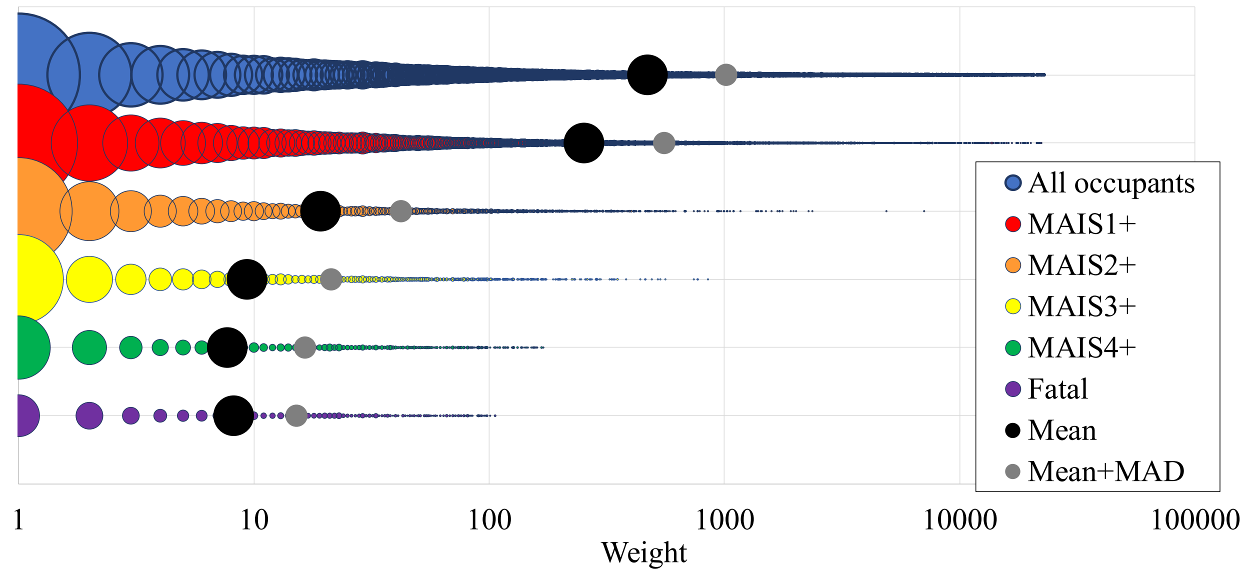


Figure 9. Bubble plot of case weight distribution for harm measures

(Bubble size is proportional to the number of cases at a given weight in the trend-adjusted dataset)

Table 29. Summary of all case weights in the trend-adjusted dataset by injury severity

Case Severity	Case Weight Mean	Case Weight Mean + MAD
All occupants	471	1017
MAIS 1+ injured occupants	253	555
MAIS 2+ injured occupants	19.2	42.2
MAIS 3+ injured occupants	9.4	21.3
MAIS 4+ injured occupants	7.7	16.5
Fatally injured occupants	8.2	15.2

To identify cases with high average case weight for further review, analysis categories with mean weight above the mean + MAD for its corresponding severity level were selected for scrutiny. For example, as shown in Table 30, the average case weight for analysis categories involving fatally injured occupants (such as fatalities by pre-crash scenario or fatalities by impact direction) were compared to the case weight mean plus MAD of 15.2 from Table 29. Categories of occupants with at least one injury assigned an estimated cost were compared to the case weight distribution for MAIS 1+ cases.

Of the 866 sets of analysis categories reviewed, most had mean case weights within the mean + MAD for their corresponding severity levels in the trend-adjusted dataset. Only eight analysis categories had mean case weights greater than the mean + MAD for their corresponding severity level:

- MAIS 3+ injured occupants, age 0-15 years in rear crashes (Figure 10),
- MAIS 3+ injured occupants in the rear seat in rear crashes (Figure 11),
- MAIS 3+ injured occupants in CUVs in all crashes, or disaggregated into frontal, frontal oblique, side, or rear crashes (Figure 12), and
- MAIS 3+ injured occupants in vans in rear crashes (Figure 12).

The mean case weight for all these categories exceeded the mean + MAD of 21.3 that was calculated across all MAIS 3+ cases. Each of these categories was reviewed to understand how high-weight cases in these categories could affect the reliability of results in these analyses. Figure 10 through Figure 12 show the average case weights for occupants in the categories under review.

Three categories involving seriously injured occupants in rear crashes had especially elevated average case weights. All three of these categories included the same single case involving a rear impact with a child in the rear seat of a CUV. This single case had an original NASS CDS case weight of 1445.3,[16] and was upweighted further by the trends applied in the model. Vehicle type trends, in particular, substantially increased this case's weight since a relatively small number of CUV cases among the source cases were upweighted to represent the growing number of CUVs expected to be in the future fleet. This case weight had substantial leverage in these analyses because of the case's high weight combined with the relatively small number of cases in these disaggregated analyses, essentially preventing analysis at this level of disaggregation. Therefore, this case was treated as an outlier, with the potential to distort results involving rear impact, rear seat, and child cases.

Instead of completely removing the potential outlier case from the source dataset, this case was downweighted to reduce its high-leverage effects. The downweighting was applied at the stage of the model where cases were re-weighted to estimate national totals, described in Sections 2.3.1 and 2.4.2. Thus, the whole model was re-run with the revised weight for this source case. The case weight of this potential outlier case was set to equal the mean weight for other cases in the bin of restrained, 0 to 15-year-old passengers with MAIS 3+ injuries. As shown in Figure 13, reweighting this single case brought the mean case weight of all analysis categories that had previously been flagged as involving potential high-leverage cases closer to the mean weights for MAIS 3+ injury cases (Figure 13). After the weight adjustment, the mean case weights for two of the three flagged analysis categories that included the outlier case (MAIS 3+ injured child and rear seat occupants in rear crashes) were below the thresholds set for their corresponding injury

[16] The case was defined by NASS CDS case identification variables: YEAR 2015, PSU 43, CASENO 126, VEHNO 2, OCCNO 3.

severity levels. The mean case weight for MAIS 3+ injured CUV occupants in rear crashes was improved, but still exceeded the threshold.

Table 30. Summary of high leverage check

Harm and Analysis Subgroup	No. of categories	Compared to case weight distribution for severity level	No. of categories with Avg Wt> Mean + MAD for corresponding severity level
Occupants by pre-crash scenario	8	Occupants	0
MAIS 2+ by pre-crash scenario	8	MAIS 2+	0
MAIS 3+ by pre-crash scenario	8	MAIS 3+	0
MAIS 4+ by pre-crash scenario	8	MAIS 4+	0
Fatalities by pre-crash scenario	8	Fatalities	0
Cost by pre-crash scenario	8	MAIS 1+	0
Occupants by impact direction	5	Occupants	0
MAIS 2+ by impact direction	5	MAIS 2+	0
MAIS 3+ by impact direction	5	MAIS 3+	0
MAIS 4+ by impact direction	5	MAIS 4+	0
Fatalities by impact direction	5	Fatal	0
Cost by impact direction	5	MAIS 1+	0
MAIS 3+ by age & impact direction	18	MAIS 3+	1
MAIS 3+ by seat position & impact direction	18	MAIS 3+	1
MAIS 3+ by vehicle type & impact direction	30	MAIS 3+	6
Occupants by injury severity & impact direction	30	Occupants	0
AIS 1+ by injury region & impact direction	54	MAIS 1+	0
AIS 2+ by injury region & impact direction	54	MAIS 2+	0
AIS 3+ by injury region & impact direction	54	MAIS 3+	0
Occupants by intersection type & pre-crash scenario	45	Occupants	0
Occupants by road curvature & pre-crash scenario	18	Occupants	0
Occupants by light condition & pre-crash scenario	27	Occupants	0
Occupants by road type & pre-crash scenario	36	Occupants	0
Occupants by surface condition & pre-crash scenario	18	Occupants	0
Occupants by impact side & pre-crash scenario	12	Occupants	0
MAIS 3+ by impact side & pre-crash scenario	12	MAIS 3+	0
MAIS 3+ by injury region & impact side	72	MAIS 3+	0
MAIS 2+ by sex	2	MAIS 2+	0
MAIS 3+ by sex	2	MAIS 3+	0
MAIS 4+ by sex	2	MAIS 4+	0
Fatalities by sex	2	Fatalities	0
MAIS 2+ by sex, impact mode, & age	45	MAIS 2+	0
MAIS 2+ by sex, impact mode, & injury region	96	MAIS 2+	0
MAIS 3+ by sex, impact mode, & age	45	MAIS 3+	0
MAIS 3+ by sex, impact mode, & injury region	96	MAIS 3+	0
Totals	866		8

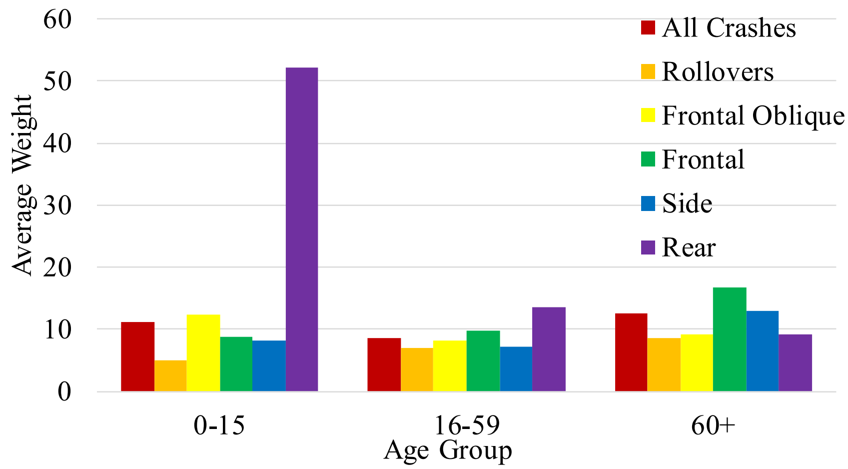


Figure 10. Average trend-adjusted case weights for MAIS 3+ injured occupants by age

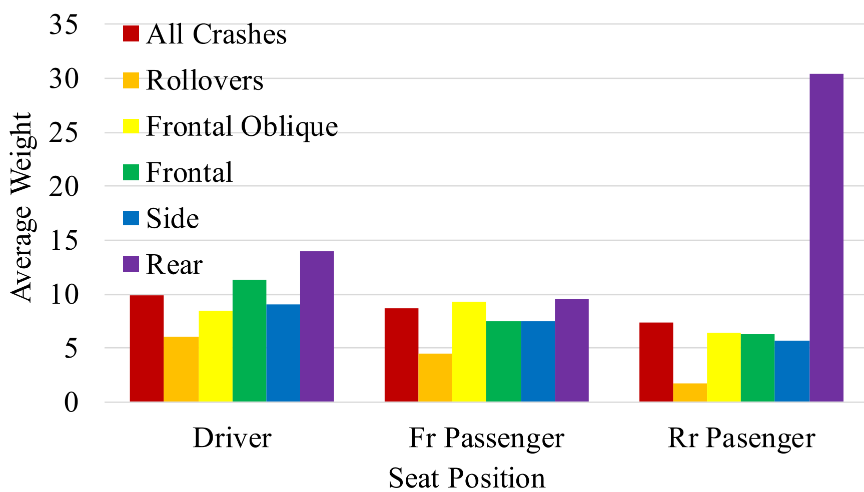


Figure 11. Average trend-adjusted case weights for MAIS 3+ injured occupants by seat position

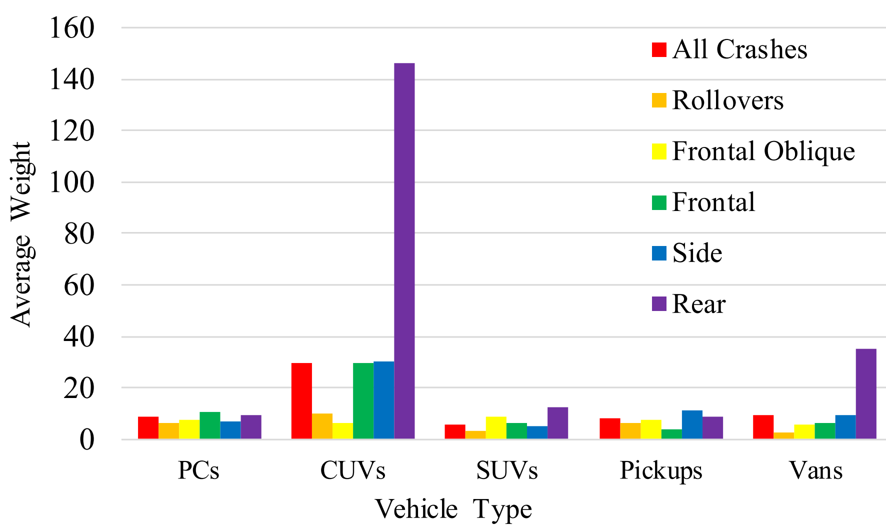


Figure 12. Average trend-adjusted case weights for MAIS 3+ injured occupants by vehicle type

The remaining MAIS 3+ categories with case weight mean + MAD exceeding the 21.3 case weight average for all MAIS 3+ cases were all disaggregated by vehicle type. These categories were vans in rear impacts and CUVs in almost all impact directions. The CUV categories did not appear to be affected by individual high-weight outlier cases, but instead seemed to be inflated by the overall upweighting of CUV cases in the application of vehicle type trends. Given this explanation for high average weight in these categories, results for these categories may be reasonable in spite of exceeding the mean case weight of MAIS 3+ cases overall but these results should be interpreted with caution.

In contrast, the category involving rear impacts in vans did seem to be overly influenced by a single case. Although the weight of that single case was only 350 (after application of trends), the category included only 14 raw cases, which dramatically increased the influence of that single case. This result suggested that disaggregating down to this level (serious injury cases in van rear impacts) was simply not reasonable. Therefore, rather than downweight this single high-leverage case (which did not appear to have high-leverage effects on any of the other analysis categories it affected), it was concluded that this category had an insufficient number of cases for analysis.

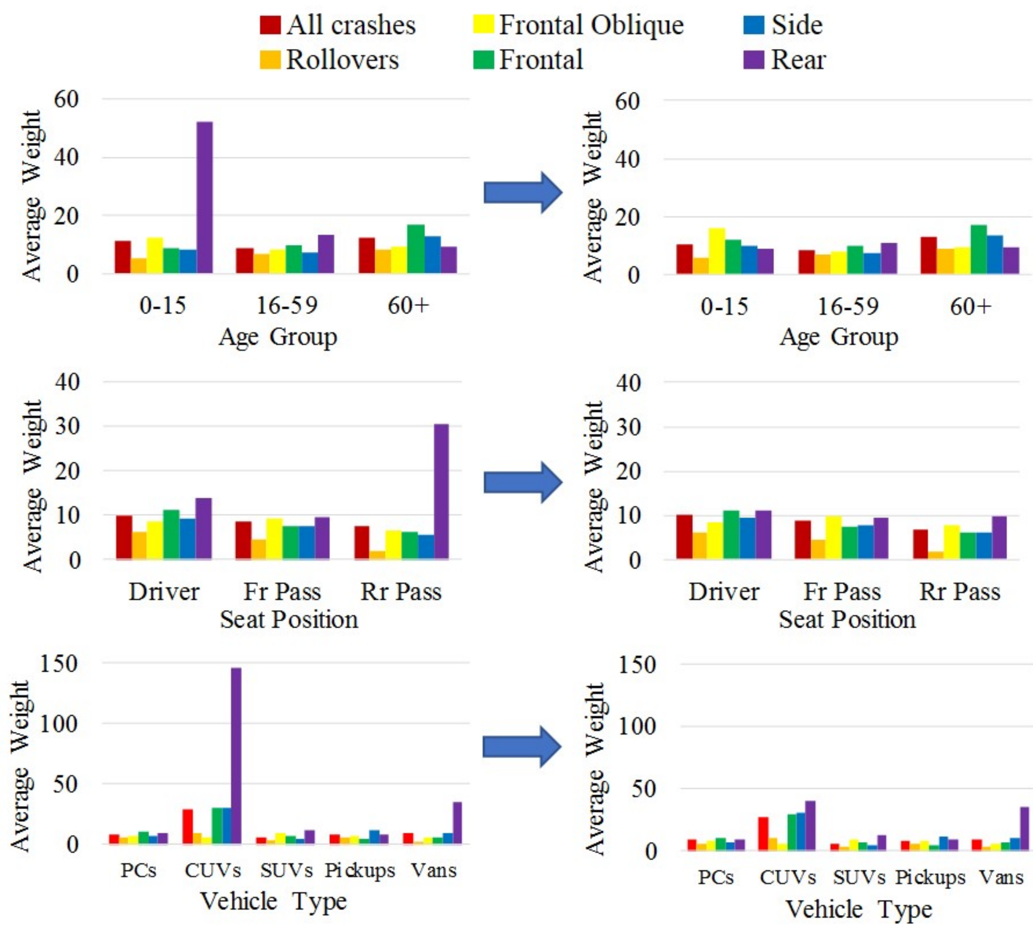


Figure 13. Average case weights before (left) and after (right) downweighting high leverage case (involving child in rear of CUV in a rear impact)

In summary, of the 866 sets of analysis categories reviewed, most had mean case weights within the mean + MAD for their corresponding severity levels in the trend-adjusted dataset. This result suggested that the level of granularity in these disaggregated datasets was reasonable overall, and that analysis by multiple categories of variables is likely appropriate. Exceptions included analyses involving CUVs. These cases were substantially upweighted in the model so that categories of CUV cases may be estimated based on a relatively small number of high-weight cases, which suggests that results should be used cautiously. Caution is also needed when interpreting any crash categories that are broken down by both vehicle type and impact direction. In particular, analyses of low case-count categories, such as rear impacts in vans may have insufficient numbers for analysis.

In addition to the quantitative analysis that identified the eight categories above exceeding the case weight mean + MAD for comparable cases at the same injury severity, average case weight in comparable categories was also reviewed qualitatively for the 866 analysis categories in Table 30. This qualitative review showed that MAIS 3+ injured occupants with thoracic-lumbar (T/L) spine injuries in frontal crashes was another category that had a relatively high mean case weight (Figure 14). Although this average case weight was lower than the mean plus MAD threshold for MAIS 3+ cases, it was higher than weights for comparable analysis categories. Several higher-weight cases contributed to this high mean weight, rather than a single outlier case. While the average weight was not dramatically different from comparison categories, and downweighting of source cases did not seem warranted, this high average weight suggested that conclusions regarding thoracic-lumbar spine injuries in frontal crashes in the projection models be made cautiously.

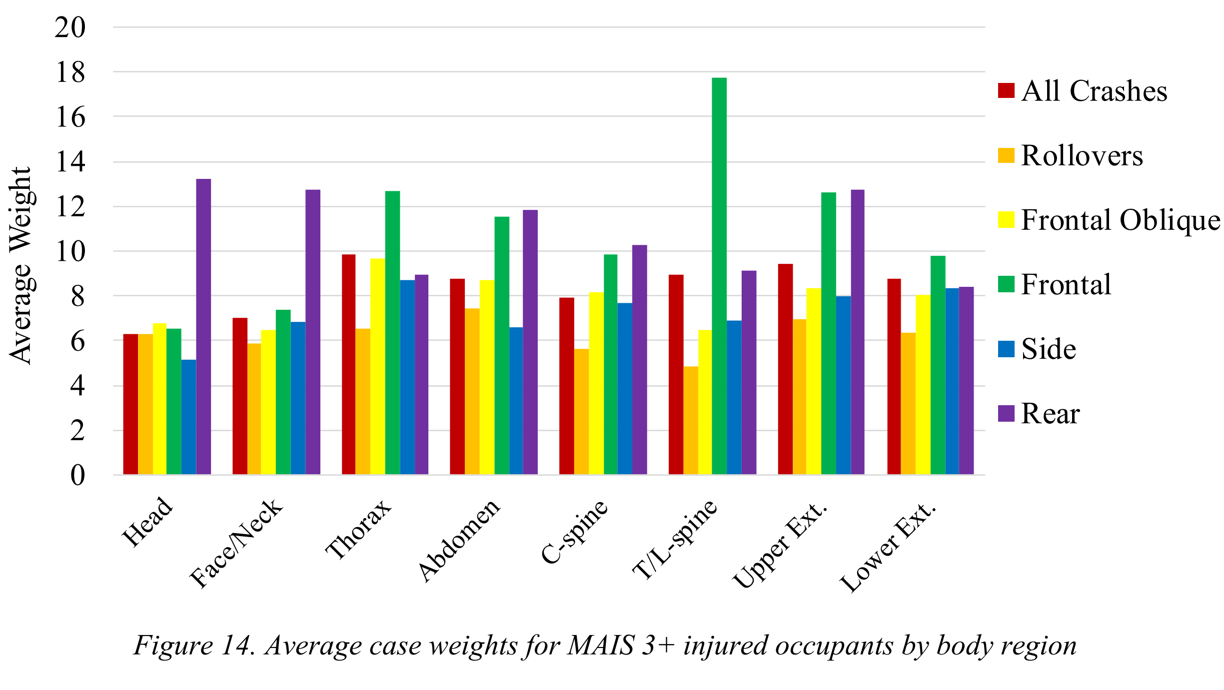


Figure 14. Average case weights for MAIS 3+ injured occupants by body region

3 Model Evaluation Against Crashes and Injuries in 2013–2015

3.1 Model Evaluation Objective and Method

The accuracy of the model projections for 2020 to 2030 cannot be validated using current crash and injury data. Therefore, the capability of the projection model to predict future crash and injury outcomes was evaluated by applying the same model methodology to a historical dataset for the projection of 2014 crash outcomes. Where the main projection model relies primarily on crash, vehicle, and population data from 2004 to 2015 to predict crash frequency and outcome in 2020 to 2030, the *evaluation version of the model* relied on retrospective data from 2004 to 2012 to predict 2014 crash frequency and outcomes (Figure 15). Predicted 2014 results were then compared to real-world results averaged over a 3-year period from 2013 to 2015 to evaluate the model's ability to identify future crash safety issues. An averaged 3-year period was necessary to approximate a comparison dataset for 2014 results because a single year of crash data has an insufficient number of cases for analysis.

The goal for the evaluation model was to replicate the function of the model in all respects, except that the evaluation version predicted outcome in 2014 rather than in a future year, allowing for comparison of the predicted outcome to actual, real-world outcomes. However, predicting outcome in 2014 for comparison to averaged 2013 to 2015 real-world data necessitated a number of adjustments to the structure of the model design (Table 31). The most obvious change in the evaluation model was that 2013 to 2015 cases in the retrospective dataset could not be used to make the projection. Therefore, the evaluation projection was based on NASS CDS cases from 2004 to 2012. For reweighting procedures in the evaluation version of the model, the 2013 to 2015 NASS GES and FARS cases used in the projection model were replaced with cases from 2010 to 2012.

Application of the evaluation model was complicated by the fact that the 2013 to 2015 NASS CDS data used to develop a dataset for comparison did not include any occupants in vehicles 10 years old or older.[17] In the full projection model, case occupants in early model vehicles (MY<2005) in the retrospective dataset were weighted to represent cases in older vehicles (older than 16 at the time of the crash) in the future crashes. However, since the 2013 to 2015 comparison dataset had no occupants in vehicles older than 9 years old at the time of the crash, it had no cases in vehicles 10 years old or older and very few occupants in early model (MY<2005) vehicles. Therefore, cases in vehicles older than 9 years old and cases in MY<2005 vehicles were also excluded from the evaluation projection model. Thus, the projected 2014 dataset was based on 2004 to 2012 retrospective occupant cases in 0- to 9-year-old MY2005+ vehicles. These retrospective cases were reweighted using the same reweighting procedures used in the full projection model (see Section 2.3), with cases from 2010 to 2012 FARS and GES that were limited to occupants in vehicles that were MY2005+ and were 0 to 9 years old at the time of the crash.

The limitations on vehicle age and model year in the evaluation version of the model were necessary to ensure that the evaluation was based on the same source data (NASS CDS, NASS

[17] Starting in crash year 2009, NASS CDS does not contain injury data for occupants in vehicles 10 years old or older at the time of the crash and occupants without injury data were not included in the VRTC projection model.

GES, and FARS) as the original projection model. The only crash-years available for the evaluation were the 2004 to 2015 datasets that were used to develop the projection model. Later crash-years were not available because crash year 2015 was the last full year for which NASS CDS and GES cases were available, and the model is not currently structured to use more recent CISS and CRSS cases. Earlier crash-years were not available because crashes prior to 2004 would not have included any of the MY2005+ vehicles that were used in the evaluation. Therefore, the data from the 2004 to 2015 crash-years had to be divided into a 2004 to 2012 dataset to make a 2014 projection and a 2013 to 2015 comparison dataset to evaluate the projection. A total of 18,816 raw NASS CDS occupant cases were available for the 2004 to 2012 dataset of cases in 0 to 9 y.o. MY2005+ vehicles and 7,490 raw NASS CDS occupant cases were available for the 2013 to 2015 comparison dataset. A resulting limitation of this method for evaluating the reliability of the model is that projections had to be made using fewer crash data years than were used in the full projection model. A related limitation is that the 3-year comparison dataset was very small compared to a typical data search that would use 10 or more years of case data to characterize national results. Therefore, the 2013 to 2015 comparison dataset could only be used to evaluate broad categories of crashes and outcomes in the evaluation version of the model. There were simply not enough cases in the 2013 to 2015 comparison dataset to disaggregate it by multiple categories such as seat position *and* impact direction, or age *and* pre-crash scenario. Even disaggregated by broad categories such as impact direction, the comparison data must be interpreted carefully because of the relatively small number of cases in this 3-year dataset, which led to low cell count when disaggregated. In other words, the evaluation version of the model cannot be used to definitively validate the model, but instead was used to get a broad assessment of the model's reliability. Crash categories where the predicted crash outcomes varied from the real-world results should flag crash types that need to be examined closely and interpreted with caution, but such mismatches should not automatically invalidate the projection model results.

The trends and countermeasures applied to the evaluation model cases included all the same trends and countermeasures to be applied to the full projection model. However, while the AF used for each trend and countermeasure in the full projection model were based on parameters and penetration rates relevant to the stepping-stone dataset years of 2013 to 2015 and the projection years of 2020, 2025, and 2030, the evaluation version of the model relied on estimates of these parameters for the stepping-stone dataset years of 2010 to 2012 and for the projection year 2014. The datasets used to develop the projection datasets and the evaluation version of the dataset are compared in Table 31.

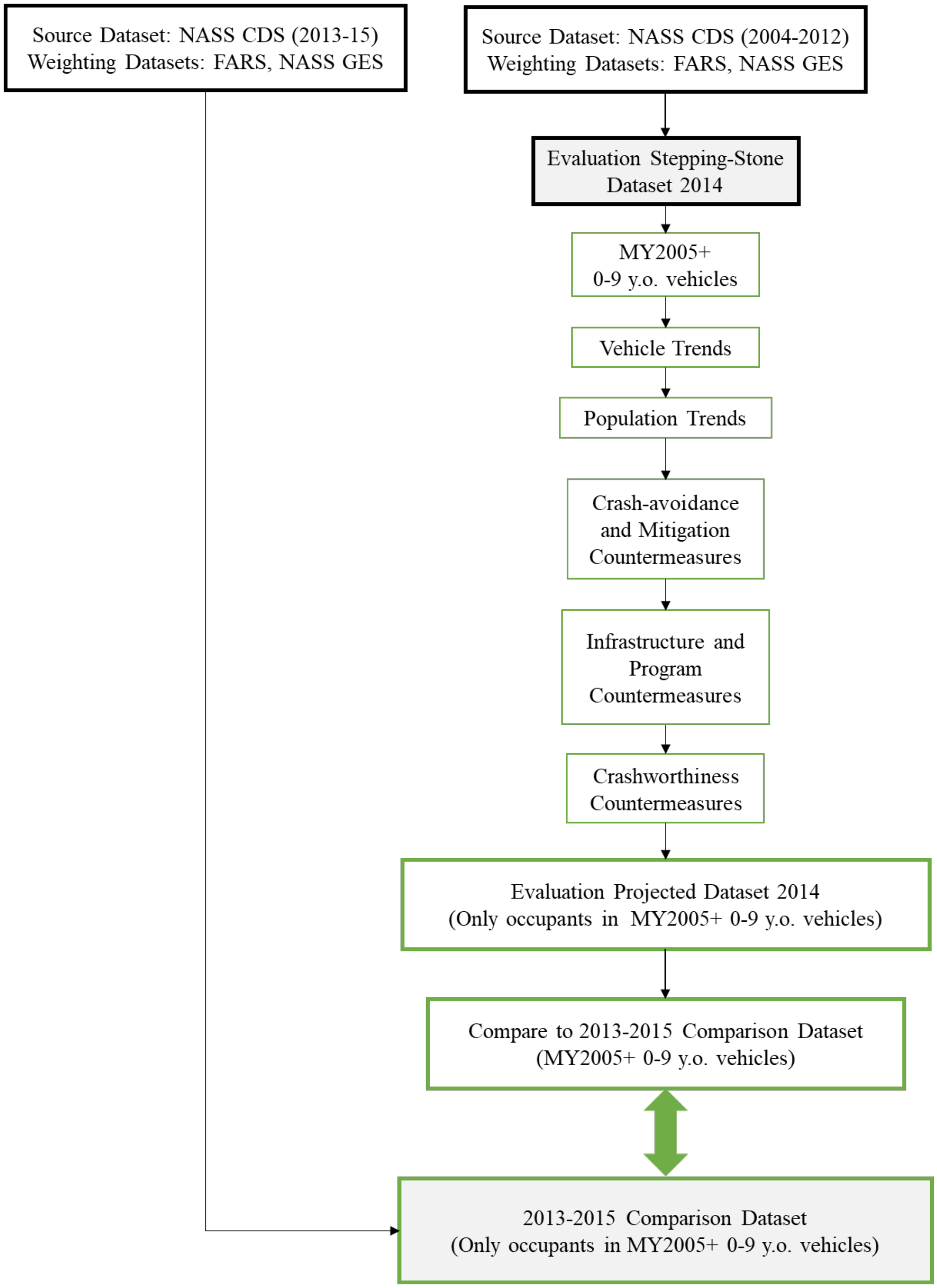


Figure 15. Design of the evaluation version of the model

Table 31. Data years used in evaluation model compared with those used in projection model

	Projection			**Evaluation**
Target output year	**2020**	**2025**	**2030**	**2014**
Baseline retrospective dataset for comparison	2004-2015 NASS CDS Reweighted with 2004-2015 NASS GES & FARS			No baseline retrospective
Source dataset for projection	2004-2015 CDS Reweighted with 2004-2015 NASS GES & FARS			2004-2012 CDS
Subsets of projection dataset by model year	MY<2005 MY2005+			MY2005+ only
Reweighting datasets for stepping-stone dataset	GES: 2013-2015 FARS: 2013-2015			GES: 2010-2012 FARS: 2010-2012
Vehicle age range used for GES/FARS cases for reweighting the older MY subset (MY<2005)	16+ y.o.	16+ y.o.	16+ y.o.	Not included
Vehicle age range used for GES/FARS cases for reweighting the newer MY subset (MY2005+)	0-15 y.o.	0-20 y.o.	0-25 y.o.	0-9 y.o. only
Years used for ratio of projected/past rates to calculate trend AF for driver and passenger crash exposures	$\frac{2020}{2013-2015}$	$\frac{2025}{2013-2015}$	$\frac{2030}{2013-2015}$	$\frac{2014 \,\&\, 2013-2015^{18}}{2010-2012}$
Years used for ratio of projected/past rates to calculate trend AF for restraint use	$\frac{2020}{2013-2015}$	$\frac{2025}{2013-2015}$	$\frac{2030}{2013-2015}$	$\frac{2014}{2010-2012}$
Dataset used to establish proportion of vehicle type in past relative to projection year	2020 Stepping-Stone	2025 Stepping-Stone	2030 Stepping-Stone	2014 Stepping-Stone
Real-world data for evaluation of accuracy	None available	None available	None available	2013-2015 Comparison Dataset NASS CDS (reweighted with GES and FARS 2013-2015) MY2005+, 0-9 y.o.

[18]Although the values used to calculate the AF for driver and passenger crash exposures in the evaluation model were calculated primarily based on estimates projected for 2014, the estimated increase in the proportion of cases that would involve 0- 9-year-old MY2005+ vehicles was averaged over 2013 to 2015 to be compatible with the real-world 2013 to 2015 dataset ultimately used for comparison.

Countermeasures developed as “hypothetical” to explore the potential effect of safety measures that are not implemented and whose future likelihood of being implemented is unknown (e.g., distraction reduction) were not included in the evaluation version of the model. Although the evaluation version of the model was coded with all other (non-hypothetical) countermeasures, only those defined to have been implemented or begun penetrating by 2014 actually had any effect on the results. The countermeasures defined in the model with penetration greater than 0 percent by 2014, i.e., the countermeasures expected to affect the evaluation results, are listed in Table 32. The parameters used to apply each of these countermeasures in this version of the model are detailed in the countermeasure appendices of this report (Appendix C, D, E, and F). These appendices include definitions of the target population for each countermeasure, estimates of countermeasure effectiveness and penetration, and the information sources used to define these parameters. Summaries of all remaining countermeasures, including those to be used in applications of the model to explore the effects of future, hypothetical, or optional countermeasures will be included in the upcoming projection model results report (Mallory et al., in press) and/or any future reports for models that incorporate new or updated countermeasures for the first time.

The procedures designed to upweight lower-severity cases (to account for the exclusion of non-towed cases in NASS CDS and the under-reporting of low-severity cases to police) were applied in the evaluation version of the model, since the default for the model was to turn these optional steps “on.”

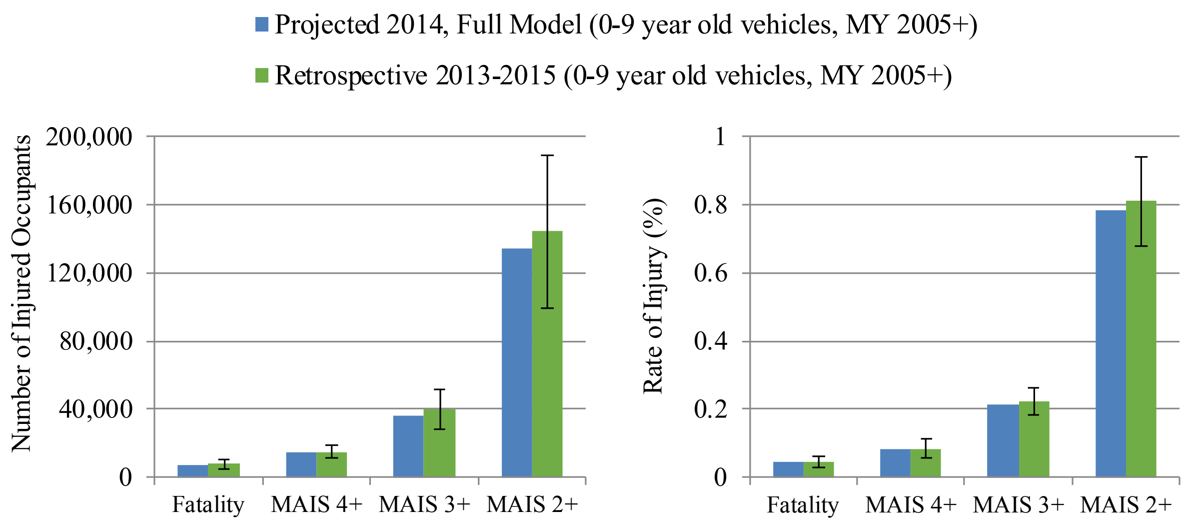
Table 32. Countermeasures affecting evaluation version of the model

	Countermeasures & Standards Updates
Crash avoidance countermeasures (Appendix C)	FMVSS No. 126 (ESC), FMVSS No. 138 (TPMS), NCAP 2004 update to rollover resistance, AEB with FCW, BSD, LDW
Crash mitigation countermeasures (Appendix D)	FMVSS No. 138 (TPMS), CIB component of AEB
Crashworthiness and occupant protection (Appendix E)	FMVSS No. 202 (Head Restraint), 208 (Advanced Air Bag), 214 (Side Impact), 216 (Roof Strength), 226 (Ejection Mitigation), 301 (Rear Impact), and NCAP 2011 update to front and side protection
Program and Infrastructure changes (Appendix F)	Maximum speed limit increases, red light cameras, rumble strips, cable median barriers

3.2 Model Evaluation Results

The results of the evaluation model, affected by all the trends coded in the model, as well as the countermeasures listed in Table 32, are shown in Figure 16 through Figure 22. The plots show the predicted outcome for crash year 2014 after countermeasures were applied to the model (Full Model projections, in blue). The Full Model projections for crash year 2014 can be compared to the corresponding average annual estimates for the 2013 to 2015 comparison dataset (in green) to evaluate the reliability of the model projection. All results are limited to occupants in vehicles that are less than 10 years old, since the comparison data was based on 2013 to 2015 NASS CDS cases, which have no injury data for occupants of older vehicles.

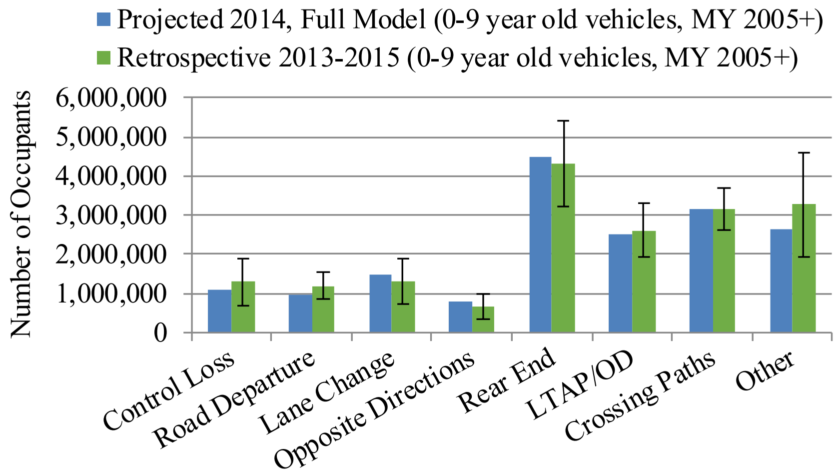
When aggregated across all crash and occupant types, the overall distribution of injury severity in the projected full model dataset was compared to the real-world 2013 to 2015 point estimates for the annual number of cases and rate of injury at each severity level in Figure 16. All projected values were well within the 95 percent confidence intervals (CI) shown for the 2013 to 2015 comparison dataset. The projections for all injury levels slightly underpredicted the real-world values, but never by more than 8.1 percent.



	Percentage Difference Between Projected and 2013-2015 Comparison Dataset (Retrospective)			
	Fatality	**MAIS 4+**	**MAIS 3+**	**MAIS 2+**
Number	-5.9%	-5.6%	-8.1%	-6.9%
Rate	-2.0%	-1.7%	-4.3%	-3.0%

Figure 16. Average annual injury frequency and rate by MAIS in evaluation model (95% CI shown for retrospective data only)

Figure 17 shows the total number of occupants in the dataset by pre-crash scenario, based on Swanson's crash-type taxonomy (Swanson et al., 2016). For every scenario, the projected annual number of occupants was within the 95 percent confidence interval for the annual number estimated from the 2013 to 2015 comparison dataset. Although some crash types were overestimated by the model (e.g., opposite direction crashes were 20.7% overestimated and lane change crashes were 12.0% overestimated), others were underestimated by the model (e.g., road departure and control loss cases were underestimated by more than 15%). However, the relative frequency of different crash types was similar in the projected data and the comparison 2013 to 2015 dataset. With the exception of occupants in crashes classified as "other," the rank-order of the number of crashes in each category in the projection matched the rank-order for the comparison dataset.

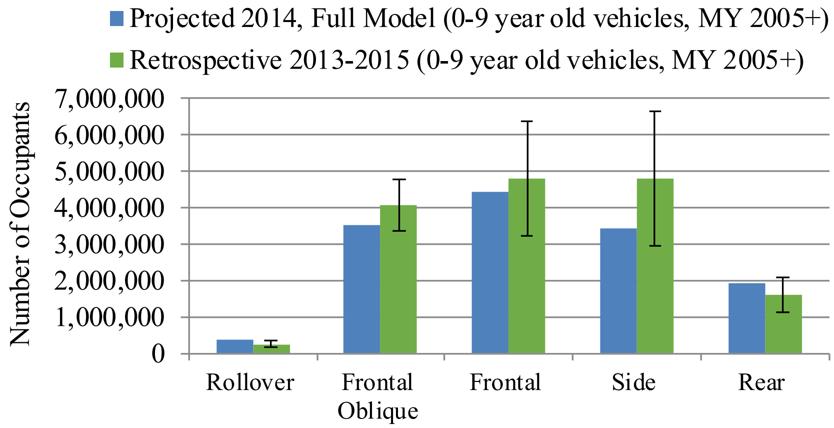


	Percentage Difference Between Projected and 2013-2015 Comparison Dataset (Retrospective)							
	Control Loss	**Road Departure**	**Lane Change**	**Opposite Directions**	**Rear End**	**LTAP/OD**	**Crossing Paths**	**Other**
Number	-16.1%	-19.2%	12.0%	20.7%	4.2%	-4.4%	0.1%	-19.5%

Figure 17. Average annual frequency of occupants in crashes by pre-crash scenario (LTAP/OD=left turn across path/opposite direction)

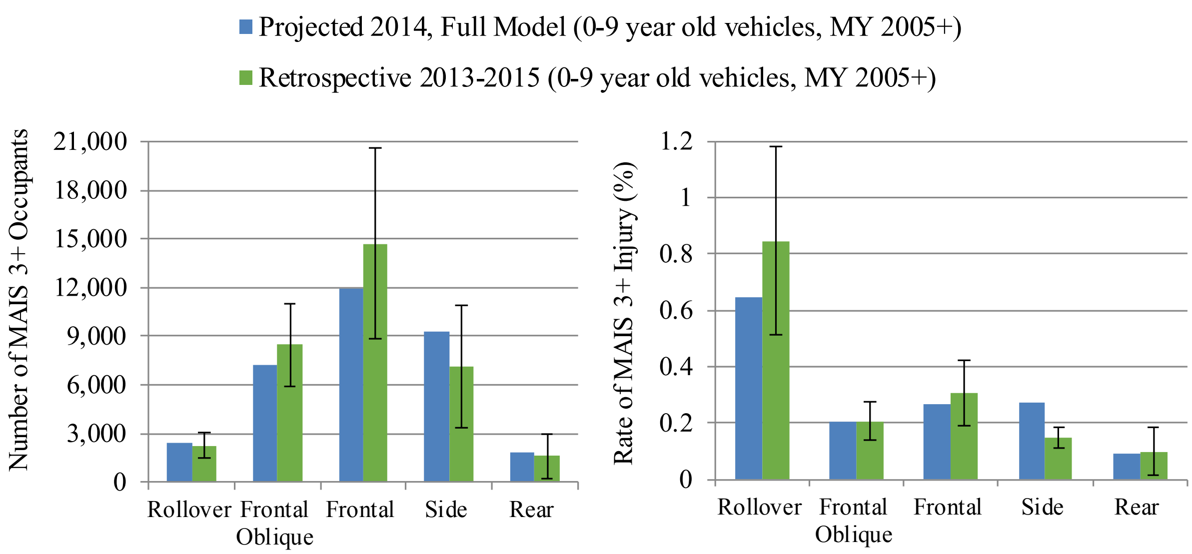
When the number of occupants in crashes was estimated by impact direction, the model estimates for 2014 were within the 95 percent confidence intervals for each planar impact category in the 2013 to 2015 comparison data. However, the projected number of rollover occupants overestimated the actual number documented in the 2013 to 2015 comparison dataset by 37.9 percent, exceeding the 95 percent confidence intervals on the comparison data. Relative to the point estimates for the 2013 to 2015 comparison dataset, the projected number of occupants in rear impact was high and the projected numbers of occupants in side and frontal oblique impact crashes was low, but still within the 95 percent confidence intervals. With respect to relative frequency by impact direction, side impact cases were more frequent than frontal oblique cases in the 2013 to 2015 comparison dataset, while the opposite was projected by the model.

Limiting the analysis to serious injury cases (MAIS 3+), the projected number of injured occupants was within the confidence interval of the estimated number for each impact direction in the comparison 2013 to 2015 dataset (Figure 19, left). Among projections of injury rate by impact direction (Figure 19, right), only the side impact rate of serious injury was outside of the confidence interval for the estimate of the injury rate in the 2013 to 2015 comparison dataset. While the estimated real-world rate of serious injury in side impacts in 2013 to 2015 was 0.15 percent (95% CI: 0.11-0.19%), the model-projected rate was 0.27 percent, an 82.8 percent overestimate. Additionally, although the projection suggested side impact was more frequent than frontal oblique crashes, the 2013 to 2015 comparison dataset showed that frontal oblique crashes were more frequent than side impacts.



	Percentage Difference Between Projected and 2013-2015 Comparison Dataset (Retrospective)				
	Rollover	**Frontal Oblique**	**Frontal**	**Side**	**Rear**
Number	37.9%	-14.3%	-7.3%	-28.6%	20.7%

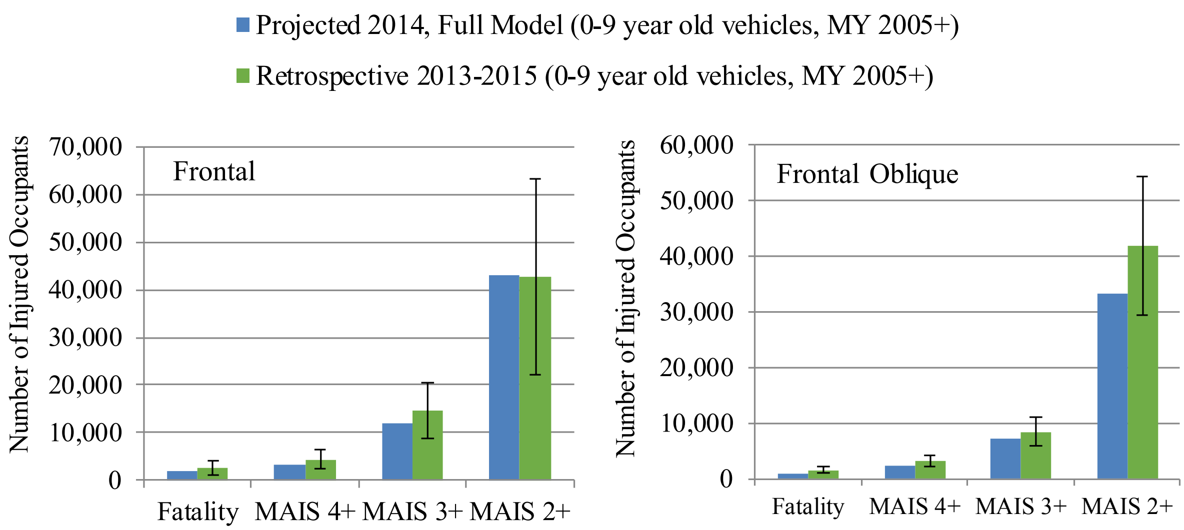
Figure 18. Average annual frequency of occupants in crashes by impact direction



	Percentage Difference Between Projected and 2013-2015 Comparison Dataset (Retrospective)				
	Rollover	**Frontal Oblique**	**Frontal**	**Side**	**Rear**
Number	5.5%	-14.3%	-18.7%	30.5%	12.8%
Rate	-23.5%	0.0%	-12.3%	82.8%	-6.5%

Figure 19. Average annual frequency and rate of MAIS 3+ injury cases by impact direction

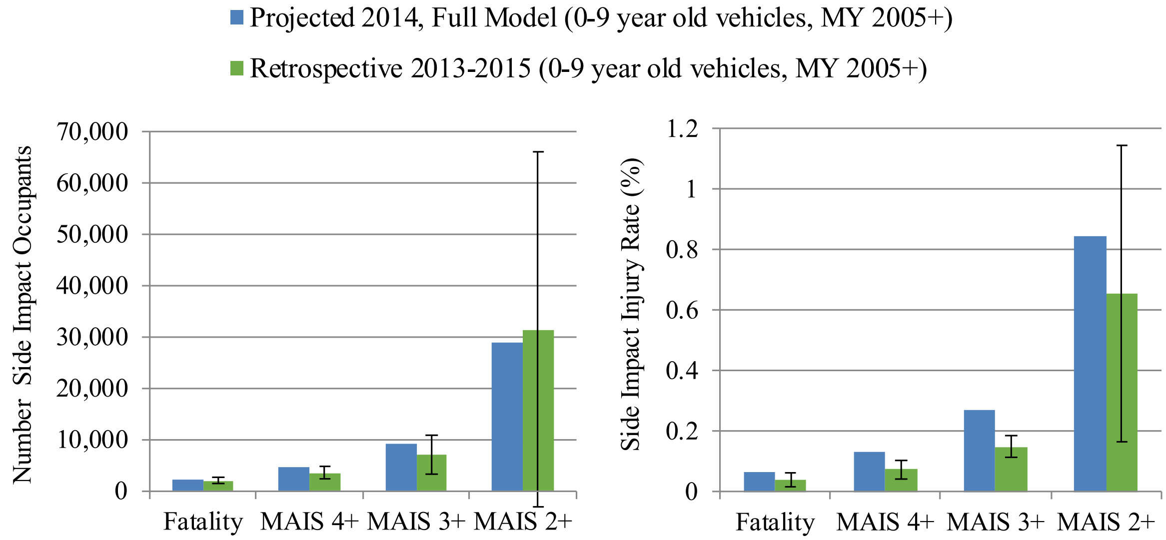
Although it is possible to further disaggregate the evaluation results, uncertainty in the 3-year comparison dataset grows as the number of cases in each bin is reduced. For example, when the results in Figure 19 were further explored by projecting the number and rate of injuries of several injury severities by impact direction, the 3-year dataset had progressively smaller numbers of source cases for comparison to higher-severity injuries, particularly for the rollover and high-severity rear impact categories. In spite of this uncertainty, the results were useful for evaluating whether the projection results were generally reasonable across impact direction and injury severities. The comparison of frontal, frontal oblique, and rear impact projections to the 2013 to 2015 comparison dataset showed that projected injury frequency and rate were within the 95 percent CI for both injury frequency and rates (shown only for frontal and frontal oblique frequency in Figure 20).



	Percentage Difference Between Projected and 2013-2015 Comparison Dataset (Retrospective)			
	Fatality	**MAIS 4+**	**MAIS 3+**	**MAIS 2+**
Frontal	-32.4%	-23.7%	-18.7%	0.5%
Frontal Oblique	-31.7%	-23.9%	-14.3%	-20.3%

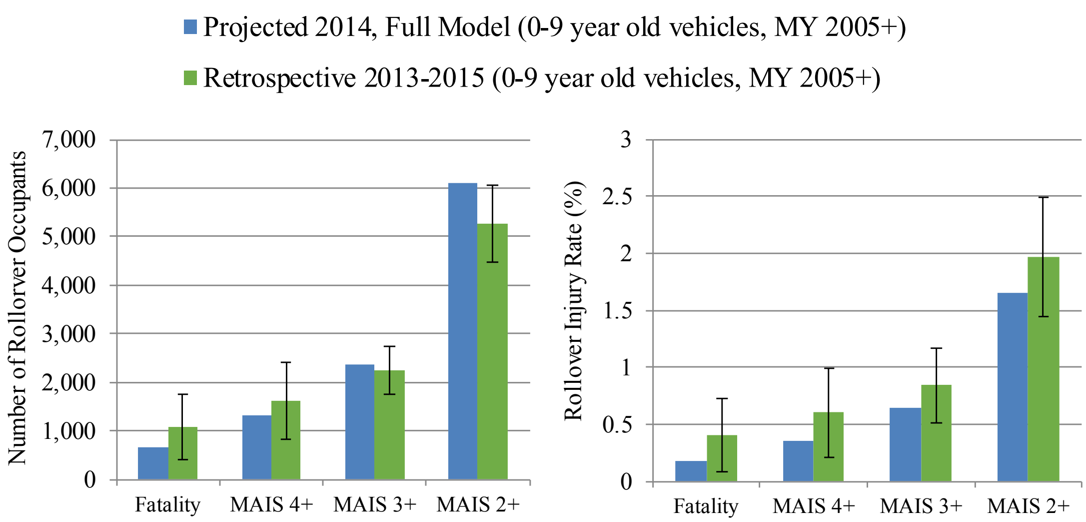
Figure 20. Average annual frequency of injury cases in frontal and frontal oblique crashes

In contrast, analysis of side impacts and rollovers showed that the projection model estimates for these crash types were not all within the 95 percent CI of the comparison retrospective data at all severity levels. For side impacts, although frequency was within the 95 percent CI for all injury severity levels, the point estimate for the rate of injury was overestimated by the projection model at every level of severity, and for MAIS 3+ and 4+ injuries, the rate of injury was outside of the 95 percent CI for the 2013 to 2015 comparison dataset (Figure 21). For rollovers (Figure 22), the projected number of rollover occupants with MAIS 2+ injuries was overestimated relative to the 2013 to 2015 95 percent CI, consistent with the overall overestimate of rollover occupants shown in Figure 18. In contrast, the projected rates of all injury categories in rollovers fell at the lower ends of the 2013 to 2015 95 percent CIs. Overall, the projection overestimated the number of rollover cases but underestimated the injury rates in those rollovers, particularly for the highest-severity injuries. These results suggest that the rollover countermeasures coded in the model may be overestimating improvements in higher-severity rollovers but possibly underestimating the improvements in lower-severity rollovers.



	Percentage Difference Between Projected and 2013-2015 Comparison Dataset (Retrospective)			
	Fatality	**MAIS 4+**	**MAIS 3+**	**MAIS 2+**
Number	10.0%	27.6%	30.5%	-7.8%
Rate	54.0%	78.7%	82.8%	29.2%

Figure 21. Average annual frequency and rate of injury cases in side impact crashes



	Percentage Difference Between Projected and 2013-2015 Comparison Dataset (Retrospective)			
	Fatality	**MAIS 4+**	**MAIS 3+**	**MAIS 2+**
Number	-37.9%	-18.4%	5.5%	15.6%
Rate	-55.0%	-40.9%	-23.5%	-16.2%

Figure 22. Average annual frequency and rate of injury cases in rollover crashes

3.3 Analysis of Mismatches in Evaluation Projection and Real-World Comparison

The mismatches between the projections and the retrospective 2013 to 2015 comparison dataset (Figure 18, Figure 21 and Figure 22) flagged potential questions for projections related to rollovers and to side impact crashes.

For the rollover projections, the 3-year comparison dataset was developed based on only 278 source cases, of which only 65 involved serious or worse injuries (MAIS 3+) injury and only 26 were fatal. This relatively small number of cases in the comparison dataset makes it difficult to draw definitive conclusions about the accuracy of the projections, other than to suggest that the model projections *may* be overestimating the number of less severe rollovers. While this ambiguity should be considered when interpreting model results involving rollover, it was not deemed certain enough to motivate a correction or adjustment to the model to decrease the projected number of rollovers in future projections.

For side impact projections, which were based on a larger number of source cases, the results suggested that the 2013 to 2015 comparison dataset needed more detailed scrutiny to understand if the mismatch between the projection and the comparison data flagged an issue with the model's projections of side impact crashes or with the real-world comparison data.

The validity of the 2013 to 2015 side impact estimate from the comparison data was explored by analyzing the dataset used to develop it. The comparison dataset for side impacts in 2013 to 2015 was comprised of 1,566 source cases including 741 serious injury cases (MAIS 3+) and only 212 fatal cases. This dataset showed unusually inconsistent year-to-year results, with the MAIS 3+ injury rate in 2014 dropping to about a third of the rates calculated for other individual data years between 2010 and 2015 (Figure 23). In contrast, the rate of AIS 2+ injury among side-impact occupants in 2014 was almost double the rate estimated for other individual years (Figure 23). Since the 2013 and 2015 injury rates in side impact were reasonably consistent with annual injury rates prior to 2013, it was suspected that the side impact results from 2014 could be spurious.

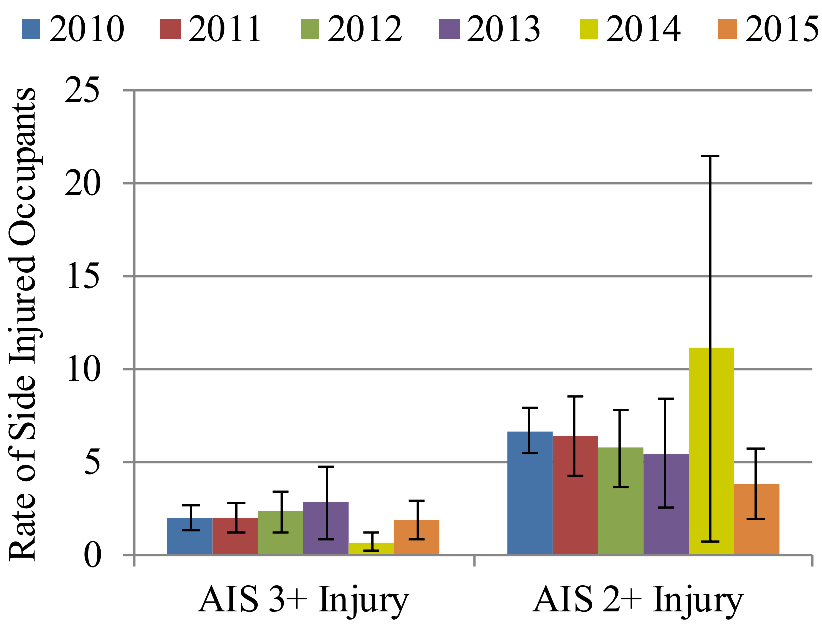


Figure 23. Average annual rates of side impact injury in NASS CDS source datasets as percentage of all occupants in side impacts

Annual spikes and dips in annual crash data are not unusual and would not be problematic in typical analyses based on ten or more years of data but may be misleading in the current analysis that uses only 3 years of crash case data for comparison. Such a small sample of cases can lead to inaccuracy in aggregated results. Although review of potential improvements in side impact protection suggested there may have been improvements that could have contributed to better side impact outcome than those projected by the model, investigational modeling of these improvements showed that none could reasonably have produced projections close to the estimates made by the 2013 to 2015 retrospective data. Therefore, it was more likely that the mismatch resulted primarily from inaccuracy in the relatively small survey-sampled 2013 to 2015 comparison dataset.

Therefore, no correction was made in the model to adjust rollover or side impact projections in response to the evaluation findings.

3.4 Discussion of Evaluation Model Results

Since there was no future dataset available to *validate* the results of the projection model, this evaluation split the source data years used in the model to compare a projection made using 2004 to 2012 to a real-world comparison dataset from 2013 to 2015. This method was a compromise in that it reduced the data available to make the projection in order to reserve a small number of cases to use as real-world comparison data. Reducing the number of data years in the source dataset for the evaluation model made the evaluation conservative in that the additional cases available in the full model would be expected to improve its reliability. Using only three years of data for the comparison dataset limited detailed analysis since these relatively small case datasets could not be broken down by multiple variables. Even broad analyses of these cases must be interpreted carefully because of the limited number of cases in this 3-year dataset. Furthermore, it was likely that a near-term projection was likely to be more accurate than the longer-term projections required to estimate outcome in 2020 to 2030. Nonetheless, the projection of 2014 crashes was the best option available to reasonably evaluate the overall reliability of the projection model results in the absence of data for true validation of the model projections. While the evaluation version of the model cannot be used to definitively validate the model, it can be used to broadly assess the potential reliability of the modeling methods. Crash categories for which the predicted crash outcomes varied from the 2013 to 2015 comparison datasets in the evaluation were analyzed in more detail, without automatically assuming that the evaluation model results invalidated the projection model.

Overall reliability of the model relative to the 2013 to 2015 comparison dataset was assessed by (1) comparing projection point estimates to the 95 percent confidence interval for the 2013 to 2015 comparison dataset, and (2) comparing the relative ranking of injury frequency and severity for different crash types between the projected and 2013 to 2015 comparison datasets, i.e., determining whether the projection model and the comparison datasets prioritize crash types in the same order.

Overall, the evaluation suggested that the projections were reasonable, insofar as the relatively small dataset of 2013 to 2015 comparison cases could be used to assess the reliability of the model. The only crash categories where the injury projections appeared to be outside of the 95 percent confidence intervals for the 2013 to 2015 comparison dataset were side impact injury rates for MAIS 3+ and 4+ injuries, and the frequency of overall rollovers and rollovers with MAIS 2+ injury. In terms of identifying relative relationships, i.e., the ranking of categories according to future injury frequency, the only one of these mismatches that led to a potentially important change in the relative ranking of results was the side impact category. The projected results indicated *total* occupants involved in oblique impacts would outnumber those in side impacts, while *seriously injured* occupants in side impacts would outnumber those in oblique impacts. In fact, these relationships were swapped in the 2013 to 2015 comparison dataset, with more occupants involved in side impact crashes overall, but more seriously injured occupants in oblique impacts.

Specific results identified by the model as potentially contradicting the 2013 to 2015 comparison results were scrutinized in more detail and corrective countermeasures to adjust the model results to match the comparison results were considered. For rollover projections, the 3-year comparison dataset was determined to be comprised of too few cases to be used reliably to try to adjust or “correct” rollover projections. Analysis of the comparison dataset for side impacts in 2013 to 2015 showed unusually inconsistent year-to-year results, with 2014 results appearing so atypical that they had the potential to skew the 3-year average annual results used as the comparison dataset. This 2013 to 2015 comparison dataset was not determined to be sufficiently reliable to be used to adjust or “correct” side impact projections.

For all crash categories, but particularly for those identified as outside or near the boundaries of the confidence intervals of the 2013 to 2015 comparison dataset, model parameters affecting these types of crashes should be reviewed and updated as new information becomes available regarding any potentially related trends or countermeasures.

4 Discussion

The objective of the projection model is to provide estimates of the specific types of crashes and injuries that are still expected to be frequent in the years beyond those for which retrospective data is available and into the future. The model is also designed to identify the occupants expected to be most vulnerable to those crashes and injuries. The projections produced by the model are based on the current understanding of safety technology and transportation trends. The resulting "peaks" in the output data are intended to allow researchers to prioritize the most critical crashes, injuries, and scenarios in developing and evaluating future injury prevention strategies. The model can also be used to explore the effects of changing predicted parameters expected to affect the frequency and outcome of future crashes.

While it would be unreasonable to expect perfect accuracy in a projection model that was developed from a large number of individual predictions and forecasts, the goal was to apply the available data as precisely as possible in order to make the best possible future projections. This section compares the strategies used in the model to other modeling efforts, summarizes results of the evaluation of the model, describes the limitations inherent to all predictive models and to this one in particular, and discusses potential applications of the model.

4.1 Comparison With Previous Projection Modeling Methods

Previous comprehensive projection models have been developed by UMTRI (Flannagan & Flannagan, 2007, 2009), Strandroth et al. (2016), and Autoliv (Lubbe et al., 2018; Östling et al., 2019a; Östling et al., 2019b; Östling et al., 2020) to make broad estimates of the crashes and injuries still expected to remain after the introduction of a wide range of safety improvements. Researchers from Toyota and Virginia Tech/Wake Forest University have developed a number of individual models of specific crash types and scenarios with similar goals (Bareiss et al., 2019; Riexinger et al., 2019a; Riexinger et al., 2019b)[19] as well as a comprehensive model to estimate residual safety problems after deployment of an integrated safety system (Sherony & Gabler, 2020). A more focused effort by TU Dresden (Liers & Unger, 2019) modelled the crashes expected to remain after application of Level 2 and Level 3 ADS systems, without addressing other contemporaneous safety improvements or trends. All five research efforts are based on retrospective counts of injury cases, adjusted to reflect the predicted effectiveness of safety countermeasures in the future, as was the case for the projection model described in this report (hereafter in section 4.1 referred to as the "VRTC projection model" for ease of comparison to the other models). Other aspects of these modeling efforts differ substantially from the VRTC projection model. This section highlights the similarities and differences among the comprehensive models that report on future crashes and injuries across *all* impact types, accounting for many safety interventions and countermeasures: UMTRI, Strandroth, Autoliv, Toyota/Virginia Tech/Wake Forest, and VRTC.

The source retrospective cases used in the UMTRI model are from NASS GES (with different versions of the model using different ranges of input year), while the Strandroth model uses 2014 data from the Swedish STRADA dataset, and the Autoliv methods have been applied to the 1999

[19] Also includes personal communications with Rini Sherony, Collaborative Safety Research Center, TEMA (Toyota Motor Engineering and Manufacturing North America, Inc.), Ann Arbor, MI, and H. Clay Gabler, Center for Injury Biomechanics, Virginia Tech, Blacksburg, VA, personal communication, November 9, 2017.

to 2016 German GIDAS dataset (Lubbe et al., 2018; Östling et al., 2019a) as well as to 1995 to 2015 NASS CDS data (Östling et al., 2019b). The Toyota/Virginia Tech/Wake Forest model used 2015 NASS CDS and GES for its source data (Sherony & Gabler, 2020). In comparison, the VRTC projection model uses 2004 to 2015 NASS CDS as a source dataset, reweighted with fatal cases from FARS and nonfatal cases from NASS GES. This broad range of data years was selected in the VRTC projection model to maximize the number of cases available for analysis by crash and occupant sub-type.

UMTRI's Unified Tool for Mapping Opportunities for Safety Technology, referred to as UTMOST in this report, provides output in terms of person, injury, and fatality counts. In comparison, the Autoliv approach reports outcome in terms of the number of crashes with at least one moderate or worse (AIS 2+) injury in the NASS CDS study and in terms of fatalities in the GIDAS study. The Toyota/Virginia Tech/Wake Forest results are reported in terms of numbers of crashes and occupants with MAIS2+F injuries. In Strandroth's study, estimates were based on RPMI (Risk of Permanent Medical Impairment). The case-by-case methods used in the VRTC projection model allows analysis of future projection cases by any harm measure that can be estimated using injury data supplied in NASS CDS, including fatality, AIS severity, or cost. Incorporation of disability estimates such as RPMI or FCI (Functional Capacity Index) is also planned in future updates to the VRTC projection model. The reason for the additional injury detail available in the VRTC projection model is that countermeasure effects are applied to individual injuries in each case rather than as an overall reduction in injury severity for the case.

The overall strategies used in the Strandroth, Autoliv, and Toyota/Virginia Tech/Wake Forest models are similar to those used in the VRTC projection model in that effectiveness estimates are applied on a case-by-case basis to the retrospective datasets, with the future effects reflected by reductions in crashes or injury in the projections. In Strandroth's study, each individual's RPMI was calculated as a function of their AIS-coded injuries in the 2014 crash. Each individual's reduced RPMI in a 2020 crash was calculated as follows (Equation (26)):

$$RPMI_{2020} = RPMI_{2014} \times \prod_j \left(1 - \left(P_j(I) \times RR_j\right)\right) \tag{26}$$

where:

P(I) is the probability for an intervention to be implemented in 2020, and

RR is the intervention's risk-reducing factor given the crash circumstances and injury level, calculated for all j interventions for which the given case is in the target population.

In the Toyota/Virginia Tech/Wake Forest model, the source CDS cases are binned into mutually exclusive target populations for each of the countermeasure technologies or combinations of technologies. Effectiveness estimates are developed by modeling real-world cases in the target population. The source cases are from 2015 NASS and data to develop individual countermeasure effectiveness estimates are drawn from the National Motor Vehicle Crash Causation Survey, EDR data, the Virginia Tech Transportation Institute's VTTI 100 dataset, and the Strategic Highway Research Program's SHRP2 NDS dataset. Specific effectiveness for sub-types of cases within the target population are developed where possible. Where a countermeasure is expected to eliminate a percentage of cases, all cases in the target population are downweighted proportionally as in the VRTC model. However, where a countermeasure is expected to reduce impact speed, risk curves predicting the risk of injury by speed are used to estimate the likelihood of injury at the expected reduced speed for each case (Bareiss et al., 2018).

In Autoliv's study, conservative and optimistic rulesets were defined for each countermeasure to define the cases potentially affected by a countermeasure. The optimistic ruleset for rear impact AEB, for example, applied this countermeasure to relevant crash types where the driving speed difference between the vehicles was less than or equal to 100 km/h. In contrast, the conservative ruleset applied the countermeasure to relevant crash types where the driving speed difference was less than or equal to 70 km/h and where weather was fine and there was no ice and snow on road, poor road conditions, or unstable vehicle conditions. All cases covered by the ruleset for any countermeasure were counted as prevented.

UTMOST, the UMTRI model, uses a very different strategy. The most recent update relies on logistic regression models to predict the risk of AIS 3+ injury to project future changes in the total number of MAIS 3+ occupants/injuries that would result from implementation of countermeasures. The regression models include covariates for delta V, occupant age and sex, belt restraint, vehicle type, and alcohol involvement so that the effect of countermeasures on any of these parameters can be used to adjust the model. For example, these models can be used to estimate the reduction in the number of AIS 3+ injuries based on a hypothesized shift in the delta V distribution within a population of crashes resulting from a severity mitigation countermeasure. Similarly, the effect of an increased percentage of belted individuals in a segment of the population can be estimated using these models. The UTMOST model was structured so that an interactive version of the model (available at http://utmost.umtri.umich.edu/) allows the user to adjust the predicted effectiveness of any combination of included countermeasures and to override predicted levels of restraint use. As of February 2021, 22 countermeasures were available in the model.

While the regression methods used in the UMTRI model offer computational advantages that allow for interactive use, they apply the effects of countermeasures as a percentage of very broad groups of cases. In contrast, the case-by-case methods used in the VRTC, Strandroth, and Autoliv models facilitate more specific application of countermeasures to defined target populations. These case-by-case methods are flexible in that each case can be in the target population for any combination of countermeasures, without double-counting.

The Strandroth model, the UMTRI model, and the Toyota/Virginia Tech/Wake Forest model all cover vulnerable road users (motorcyclists, pedestrians, and bicyclists) while the VRTC projection model is limited to the vehicle occupants included in NASS CDS and the Autoliv studies focus on passenger vehicle occupants in the NASS CDS and GIDAS studies. In the VRTC projection model, output can be analyzed by vehicle seat position. The Strandroth, UMTRI, and Autoliv models cover all vehicle occupants but do not break results down by seat position. The Toyota/Virginia Tech/Wake Forest model includes only front seat occupants. Expansion of the VRTC projection model to include vulnerable road users would be valuable.

The passenger vehicle interventions included in Strandroth et al.'s analysis were seat belt reminders, electronic stability control, lane-keeping assist, autonomous emergency steering and braking, pedestrian protection, and a single broad category of "crashworthiness" interventions.

Interventions for heavy-goods vehicles, powered two-wheelers, and infrastructure were also included. Estimated target populations, risk-reducing factors, and probability of implementation by model year were tabulated along with references for source data. Data was drawn from literature where available, as well as from information from manufacturers, industry and Swedish government experts.

In the UMTRI model, the countermeasures, which continue to be updated, are primarily crash avoidance technologies. Policy measures in the model include graduated licensing, and laws related to seat belt and helmet use. In 2020 new categories added included the effects of "vehicle age," as well as "seat position population," which allowed users to adjust the proportion of occupants facing forward, rearward and to one side in anticipation of changing seating configurations in automated vehicles. For some countermeasures, a single effectiveness value applies, while for others different values apply to different populations/scenarios. For example, the default effectiveness of electronic stability control was estimated to be 40 percent for a target population of all single-vehicle crashes, but automatic emergency braking could be set to different levels of effectiveness in crashes with the lead vehicle moving slower, braking, or stopped. Citations are provided for default effectiveness estimates.

In Autoliv's NASS CDS study, 15 crash avoidance technologies were applied to the model. Optimistic and conservative rulesets were determined by the authors, using data on applicable speed ranges for each countermeasure from Euro NCAP assessment procedures, Euro NCAP test results, driver manuals and web pages. The optimistic and conservative rulesets were compared to effectiveness estimates from the literature for each countermeasure. In Autoliv's GIDAS study, additional countermeasures in the model included frontal and side air bags as well as seat-belt reminders.

The Autoliv GIDAS study model and the VRTC projection model are the only ones that currently include specific crashworthiness countermeasures. No crashworthiness countermeasures are included in the current interactive UMTRI model. In the Strandroth model, a single composite crashworthiness countermeasure was estimated to have a risk-reducing factor of 0.01/year to 2020. In the Toyota/Virginia Tech/Wake Forest model, improvements in passive safety are incorporated by using injury risk curves that correspond to vehicles with best-performing passive restraints based on data from the NCAP 5-star and IIHS TSP programs (Bareiss et al., 2018).

In the UMTRI study, results can be viewed as counts of annual injuries or occupants with injuries disaggregated by variables such as crash type, vehicle type, and occupant age or sex. Strandroth et al. reported their results as the predicted number of occupants at given levels of RPMI, by road user type (passenger cars, pedestrians, bicyclists, powered 2-wheelers, heavy-goods vehicles, buses, and other). Passenger car occupants were further broken down by crash type (intersection, head-on, single-vehicle, rear-end, wildlife, and other) and bicyclists were broken down by crash partner (motor vehicles, pedestrians, other bicycles, mopeds, and single-vehicle crashes). The Autoliv model presented results in terms of the percentage of residual crashes that are expected to fall in each crash type or category. The Toyota/Virginia Tech/Wake Forest results can be reported by crash scenario in terms of the numbers of crashes prevented or the number of front seat occupants with AIS 2+F injuries. Results can also be analyzed using varying assumptions regarding sensor response and penetration into the fleet. The VRTC projection model has significant flexibility for output analysis since the original retrospective case parameters that are unchanged by countermeasures are retained with the projected case. Therefore, results can be analyzed by categories including pre-crash scenario, roadway type and surface condition, lighting, impact direction, vehicle type, and occupant age, seat position, or restraint use. The granularity of the results is limited only by the number of case occupants in each of these sub-groups. Given the similar case-by-case methodology used in the Strandroth and Autoliv models, the output for these models have similar potential flexibility although the Standroth model was limited by use of a relatively small set of input cases.

Strandroth's predictions are for the crash years 2020 and 2030. The UMTRI and Autoliv models are not associated with a specific crash year. In both, default penetration rates are set to 100 percent, but in UMTRI's interactive version, penetration can be adjusted by the user. The Toyota/Virginia Tech/Wake Forest model predicts 2025 and 2040 outcomes, under realistic predictions of penetration as well as with an assumption of 100 percent deployment of integrated safety systems. The VRTC projection model is designed to output projections to 2020, 2025, and 2030.

In terms of trends, Strandroth adjusts future crash rates based on a projected increase in traffic volume. The UMTRI model allows user adjustments of restraint use. The Toyota/Virginia Tech/Wake Forest model applies an optional VMT increase of 1.01 percent per year. The VRTC projection model accounts for forecasted population growth by age group, shifts in passenger vehicle types, licensing rate trends, economic trends, and increasing restraint use.

Among the previous modeling studies, the Strandroth and Autoliv studies present ranges for results. In Strandroth's work, best- and worst-case sensitivity analyses were based on implementation of all interventions five years earlier than estimated and 50 percent more effective than predicted, and implementation of all interventions delayed five years and 50 percent less effective than predicted. The Autoliv studies report results for their conservative and optimistic rulesets. Versions of the VRTC projection to be included in the upcoming results report include variations run with hypothetical ranges of input parameters for select countermeasures and trends, but no systematic procedures for sensitivity analysis have been developed.

The main strength of the detailed case-by-case approach taken for the VRTC projection model is the capability to disaggregate future crashes by a variety of parameters to help to identify the specific safety issues that will remain in the future. Each case is individually compared to the target population for each countermeasure, and countermeasures expected to reduce or prevent injuries are applied selectively to the injuries in each case, using the expected effectiveness that applies to each target population. As a result, the output of the model can be broken down into categories that will offer insight not just into the overall pre-crash scenarios or impact directions that are expected to be high-risk in the future but the specific crash types and populations that deserve attention. The disadvantage of this more complex approach, compared to models that adjust injury risk more broadly across whole target populations or on an occupant-level rather than at an injury level, is that more detailed information is needed for each countermeasure and for each retrospective case.

Additional strengths of the VRTC projection model include:

- The incorporation of population and transportation trends,
- The capability to analyze diverse countermeasures (including those targeted at crashworthiness, crash avoidance and mitigation, occupant behavior, or infrastructure) in combination on a single set of real-world cases without double-counting countermeasure effects, and
- Use of a large set of input cases, which makes it possible to analyze results by crash, occupant, or injury characteristics.

4.2 Model Limitations

Uncertainty is inherent to a model projecting into the future. The projection model described in this report, based on a survey-sampled retrospective dataset with a high level of uncertainty, is also subject to the compounded uncertainty of each included trend and countermeasure. Furthermore, even assumptions made with the best available data may lead to inaccurate projections if new technologies or transportation trends have the potential to drastically change crash outcomes. However, while the absolute magnitude of the projected crash and injury parameters should certainly be interpreted as approximate estimates, they can be expected to represent the best available estimates if the input data is drawn from the best available information on the modeled trends and countermeasures. The resulting projections from such a model, based on the combined forecasts of future transportation and population trends as well as on estimates of the effectiveness of current and future safety countermeasures, have the potential to offer a more comprehensive picture of future crashes than can be obtained using retrospective data alone, by accounting for the factors that can change crash outcomes over time.

As currently designed, 95 percent confidence intervals can be estimated for most retrospective data in the model output but not for future projections in the model. For projected data, the complexity of adjustments made to the data prevents reasonable estimation of confidence intervals that reflect the compounded layers of uncertainty in every calculation. Similarly, confidence intervals could not be estimated for results involving complex calculations, such as attributable fatality or equivalent lives lost, even for the retrospective datasets. Future plans for evaluating model certainty include use of sensitivity analyses (refer to Section 4.3).

As in any analysis of crash data, the detail or granularity of the results is limited by the size of the source datasets. Calculation of mean case weights in potential analysis categories (in Section 2.8) showed that disaggregation of the data by multiple variables is likely reasonable for most analysis categories considered. Exceptions included certain analyses disaggregated by vehicle type, which should be done with caution.

Current projections are based on crash data from 2004 to 2015 because 2015 was the last year for which NASS CDS and GES datasets were available. The model is not currently structured to use more recent CISS and CRSS cases. If the model could be redesigned to base projections based on retrospective data CISS and CRSS, or to pool data from CDS/GES and from CISS/CRSS, projections could be based on more recent real-world data and could be updated annually. Use of the enhanced CISS variables associated with pre-crash scenarios and crash avoidance technologies may also improve the definitions of target population and penetration in the model.

The current version of the model includes only passenger vehicle occupants, because the foundational NASS CDS dataset excludes pedestrians, bicyclists, and motorcyclists. Similarly, no heavy-truck crashes are included in the model since these are also excluded from NASS CDS. Future inclusion of these other road users in the current projection model, based on 2004 to 2015 NASS CDS retrospective cases, will necessitate use of additional datasets as discussed in Section 4.3.

In addition to the measures of harm that the model can currently output, early versions of the model quantified harm in terms of disability and attributable disability, using the Functional Capacity Index (FCI). Preliminary results, however, have shown that the methods used were ineffective in capturing the effects of injuries associated with whiplash associated disorder or mild traumatic brain injury. Therefore, no disability results are currently output by the model. Plans for the addition of a disability harm measure are summarized in Section 4.3. In the absence of a harm measure reflecting disability, low-AIS injuries such as soft-tissue neck injuries or mild traumatic head injury are not captured by the model output. Therefore, many countermeasures are not coded in the current model to affect AIS 1 injuries, even if the countermeasure was expected to address them. Incorporation of a disability harm measure is being explored. Once model results can be analyzed relative to AIS 1 injuries, countermeasures that could potentially address these lower-AIS injuries will need to be revised accordingly.

As discussed in Section 2.3, reweighting of the retrospective datasets using KABCO-AIS methods to account for exclusion of cases missing AIS codes has the potential to lead to overestimation of the frequency of the most severe and least severe cases in the reweighted dataset since the injury severity distribution was expected to be different among cases that are coded with AIS and cases without AIS codes. Even among cases with the same KABCO score, severity may vary for cases with or without AIS codes. However, the error introduced with this reweighting step was less than the resulting error that would be expected if no adjustment were made to account for exclusion of cases without AIS codes. Furthermore, reweighting of the stepping-stone datasets (Section 2.4) used to develop future projections was performed using the same methods, so that any bias introduced into the projections was also present in the retrospective dataset used for comparison.

Analysis of initial model results has illustrated a potential issue with the use of the initial case reweighting scheme outlined in Section 2.3.1. By reweighting by occupant, rather than by crash, there was a potential for unexpected results, e.g., unequal increases in the number of striking vehicles and struck vehicles in certain impact configurations. Potential future improvements include reweighting by crash, rather than by occupant, for selected reweighting variables.

Crash avoidance countermeasures in the projection model primarily focus on 2-vehicle crashes because use of the accident type variable categorizes crash interactions between two vehicles. Categorization of multi-vehicle crashes was problematic and sometimes less accurate. Improved algorithms for addressing individual crashes within multiple-vehicle crashes would help to better identify crashes associated with specific crash avoidance countermeasures.

In the current version of the model, vehicle type trends are applied after the stepping-stone datasets have been reweighted to match GES/FARS proportions of occupants by seat position, age, restraint use and injury severity. That sequence means that the upweighting or downweighting of cases to reflect shifting vehicle types also has the potential to shift other proportions in the dataset. For example, if more younger adults drive SUVs in the dataset, then upweighting of SUVs in the future could increase the proportion of young adults among drivers in the future dataset. Similarly, restraint use trends were applied after initial reweighting by seat position, age, restraint use, injury severity, and vehicle type. This sequence has the potential to lead to unintended shifts in the proportion of these variables in the dataset. For example, downweighting of cases involving unrestrained occupants would have the potential to lead to a decrease in the number of crashes involving pickup trucks, since belt use rates are typically lower in pickups than in other vehicles. Among these unintended consequences of the sequential application of trends, the worst potential effects were identified as the potential shifts in age distribution and vehicle type that resulted from reweighting by restraint use. As a result, the application of the belt use trend was designed to minimize this potential error. In the front seat, reweighting of cases by belt use was done by vehicle type because front seat belt use rates varied substantially by vehicle type. In the rear seat, reweighting by belt use was done by age group, since belt use varied more by age than by vehicle type for this group of occupants. This disaggregation, and its role in reducing the potential unintended inflation of certain crash and occupant characteristics, is discussed in more detail in Section 2.5.4. However, while this strategy minimized the effects of the sequential application of trends, development of more comprehensive methods to apply competing trends to the projections should be considered in the future.

Occupants in older and newer vehicles can differ substantially with respect to demographics and behavior. The reweighting scheme used in the projection model does not fully account for these differences in that the 2004 to 2015 source cases used in the stepping-stone datasets are biased toward newer vehicles. Vehicles older than model year 2005 were included in the model but were not adjusted for vehicle-based countermeasures and were simply downweighted in the future datasets to represent the shrinking number of MY<2005 vehicles still expected to be on the road in the future. The lack of injury data in later years of NASS CDS for occupants in vehicles older than 9 years-old further reduced the older-vehicle cases in the dataset, even in the MY2005+ subset. As a result of these issues, the types of occupants most frequently associated with older vehicles are likely under-represented in the projection datasets. In the 2020 projection, the cases involving MY 2005 to 2015 vehicles (which were 0-10 years old at the time of the crash) were used to represent crashes in 0- to 15-year-old vehicles. By the 2030 projection, these same cases were used to represent crashes in 0- to 25-year-old vehicles. This limitation may have a major influence on results and is a priority for future model refinements. Methods for improving the representation of occupant and crash characteristics typical of older-vehicle crashes are being explored for future versions of the model.

Trends related to driver distraction since the 2004 to 2015 retrospective cases are not captured in the model. Analysis of the cases in the retrospective dataset showed that only 13.2 percent of occupants were coded as being in crashes associated with driver distraction, with only 1.8 percent specifically attributed to distraction by in-vehicle controls, phones, or other devices and objects. More often, distraction was associated with a person, object or event outside the vehicle (2.7%), sleeping or dozing (2.4%), or other occupants in the vehicle (2.4%). Distraction status was coded as unknown in 22 percent of cases. These estimates may underestimate the actual role of distraction in crashes from 2004 to 2015. Furthermore, no adjustment has been made to account for the possible increase in driver distraction over the 2004 to 2015 retrospective period, between 2015 and the present, or any possible increase in the future. A hypothetical countermeasure for exploring the effects of reducing distraction associated with in-vehicle controls and accessories or with hand-held devices has been developed (Mallory et al., in press), but its usefulness is limited by the possible underestimates of distraction in both the source cases and in the future projections. In order to more accurately account for the outcome of driver distraction in future crashes, additional data on distraction frequency and outcome among past, current, and future road-users are needed.

Similarly, insufficient information was available to model trends in drug use in the future. In order to model the effects of shifting patterns in drug use and of changes in laws governing the use of drugs such as marijuana, more information would be needed on the prevalence of drug use among drivers in the retrospective dataset, the expected effect of these drugs on crash risk, and the expected future prevalence of drug use among drivers.

4.3 Future Model Enhancements and Applications

The model output is reliant on hundreds of parameters to adjust cases in the retrospective dataset to represent future cases. While efforts were made to find the most reliable information available to define all these required parameters, the model and its countermeasures can be updated as any new and better source information becomes available. Potential updates include revisions to parameter estimates with revised values from updated research or to parameter estimates that have been coded with temporary estimates as a result of missing information, as described in the countermeasure summaries in the appendices. In the future, results will always be accompanied by detailed summaries of the parameters used for each countermeasure used in the reported model since these are expected be updated and refined frequently.

Application of countermeasures often relies on target population variables such as delta V that are not available in every case. In the current version of the model, cases with missing values for such variables are addressed individually for each countermeasure as defined in the corresponding appendices. Future versions of the model could be revised with imputed variables for key case parameters that are needed for target populations.

Trends applied by age group in the current version of the model include population growth, as well as behavioral trends, such as restraint use and licensure rates. Estimated population growth, projected from census data, takes into account the aging of particular cohorts of the population. For example, the size of the population in a particular age decade in 2030 is linked to the size of the same cohort that was a decade younger in 2020. In contrast, behavioral trends have not accounted for the aging of specific cohorts of occupants. For example, restraint use among the 70+ age group was projected based on restraint use in the 70+ age group in the past. For future versions of the model, methods could be explored for using age data on each specific age cohort over time for projecting behavior trends. For example, projected restraint use among the 70+ age group could rely, in part, on the historical restraint use of that specific group of occupants when they were in the 50-59 and 60-69 age groups.

Although initial runs of the model have included versions that explore the effect of varying individual model, trend, or countermeasure parameters (Mallory et al., in press), or even combinations of these parameters, a comprehensive sensitivity analysis has not yet been performed. It is proposed that future sensitivity analysis could be systematically conducted using ranges of input values in place of the point estimates used in the current projection model. Low and high estimates of model parameters for a sensitivity analysis could come from previously reported data, such as the confidence intervals provided in the effectiveness studies used to develop the model. Where no confidence intervals are available for the input values used as parameters in the projection model, systematic ranges could be estimated using methods like those used by Strandroth's group, who bracketed effectiveness estimates with values 50 percent higher and 50 percent lower (Strandroth et al., 2016).

Enhancements to the attributable fatality and disability harm measures used to analyze model output are planned. The optimized parameters used in the current attributable fatality methodology are based on a 2017 update to Martin's originally derived parameters (Mallory et al., 2017). Additional updates to these parameters are planned, with re-grouping of injury types and age as a covariate to better estimate fatality risk. Addition of a measure of disability into model output is also anticipated. Previous harm calculations based on Functional Capacity Index (FCI) were ineffective at estimating disability from low-AIS injuries. Therefore, other disability methods, including the revised FCI version incorporated into recent updates of the AIS system and the RPMI scale, will be evaluated for use with the model.

Explorations for the addition of vulnerable road users to the current projection model (based on 2004 to 2015 retrospective cases) includes the use of NASS GES pedestrian, cyclist, and motorcyclist cases. Alternatively, vulnerable occupant data could be drawn from CRSS if the model were updated in the future to incorporate CRSS and CISS source cases in addition to, or instead of, GES and CDS cases. Supplemental data will be needed to estimate how many of these cases would be in the target populations for countermeasures such as crash avoidance technology, pedestrian-friendly design, dedicated bicyclist lanes, or helmet-use laws. Ideally, the supplemental case data would be detailed enough to provide a detailed picture of the sub-types of these crashes and the associated injuries that would remain after introduction of these countermeasures. The supplemental data could come from the NHTSA's Pedestrian Crash Data Study, the NTDB, or possibly from international datasets such as GIDAS. For example, pedestrian, bicyclist, and motorcycle injuries could be drawn from NTDB and weighted by parameters such as age group and injury severity to match NASS GES annual numbers of cases. For pedestrians, crash conditions such as impact speed and injury source could be imputed from data in the Pedestrian Crash Data Study based on injury patterns and case parameters. Similar approaches can also be explored for micromobility devices (such as scooters) as information comes available. It may also be possible to add heavy vehicles to the analysis using sources such as the *Trucks Involved in Fatal Accidents and Buses Involved in Fatal Accidents* datasets.

A number of countermeasures expected to be effective in preventing or mitigating crashes during the period of the source cases in the projection model or expected to be effective in the future, were not included in the current version of the model. The rationale for, and potential implications of, excluding these countermeasures is discussed along with the potential for future inclusion of each one in the model:

- **Updates to the FMVSS No. 139 tire safety standard**: FMVSS No. 139 was updated in 2002 and in 2003. The Final Regulatory Evaluation for the 2002 update stated that NHTSA believed this regulation would lead to increasing public awareness of tire safety and tire maintenance, which should result in fewer tire-related crashes (NHTSA, 2002). However, the FRE also stated that quantitative estimates of the benefits were difficult to establish, in part because it is difficult to predict drivers' response to changing awareness and therefore the ultimate effectiveness of FMVSS No. 139. If information on effectiveness could be determined, this countermeasure could easily be combined with the FMVSS No. 138 countermeasure already included in the model since it is likely that FMVSS No. 139 would apply to the same target population as FMVSS No. 138. The FRE for the 2003 update to FMVSS No. 138 indicated that upgrades to performance tests were expected to increase the strength, endurance, and heat resistance of tires (NHTSA, 2003a). Although benefits were estimated based on assumptions of how hard these tests might be to pass, the FRE indicated that "good estimates of effectiveness" were not available. Due to the lack of available information on effectiveness, the 2002 and 2003 upgrades to FMVSS No. 139 are currently excluded from the current model.
- **V2V applications**: Exploratory versions of the model have included a hypothetical V2V (vehicle-to-vehicle communications) countermeasure with the intersection movement assist and left turn across path applications (apps). Insufficient data was available to model the effects of other potential V2V crash avoidance apps such as forward collision warning, blind-spot or lane-change warning, and do-not-pass warnings. The timeline and ultimate future penetration of V2V technologies is unclear. Therefore, although the hypothetical effects of V2V apps will be explored with the model, these countermeasures have not been included in the primary model.
- **V2X**: Beyond V2V applications, other V2X applications (such as those associated with vehicle-to-infrastructure communication) have not yet been incorporated into the model. The primary reason for excluding this family of crash avoidance technologies is the lack of information available to quantify effectiveness and expected penetration. As data becomes available on the developing technologies based on dedicated short range communication and cellular communication, they can be coded into the model. In the meantime, the contribution of these V2X countermeasures was captured by the very general automated driving system countermeasure, which incorporates the expected overall benefit of all safety countermeasures on automated vehicles, including crash avoidance features that may be provided by V2X capabilities or by vehicle-resident technology.
- **Automatic crash notification**: While the current model is focused on the immediate outcome of the crash, future versions of the model could incorporate the effects of post-crash response and care, including advanced automatic crash notification, on the ultimate outcome of crash injuries.
- **Hypothetical countermeasures targeting speed reduction**: Future versions of the model could incorporate hypothetical countermeasure modules to explore the potential effects of safety interventions and programs that would reduce travel speeds.
- **Distraction countermeasures such as NHTSA's Distraction Guidelines, text/talk and drive laws, phone-block technology**: In the absence of reliable estimates of the effectiveness or penetration of individual distraction countermeasures, the model includes

a hypothetical distraction reduction countermeasure that can be used to demonstrate the effect of a hypothetical magnitude of distraction reduction from any source. Specific distraction countermeasures can be incorporated into the model as more information is available on countermeasures and as estimates of historical and future levels of distraction are made.

- **Belt-use programs and interventions (such as ignition interlocks)**: It was assumed that programs encouraging increased belt-use would continue at the same rate they have in the past, so that belt-use conversion rates in the future could be based on past trends in belt-use improvements. Hypothetical countermeasures to explore the potential effect of generic increased efforts or effectiveness of belt-use programs, or the potential effects of ignition interlock systems, have been developed for future application to the model.
- **Sobriety checkpoints and other countermeasures for crashes involving impaired driving**: Although interventions such as sobriety checkpoints and public safety messaging campaigns have been proven to be effective in reducing crashes associated with impaired driving, future predictions of implementation did not suggest any substantial change was expected in the future, compared to the baseline retrospective period when the source cases were collected. Therefore, future penetration over the levels reported during the era of the source cases would have essentially been zero. A hypothetical impaired-driving reduction countermeasure has been developed to explore the potential benefit of increasing the implementation of sobriety checkpoints or other countermeasures targeted at the reduction of alcohol involved crashes. This hypothetical countermeasure will be applied in future exploratory versions of the model.
- **Antilock braking systems**: It is assumed that all passenger vehicles with ESC were also equipped with anti-lock braking systems. The converse, however, is not true so that some of the vehicles in the source CDS cases were equipped with ABS, but not ESC. It was decided that it would be redundant to include ABS as a standalone countermeasure in the model. ESC estimates of effectiveness were based on post-implementation evaluations of real-world data. These estimates compared crashes involving vehicles without ESC to crashes involving vehicles with ESC. Among the crashes involving vehicles without ESC, some vehicles would have been equipped with ABS and some would not have had ABS. Therefore, the estimated effectiveness of ESC reflects the difference in risk between a fleet of vehicles without ESC but with a mix of vehicles with/without ABS and a fleet of vehicles with ESC and ABS. Therefore, the projection forward to vehicles on the road in 2020 to 2030 already accounts for the improvement of no-ABS vehicles to vehicles equipped with both ABS and ESC as well as the improvement of ABS-equipped vehicles to vehicles equipped with both ABS and ESC. Although the proportion of vehicles in the pre-ESC era that are equipped with ABS in the ESC evaluation may not be identical to the proportion of pre-ESC vehicles with ABS in the retrospective datasets, this approximation was believed to introduce less error than potentially double-counting the benefit of ABS by including ABS as an additional countermeasure in the model.
- **Updates to child restraint regulations (FMVSS No. 213 and 225)**: Previous updates to FMVSS No. 213 and 225 either did not have quantifiable safety benefits or had phased in prior to 2005. While there have been Notices of Proposed Rulemaking about future updates to FMVSS No. 213 and 225, including the addition of a side impact procedure to FMVSS No. 213, these updates have not been included in the current version of the model due to uncertainty on the phase-in timeline (which informs the fleet penetration

used in the model) and the effectiveness (which may vary based on the final test procedures).

- **Adaptive cruise control and cooperative adaptive cruise control**: The crash avoidance effectiveness and penetration of ACC and CACC, which uses V2V technology to enhance ACC capabilities, are difficult to estimate accurately. Considering that vehicles equipped with this technology also typically have FCW and sometimes AEB, the effectiveness of ACC/CACC cannot be isolated and is expected to be low in comparison to these other crash avoidance features. Kessler et al. estimated that, even with 100 percent penetration of ACC in the fleet, injury crashes would only be reduced by about 2 percent (Kessler et al., 2012). Additionally, future penetration of ACC/CACC is difficult to estimate. While estimated future *availability* of this technology exists, estimates of driver use are limited and self-reported. If more accurate effectiveness and penetration estimates become available for ACC/CACC, these countermeasures could be added to future versions of the projection model.
- **Traffic jam assist**: TJA is similar to ACC, but specifically designed for lower speeds. This technology is found in vehicles that also have ACC, FCW, and AEB. Since all these technologies work cooperatively together, it is difficult to parse out the effectiveness of TJA alone. Additionally, the primary functions of TJA are to ease the mental workload of the driver and provide enough space between vehicles to allow FCW and AEB to be fully effective at avoiding a crash (Brookhuis et al., 2009). TJA was excluded due to potential duplication of FCW and AEB, as well as unknown effectiveness.
- **Automatic emergency steering**: While AEB assists with longitudinal control of the car and only monitors the object directly ahead, AES provides lateral control by automatically making an evasive maneuver to avoid a crash. Currently, penetration of AES is very small as it has only been available since model year 2018 in a limited number of luxury vehicles. Future penetration is expected to lag behind other crash avoidance technologies because driver response to AES is not well understood (Sieber et al., 2015).

Other countermeasures and trends to be considered for future incorporation into the model include: IIHS consumer testing, graduated licensing programs, advanced headlights, intersection AEB, increased penetration of electric vehicles, and center console air bags.

Additionally, several trends are under consideration for future incorporation into the model:

- **Telecommuting**: With many employers offering telework options, it is expected that a reduced number of commuters on the road will result in fewer motor vehicle crashes in the future. Global Workplace Analytics estimated that teleworking eliminated 7.8 billion vehicle miles traveled in the United States in 2017 (Global Workplace Analytics & Flexjobs, 2017). Considering this savings accounts for less than 0.4 percent of vehicle miles traveled, the effect of teleworking on vehicle safety is negligible in the projection model. If the teleworking trends triggered by the COVID-19 pandemic lead to sustained substantial increases, this trend should be added to future versions of the projection model.

- **Ride hailing**: The effect of ride hailing apps, like Uber and Lyft, has been excluded from the projection model because there are limited studies with conflicting results on the safety effect of these services. Some studies indicate that ride hailing decreases crashes (Greenwood & Wattal, 2017; Dills & Mulholland, 2018), while others show increases in crashes (Barrios et al., 2018) or no association at all (Brazil & Kirk 2016). Although it is expected that use of these services increases rear-seat occupancy, no data on this shift in seat position frequency has been identified. The effect of ride hailing on crash frequency and seat position could be included in future versions of the projection model if data on the widespread effects come available.
- **Alternative seating associated with automated driving systems**: The effect of alternative seating arrangements in ADS-equipped-vehicles is not included in the current projection model due to lack of information on the effect or likelihood of adoption of different candidate configurations. Studies have focused on comparative modeling (Kitagawa et al., 2017; Gayzik et al., 2018; Jin et al., 2018) or out-of-position cases in crash databases (Panzer et al., 2017), but none have provided a quantifiable change in injury risk that could be applied to cases in the projection dataset. Additionally, no reliable estimates are available yet on the percentage of occupants expected to be travelling in reclined or rotated seats. The model should be updated with information on these trends as research in this area is completed.
- **COVID-19 pandemic**: The effects of the COVID-19 pandemic on U.S. road use and crash patterns have not yet been incorporated into the model. The effects of the pandemic and associated stay-at-home orders and increases in unemployment are expected to have substantial effects on the 2020 projections. Longer term effects could also affect 2025 and 2030 projections. For example, reductions in the number and types of vehicles sold in the near-term will affect the age of vehicles and distribution of vehicle types in the fleet, which will affect the penetration of recent technology for several years into the future. Increased mortality in older populations could potentially affect the distribution of the future population growth by age group. Additionally, the temporary increase in remote work could lead to long-term changes in commuting habits. Although these pandemic-related adjustments are expected to have a substantial impact on the projected number of 2020 crash exposures, as well as on the distribution of impact types, occupants, and injuries in those crashes, the likely effect on 2025 to 2030 crash outcomes is less clear.

The projection results for the full model in future reports will be disaggregated by the crash and occupant parameters discussed in Section 2.7.2 and analyzed by all the harm measures discussed in Section 2.7.1. These results will represent the best estimate of future crash outcomes, given the available predictions and estimates applied to each version of the model. Individual model versions can also be used to explore the effect of specific variations in applied trends, countermeasures, or modeling methods. Potential future model versions could include the following:

Application of optional model components:

- Suppression of the default procedures that upweight low-severity cases to account for the exclusion of cases in non-towed vehicles in NASS CDS and the under-reporting of low-severity crashes to police.

Addition of hypothetical countermeasures:

- Countermeasures whose effectiveness or penetration is so uncertain that they were not added to the primary model (e.g., V2V applications).
- Countermeasures whose predicted penetration is expected to be negligibly low, to explore how substantially higher penetration could affect future outcomes (e.g., roundabouts).
- Hypothetical updates to regulatory or consumer testing requirements or performance targets.
- Generic countermeasures for the reduction of crashes associated with alcohol or distraction to illustrate the benefit of reducing these crashes by any means.

Deletion of individual countermeasures:

- For some individual countermeasures, the effect of the countermeasures can be explored by deleting them from the full model.

Variation in predicted trends:

- Parametric variation in applied economic predictions to explore the effects of better-than-predicted and worse-than-predicted future unemployment rates as an indicator of the status of the economy.
- Variation of predicted future increases in restraint use to explore the effects of faster-than-predicted and slower-than-predicted improvements in restraint use rates, as well as a hypothetical version showing the potential effect of 100 percent restraint use.

Sensitivity to countermeasure parameters:

- Sensitivity of results to effectiveness estimates can be explored with a percentage change in effectiveness for countermeasures in the model.
- Sensitivity of results to target population definition can be explored by broadening the target population for specific countermeasures (e.g., expanding the effect of NCAP 2011 side impact updates to apply to a much broader subset of side impacts than the narrowly defined target population used in the primary model).
- Sensitivity of results to penetration can be explored with versions of specific countermeasures under the hypothetical assumptions that penetration would occur twice as fast, or half as fast, as anticipated.

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Appendix A: Vehicles in Crashes by Age

A.1 Vehicle Age Distribution

The estimated distribution of vehicle age in crash exposures is needed in multiple components in the projection model. This distribution corresponds to the proportion of occupants exposed to potential crashes by the age of their vehicles at the time of the crash. Distribution of vehicle age in past and projected datasets was estimated using historical data from NASS GES (years 2006 to 2008) in Table 33 and Figure 24. This period was selected because it was more stable than in subsequent years. Vehicle sales in 2009 and later were affected by the economic downturn in the U.S., resulting in an initial reduction in sales followed by a rebound, affecting the vehicle-age distribution of occupants in crashes for many subsequent years.

Table 33. Vehicle age distribution

Vehicle Age at Time of Crash	Percentage of Weighted Occupants in CDS-Eligible Cases in NASS GES 2006-2008
0	5.517757
1	7.029345
2	6.982753
3	7.145462
4	7.265463
5	7.351633
6	7.425612
7	7.147121
8	6.826811
9	6.225404
10	5.431873
11	4.930905
12	4.437301
13	3.656767
14	2.901561
15	2.228664
16	1.833639
17	1.345905
18	1.130853
19	0.77777
20	0.608425
21	0.415741
22	0.321019
23	0.214166
24	0.157311
25	0.091023
26	0.063099
27	0.070086
28	0.066268
29	0.07535
30+	0.324912

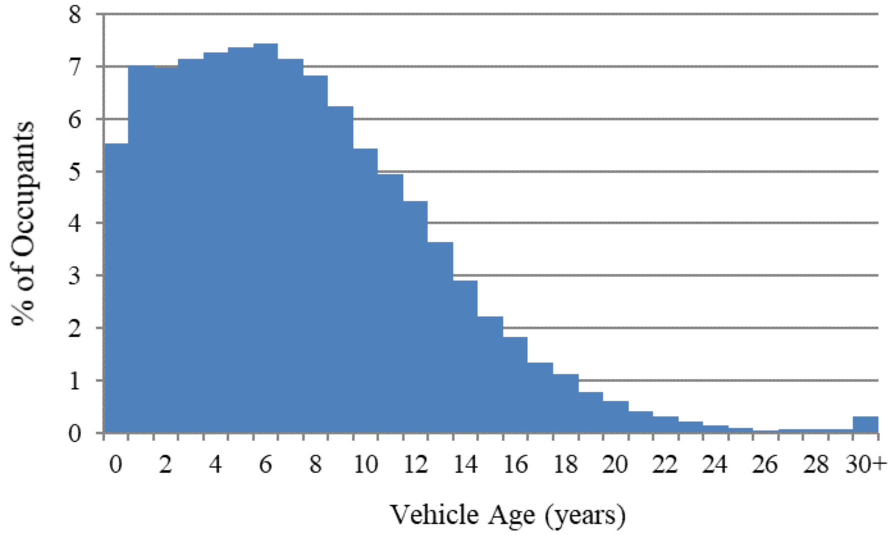

Figure 24. Vehicle age distribution (NASS GES 2006–2008)

A.2 Vehicle Model Year Distribution

Since the MY<2005 vehicles in the stepping-stone dataset continue to represent MY<2005 vehicles in the projection datasets, cases involving occupants in MY<2005 vehicles are not adjusted in the model for vehicle trends such as shifting proportions of vehicle types or vehicle-based countermeasures introduced after model year 2005. Application of vehicle trends and vehicle countermeasures to MY2005+ vehicles in the projection model therefore requires estimation of the vehicle model year distribution among only MY2005+ vehicles. This distribution is needed for the 2013 to 2015 crash-year period in the stepping-stone dataset as well as for the 2020, 2025, and 2030 projection years. For the 2030 projection, for example, the vehicle age distribution among occupants in MY2005+ vehicles provides the estimated percentage of cases in vehicles of each model year *among only case occupants in vehicles 25 years or newer*. The resulting vehicle model year distributions for each time period of interest are shown in Table 34 through Table 39, based on the data in Appendix A.1.

Table 34. Vehicle age distribution for the crash year 2013

Model Year	Percentage of Weighted Occupants (from Appendix A.1)	Percentage of Weighted Occupants Among Occupants in MY2005+ Vehicles
2013	5.52%	8.80%
2012	7.03%	11.21%
2011	6.98%	11.14%
2010	7.15%	11.40%
2009	7.27%	11.59%
2008	7.35%	11.73%
2007	7.43%	11.84%
2006	7.15%	11.40%
2005	6.83%	10.89%
Total	62.69%	100.0%

Table 35. Vehicle age distribution for the crash year 2014

Model Year	Percentage of Weighted Occupants (from Appendix A.1)	Percentage of Weighted Occupants Among Occupants in MY2005+ Vehicles
2014	5.52%	8.01%
2013	7.03%	10.20%
2012	6.98%	10.13%
2011	7.15%	10.37%
2010	7.27%	10.54%
2009	7.35%	10.67%
2008	7.43%	10.77%
2007	7.15%	10.37%
2006	6.83%	9.91%
2005	6.23%	9.03%
Total	68.92%	100.0%

Table 36. Vehicle age distribution for the crash year 2015

Model Year	Percentage of Weighted Occupants (from Appendix A.1)	Percentage of Weighted Occupants Among Occupants in MY2005+ Vehicles
2015	5.52%	7.42%
2014	7.03%	9.45%
2013	6.98%	9.39%
2012	7.15%	9.61%
2011	7.27%	9.77%
2010	7.35%	9.89%
2009	7.43%	9.99%
2008	7.15%	9.61%
2007	6.83%	9.18%
2006	6.23%	8.37%
2005	5.43%	7.31%
Total	74.35%	100.0%

Table 37. Vehicle age distribution for the crash year 2020

Model Year	Percentage of Weighted Occupants (from Appendix A.1)	Percentage of Weighted Occupants Among Occupants in MY2005+ Vehicles
2020	5.52%	5.96%
2019	7.03%	7.60%
2018	6.98%	7.55%
2017	7.15%	7.72%
2016	7.27%	7.85%
2015	7.35%	7.95%
2014	7.43%	8.03%
2013	7.15%	7.73%
2012	6.83%	7.38%
2011	6.23%	6.73%
2010	5.43%	5.87%
2009	4.93%	5.33%
2008	4.44%	4.80%
2007	3.66%	3.95%
2006	2.90%	3.14%
2005	2.23%	2.41%
Total	92.50%	100.0%

Table 38. Vehicle age distribution for the crash year 2025

Model Year	Percentage of Weighted Occupants (from Appendix A.1)	Percentage of Weighted Occupants Among Occupants in MY2005+ Vehicles
2025	5.52%	5.62%
2024	7.03%	7.16%
2023	6.98%	7.11%
2022	7.15%	7.28%
2021	7.27%	7.40%
2020	7.35%	7.49%
2019	7.43%	7.56%
2018	7.15%	7.28%
2017	6.83%	6.95%
2016	6.23%	6.34%
2015	5.43%	5.53%
2014	4.93%	5.02%
2013	4.44%	4.52%
2012	3.66%	3.72%
2011	2.90%	2.95%
2010	2.23%	2.27%
2009	1.83%	1.87%
2008	1.35%	1.37%
2007	1.13%	1.15%
2006	0.78%	0.79%
2005	0.61%	0.62%
Total	98.20%	100.0%

Table 39. Vehicle age distribution for the crash year 2030

Model Year	Percentage of Weighted Occupants (from Appendix A.1)	Percentage of Weighted Occupants Among Occupants in MY2005+ Vehicles
2030	5.52%	5.55%
2029	7.03%	7.07%
2028	6.98%	7.02%
2027	7.15%	7.19%
2026	7.27%	7.31%
2025	7.35%	7.40%
2024	7.43%	7.47%
2023	7.15%	7.19%
2022	6.83%	6.87%
2021	6.23%	6.26%
2020	5.43%	5.46%
2019	4.93%	4.96%
2018	4.44%	4.46%
2017	3.66%	3.68%
2016	2.90%	2.92%
2015	2.23%	2.24%
2014	1.83%	1.84%
2013	1.35%	1.35%
2012	1.13%	1.14%
2011	0.78%	0.78%
2010	0.61%	0.61%
2009	0.42%	0.42%
2008	0.32%	0.32%
2007	0.21%	0.22%
2006	0.16%	0.16%
2005	0.09%	0.09%
Total	99.40%	100.00%

Appendix B: Projected Trends

B.1 Vehicle Type Trend Application

As discussed in Section 2.5.1, the proportion of each vehicle type expected to be exposed to potential crashes in the future was adjusted according to predicted shifts in the on-road vehicle type distribution. This adjustment was made by reweighting the cases in the stepping-stone dataset so that the distribution of cases by vehicle type matched the predicted distribution of vehicles exposed to crashes in the target projection year. The estimated distribution of vehicle types in future crash exposures was primarily based on:

- historical year-by-year sales data from the Environmental Protection Agency (EPA, 2015, 2019) adjusted for SUV sales data from NHTSA (Puckett & Kindelberger, 2016),
- predicted sales data in future years from the Energy Information Administration 2018 Annual Energy Outlook (EIA, 2017, 2018), and
- estimated vehicle age distribution in future crashes.

This appendix includes supplemental information used to distinguish CUVs from other SUVs (B.1.1) as well as the source data used to estimate the proportion of different vehicle types sold in the past (B.1.2) and expected in the future (B.1.3). The resulting projected distribution of different vehicle types in the projection model is summarized in Appendix B.1.4.

B.1.1 Classification of CUVs

The vehicles in Table 40 were classified as CUVs in the projection model.[20]

Table 40. CUVs by make, model, and model year

Make	Model	Model Year
Acura	MDX	2001:2016
Acura	RDX	2007:2016
Acura	ZDX	2010:2013
Audi	Allroad	2001:2005, 2013:2016
Audi	Q5	2009:2016
Audi	Q7	2007:2015
BMW	X1	2013:2016
BMW	X3	2004:2016
BMW	X5	2000:2016
BMW	X6	2008:2016
Buick	Enclave	2008:2016
Buick	Encore 4-door CUV	2013:2016
Buick	Rendezvous	2002:2007
Cadillac	SRX	2004:2016
Chevrolet	Captiva	2011:2015
Chevrolet	Equinox	2005:2016

[20] Charles J. Kahane, Bowhead Logistics Solutions, LLC, Alexandria, VA, personal communication, 2018.

Make	Model	Model Year
Chevrolet	HHR	2006:2011
Chevrolet	Traverse	2009:2016
Chrysler	Pacifica	2004:2008
Chrysler	PT Cruiser	2001:2010
Dodge	Journey	2009:2016
Dodge	Magnum	2005:2008
Ford	Edge	2007:2016
Ford	Escape	2013:2016
Ford	Escape 4dr	2001:2012
Ford	Flex	2009:2016
Ford	Freestyle	2005:2007
Ford	Taurus X	2008:2009
GMC	Acadia	2007:2016
GMC	Terrain	2010:2016
Honda	Accord Crosstour	2010:2015
Honda	CR-V	1997:2016
Honda	Element	2003:2011
Honda	Pilot	2003:2016
Hyundai	Santa Fe	2002:2014
Hyundai	Santa Fe Sport	2013:2016
Hyundai	Tucson	2005:2016
Hyundai	Veracruz	2007:2012
Hyundai	Veracruz 4x4	2007:2012
Infiniti	EX35	2008:2012
Infiniti	FX35/FX45 4dr	2003:2008
Infiniti	QX50	2014:2016
Infiniti	QX60 4dr	2014:2016
Infiniti	QX70	2014:2015
Jeep	Compass/Patriot	2007:2016
Kia	Sorento	2011:2016
Kia	Sportage 4dr	2005:2016
Kia	Sportage 4dr 4x4	2005:2010
Land	Rover Discovery Sport 4dr	2015:2016
Land	Rover LR2 4dr 4x4	2008:2015
Land	Rover Range Rover Evoque 2dr 4x4	2012:2016
Land	Rover Range Rover Evoque 4dr 4x4	2012:2016
Land	Rover Range Rover LWB 4x4	2014:2016
Lexus	NX	2015:2016
Lexus	RX300 4dr	1999:2003
Lexus	RX330/RX350 4dr	2004:2009
Lexus	RX350/RX450h	2016
Lexus	RX350/RX450h 4dr	2010:2015

Make	Model	Model Year
Lincoln	MKC	2015:2016
Lincoln	MKT	2010:2016
Lincoln	MKX	2007:2016
Mazda	5	2012:2015
Mazda	CX-5	2013:2016
Mazda	CX-7	2007:2012
Mazda	CX-9	2007:2016
Mazda	Tribute	2001:2011
Mazda	Tribute 4x4	2001:2011
Mercedes	Benz GL-320/450	2007:2012
Mercedes	Benz GL-350/550	2013:2016
Mercedes	Benz GLK-350	2010:2015
Mercedes	Benz R 350 4dr	2008
Mercedes	Benz R 350/500 4dr.	2006:2012
Mercury	Mariner	2005:2011
Mercury	Mariner 4x4	2005:2011
Mitsubishi	Endeavor	2004:2008, 2010:2011
Mitsubishi	Outlander	2003:2016
Nissan	Cube	2009:2014
Nissan	Juke	2011:2016
Nissan	Murano 2CV	2011:2014
Nissan	Murano 4dr	2003:2016
Nissan	Pathfinder 4dr	2013:2016
Nissan	Rogue	2008:2016
Pontiac	Aztek	2001:2005
Pontiac	Torrent	2006:2009
Porsche	Cayenne	2003:2006, 2008:2016
Porsche	Macan	2015:2016
Saturn	Outlook	2007:2010
Saturn	Vue	2002:2010
Subaru	B9 Tribeca	2006:2014
Subaru	Crosstrek	2013:2016
Subaru	Forester	1998:2016
Subaru	Outback	2005:2016
Suzuki	Grand Vitara XL-7 4x4	2001:2006
Suzuki	XL-7	2007:2009
Toyota	Highlander	2001:2016
Toyota	RAV4	2013:2014
Toyota	RAV4 2dr 4x2	1996:1999
Toyota	RAV4 2dr 4x4	1996:1999
Toyota	RAV4 4dr	2006:2016
Toyota	RAV4 4dr 4x2	1996:2012

Make	Model	Model Year
Toyota	RAV4 4dr 4x4	1996:2005
Toyota	Venza	2009:2015
Volvo	XC60	2010:2016
Volvo	XC70	2001:2016
Volvo	XC90	2003:2014, 2016
VW	Tiguan	2009:2016
VW	Touareg	2004:2016

B.1.2 Source Data: Historical Vehicle Sales (2005–2016)

Light-duty vehicle sales numbers by vehicle type were available from the EPA for years 1975 to 2016, while light-duty vehicle sales proportions by vehicle type were available from NHTSA for 2003 to 2010. Because the vehicle type trend is only applied to vehicles of MY2005+, only vehicle sales for 2005 and later are shown in this section.

The number and types of light-duty vehicles sold in the United States from 2005 to 2016, based on EPA sales data, are shown in Table 41 (EPA, 2019). Table 42 shows the corresponding sales proportions by vehicle type for this data. The proportion of light-duty vehicle sales by vehicle type based on NHTSA data (Puckett & Kindelberger, 2016) is shown in Table 43.

Table 41. EPA-reported new light-duty vehicles sold in U.S. by vehicle type (EPA, 2019)

New Light-Duty Vehicles Sold in U.S. (Thousands)						
Model Year	**Car**	**CUVs**	**Truck-SUVs**	**Vans**	**Pickups**	**Total**
2005	8,026.53	812.83	3,271.67	1,480.85	2,300.39	15,892.26
2006	7,993.01	751.49	3,005.87	1,166.05	2,188.07	15,104.49
2007	8,081.83	919.19	3,314.39	847.23	2,113.17	15,275.82
2008	7,318.68	923.84	3,072.07	789.89	1,793.88	13,898.36
2009	5,636.22	608.22	1,713.85	368.07	989.48	9,315.85
2010	6,060.64	914.92	2,305.41	559.14	1,276.30	11,116.40
2011	5,742.73	1,206.61	3,069.22	520.97	1,478.87	12,018.40
2012	7,393.34	1,265.33	2,771.39	662.28	1,356.55	13,448.89
2013	8,225.89	1,514.03	3,309.62	571.07	1,576.98	15,197.59
2014	7,638.74	1,566.36	3,706.17	671.61	1,928.87	15,511.75
2015	7,899.49	1,701.27	4,696.85	654.91	1,785.99	16,738.52
2016	7,130.05	1,870.09	4,729.87	629.95	1,906.71	16,266.67

Table 42. Proportion of light-duty vehicles sold in U.S. by vehicle type (calculated from Table 41)

New Light-Duty Vehicles Sold in U.S. (% of total light-duty vehicle sales)					
Model Year	**Car**	**CUVs**	**Truck-SUVs**	**Vans**	**Pickups**
2005	50.51%	5.11%	20.59%	9.32%	14.47%
2006	52.92%	4.98%	19.90%	7.72%	14.49%
2007	52.91%	6.02%	21.70%	5.55%	13.83%
2008	52.66%	6.65%	22.10%	5.68%	12.91%
2009	60.50%	6.53%	18.40%	3.95%	10.62%
2010	54.52%	8.23%	20.74%	5.03%	11.48%
2011	47.78%	10.04%	25.54%	4.33%	12.31%
2012	54.97%	9.41%	20.61%	4.92%	10.09%
2013	54.13%	9.96%	21.78%	3.76%	10.38%
2014	49.24%	10.10%	23.89%	4.33%	12.43%
2015	47.19%	10.16%	28.06%	3.91%	10.67%
2016	43.83%	11.50%	29.08%	3.87%	11.72%

Table 43. NHTSA-reported proportion of light-duty vehicles sold in U.S. by vehicle type

New Light-Duty Vehicles Sold in U.S. (% of total light-duty vehicle sales)					
Model Year	**Car**	**CUVs**	**Truck-SUVs**	**Vans**	**Pickups**
2005	47.83%	13.41%	13.88%	8.99%	15.89%
2006	48.91%	14.01%	11.97%	8.11%	17.00%
2007	51.30%	15.73%	13.17%	5.79%	14.01%
2008	51.09%	17.17%	11.29%	5.95%	14.50%
2009	59.68%	14.83%	10.02%	4.32%	11.14%
2010	54.20%	15.22%	12.99%	5.50%	12.08%

Because the sales mix was relatively consistent between the EPA data in Table 42 and the NHTSA data in Table 43 for all categories except CUVs and truck-based SUVs, it was assumed that the two datasets used compatible definitions of passenger cars, pickup trucks, and vans, but that the definition of CUVs and truck-based SUVs likely varied between the two. In other words, it was likely that NHTSA used a broader definition of CUVs, given that from year-to-year, the percentage of CUVs was substantially higher than in the EPA dataset. Because the projection model uses a system for distinguishing CUVs and truck-based SUVs that is expected to be consistent with the definition used by NHTSA (for more detail on the system used for distinguishing SUV types, see Section 2.5.1), an adjustment was applied to the EPA data for all years for which both EPA data and NHTSA data was available. As shown in Table 44, it was estimated that, on average, 40.59 percent of vehicles categorized as truck-SUVs in the EPA data would have been categorized as CUVs by NHTSA. Therefore, the truck-SUV sales in the EPA data were reduced by 40.59 percent and the corresponding sales were added to the CUV sales for each year from 2005 to 2010.

Table 44. Truck-SUV adjustment calculation (2005–2010)

	$TS_{total, EPA}$ Truck-SUV Sales (Thousands)	$LV_{total, EPA}$ Total Light-Duty Vehicle Sales (Thousands)	$TS_{percent, NHTSA}$ Truck-SUVs (% of Total Vehicle Sales)	Conversion % of Truck-SUV Sales to Convert to CUV Sales
Source	**EPA**	**EPA**	**NHTSA**	**Calculation (Equation (27))**
2005	3,271.67	15,892.26	13.88%	32.58%
2006	3,005.87	15,104.49	11.97%	39.85%
2007	3,314.39	15,275.82	13.17%	39.30%
2008	3,072.07	13,898.36	11.29%	48.92%
2009	1,713.85	9,315.85	10.02%	45.54%
2010	2,305.41	11,116.40	12.99%	37.36%
Average				40.59%

$$Conversion = \frac{TS_{total,EPA} - (LV_{total,EPA} \; x \; TS_{percent,NHTSA})}{TS_{total,EPA}} \tag{27}$$

where parameters are defined in Table 44.

Based on this conversion, the vehicle sales proportions used in the projection model for 2005 to 2010 (Table 45) were from EPA estimates, adjusted as shown above to match the NHTSA definition of CUVs and truck-based SUVs. For 2011 to 2016, in the absence of other available data, it was estimated that any increase in the proportion of light truck sales in the EPA estimates was due to SUVs that were categorized as truck-SUVs by the EPA, but that would have been categorized as CUVs by NHTSA. This approximation was based on the observation that most growth in SUV sales during this period came from the small SUV market segment. Therefore, to adjust the EPA estimates to correspond to NHTSA's definitions of CUVs and truck-based SUVs, the number of truck-SUVs in 2011 to 2016 was reduced to hold the total percentage of light truck sales (Truck-SUVs + Vans + Pickups) constant at 2010 levels (28.8% of total vehicles according to Table 45). The number of vehicles *subtracted* from truck-SUVs to hold the light truck sales percentage constant in each model year were *added* to CUV sales for that model year. The resulting adjusted EPA distribution estimates for 2011 to 2016 are shown in Table 45.

Table 45. New light-duty vehicles sold in U.S. by vehicle type, adjusted (thousands)

Model Year	Car	CUVs	Truck-SUVs	Vans	Pickups	Total
2005	8,027	2,141	1,944	1,481	2,300	15,892
2006	7,993	1,972	1,786	1,166	2,188	15,104
2007	8,082	2,265	1,969	847	2,113	15,276
2008	7,319	2,171	1,825	790	1,794	13,898
2009	5,636	1,304	1,018	368	989	9,316
2010	6,061	1,851	1,370	559	1,276	11,116
2011	5,743	2,811	1,465	521	1,479	12,018
2012	7,393	2,178	1,859	662	1,357	13,449
2013	8,226	2,590	2,234	571	1,577	15,198
2014	7,639	3,401	1,872	672	1,929	15,512
2015	7,899	4,013	2,385	655	1,786	16,739
2016	7,130	4,447	2,153	630	1,907	16,267

B.1.3 Source Data: Prediction of Vehicle Sales (2017–2050)

Predicted sales data, made by the U.S. Energy Information Administration as part of their Annual Energy Outlook for 2018, are shown in Table 46 and Figure 25 (EPA, 2019). The EIA produces many versions of their predictions representing different scenarios, but the one used in Table 46 was the "reference case" that assumes: (1) trend improvement in known technologies and (2) economic and demographic trends reflecting "the current central views of leading economic forecasters and demographers."

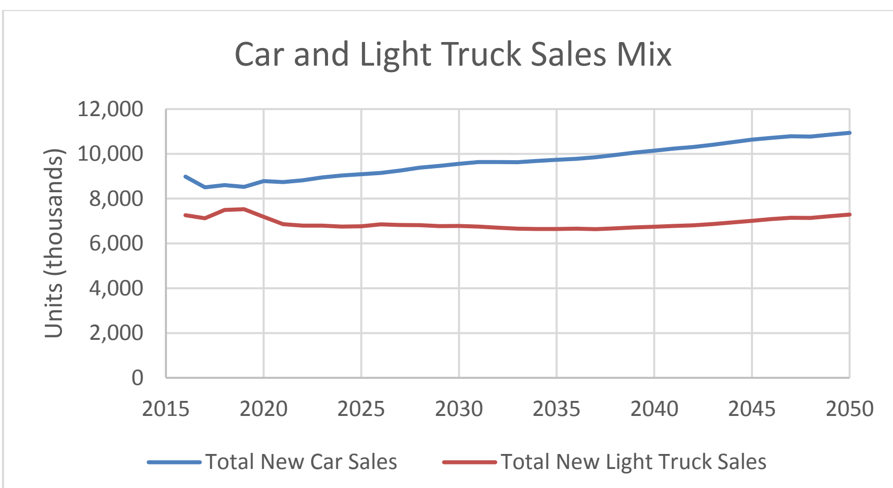

Figure 25. Estimate of distribution of new car sales by model year (from Table 39 in www.eia.gov/outlooks/aeo/tables_ref.php)

Table 46. Predicted light-duty vehicle sales in U.S. in thousands (EIA, 2018)

Year	Total New Car Sales	Total New Light Truck Sales	Total Vehicles Sales
2017	8,505.3	7,124.1	15,629.4
2018	8,605.6	7,497.4	16,103.0
2019	8,524.1	7,527.9	16,052.1
2020	8,780.2	7,190.8	15,971.0
2021	8,738.3	6,857.9	15,596.2
2022	8,816.4	6,798.1	15,614.4
2023	8,950.7	6,791.5	15,742.2
2024	9,036.2	6,750.2	15,786.4
2025	9,088.8	6,768.0	15,856.8
2026	9,145.8	6,855.3	16,001.2
2027	9,253.0	6,820.2	16,073.2
2028	9,385.6	6,814.3	16,199.9
2029	9,464.1	6,771.2	16,235.3
2030	9,555.8	6,778.3	16,334.1
2031	9,635.8	6,752.2	16,388.0
2032	9,634.7	6,701.3	16,336.0
2033	9,627.0	6,656.6	16,283.5
2034	9,685.6	6,648.1	16,333.7
2035	9,730.6	6,647.3	16,378.0
2036	9,779.8	6,660.0	16,439.8
2037	9,847.1	6,637.5	16,484.6
2038	9,945.1	6,674.6	16,619.8
2039	10,054.6	6,718.5	16,773.1
2040	10,138.2	6,742.1	16,880.3
2041	10,233.8	6,782.2	17,016.0
2042	10,303.8	6,809.1	17,112.9
2043	10,404.6	6,866.3	17,270.8
2044	10,523.6	6,939.3	17,462.9
2045	10,636.0	7,010.1	17,646.1
2046	10,716.8	7,089.1	17,805.9
2047	10,784.6	7,143.6	17,928.1
2048	10,769.1	7,135.8	17,904.9
2049	10,856.7	7,215.9	18,072.7
2050	10,937.9	7,287.4	18,225.3

As with the historical vehicle sales data in the previous section, it was estimated that any increase in the proportion of light truck sales was due to SUVs categorized as truck-SUVs that would have been categorized as CUVs by NHTSA. Therefore, to adjust the EIA estimates to correspond to NHTSA's definitions of CUVs and truck-based SUVs, the number of light trucks was reduced to hold the total percentage of light truck sales (Truck-SUVs + Vans + Pickups) constant at 2010 levels (28.8% of total vehicles according to Table 45). The number of vehicles *subtracted* from light trucks to hold the light truck sales percentage constant in each model year were *added* to car sales for that model year (Table 47). Additionally, in the absence of available data, it was estimated that the relative proportions of the sub-types of light trucks (truck-SUVs, pickups, and vans) and the sub-types of cars (passenger cars and CUVs) will remain at the adjusted 2016 levels (45.9% truck-SUVs, 13.4% vans, 40.7% pickups among light trucks; 61.6% passenger cars and 38.4% CUVs among cars). The resulting adjusted vehicle sales predictions for 2017 to 2030 are shown in Table 48.

Table 47. Adjustment of EIA-estimated vehicle sales to correspond to NHTSA's definitions of vehicle types

Model Year	EIA Estimated Sales			Adjustment (Subtracted From Light Trucks & Added to Cars)	Adjusted Estimated Sales				
	Cars	Light Trucks	Total		Cars	Light Trucks	Total	Car %	Light Truck %
2017	8,505	7,124	15,629	2,617.9	11,123	4,506	15,629	71.2	28.8
2018	8,606	7,497	16,103	2,854.6	11,460	4,643	16,103	71.2	28.8
2019	8,524	7,528	16,052	2,899.9	11,424	4,628	16,052	71.2	28.8
2020	8,780	7,191	15,971	2,586.1	11,366	4,605	15,971	71.2	28.8
2021	8,738	6,858	15,596	2,361.3	11,100	4,497	15,596	71.2	28.8
2022	8,816	6,798	15,614	2,296.2	11,113	4,502	15,614	71.2	28.8
2023	8,951	6,792	15,742	2,252.8	11,203	4,539	15,742	71.2	28.8
2024	9,036	6,750	15,786	2,198.7	11,235	4,551	15,786	71.2	28.8
2025	9,089	6,768	15,857	2,196.2	11,285	4,572	15,857	71.2	28.8
2026	9,146	6,855	16,001	2,241.9	11,388	4,613	16,001	71.2	28.8
2027	9,253	6,820	16,073	2,186.1	11,439	4,634	16,073	71.2	28.8
2028	9,386	6,814	16,200	2,143.6	11,529	4,671	16,200	71.2	28.8
2029	9,464	6,771	16,235	2,090.3	11,554	4,681	16,235	71.2	28.8
2030	9,556	6,778	16,334	2,068.9	11,625	4,709	16,334	71.2	28.8

Table 48. Predicted light-duty vehicle sales in U.S., adjusted (thousands)

Model Year	Car	CUVs	Truck-SUVs	Vans	Pickups	Total
2017	6,851	4,272	2,069	605	1,832	15,629
2018	7,058	4,402	2,132	624	1,888	16,103
2019	7,036	4,388	2,125	622	1,882	16,052
2020	7,000	4,366	2,114	618	1,872	15,971
2021	6,836	4,263	2,065	604	1,828	15,596
2022	6,844	4,268	2,067	605	1,830	15,614
2023	6,900	4,303	2,084	610	1,845	15,742
2024	6,920	4,315	2,090	611	1,850	15,786
2025	6,950	4,335	2,099	614	1,859	15,857
2026	7,014	4,374	2,118	620	1,876	16,001
2027	7,045	4,394	2,128	622	1,884	16,073
2028	7,101	4,428	2,144	627	1,899	16,200
2029	7,116	4,438	2,149	629	1,903	16,235
2030	7,160	4,465	2,162	633	1,915	16,334

B.1.4 Distribution of Vehicle Types Exposed to Potential Crashes

The vehicle age distribution, as described in Appendix A, was used to estimate the vehicle model-year distribution for crash exposed occupants for projection years (2020, 2025, and 2030).[21] For each time period of interest, the proportions of crash-exposed occupants in vehicles from each model year (CE Occupants$_{MY}$), from Table 34 through Table 39, were combined with the proportions of vehicle type by model year, from Table 41 and Table 48, using Equation (28). The resulting proportions of vehicle types among crash-exposed occupants in passenger vehicles are shown in Table 49.

$$P_{Vehicle\ Type} = \sum_{MY} \left[\left(\frac{Vehicles\ Sold_{Vehicle\ Type}}{Vehicles\ Sold_{Total}} \right)_{MY} * \ CE\ Occupants_{MY} \right] \tag{28}$$

where:

P is the estimated proportion of crash exposures for a given vehicle type over a given range of model years,

Vehicles Sold are annual counts from Tables 41 and 48 by model year, and

CE Occupants is the proportion of crash-exposed occupants in the given vehicle type for the given model year.

[21] Since the MY<2005 vehicles in the stepping-stone dataset continue to represent MY<2005 vehicles in the projection datasets and will not be adjusted for vehicle trends such as shifting proportions of vehicle types, the vehicle age distribution for application to this trend is limited to MY2005+ vehicles. For example, for 2030, the vehicle age distribution for vehicles to be adjusted for shifting vehicle type proportions would be limited to vehicles 25-years-old and newer.

Table 49. Estimated proportion of crash exposure by vehicle type (from Equation (28))

Dataset	Calculated Over Model Years	Cars	CUVs	Vans	Truck-SUVs	Pickups
Stepping-Stone 2013-2015	2005-2015	52.79%	15.10%	6.47%	12.44%	13.20%
2020	2005-2020	49.16%	21.57%	4.49%	13.05%	11.73%
2025	2005-2025	46.18%	24.89%	4.08%	13.20%	11.65%
2030	2005-2030	44.51%	26.64%	3.92%	13.24%	11.69%

B.1.5 Adjustment Factors

B.1.5.1 Downweighting: Adjustment Factors for Cars, Pickup Trucks, and Vans

Cars, pickup trucks, and vans are expected to be less common in the future, and thus will be downweighted, as explained in Section 2.5.1. Downweighting AF adjustment factor variables for cars, pickup trucks, and vans are shown in Table 50. For each future projection year, the AF for each vehicle type was estimated as a function of the proportion of crash exposure in both the projection year and in the stepping-stone year range (from Table 49) as shown in Equation (29). For example, occupants in passenger cars were estimated to make up 52.79 percent of crash-exposed occupants in MY2005+ vehicles in the stepping-stone dataset compared to only 44.51 percent of crash-exposed occupants in MY2005+ vehicles in the 2030 projection year. Therefore, passenger car occupant cases in the 2030 projection dataset were downweighted by a factor of 0.843 (44.51/52.79) to reflect the predicted future reduction in passenger car occupants in future crashes.

$$AF(2030)_{Vehicle\ Type} = \left(\frac{P_{2030}}{P_{stepping\ stone}}\right)_{Vehicle\ Type} \qquad (29)$$

where:

AF is the adjustment factor for cases involving that vehicle type, and

P is the estimated proportion of crash exposure for the vehicle type in a given year/range.

Table 50. Trend adjustment factors for cars, pickup trucks, and vans in projection years

Crash Year	Proportion of Crash Exposure (%) P_{Car}	Adjustment Factor for Cars AF_{Car}	Proportion of Crash Exposure (%) P_{Van}	Adjustment Factor for Vans AF_{Van}	Proportion of Crash Exposure (%) P_{pickup}	Adjustment Factor for Pickups $AF_{pickups}$
Stepping-Stone Dataset	52.79%	--	6.47%	--	13.20%	
2020	49.16%	0.931	4.49%	0.694	11.73%	0.889
2025	46.18%	0.875	4.08%	0.631	11.65%	0.882
2030	44.51%	0.843	3.92%	0.607	11.69%	0.885

B.1.5.2 Upweighting: Adjustment Factors for CUVs and SUVs

As explained in Section 2.5.1, because both CUVs and truck-SUVs are expected to be more common in the future, they are upweighted in the future datasets. Upweighting AFs to be applied to cases involving CUVs and truck-SUVs in the stepping-stone dataset were calculated so that the total number of vehicles in the dataset did not change. In other words, the AF for CUVs and truck-SUVs were calculated to ensure that a decrease in the total weighted number of cars, pickup trucks, and vans was matched by an increase of the same magnitude in the total weighted number of CUVs and truck-SUVs. Since the AF for CUVs and truck-SUVs varies with the dataset to which it is applied, the examples given in this section are for illustration only and do not reflect actual calculated AF for CUVs and truck-SUVs in any specific run of the projection model.

For each future projection year, the number of occupants expected to convert from cars, pickup trucks, and vans to CUVs and truck-SUVs (N_c) was estimated as a function of the weighted numbers of cars (N_{car}), pickup trucks (N_{pickup}) and vans (N_{van}) in the stepping-stone dataset, as well as the previously calculated AF for cars (AF_{car}), pickup trucks (AF_{pickup}) and vans (AF_{van}), using Equation (30). The proportion of the number of converted occupants (N_c) expected to convert to CUVs (C_{CUV}) was estimated as a function of the increase in the proportion of CUVs relative to the increase in the proportion of truck-SUVs, using Equation (31). The corresponding AF for CUVs (AF_{CUV}) can then be calculated using Equation (32). The proportion of the number of converted occupants (N_c) expected to convert to truck-SUVs ($C_{truck\text{-}SUV}$) and the corresponding AF for truck-SUVs ($AF_{truck\text{-}SUV}$) are calculated using the same method.

$$N_C = N_{car} \times (1 - AF_{car}) + N_{pickup} \times \left(1 - AF_{pickup}\right) + N_{van} \times (1 - AF_{van}) \qquad (30)$$

$$C_{CUV} = \frac{(P_{stepping-stone} - P_{2030})_{CUV}}{(P_{stepping-stone} - P_{2030})_{CUV} + (P_{stepping-stone} - P_{2030})_{truck\ SUV}} \qquad (31)$$

$$AF_{CUV} = \frac{N_{CUV} + (C_{CUV} * N_C)}{N_{CUV}} \qquad (32)$$

where:

N_c is the number off occupants expected to convert from cars, pickup trucks and vans to CUVs and truck-SUVs,

$N_{vehicle\ type}$ are the weighted numbers of occupants in these vehicle types in the stepping-stone dataset

AF are the adjustment factors calculated for each vehicle type, and

C_{CUV} is the proportion of the increase of CUVs relative to the increase in all SUVs.

Examples of the AF for CUVs and truck-SUVs are shown in Table 51. These examples use dummy values for N_{car}, N_{van}, N_{pickup}, N_{CUV}, and $N_{truck\text{-}SUV}$ to step through the calculation of AF for CUVs and truck-SUVs. Note that values displayed in the table are rounded although all calculations were performed on unrounded values.

Table 51. Illustrative example of calculation of AF for SUVs and pickups

		2020	2025	2030
Weighted annual average number of cars in stepping-stone dataset	N_{car}	50,000*		
Weighted annual average number of CUVs in stepping-stone dataset	N_{CUV}	10,000*		
Weighted annual average number of vans in stepping-stone dataset	N_{van}	5,000*		
Weighted annual average number of pickups in stepping-stone dataset	N_{pickup}	15,000*		
Weighted annual average number of truck-SUVs in stepping-stone dataset	$N_{truck\text{-}SUV}$	20,000*		
Adjustment factor for cars	AF_{car}	0.931	0.875	0.843
Adjustment factor for vans	AF_{van}	0.694	0.631	0.607
Adjustment factor for pickups	AF_{pickup}	0.889	0.882	0.885
Weighted number of cases converted from cars, pickups, and vans to SUVs and CUVs	N_C	6634	9867	11527
Proportion of converted cases to be assigned to CUVs	C_{CUV}	91.5%	92.8%	93.6%
Proportion of converted cases to be assigned to truck-SUVs	$C_{truck\text{-}SUV}$	8.5%	7.2%	6.4%
Adjustment factor for CUVs*	AF_{CUV}	1.607	1.916	2.079
Adjustment factor for truck-SUVs*	$AF_{truck\text{-}SUV}$	1.028	1.036	1.037

**Hypothetical values for illustration only.*

B.2 Belt Use Trend Application

Belt use trends were applied as discussed in Section 2.5.4. Source data and more detailed calculations for application to cases in crashes with no fatalities are provided in this appendix. Procedures for adjustment for cases in potentially fatal crashes are described in Section 2.5.4.

Historical levels of belt use for the subgroups used in this study were drawn from NOPUS, the National Occupant Protection Use Survey. NOPUS results were disaggregated by seat position, vehicle type, and age group[22] as shown in Table 52. The SUV vehicle type category includes CUVs as well as truck-based SUVs. Annual conversion rates for these bins are shown in Table 53. The conversion rate for front seat passenger car occupants from 2008 to 2009 of 7.9 percent reflects, for example, that belt non-use dropped from 15.635 percent in 2008 to 14.395 percent in

[22] Subramanian, Rajesh, chief, Mathematical Analysis Division, National Center for Statistics and Analysis, NHTSA, personal communication, June 6, 2017.

2009. This drop equates to a 7.9 percent reduction in belt non-use, or conversion of 7.9 percent of unbelted occupants to belted occupants. Average conversion rates over the 2008 to 2016 period are shown in Table 54, along with the estimated future conversion rates calculated to be half of the historical annual conversion rate in each category.

Table 52. Estimated belt use rates by seat position, vehicle type, and age group

Front Seat										
		2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
All ages (by vehicle type)	Passenger Car	84.4%	85.6%	86.2%	84.9%	87.0%	88.4%	88.1%	90.3%	91.1%
	Van/SUV	86.1%	86.9%	88.0%	87.0%	88.9%	89.6%	89.1%	90.3%	92.3%
	Pickup Trucks	73.9%	74.1%	75.5%	73.6%	77.0%	78.0%	77.2%	80.8%	83.2%
Rear Seat										
		2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
All vehicle types (by age group)	Age 8-15	80.5%	76.2%	75.4%	79.6%	83.1%	82.6%	82.2%	82.0%	86.0%
	Age 16-24	69.4%	65.9%	73.4%	71.0%	67.2%	77.5%	68.0%	72.6%	78.2%
	Age 25-69	71.2%	63.9%	70.7%	69.9%	71.4%	73.1%	63.9%	64.4%	76.8%
	Age 70+	74.3%	82.4%	81.4%	72.8%	80.3%	81.8%	80.9%	81.3%	74.9%

Table 53. Annual belt use conversion rates by seat position, vehicle type, and age group

Front Seat									
		2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
All ages (by vehicle type)	Passenger Car	7.9%	4.4%	-9.5%	13.9%	10.4%	-2.7%	18.8%	7.9%
	Van/SUV	6.1%	8.4%	-8.5%	14.2%	7.0%	-5.1%	11.2%	20.6%
	Pickup Trucks	0.9%	5.3%	-7.4%	12.9%	4.2%	-3.7%	15.6%	12.5%
Rear Seat									
		2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
All vehicle types (by age group)	Age 8-15	-22.2%	-3.2%	17.1%	17.0%	-2.8%	-2.6%	-0.9%	22.3%
	Age 16-24	-11.4%	21.9%	-8.9%	-13.1%	31.3%	-42.2%	14.4%	20.5%
	Age 25-69	-25.0%	18.7%	-2.6%	5.0%	5.9%	-34.1%	1.4%	34.7%
	Age 70+	31.6%	-5.7%	-46.7%	27.7%	7.5%	-5.0%	2.0%	-33.9%

Table 54. Average annual conversion rates by seat position, vehicle type, and age group

			Average Historical Conversion Rates 2008-2016	Predicted Future Conversion Rate (Half of Average Historical Conversion Rates 2008-2016)
Front Seat				
All ages (by vehicle type)		Passenger Car	6.39%	3.20%
		Van/SUV	6.73%	3.37%
		Pickup Trucks	5.04%	2.52%
Rear Seat				
All vehicle types (by age group)		Age 8-15	3.09%	1.54%
		Age 16-24	1.56%	0.78%
		Age 25-69	0.50%	0.25%
		Age 70+ *	-2.81% *	-1.41% *

**As discussed in Section 2.5.4, estimated conversion rates shown here for rear-seat occupants 70 or older were deemed to be unreliable and not used for the projection model.*

Rates of belt non-use for the past were calculated by subtracting the belt use rates in Table 52 from 100 percent. Rates of belt non-use for the future were estimated using the conservative estimate that future annual conversion rates will be half of historical rates, shown in Table 54. These predicted future rates are shown in Table 55. Calculation of the case weight AF for belt non-use in Table 12 were estimated as a function of past non-use rates (calculated from data in Table 52) as well as the future non-use rates estimated in Table 55. For example, non-use of belts among front-seat passenger car occupants was expected to drop from 11.1 percent in 2013 to 2015 to 7.8 percent in 2020. Therefore, unbelted front-seat passenger car occupants in the 2020 dataset were downweighted using an AF of 0.707 (7.84/11.08) to reflect this expected drop in non-use. The steps of this calculation are shown in Table 56. Note that values displayed in the table are rounded although all calculations were performed on unrounded values.

Table 55. Predicted future rates of belt non-use

Front Seat								
		2016	**2017**	**2018**	**2019**	**2020**	**2025**	**2030**
All ages (by vehicle type)	Passenger Car	8.9%	8.6%	8.4%	8.1%	7.8%	6.7%	5.7%
	Van/SUV	7.7%	7.4%	7.2%	6.9%	6.7%	5.6%	4.8%
	Pickup Trucks	16.8%	16.4%	16.0%	15.6%	15.2%	13.4%	11.8%
Rear Seat								
		2016	**2017**	**2018**	**2019**	**2020**	**2025**	**2030**
All vehicle types (by age group)	Age 8-15	14.0%	13.8%	13.6%	13.4%	13.2%	12.2%	11.3%
	Age 16-24	21.8%	21.6%	21.4%	21.3%	21.1%	20.3%	19.5%
	Age 25-69	23.2%	23.1%	23.1%	23.0%	23.0%	22.7%	22.4%
	Age 70+*	25.1%	25.4%	25.8%	26.1%	26.5%	28.2%	29.9%

* As discussed in Section 2.5.4, estimated conversion rates for rear-seat occupants 70 or older were deemed to be unreliable. The corresponding non-use rates for this age group are shown in this table but were not used for the projection model.

Table 56. Adjustment factors for cases of belt non-use for projection models

Front Seat								
		Rate Non-Use				**Adjustment Factor for Belt Non-Use Cases**		
		2013-2015 Average	**2020**	**2025**	**2030**	**2020**	**2025**	**2030**
All ages (by vehicle type)	Passenger Car	11.1%	7.8%	6.7%	5.7%	0.707	0.601	0.511
	Van/SUV	10.3%	6.7%	5.6%	4.8%	0.650	0.547	0.461
	Pickup Trucks	21.3%	15.2%	13.4%	11.8%	0.712	0.627	0.552
Rear Seat								
		Rate Non-Use				**Adjustment Factor for Belt Non-Use Cases**		
		2013-2015 Average	**2020**	**2025**	**2030**	**2020**	**2025**	**2030**
All vehicle types (by age group)	Age 8-15	17.8%	13.2%	12.2%	11.3%	0.741	0.685	0.634
	Age 16-24	27.3%	21.1%	20.3%	19.5%	0.773	0.743	0.715
	Age 25-69	32.8%	23.0%	22.7%	22.4%	0.700	0.691	0.682
	Age 70+*	18.7%	26.5%	28.2%	29.9%	1.0*	1.0*	1.0*

** As discussed in Section 2.5.4, estimated conversion rates for rear-seat occupants 70 or older were deemed to be unreliable. The corresponding non-use rates for this age group are shown in this table but were not used for the projection model.*

B.3 Child Restraint Use Trend Application

Child restraint use trends were applied as described in Section 2.5.5. Source data and more detailed calculations are provided in this appendix.

Historical levels of age-appropriate restraint use for children 7 or younger were drawn from usage rates documented in the annual National Survey of the Use of Booster Seats (Glassbrenner & Ye 2007; Glassbrenner & Ye 2008; Pickrell & Ye 2010; Pickrell & Ye 2013; Pickrell & Choi 2014; Li et al., 2016). As explained in Section 2.5.5, children in NSUBS who were documented as using the type of restraint recommended at NHTSA's safercar.gov website for their observed age group were defined in the projection model as appropriately restrained. This classification was made for the purpose of regrouping cases for reweighting, and does not assume that child restraints were used properly, or that outcomes in cases involving child restraint misuse are similar to cases involving proper-use.

The compiled rates of observed restraint use by restraint-type are summarized in Table 57. While the rates from previous years were rounded to the nearest percent, the 2015 rates were provided to one-tenth of a percent; this more detailed information was used in the analysis since it was available. Additionally, note that the percentages of children in each age group do not all sum to 100%, reflecting cases of unknown restraint use. The percentages of children in each age group estimated to be in appropriate restraints therefore show the percentage of children with *known* restraint status who are in appropriate restraints. For example, the 72 percent of children under age 1 who were documented in rear-facing child safety seats in 2006 (Table 57) was equivalent to the estimate that 75 percent of children with known restraint status were in age-appropriate restraints (Table 58).

Table 57. Estimated restraint use by age
*(**bold** rates indicate age-appropriate use as defined in Section 2.5.5)*

Age (years)		2006	2007	2008	2009	2011	2013	2015
<1	Rear-Facing Child Safety Seat	**72%**	**81%**	**86%**	**83%**	**86%**	**90%**	**87.4%**
	Front-Facing Child Safety Seat	21%	14%	12%	15%	11%	7%	9.2%
	Booster Seat (Overall)							
	High- Backed Booster Seat							
	Backless Booster Seat							
	Seat Belt	2%						
	No Restraint Observed	1%	2%	1%	2%	2%	2%	2.6%
1-3	Rear-Facing Child Safety Seat	**4%**	**3%**	**2%**	**3%**	**7%**	**10%**	**9.4%**
	Front-Facing Child Safety Seat	**69%**	**73%**	**72%**	**76%**	**75%**	**73%**	**67.6%**
	Booster Seat (Overall)	19%						13.6%
	High- Backed Booster Seat		9%	11%	11%	9%	7%	11.0%
	Backless Booster Seat		5%	3%	3%	3%	3%	2.6%
	Seat Belt	5%	6%	4%	4%	2%	3%	3.7%
	No Restraint Observed	3%	4%	8%	4%	4%	5%	5.7%
4-7	Rear-Facing Child Safety Seat					**0**		**0.2%**
	Front-Facing Child Safety Seat	**17%**	**13%**	**12%**	**14%**	**18%**	**20%**	**17.9%**
	Booster Seat (Overall)	**41%**						**44.5%**
	High- Backed Booster Seat		**22%**	**26%**	**24%**	**25%**	**26%**	**22.6%**
	Backless Booster Seat		**15%**	**17%**	**17%**	**21%**	**20%**	**21.9%**
	Seat Belt	33%	35%	34%	32%	25%	24%	25.8%
	No Restraint Observed	9%	15%	11%	13%	10%	9%	11.6%

Table 58. Appropriate restraint use as percentage of children with known restraint status

Age (years)		2006	2007	2008	2009	2011	2013	2015
<1	Appropriate Restraint	75.0%	83.5%	86.9%	83.0%	86.9%	90.9%	88.1%
	Inappropriate Restraint	25.0%	16.5%	13.1%	17.0%	13.1%	9.1%	11.9%
1-3	Appropriate Restraint	73.0%	76.0%	74.0%	78.2%	82.0%	82.2%	77.0%
	Inappropriate Restraint	27.0%	24.0%	26.0%	21.8%	18.0%	17.8%	23.0%
4-7	Appropriate Restraint	58.0%	50.0%	55.0%	55.0%	64.6%	66.7%	62.6%
	Inappropriate Restraint	42.0%	50.0%	45.0%	45.0%	35.4%	33.3%	37.4%

B.3.1 Conversion Rates to Appropriate Child Restraint Use

Conversion rates from inappropriate restraint to appropriate restraint in each age group are shown in Table 59. Using Equation (33), the 34 percent conversion rate for infants under age 1 from 2006 to 2007 reflects, for example, that inappropriate restraint dropped from 25 percent in 2006 to 16.5 percent in 2007: (25% - 16.5%)/25%=34%. This drop represents a move of 34 percent of inappropriately restrained children to appropriate restraints.

$$Conversion\ Rate\ (year\ n) = \frac{(Inappropriate_{n-1} - Inappropriate_n)}{Inappropriate_n} \tag{33}$$

where:
Conversion Rate is the proportion of inappropriately restrained children who convert to appropriate use the following year, and
$Inappropriate_n$ is the inappropriate use rate in year n

For years where appropriate restraint data were unavailable (2010, 2012, 2014), annual conversion rates were estimated in the missing year and the subsequent year using Equation (34), assuming equal conversion rates in consecutive years to account for the two-year change in restraint use.

$$Conversion\ Rate\ (year\ n) = ConversionRate\ (Year\ n+1) = 1 - \sqrt{\frac{Inappropriate_{n+1}}{Inappropriate_{n-1}}} \tag{34}$$

Table 59. Annual conversion rate to appropriate restraint use

Age (years)	2007	2008	2009	2010	2011	2012	2013	2014	2015
<1	34.0%	20.4%	-29.5%	12.1%	12.1%	16.8%	16.8%	-14.4%	-14.4%
1-3	11.1%	-8.3%	16.2%	9.1%	9.1%	0.5%	0.5%	-13.6%	-13.6%
4-7	-19.0%	10.0%	0.0%	11.4%	11.4%	2.9%	2.9%	-5.9%	-5.9%

Average conversion rates over the 2007 to 2015 period are shown in Table 60, along with the more conservative estimates used for projections of half of the historical annual conversion rates.

Table 60. Average annual conversion to appropriate restraint rates by age group

Age (years)	Average Historical Conversion Rates 2007-2015	Half of Average Historical Conversion Rates 2007-2015
<1	6.00%	3.00%
1-3	1.22%	0.61%
4-7	0.85%	0.42%

B.3.2 Adjustment Factors

Adjustment factors for inappropriate restraint use: Rates of inappropriate restraint use for the 2013 to 2015 period were drawn from data in Table 58, with missing 2014 estimates calculated using estimated 2014 conversion rates from Equation (34). Rates of inappropriate restraint use for the projection years (2020, 2025, and 2030) were estimated by application of the conservative estimate of future conversion rates (half of historical rates). Summarized rates are shown in Table 61. The AF to be multiplied by the case weight for each stepping-stone case involving a child who was not in an age-appropriate restraint was calculated as a ratio of the predicted inappropriate-restraint rate in the targeted future year divided by the inappropriate-restraint rate in 2013 to 2015 for that category. The resulting case-reweighting AF for each age group in the projection years 2020, 2025, and 2030 are shown in Table 62.

Table 61. Estimated annual rates of inappropriate use

Age (years)	2013	2014	2015	Average 2013-2015	2020	2025	2030
<1	9.1%	10.4%	11.9%	10.46%	10.22%	8.77%	7.53%
1-3	17.8%	20.2%	23.0%	20.36%	22.31%	21.64%	20.98%
4-7	33.3%	35.3%	37.4%	35.35%	36.61%	35.84%	35.09%

Table 62. Adjustment factors for cases involving inappropriately restrained children

Age (years)	2020	2025	2030
<1	0.976	0.839	0.720
1-3	1.096	1.063	1.031
4-7	1.036	1.014	0.993

Adjustment factors for appropriate restraint use: As explained in Section 2.5.5, the AF to be applied to cases involving appropriately restrained children in the stepping-stone dataset was calculated so that the total number of cases in each age group did not change. In other words, the case weight AF for cases involving appropriately restrained children is determined to guarantee that an increase/decrease in the total weighted number of inappropriately restrained cases was matched by a decrease/increase of the same magnitude in the total weighted number of appropriately restrained cases. Accordingly, the AF calculated for each category of appropriately restrained cases is a function of results from the stepping-stone dataset, in contrast to the AF for inappropriately restrained children that is estimated solely based on child restraint use projections in the population. Since the AF for appropriate restraint use varies with the dataset to which it is applied, the examples given in this section are for illustration only and do not reflect the actual calculated AF for appropriate restraint use in any specific run of the projection model.

For each future projection year in each age group, the AF in appropriate-use cases was estimated as a function of the weighted numbers of inappropriate use cases (N_I) and appropriate use cases (N_A) in the stepping-stone dataset, as well as the previously calculated AF for inappropriate use (AF_I) for the age group. Using these estimates, the weighted number of children in an age group expected to convert *from* inappropriate use or non-use (N_C) can be estimated by Equation (35). The corresponding AF for appropriate restraint use cases (AF_A) can then be calculated so that the same number of children (N_C) are estimated to convert *to* appropriate restraint use (Equation (36)).

$$N_C = N_I \times (1 - AF_I) \tag{35}$$

$$AF_A = \frac{N_A + N_C}{N_A} \tag{36}$$

where:
N_I and N_A are the numbers of inappropriate and appropriate restraint cases in the stepping-stone dataset,
N_C is the number of inappropriate restraint cases expected to convert to appropriate restraint, and
AF_A is the adjustment factor for appropriate restraint cases.

Examples of AF calculated using Equations (35) and (36) for the under-1-year-old group are shown in Table 63. These examples use dummy values for N_I and N_A and step through the calculation of the AF for appropriate restraint cases. Table 63 shows, for this illustrative example, that the AF for appropriate restraint cases with children under 1 year old in the 2030 projection would be 1.042 reflecting that the 420 children conservatively estimated to be converted *from* the inappropriate use or non-use category will be converted *to* the appropriate use category. Thus, the final 2030 projection dataset in this example would still have a total of 11,500 weighted child cases in this age range, but the proportion of appropriately restrained children would be increased.

Table 63. Illustration of calculation of AF for appropriate restraint cases (AF_A)
(for children less than 1 year old, using the more conservatively estimated AF_I values estimated in Table 62)

	Weighted annual average number inappropriately restrained cases in stepping-stone dataset	Weighted annual average number appropriately restrained cases in stepping-stone dataset	Adjustment factor for inappropriate restraint cases (from Table 62)	Weighted number of cases converted from Inappropriate to appropriate restraint	Adjustment factor for appropriate Restraint cases
	N_I	N_A	AF_I	N_C	AF_A
2020	1,500	10,000	0.976	36	1.004
2025			0.839	241.5	1.024
2030			0.720	420	1.042

Appendix C: Crash Avoidance Countermeasures

C.1 FMVSS No. 126 Electronic Stability Control

C.1.1 ESC Target Population

The target population for ESC and subsets of that population were defined based on the categories used in the ESC Final Regulatory Impact Analysis (NHTSA, 2007a). The subpopulations were defined using the following crash parameters:

- Fatal/non-fatal crashes,
- Crash type: single vehicle rollover/other single vehicle crash excluding pedestrian or animal/culpable multi-vehicle crashes, and
- Vehicle type: passenger car/light truck or van.

Cases were sorted into these categories using the following NASS CDS variables.

Fatal crash: The crash was categorized as fatal if any of the following were true, and non-fatal otherwise. The code used the following NASS CDS variable definitions:

- OA/TREATMENT=1, for at least one person in the crash (not just same occupant or vehicle as the case occupant), or
- ACC/ATREAT=1. This derived variable indicates the most intensive treatment given to any occupant of a towed in-transport CDS applicable vehicle in the crash.

Single-vehicle rollover: Rollovers in the target population were identified to establish a rollover population comparable to that used in estimation of ESC effectiveness rates using the following NASS CDS variable definitions:

- ACC/VEHFORMS=1 (single vehicle crash), and
- GV/ROLLOVER>=1 (quarter turns) for the occupant's vehicle, and
- For EVENT/accseq=1: EVENT/OBJCONT=31 (Rollover-Overturn), 32 (Rollover-Endover), 34 (Jackknife), 61(Ground)[23], and
- GV/ROLLOBJ, nothing but: Turn/Fall-Over (31), End-over-end (32), Jackknife (34), ground (61).[24]

Single-vehicle crashes, not including pedestrians/animals: The following NASS CDS variables were used to identify cases in this category:

- GV/ACCTYPE=1, 2, 4-7, 9-12, 14-16

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[23] For the cases in the source dataset where this variable was unknown (0.25% of events), it was assumed that the case was NOT in the target population.

[24] In cases in our source dataset, this variable was unknown in approximately 1.4 percent of crashes. Given that 88 percent of crashes were not rollovers, this proportion means that this variable may have been unknown in more than 10 percent of rollover crashes. ROLLOBJ was in one of the defined target population categories in the majority of rollover crashes where this variable was known, so it was assumed for the purpose of this analysis that rollover cases with "unknown" ROLLOBJ cases are in the target population.

Note that this definition included impact with stationary objects (12) and parked vehicles (11), but excluded pedestrian/animal (13) and bicycle (73) impacts.

Culpable multi-vehicle crashes: If the occupant's vehicle is a "culpable vehicle" by the definition below, then vehicle type, effectiveness, and penetration are based on the occupant's vehicle. If another vehicle is the "culpable vehicle" then effectiveness for an occupant case is calculated based on the other (culpable) vehicle's vehicle type and model year, even if the other vehicle is an older-model vehicle that would not otherwise be included in the analysis. To identify the culpable vehicle in a crash, the following definition was coded, using NASS CDS variables:

- GV/ACCTYPE=20, 24, 28, 34:93 *(all multivehicle except struck vehicles in front-to-rear crashes)*

AND

- GV/PREEVENT in
  - 05='POOR ROAD CONDIT'
  - 06='TRAVEL TOO FAST'
  - 08='OTH CONTROL LOSS'
  - 09='UNK CONTROL LOSS'

AND NOT

- Any one of the following:
  - TRAVELSP<=10 mph
  - MANEUVER in 0, 1 (no driver, no maneuver)
  - PREMOVE in 0:4, 5, 13, 7, 8, 9 (no driver, stopped or starting in road, backing up, disabled or parked in travel lane, leaving or entering a parking space
  - PREISTAB in 0, 1, 7, U (no driver, tracking, other vehicle loss of control, unknown)

Vehicle type (PC/LTV): Vehicle type was categorized as in Table 64, using the GV/BODYTYPE variable.

Table 64. Vehicle type categories for application of ESC

PC	LTV
NASS CDS variable GV/Body Type in: VALUE BODYTYPE 01='CONVERTIBLE' 02='2DR SEDAN/HT/CPE' 03='3DR/2DR HATCHBAK' 04='4-DR SEDAN/HDTOP' 05='5DR/4DR HATCHBAK' 06='STATION WAGON' 07='HATCHBACK DR UNK' 08='OTHER AUTOMOBILE' 09='UNK AUTO TYPE' 10='AUTO BASE PICKUP' 11='AUTO BASED PANEL' 12='LARGE LIMOUSINE' 13='THREE-WHEEL AUTO' 17='3-DOOR COUPE' 49='UNK LIGHT VEH'	NASS CDS variable GV/Body Type in: 14='COMPACT UTILITY' 15='LARGE UTILITY' 16='UTILITY STAWAGON' 19='UTILITY UNK BODY' 20='MINIVAN' 21='LARGE VAN' 22='STEP VAN <10K LB' 24='VAN BASED SCHBUS' 25='VAN BASED OTHBUS' 28='OTHER VAN TYPE' 29='UNKNOWN VAN TYPE' 30='COMPACT PICKUP' 31='LARGE PICKUP' 32='PICKUP/CAMPER' 33='CONVERT PICKUP' 39='UNK PICKUP TRUCK' 40='CAB CHASSIS' 41='TRUCK BASE PANEL' 42='LT TRK MOTORHOME' 45='OTH LIGHT TRUCK' 48='UNK LIGHT TRUCK' 79='UNKNOWN TRUCK'* *IF TOWHITCH=0 or 9

C.1.2 ESC Effectiveness

ESC effectiveness reflects the percentage of crashes in each subpopulation of the target population that are completely prevented, i.e., the percentage by which case weight is reduced when the countermeasure is applied.

Effectiveness estimates for fatal target subpopulation categories were from Kahane (2014b). ESC effectiveness for each non-fatal target subpopulation category was based on analyses by Dang (2007) and Sivinski (2011), which are summarized in Table 65. Table 66 summarizes the effectiveness values ultimately used for each target population in the model, based on all these sources. For non-fatal, single-vehicle crashes, the effectiveness in this model was calculated by averaging the estimates made by Dang and Sivinski, as an average of log(1-E) and effectiveness in culpable multi-vehicle crashes was based on Dang's estimate, which was believed to be more likely based on positive effectiveness fatality analyses.[25] Confidence intervals were reported where available for potential use in future sensitivity analysis.

[25] Charles J. Kahane, Bowhead Logistics Solutions, LLC, Alexandria, VA, personal communication, 2018.

Table 65. Effectiveness estimates (%) from source studies for non-fatal subpopulations of the ESC target population (with confidence intervals where available)

	PC	LTV
NON-FATAL (Sivinski, 2011)		
Single-vehicle rollover	72.2% (14.3 – 91.0%)	64.1% (45.9 – 76.1%)
Other single-vehicle excl ped/animal	32.3% (-1.3 – 54.8%)	56.8% (48.8 – 63.6%)
Culpable multi-vehicle	0%	0
NON-FATAL (Dang, 2007)		
Single-vehicle rollover	64% (50-75%)	85% (79-90%)
Other single-vehicle/run off road excl ped/animal	45	69
Culpable multi-vehicle	13% (7-18%)	16% (7-23%)

Table 66. Final ESC effectiveness estimates used in the model (with confidence intervals where available)

	PC	LTV
FATAL (at least one in crash) (Kahane, 2014b)		
Single-vehicle rollover	59.5% (48.7 – 68.1%)	74.0% (67.7 – 79.1%)
Other single-vehicle excl ped/animal	31.3% (22.1 – 39.4%)	45.5% (39.2 – 51.1%)
Culpable multi-vehicle	16.1% (4.3 – 26.1%)	16.1% (7.8 – 23.7%)
NON-FATAL		
Single-vehicle rollover	68.3%	76.8%
Other single-vehicle excl ped/animal	38.0%	68.0%
Culpable multi-vehicle	13.0% (7 – 18%)	16.0% (7 – 23%)

The source studies used to develop the effectiveness estimates based their analyses on the risk of ESC relevant crashes (relative to control group crashes) in vehicle models prior to the introduction of ESC versus following the addition of ESC. Sivinksi noted that this strategy led to bias due to changes other than ESC that took place at this time, contributing to the calculated effectiveness. However, because major vehicle redesigns were already taken into account and Sivinski indicated that there were no significant changes in static stability factor during the period of his analysis, it was not likely that such changes during the period of these effectiveness studies were also addressed in any other countermeasure in the projection model. Therefore, although it is possible that some of the improvements captured in these effectiveness studies may have resulted from improvements other than ESC, there was little risk of double-counting those other improvements in the model. In other words, although some of the improvements captured may not have been a direct result of ESC, they are expected to reflect real improvements not otherwise captured by the model and are therefore appropriate to include in the model.

C.1.3 ESC Fleet Penetration

The following sources were used to estimate penetration of ESC into vehicles by model year in Table 67:

- 2005 – 2009 Digitized from Sivinski (2011)
- 2010 and later, from Ward's Automotive Yearbook 2007 to 2016 per Webb (2017)

Table 67. Penetration of ESC by vehicle model year (α_{MY})

Model Year	α_{MY} (%)	
	PC	LTV
≤ 2004	16.4	16.8
2005	14.3	21.6
2006	20.2	33.7
2007	22.1	53.5
2008	25.0	69.3
2009	47.1	84.7
2010	76.0	87.0
2011	92.0	94.0
2012-2030	100.0	100.0

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of ESC among vehicles in projection crash years was estimated in Table 68. For example, the table shows that 99 percent of passenger vehicle occupants will be in vehicles equipped with ESC by 2030. By that time, only 1 percent of occupants are projected to be in older vehicles without ESC.

Table 68. Penetration of ESC in projection target years (Overall β_{TY})

Crash Year	β_{TY} (%)	
	PC	LTV
2014	59.2	74.6
2020	84.0	90.7
2025	95.1	97.3
2030	99.0	99.4

C.2 Automatic Emergency Braking With Forward Collision Warning

The effectiveness of the very diverse forward collision avoidance systems in the past and future U.S. fleet was estimated based on past field data for vehicles that had FCW and AEB systems as an option. These estimates can be updated as information becomes available for more recent designs. Past penetration into the fleet was based on data collected by NCAP on recommended safety technologies in the fleet. Estimates of future system penetration were based on the 2016 voluntary agreement on AEB by U.S. manufacturers, NHTSA, and IIHS which can be found in NHTSA's Docket on AEB initiatives. Manufacturers representing 99% of the U.S. passenger vehicle fleet committed to a voluntary agreement with NHTSA and IIHS to make AEB systems, including an FCW component and a CIB (crash imminent braking) component, standard on substantially all their vehicles. The systems meeting the agreement are required to pass certain minimum standards. Note that although separate effectiveness estimates have been made for vehicles with FCW alone and vehicles with AEB (including FCW and CIB), penetration estimates to date have shown that auto-braking systems such as CIB or AEB have been introduced at a similar pace as FCW. Therefore, in the absence of separate estimates of the crash prevention effectiveness of the CIB components of AEB, AEB was modeled in a single crash avoidance countermeasure in the current projection model. The crash mitigation effectiveness of AEB systems was estimated separately in Appendix D.1.2.

C.2.1 AEB with FCW Target Population

For the purposes of this analysis, the target population for frontal crash avoidance technology (AEB with FCW) was defined to include CDS-eligible crashes between the front of a striking vehicle and the rear of a struck vehicle. The following NASS CDS variables were used to define the case vehicles in this target population:

Crashes in target population:

- Light vehicles: BODYTYPE in (0:22, 24:49), and
- ACCTYPE in (11, 20:33).
  - Striking vehicles:
    - ACCTYPE in (11, 20, 24, 28) or other vehicle ACCTYPE in (21:23, 25:27, 29:30),
    - ACCTYPE in (32, 33) and PREEVENT in (50:52), or
    - ACCTYPE in (32, 33) and other vehicle PREMOVE not in (8:13,15:17).
  - Struck vehicles:
    - ACCTYPE in (21:23, 25:27, 29:30) or other vehicle ACCTYPE in (11, 20, 24, 28),
    - ACCTYPE in (32, 33) and other vehicle PREEVENT in (53), or
    - ACCTYPE in (32, 33) and other vehicle PREMOVE in (1:7, 14).

Previous estimates of the effectiveness of forward collision avoidance technologies (NHTSA, 2014) excluded the following types of cases from the target population because they were believed to be so severe that current crash avoidance technology would not be able to prevent them:

- Crashes with closing speeds greater than 50 mph in which there was a fatality in the lead vehicle,
- Crashes in which there was a fatality in the striking vehicle after an impact with a large truck or trailer, and
- Crashes involving the lead vehicle cutting into the lane of the striking vehicle.

Since closing speeds could not be reliably estimated from data in the source cases, all crashes involving a fatality were excluded from the target population in the projection model. Crashes involving the lead vehicle cutting into the lane of the striking vehicle were excluded by the target population definition above.

Although it has been suggested that a vehicle approaching the rear of another but skidding sideways as a result of braking, with its side colliding with the vehicle ahead, would be in the target population for rear-impact crash avoidance (NTSB 2015), these crashes were not included in the target population in the current analysis. Head-on frontal crashes, frontal crashes into fixed objects, and intersection crashes were also excluded from the target population. Although these crash scenarios have been identified as potentially benefitting from frontal crash avoidance technology (Anderson et al., 2012), they are outside of the scope of the target population defined by the effectiveness estimates used in this version of the model.

C.2.2 AEB with FCW Effectiveness

Studies estimating the solo effectiveness of FCW have used simulation, field data, and NCAP results to estimate that it can prevent 6-38 percent of rear-impact crashes (Najm et al., 2006; Kusano et al., 2014; Fildes et al., 2015; Cicchino, 2016). Some of these studies have had a specific target population; for example, Kusano et al., estimated average 29 percent effectiveness in lead-vehicle stopped rear impacts with a closing speed of less than 45 mph. Estimates based on simulation or laboratory studies additionally need to be adjusted for turn-off rates that have been estimated at 17 percent for auditory warning systems, 6 percent for haptic systems (Flannagan et al., 2016) and 7 percent averaged across several types of systems (Reagan et al., 2018).

More recent field data collected on vehicles where frontal crash avoidance systems were optional analyzed insurance and State police data to compare the crash histories of paired models of vehicles with and without AEB systems with FCW (Cicchino, 2017a, 2019). Results from these studies, which showed 50 percent overall average effectiveness at rear impact crash prevention, were selected for application in the projection model because they were the most recent field data available. Since these results reflect field experience with vehicles where the system may be turned off, no adjustment needs to be made to account for turn-off rates.

The Cicchino insurance-based studies estimated higher crash prevention effectiveness for crashes with an injury in the striking vehicle (56%) or the struck vehicle (59%) than for all crashes on average. These higher levels of effectiveness were not applied to the subpopulations of crashes in the projection model with injuries, given that the crash mitigation effects of AEB were also modeled (see Appendix D.1), which would be expected to further contribute to the reduction of rear-impact injury crashes.

C.2.3 AEB With FCW Fleet Penetration

For this countermeasure, adjusted effectiveness for occupants in both striking and struck vehicles was calculated based on the estimated likelihood that the striking vehicle would be equipped with AEB technology with FCW. Therefore, all penetration estimates for this countermeasure were based on the model year of the striking vehicle.

The following sources were used to estimate penetration by model year in Table 69:

- 2013 to 2018: Data collected by the NCAP program on the installation rate of crash avoidance technology (NHTSA, 2018b), specifically CIB and FCW, and

- 2019+: March 2016 voluntary industry commitment to advance AEB technology (NHTSA, 2016b).

For the purpose of estimation in the projection model, the penetration of AEB in model years prior to 2013 was defined to be 0 percent since the 2013 rate was less than 1 percent. For 2013 to 2018, the penetration rates for FCW and CIB estimated from NCAP data were similar since they are often concomitant technologies. Therefore, these values were averaged for use in the combined AEB with FCW countermeasure. Based on the March 2016 AEB voluntary agreement, it was estimated that the penetration of AEB systems with FCW would peak at 2023 and be installed in 94.1 percent of vehicles. This estimate corresponds to FCW and AEB being applied to 95 percent of 99 percent of the fleet, since manufacturers of 99 percent of the fleet committed to making 95 percent of their vehicles compliant with the voluntary agreement. To estimate penetration in 2019 and later, penetration estimates were linearly interpolated from 2018 (last available year of NCAP data) to 2023.

Table 69. Penetration of AEB with FCW by vehicle model year (α_{MY})

Model Year	α_{MY} (%)
≤ 2012	0.0
2013	0.9
2014	5.9
2015	9.1
2016	9.9
2017	22.7
2018	40.2
2019	50.9
2020	61.7
2021	72.5
2022	83.3
2023-2030	94.1

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of FCW and AEB among vehicles in projection crash years was estimated in Table 70.

Table 70. Penetration of FCW and AEB in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)
2014	0.6
2020	14.4
2025	44.6
2030	72.3

C.3 NCAP 2004 Static Stability Factor Enhancements

The NCAP rollover rating was updated in 2003 and applied beginning in MY 2004. The rating was based on the risk of rollover as a function of vehicle static stability factor, which was calculated from wheelbase dimensions and the height of the vehicle center of gravity. In the 2004

NCAP update, separate rollover SSF risk curves were recalculated for tip-up and no tip-up scenarios using logistic regression, and a dynamic test was added. Based on the outcome of the dynamic test, either the tip-up or no tip-up risk curve was used to calculate the rollover risk and associated star value.

In a 2017 report, NCSA evaluated the change in average SSF after the 2004 NCAP rollover rating enhancement (through model year 2013), as well as the effects of a change in SSF on single-vehicle and multi-vehicle crash rollover rates (Pai, 2017). Using SSF data from the NCAP rollover program and the sales volume of each new vehicle tested in the program, weighted average SSF values were calculated by vehicle type and model year. Using crash data from the State Data System and logistic regression, estimated rate reductions of rollovers in single-vehicle crashes and multi-vehicle crashes, respectively, were calculated for every 0.01 increase in SSF.

C.3.1 SSF Target Population

Target populations were defined in the projection model based on the target crashes analyzed by NCSA to calculate the effect of a change in SSF. The definitions are listed below, along with the NASS CDS variables used to code them in the model:

- First-event rollovers in single vehicle crashes, excluding crashes involving collisions with pedestrians, cyclists, animals, or trains and excluding emergency vehicles and vehicles with trailers or attachments:
  - ACC/VEHFORMS=1
  - GV/ACCTYPE=1:12, 14:16
  - GV/ROLLOVER^=0
  - For EVENT/ACCSEQ=1, OBJCONT=31,32
  - For EVENT/ACCSEQ>1, OBJCONT^=72:77
  - GV/TOWHITCH=0
  - GV/VEHUSE^=5:8
- Subsequent rollovers after two-vehicle, side-impact crashes, excluding crashes involving collisions with pedestrians, cyclists, animals, or trains and excluding emergency vehicles and vehicles with trailers or attachments:
  - ACC/VEHFORMS=2
  - GV/ROLLOVER^=0
  - GV/ACCTYPE=64:91
  - For EVENT/ACCSEQ=1, OBJCONT=1:11
  - For EVENT/ACCSEQ=2, OBJCONT=31,32
  - For EVENT/ACCSEQ>3, OBJCONT^=72:77
  - GV/TOWHITCH=0
  - GV/VEHUSE^=5:8

C.3.2 SSF Effectiveness

The effectiveness of increased rollover resistance associated with the 2004 NCAP enhancements was estimated based on the change in average SSF scores for NCAP-tested vehicles. This change in average SSF values was then used to calculate changes in rollover risk using the rollover rate reduction estimates from the 2017 Pai report. Single vehicle and multi-vehicle crashes were analyzed separately due to differences in the interaction of ESC with SSF in these crash types, as well as differences in the application of effectiveness to the model.

The improvements associated with these effectiveness calculations may have been motivated by the NCAP program or by any other factors that led to more rollover-resistant vehicle designs during that same period, so improvements in NCAP performance during those years do not define a direct benefit of NCAP but are simply a reflection of rollover risk reduction during that period. The influence of ESC was addressed in the effectiveness calculations, and it was not likely other changes in rollover resistances are addressed in any other countermeasure; therefore, although it was likely that some of the improvements captured may not have resulted directly from the NCAP enhancement, there was little risk of double-counting. In other words, although some of the improvements captured may not have been a direct result of the NCAP SSF update, they are assumed to reflect real improvements not otherwise captured by the model and are therefore appropriate to include in the model.

Changes in SSF

For this analysis, the change in SSF was calculated as the difference between the average MY 2004 SSF scores and the average MY 2013 SSF scores, as shown in Table 71 (Pai, 2017).[26] The gray column indicates values calculated for the projection model, while the white columns indicate values reported by Pai. MY 2013 was selected as the endpoint in order to capture the full change in response to the NCAP enhancements, as the SSF scores for SUVs appear to continue to trend upwards from 2004, throughout the entire period reported by Pai.

During the period from 2004 to 2013, there were no consistent trends in SSF for minivans, full size vans, and passenger cars and Pai concluded that SSF did not change significantly in passenger vehicles other than pickup trucks and SUVs. Therefore, for the purposes of this model, it was estimated that there was no overall change in SSF for minivans, full size vans, and passenger cars so these vehicle types were not included in the effectiveness calculations in the following sections.

[26] Although the average changes in SSF from MY 2004 to MY 2013 in each vehicle type reflect that some vehicle models changed very little and some changed much more, this average change was applied to every vehicle of a given type in the target population, regardless of the specific vehicle model. In effect, this countermeasure is applied to the model as a binary change such that it is assumed that every vehicle in the target population would either be associated with the average change in SSF, or no change in SSF, and the percentage of vehicles with this binary change was increased incrementally according to the penetration of SFF, which was estimated using the same methods used for penetration of other safety countermeasures, equivalent to estimating the percentage of vehicles in the vehicle model year that had received the change in SSF compared to the 2004 baseline. The application of this average change in SSF can also be thought of as an incremental change in the SSF of all vehicles over time. In other words, each year, the SSF of each vehicle in the target population was increased incrementally up to the total average change in SSF.

Table 71. Change in Average SSF, MY 2004 to MY 2013

Vehicle type	Average SSF MY 2004	Average SSF MY 2013	Change in SSF
PC	1.41	1.41	0.00*
Truck-SUV	1.14	1.19	0.05
CUV	1.25	1.22	-0.03
Pickups	1.21	1.18	-0.03
Minivans	1.28	1.27	-0.01*
Full size vans	1.09	1.07	-0.02*

**Year-to-year trends inconsistent, overall change from 2004 to 2013 not significant.*

Calculation of Effectiveness for Single Vehicle Crashes

For single-vehicle crashes, Pai reported that ESC had a significant interaction with SSF, i.e., that the effects of changes in SSF were different in vehicles equipped with ESC. Because of this effect, it was necessary to account for the penetration of ESC when calculating the effectiveness of improved SSF after the 2004 NCAP enhancement. Therefore, the unadjusted effectiveness was first calculated separately for vehicles with and without ESC using Equations (37) and (38), as shown in Table 72. The gray columns indicate values calculated for the projection model, while the white columns indicate values reported by Pai.

$$(E_{with\ ESC})_{unadj} = \frac{(SSF_{2013} - SSF_{2004})}{0.01} * R_{with\ ESC} \tag{37}$$

where R is the rollover rate reduction given a 0.01 increase in SSF

$$(E_{without\ ESC})_{unadj} = \frac{(SSF_{2013} - SSF_{2004})}{0.01} * R_{without\ ESC} \tag{38}$$

where R is the rollover rate reduction given a 0.01 increase in SSF.

Table 72. Unadjusted SSF effectiveness estimates for single vehicle crashes, with/without ESC

Vehicle type	Change in SSF	Without ESC		With ESC	
		Rollover rate reduction for 0.01 increase in SSF	Effectiveness	Rollover rate reduction for 0.01 increase in SSF	Effectiveness
Truck-SUV	0.05	4.87%	24.35%	4.75%	23.75%
CUV	-0.03		-14.61%		-14.25%
Pickups	-0.03		-14.61%		-14.25%

The unadjusted effectiveness estimates were then adjusted for the implementation timing of the NCAP 2004 update, where α' represents the likelihood that a case occupant's vehicle had the improvements associated with the NCAP update, and β_{TY} was the predicted penetration of associated improvements in the targeted projection year. (Equations (39) and (40)).

$$(E_{with\,ESC})_{adj} = (E_{with\,ESC})_{unadj} * (\beta_{TY,NCAP\,2004} - \alpha'_{NCAP\,2004}) \quad (39)$$

$$(E_{without\,ESC})_{adj} = (E_{without\,ESC})_{unadj} * (\beta_{TY,NCAP\,2004} - \alpha'_{NCAP\,2004}) \quad (40)$$

Finally, the separate effectiveness estimates with and without ESC were combined using Equation (41). Because it was unknown for any given case whether the vehicle would be equipped with ESC in the future, the effectiveness estimates were weighted and combined using the penetration of ESC ($\beta_{TY,ESC}$) which was set to the Overall β_{TY} defined for ESC in C.1.3. In the absence of information to the contrary, the penetration of ESC and the reduction of SSF during implementation of NCAP testing were treated as independent.

$$\begin{aligned} E_{adj} &= \beta_{TY,ESC}(E_{with\,ESC})_{adj} + (1-\beta_{TY,ESC})(E_{without\,ESC})_{adj} \\ &= \left[\beta_{TY,ESC}(E_{with\,ESC})_{unadj} + (1-\beta_{TY,ESC})(E_{without\,ESC})_{unadj}\right] \\ &\quad * (\beta_{NCAP\,2004} - \alpha'_{NCAP\,2004}) \end{aligned} \quad (41)$$

Application of Effectiveness in Single-Vehicle Crashes

For single vehicle crashes, the effectiveness of SSF was defined as a percentage of rollover crashes that would be completely prevented. The effectiveness estimates resulting from Equation (41) were applied to all cases in the target population, resulting in the reduction of the case weight of every case in the target population. In cases of negative effectiveness, the result was an increase of the case weight of any case in the target population.

Calculation of Effectiveness for Multi-Vehicle Crashes

For multi-vehicle crashes, Pai reported that ESC did not have a significant interaction with SSF (Pai, 2017). Therefore, it was not necessary to calculate separate effectiveness values for vehicles with and without ESC. Pai reported that roadway condition (wet versus dry) had a significant interaction with SSF for passenger cars, but not for LTVs, in multi-vehicle crashes. However, because there was no change in average SSF for passenger cars over the time period of interest, it was not necessary to account for the effect of roadway condition. Therefore, only one unadjusted effectiveness value was calculated for each vehicle type, as shown in Equation (42) and Table 73. The gray columns indicate values calculated for the projection model, while the white columns indicate values reported by Pai.

$$E = \frac{(SSF_{2013} - SSF_{2004})}{0.01} * R \quad (42)$$

where R is the rollover rate reduction given a 0.01 increase in SSF.

Table 73. Unadjusted SSF effectiveness estimates for multi-vehicle crashes

Vehicle type	Change in SSF	Rollover rate reduction for 0.01 increase in SSF	Effectiveness
Truck-SUV	0.05	7.47%	37.35%
CUV	-0.03		-22.41%
Pickups	-0.03		-22.41%

Application of Effectiveness in Multi-Vehicle Crashes

For multi-vehicle crashes, the effectiveness of SSF was defined as a reduction in subsequent rollovers, given an initial side impact crash. In other words, only the rollover was prevented, not the entire crash. Therefore, unlike with single-vehicle crashes, the case weight of the entire case was not reduced, but rather the rollover and the injuries caused by the rollover were deleted from a percentage of the cases in the target population. However, it was not possible to determine which injuries were associated specifically with the rollover, versus other events in the crash. Therefore, for the purposes of this analysis, any roof-contact or ejection associated injury was treated as if it were related to the rollover. These injuries were identified based on injury source using the following NASS CDS variables:

- Roof-contact injuries: OI/INJSOU = (3, 20, 201: 208, 410)
- Ejection injuries: OI/INJSOU = (451: 454, 551, 598, 599)

In the case of positive effectiveness resulting from increases in SSF, a pseudo-case was created for each case in the target population with all injuries associated with either roof contact or ejection deleted. The weight of this pseudo-case was determined by the SSF effectiveness, as shown in Table 74.

Table 74. Pseudo-cases for multi-vehicle crashes with positive effectiveness

Rollover	Injury	Case Weight Multiplier
Yes (no change)	No change	$1 - E_{adj(SSF)}$
No (rollover eliminated)	Roof-contact and ejection injuries deleted	$E_{adj(SSF)}$

In the case of negative effectiveness resulting from decreased SSF, some side impact cases that did not originally result in rollovers needed to be adjusted to include a subsequent rollover. In order to code this added rollover into the model, pseudo-cases were created with a change in the rollover status of a case and the addition of roof contact and ejection related injuries. Because side impacts at very low speeds are expected to be less likely to lead to a subsequent rollover, only side impacts with lateral delta V greater than or equal to 15 km/h were adjusted to include a rollover. The resulting target population for the side impact cases to be adjusted to include subsequent rollovers as a result of negative effectiveness was defined using NASS CDS variables as follows on the next page:

- ACC/VEHFORMS=2,
- GV/ROLLOVER=0,
- GV/ACCTYPE=64:91,
- For EVENT/ACCSEQ=1, OBJCONT=1:11,
- For EVENT/ACCSEQ>2, OBJCONT^=72:77,
- GV/TOWHITCH=0,
- GV/VEHUSE^=5:8, and
- GV/DVLAT>=15.

The proportion of pseudo-cases for which roof-contact and/or ejection related injuries were added was based on the likelihood of the occupant being ejected and the proportion of occupants in rollovers with roof-contact related injuries. Based on data that 20 percent of unbelted occupants are completely ejected in a rollover, while only 0.03 percent of belted occupants are completely ejected (Funk et al., 2012), belted occupants were treated separately from unbelted occupants.

Because the ejection rate was so low for belted occupants, no ejection-related injuries were added to belted occupant cases. Additionally, not all occupants in a rollover will necessarily sustain a roof-contact injury; an analysis of the retrospective baseline dataset determined that approximately 21 percent of AIS 2+ injured occupants in side impact crashes with a subsequent rollover had a roof-contact related injury. Based on this data, it was approximated that 21 percent of belted occupants would sustain a roof-contact injury if a rollover occurred. Therefore, as shown in Table 75, three pseudo-cases were created for each belted occupant in the target population:

1) Unchanged pseudo-case,
2) Rollover pseudo-case with no change in injury, and
3) Rollover pseudo-case with a roof-contact injury added.

For unbelted rollover occupants, it was approximated that the 20 percent expected to be completely ejected (Funk et al., 2012) would sustain ejection related injuries. As with belted occupants, it was also estimated that 21 percent of unbelted occupants would sustain a roof-contact injury if a rollover occurred. Therefore, as shown in Table 75, five pseudo-cases were created for each unbelted occupant in the target population:

1) Unchanged pseudo-case,
2) Rollover pseudo-case with no change in injury or ejection status,
3) Rollover pseudo-case with a roof-contact injury but no change in ejection status,
4) Rollover pseudo-case with ejection injuries, but no roof-contact injury, and
5) Rollover pseudo-case with both roof-contact and ejection injuries.

Table 75. Pseudo-cases for multi-vehicle crashes with negative effectiveness

Seat Belt Use	Rollover	Ejection	Injury	Case Weight Multiplier*
Belted	No	No	No change	$1 - E_{adj(SSF)}$
	Yes	No	No change	$E_{adj(SSF)} * 0.79$
	Yes	No	Roof-contact head injury added	$E_{adj(SSF)} * 0.21$
Unbelted	No	No	No change	$1 - E_{adj(SSF)}$
	Yes	No	No change	$E_{adj(SSF)} * 0.80 * 0.79$
	Yes	No	Roof-contact head injury added	$E_{adj(SSF)} * 0.80 * 0.21$
	Yes	Yes**	Ejection head and thorax injuries added	$E_{adj(SSF)} * 0.20 * 0.79$
	Yes	Yes**	Roof-contact head injury, ejection head and thorax injuries added	$E_{adj(SSF)} * 0.20 * 0.21$

** The absolute value of effectiveness should be used.*
*** Complete ejection.*

Based on a review of the baseline retrospective dataset, loss of consciousness injuries are among the most frequent AIS 2+ roof-contact related injuries in multi-vehicle rollover crashes. Additionally, subarachnoid hemorrhages and multiple rib fracture injuries with hemo/pneumothorax are among the most frequent AIS 2+ ejection related injuries in multi-vehicle rollover crashes. Therefore, the following AIS-coded injuries were identified as typical and were added to the pseudo-cases to represent roof-contact and ejection related injuries:

- Roof-contact injury: 160414.2
- Ejection injuries: 140684.3, 450211.3

It is acknowledged that addition of typical rollover injuries to cases with negative effectiveness relies on substantial approximations and generalizations. However, the alternative method considered, which involved downweighting cases with side impact only and upweighting cases with side impact and rollover, was expected to lead to an unrealistic increase in crash severity since overall crash severity was expected to be worse in side impacts associated with rollovers than in side impacts that do not lead to rollovers.

C.3.3 Relationship Between SSF and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure was applied to every individual case in its target population based on case variables. The rollover pseudo-cases that result from application of the SSF countermeasure may be affected by other countermeasures in the model. Therefore, the SSF countermeasure must be applied prior to any other countermeasures in the projection model for which the addition of a rollover (with and without ejection) in the SSF pseudo-cases would move the case into, or out of, the target population. In Table 76, all other countermeasures for which there was a potential overlap in target population with SSF were evaluated to determine if application of SSF would move cases either into, or out of, the target population for these other countermeasures. Countermeasures whose target populations do not overlap with SSFs are not included in this table. For example, only front-to-rear crashes are included in the target population for AEB with FCW, while only side impacts with or without subsequent rollovers are included in the multi-vehicle target population for SSF. Therefore, there are no conditions in which FCW will be applied to the pseudo-cases created by the application of SSF, so the two countermeasures can be applied in any order without regard to the effects of FCW on SSF pseudo-cases. As summarized in Table 76, cases would be expected to have the same target population status for FMVSS No. 126 (ESC) *before* and *after* application of SSF so that this countermeasure can be applied before or after the SSF countermeasure, without regard for the addition of rollover to SSF pseudo-cases. In contrast, addition of rollover injuries to an SSF pseudo-case could put it into the target population for the FMVSS No. 216 (Roof Strength) or FMVSS No. 226 (Ejection Mitigation) countermeasures when its parent case without rollover was not initially in the target population. Therefore, SSF needs to be applied in the model prior to FMVSS No. 216 and FMVSS No. 226. Similarly, the addition of ejection injuries to an SSF pseudo-case could exclude it from the target population for the FMVSS No. 214 and NCAP 2011 countermeasures when its parent case without ejection was initially included in the target population. Therefore, SSF needs to be applied in the model prior to FMVSS No. 214 and NCAP 2011.

Because it was not feasible to adjust all variables associated with adding or removing a rollover or ejection from a case in the model (such as ejection route or number of rolls), it was necessary to individually consider which pseudo-cases resulting from the application of SSF to multi-vehicle crashes should be included in the target populations of FMVSS No. 216, FMVSS No. 226, FMVSS No. 214, and NCAP 2011. Table 76 summarizes the rationale used to determine which cases would be added to the target populations for these other countermeasures.

Table 76. Application of target population criteria for other countermeasures to SSF pseudo-cases

Countermeasure	Potential overlap in target population with SSF?	Target population status for SSF pseudo-cases
FMVSS No. 126 (ESC)	Yes – Culpable multiple vehicle only (Appendix C.1.1)	Rollover and ejection status have no impact on the culpable multi-vehicle target population. **Conclusion**: Each SSF pseudo-case would have the same FMVSS No. 126 target population status as its parent case before application of SSF.
FMVSS No. 214 (Side Impact)	Yes – MDB test target population only (Appendix E.3.1)	First-event rollover cases are excluded from the FMVSS No. 214 target population, but subsequent rollovers are not excluded from the FMVSS No. 214 target population. Since only subsequent rollovers are affected by the SSF countermeasure, the pseudo-rollover status does not need to be considered in the application of FMVSS No. 214. However, completely ejected occupants are excluded from the FMVSS No. 214 target population, regardless of rollover status. Cases with pseudo-ejection added by the application of SSF will be similarly excluded. Therefore, a case in which a pseudo-rollover with ejection was added would be excluded (while its parent case may not have been). Cases in which an ejection was deleted by the application of SSF will not be excluded from the 214 target population based on ejection status (but they could be excluded based another target population limitation). **Conclusion:** An SSF pseudo-case with ejection could have different FMVSS No. 214 target population status than its parent case.

Countermeasure	Potential overlap in target population with SSF?	Target population status for SSF pseudo-cases
FMVSS No. 216 (Roof Strength)	Yes (Appendix E.4.1)	The FMVSS No. 216 target population includes roof-involved rollovers, defined as all rollovers except ¼ turn and unknown number of turns. The FMVSS No. 216 target population was limited to injuries from a vertically intruding roof component. Therefore, cases with a pseudo-rollover and a pseudo-roof-contact head injury added by the application of SSF will be assigned to fall in the FMVSS No. 216 target population. However, cases with a pseudo-rollover and no added roof-contact head injury will not be assigned to fall in the FMVSS No. 216 target population. An analysis of the baseline retrospective dataset determined that the average roof intrusion experienced by occupants in side impact crashes with a subsequent rollover was approximately 14 cm. Based on this data, it was estimated that occupants for which a pseudo-roof-contact head injury was added experienced vertical intrusion of a roof component equal to 14 cm. **Conclusion**: An SSF pseudo-case with roof-contact head injuries could have different FMVSS No. 216 target population status than its parent case.
FMVSS No. 226 (Ejection Mitigation)	Yes (Appendix E.6.1)	Pseudo-ejected occupants will be assigned the following characteristics for the FMVSS No. 226 target population definition. As with other cases with unknown variables in the FMVSS No. 226 target population, these cases will be assigned a percentage that corresponds to the distribution of NASS CDS ejection variables among known cases. - EJECTION=1 (complete ejection) - EJCTAREA=99 (unknown) - EJCTMED=U (unknown) Multi-vehicle crashes in which a pseudo-rollover has been added by the application of SSF will be assigned to the "side impact with subsequent rollover" subpopulation within the FMVSS No. 226 target population. Multi-vehicle crashes in which the rollover has been deleted by the application of SSF would be coded to fall into the "side impact without rollover" subpopulation within the FMVSS No. 226 target population. However, it was assumed that if the parent case had an ejected occupant, the ejection would be deleted when the rollover was deleted. Therefore, these cases would be excluded from the FMVSS No. 226 global target population based on ejection status. **Conclusion**: An SSF pseudo-case could have different FMVSS No. 226 target population status than its parent case.

Countermeasure	Potential overlap in target population with SSF?	Target population status for SSF pseudo-cases
NCAP 2011 (Side Impact	Yes – MDB test target population only (Appendix E.5.1)	First-event rollover cases are excluded from the NCAP 2011 side impact target population, but subsequent rollovers are not excluded from the NCAP 2011 side impact target population. Since the SSF countermeasure only affects rollover injuries and not injuries from initial side impacts, the pseudo-rollover status does not need to be considered in the application of NCAP 2011 side impact. However, completely ejected occupants are excluded from the NCAP 2011 side impact target population, regardless of rollover status. Cases with pseudo-ejection added by the application of SSF will be similarly excluded. Therefore, a case in which a pseudo-rollover with ejection was added would be excluded (while its parent case may not have been). Cases in which an ejection was deleted by the application of SSF will not be excluded from the NCAP 2011 target population based on ejection status (but they could be excluded based another target population limitation). **Conclusion**: Each SSF pseudo-case with ejection could have different NCAP 2011 side impact target population status than its parent case.

C.3.4 SSF Fleet Penetration

Vehicle improvements in response to the NCAP enhancement are assumed to have occurred incrementally between 2004 and 2013. While it was not assumed that all improvements in SSF and rollover risk were motivated by the NCAP program, it was assumed that rollover risk improvements that occurred during the period analyzed by Pai occurred incrementally between 2004 and 2013. Therefore, penetration of the NCAP 2004 updates was defined as the percentage of vehicles that improved from 2004 levels to 2013 levels. Based on Pai's statement that the NCAP rollover resistance program attempted to cover at least 80 percent of passenger vehicles in the market between 2004 and 2013, it was estimated that the improvements in tested vehicles reflect performance improvements in about 80 percent of vehicles in the fleet. The resulting penetration estimates by model year are shown in Table 77.

Table 77. Penetration of SSF by vehicle model year (α_{MY})

Model Year	α_{MY} (%)
≤ 2004	0.0
2005	8.9
2006	17.8
2007	26.7
2008	35.6
2009	44.4
2010	53.3

Model Year	α_{MY} (%)
2011	62.2
2012	71.1
2013-2030	80.0

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of SSF among vehicles in projection crash years was estimated in Table 78.

Table 78. Penetration of SSF in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)
2014	47.8
2020	66.8
2025	75.7
2030	79.0

C.4 Blind Spot Detection

Blind spot detection systems are intended to warn the driver when a vehicle is in their blind spot by using cameras or sensors to monitor areas on the side of a vehicle. BSD systems are expected to be most effective at preventing lane change crashes. Although there is no specific FMVSS for BSD systems, these systems were available from most manufacturers by the end of the baseline retrospective data period (2015) and are predicted to become increasingly common in future model years (Highway Loss Data Institute, 2017).

C.4.1 BSD Target Population

The target population for BSD was generally expected to be limited to lane change crashes where the vehicles were travelling in the same direction and the movement of one vehicle into the travel lane of another was the primary cause of the crash. Target populations were defined based on the evaluation of the effects of blind spot monitoring systems performed by IIHS (Cicchino, 2017b). The target population definitions and the NASS CDS variables used to code them in the model were as follows.

Crash type: Multiple vehicle crashes where the subject vehicle or the vehicle contacted by the subject vehicle was changing lanes or merging prior to the crash, coded using the following NASS CDS variables:

- VEHFORMS>=2 AND
- PREMOVE in (15,16)

Exclusions: Crashes in which the lane-changing vehicle rear-ended another vehicle and/or the two vehicles involved were initially traveling in opposite or perpendicular directions were not considered relevant for BSD systems. This exclusion was coded using the following NASS CDS variable:

- ACCTYPE in (20:43, 50:67, 76:91)

While BSD systems are likely inactive or ineffective below certain traveling speeds and in some weather conditions, the Cicchino analysis did not include any restrictions on speed or weather. Thus, the resulting effectiveness values apply to a broad target population of all relevant lane-change crashes (regardless of speed or weather conditions). This target population does not include crashes in which the lane-change vehicle encroaches into the blind-spot vehicle's lane, causing the blind-spot vehicle to crash without impacting the lane-change vehicle. These types of crashes would likely benefit from BSD systems but cannot be identified in the projection model.

Case occupants in a crash in the target population could be affected by implementation of BSD technology whether they are in the vehicle making a lane change or in the vehicle in the blind spot since BSD in the lane-change vehicle has the potential to prevent the crash for both vehicles, regardless of which vehicle the case occupant was in. However, the vehicle changing lanes and the vehicle in the blind spot need to be distinguished in order to apply the appropriate likelihood of BSD technology to the lane-changing vehicle, i.e., penetration. NASS CDS variables coded to distinguish between the two vehicles involved in a crash in the target population are shown below.

Lane-change vehicle: This vehicle was the one that would need to have BSD to have an effect on case outcome in the model:

- ACCTYPE in (44:49, 70:75) and PREEVENT in (10:13, 15:16) OR
- ACCTYPE in (44:49, 70:75) and PREEVENT of other vehicle in (60,61,63)

Blind-spot vehicle: This vehicle was the one that would not need to have BSD:

- ACCTYPE in (44:49, 70:75) and PREEVENT of other vehicle in (10:13, 15:16) OR
- ACCTYPE in (44:49, 70:75) and PREEVENT in (60,61,63))

C.4.2 BSD Effectiveness

Cicchino evaluated the effects of blind spot monitoring systems using Poisson regression to compare police-reported lane-change crash involvement rates between vehicles with BSD systems and the same vehicle models without the optional BSD systems (Cicchino, 2017b). State crash data was used for that analysis and was linked to insurance exposure data using vehicle identification numbers. The analysis controlled for a number of factors, including vehicle model year, the presence of other relevant crash avoidance systems, and driver demographics. A variety of vehicle models and manufacturers were included in the analysis, so the results represented the average effectiveness for a range of BSD systems, rather than the effectiveness of any specific system, which was likely to depend on the alert modality (means of alert) and the detection range, among other factors.

Cicchino reported that BSD systems reduced police-reported lane-change crash involvement rates in crashes of all severities by 14 percent on average and in injury crashes by 23 percent on average. To apply these results to injury crashes and non-injury crashes in the projection model without double-counting benefits, a non-injury effectiveness was estimated using Equations (43) and (44). The resulting effectiveness is shown in Table 79. In the projection model, injury crashes were defined as any crash with at least one injured occupant, and effectiveness was a measure of the percentage of cases in the given target population that were completely prevented.

$$E_{all} = \frac{E_{inj} * N_{inj} + E_{noninj} * N_{noninj}}{N_{inj} + N_{noninj}} \tag{43}$$

$$E_{noninj} = \frac{E_{all} * \left(N_{inj} + N_{noninj}\right) - E_{inj} * N_{inj}}{N_{noninj}} \tag{44}$$

where:
E_{all} is the effectiveness estimated by Cicchino across all crash severities,
E_{inj} is the effectiveness estimated by Cicchino for injury crashes,
E_{noninj} is the unknown effectiveness value for non-injury crashes, and
N_{inj} and N_{noninj} are the number of injury and non-injury lane-change crashes in the Cicchino dataset, respectively.

Table 79. Calculation of effectiveness for non-injury crashes

From Source Data on Effectiveness (Cicchino, 2017b)				**Calculated With Equation (44)**
E_{all}	**E_{inj}**	**N_{inj}**	**$N_{non-inj}$**	**$E_{non-inj}$**
14%	23%	568	4052	12.7%

IIHS reported in 2018 that 99 percent of BSD systems were enabled (Reagan et al., 2018). The 1 percent of systems that were disabled were already accounted for in the effectiveness reported by Cicchino, because the analysis compared real-world crash involvement rates for vehicles with and without the technology *installed* rather than for vehicles with and without the technology *enabled*. Therefore, no adjustment to Cicchino's estimates were required to account for disabled systems.

C.4.3 BSD Fleet Penetration

For BSD, adjusted effectiveness for occupants in both the lane-change vehicle and the blind-spot vehicle was calculated based on the likelihood that the lane-change vehicle would be equipped with BSD technology. Therefore, all penetration estimates for this countermeasure were based on the model year of the lane-change vehicle.

The following sources were used to estimate BSD penetration:

- Data collected by the NCAP program on the installation rate of BSD technology (NHTSA, 2018b), and
- Predicted future installations (Highway Loss Data Institute, 2017).

For 2013 through 2018, model year penetration (α_{MY}) in Table 80 was estimated using the BSD penetration rates estimated from NCAP program data (NHTSA, 2018b). For the purpose of estimation in the projection model, it was estimated that penetration of BSD by model year (α_{MY}) prior to 2013 was near 0 percent since the 2013 rate was 3.2 percent.

Table 80. Penetration of BSD by vehicle model year (α_{MY})

Model Year	α_{MY} (%)
≤ 2012	0.0
2013	3.2
2014	9.0
2015	14.6
2016	17.0
2017	34.1
2018	30.7

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of BSD among vehicles in 2014 was estimated in Table 81. For projection years (2020-2030), overall β_{TY} for this countermeasure was approximated by the expected fleet-wide penetration predicted by the Highway Loss Data Institute (2017) in the targeted projected years.

Table 81. Penetration of BSD in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)
2014	1.1
2020	23.0
2025	51.0
2030	72.0

C.5 Lane Departure Warning

Lane departure warning systems use cameras to monitor lane markings and are intended to alert the driver if they drift out of the lane without a turn signal. LDW systems are expected to be most effective at preventing road departure, sideswipe, and opposite direction crashes. LDW is one of the advanced crash avoidance technologies recommended by NHTSA through NCAP, which tests for the presence of LDW using a pass/fail test-track confirmation test.

Because LDW systems are still relatively rare in the on-road fleet, most previous studies evaluating LDW effectiveness have been field operation tests and simulations using crash data (Wilson et al., 2007; Sayer et al., 2011; Kusano et al., 2014; Harper et al., 2016; LeBlanc et al., 2017). The projection model relies on LDW effectiveness results published by IIHS based on police-reported crash involvement rates for vehicles with LDW systems and the same vehicle models without the optional LDW systems. These real-world results were relatively consistent with previous field operation tests and simulation studies.

C.5.1 LDW Target Population

The target population for lane departure warning is generally expected to be limited to lane and road departure crashes where the movement of one vehicle out of its travel lane is the primary cause of the crash. The target population in the projection model was defined based on the evaluation of the effects of LDW systems performed by IIHS (Cicchino, 2017c). The global target population definition, and the NASS CDS variables used to code it in the projection model, is based on crash type, as listed below.

Crash type: Single-vehicle, head-on, and sideswipe crashes, defined using the following NASS CDS variable.

- ACCTYPE in (1:16, 44:49, 50:67)

Additional exclusions from the target population were based on the target populations used in the studies relied on for effectiveness estimates for the LDW countermeasures. The target populations exclusions were defined in the model as follows.

Exclusions (and NASS CDS variables used to code them):

- Either crash-involved vehicle was changing lanes, merging, passing, turning, or backing prior to the crash: PREMOVE or PREMOVE2 in (6, 10:13, 15:17)
- Either vehicle was traveling on a road with speed limit under 40 mph: SPLIMIT<64 km/h
- Either vehicle was traveling on a road that was covered with snow or ice:
  - Pre-2009: SURCOND in (3:4)
  - 2009+: SURCOND in (3:5)
- Head-on crashes where vehicles were travelling in the same or perpendicular directions prior to the crash: excluded based on ACCTYPE codes used in crash type definition
- Two-vehicle sideswipe crashes where the vehicles were initially travelling on perpendicular paths: excluded based on ACCTYPE codes used in crash type definition
- Single-vehicle crashes between a vehicle and a pedestrian or bicyclist: excluded based on ACCTYPE codes used in the crash type definition

While LDW systems are likely inactive below certain travel speeds, the Cicchino analysis does not include any minimum restrictions on speed. Thus, the resulting effectiveness values apply to a broad target population of all relevant single-vehicle, head-on, and sideswipe crashes, limited only by the exclusions above.

For two-vehicle crashes in the target population, case occupants could be affected by implementation of LDW technology whether they are in the vehicle leaving its lane or in the struck vehicle since LDW in the lane-exiting vehicle has the potential to prevent the crash for both vehicles, regardless of which vehicle the case occupant was in. However, the lane-exiting vehicle and the struck vehicle need to be distinguished in order to apply the appropriate likelihood of LDW detection to the lane-exiting vehicle, i.e., penetration. The NASS CDS variables coded to distinguish between the two vehicles involved in a crash in the target population are shown below.

Lane-exiting vehicle: this vehicle is the one that would need to have LDW in order to have an effect on the crash outcome:

- ACCTYPE in (44:49, 50:67) and PREEVENT in (10:13) OR
- ACCTYPE in (44:49, 50:67) and PREEVENT of other vehicle in (51:54, 60:63, 78)

Struck vehicle: this vehicle is the one that would not need to have LDW:

- ACCTYPE in (44:49, 50:67) and PREEVENT of other vehicle in (10:13) OR
- ACCTYPE in (44:49, 50:67) and PREEVENT in (51:54, 60:63, 78)

C.5.2 LDW Effectiveness

In 2014, UMTRI conducted a review of the current research on LDW effectiveness and reported a crash reduction in the target population of 6 percent to 34 percent, which was relatively consistent with simulation studies available at the time (Blower, 2014). NHTSA conducted field operation tests on road departure crash warning systems (Wilson et al., 2007) and integrated crash warning systems (Sayer et al., 2011). These studies reported an effectiveness of 7 percent to 57 percent and 6 percent to 29 percent, respectively; however, each study evaluated multiple technologies so these effectiveness results cannot be attributed to LDW alone.

More recently, Harper and colleagues estimated the benefits of LDW using an upper and lower bound (Harper et al., 2016). The upper bound was defined using the assumption that the technology would be 100 percent effective at preventing relevant crashes, and the lower bound was defined using data on the current technology effectiveness from IIHS/HLDI data, by comparing claim frequency among vehicles with LDW to those without the technology. However, using the upper bound of 100 percent effectiveness would be unrealistically optimistic for the projection model, and the application of the lower bound requires assumptions that the distribution of insurance collision claims was similar to the distribution of crashes in NASS and that all changes in collision claim frequency were caused by the prevention of target population crashes.

Kusano and Gabler have published multiple benefit estimate models that use crash data to simulate the effectiveness of LDW, resulting in estimates of 11 percent to 29 percent of target crashes prevented, depending on the system parameters used (Kusano et al., 2014; Kusano et al., 2014; Kusano & Gabler 2015). The model in their 2015 paper used results from NCAP confirmation tests to simulate the effectiveness of production LDW systems and reported an effectiveness of 15.4 percent. After adjusting for the lower operating speed threshold of LDW systems, cases that were manually excluded in the Kusano and Gabler (2015) analysis, and the percentage of LDW systems that are disabled by drivers, this estimate equated to an effectiveness of approximately 9 percent.

UMTRI has also published effectiveness values based on simulations of LDW and lane keeping support systems, which range from 6.1 percent to 8.7 percent for LDW alone, depending on the driver response inputs used (LeBlanc et al., 2017).

The projection model uses LDW effectiveness results published by IIHS based on real-world outcome rather than on experimental or simulation results (Cicchino, 2017c). Cicchino used Poisson regression to compare police-reported target crash involvement rates between vehicles with LDW systems and the same vehicle models without the optional LDW systems. State crash data was used for this analysis and was linked to insurance exposure data using vehicle identification numbers. The analysis controlled for a number of factors, including vehicle model year, the presence of other relevant crash avoidance systems, and driver demographics. The resulting effectiveness estimates ranged from 11 percent to 21 percent and were relatively consistent with the NHTSA field operation tests and other simulation studies.

Cicchino reported that LDW systems reduced police-reported relevant crash involvement rates in crashes of all severities by 11 percent on average and in injury crashes by 21 percent on average (Cicchino, 2017c). To apply these results to injury crashes and non-injury crashes in the projection model without double-counting benefits, a non-injury effectiveness was estimated using Equations (45) and (46). The resulting effectiveness is shown in Table 82. In the projection model, injury crashes were defined as any crash with at least one injured occupant and effectiveness was a measure of the percentage of cases in the target population that would be prevented.

$$E_{all} = \frac{E_{inj} * N_{inj} + E_{noninj} * N_{noninj}}{N_{inj} + N_{noninj}} \tag{45}$$

$$E_{noninj} = \frac{E_{all} * \left(N_{inj} + N_{noninj}\right) - E_{inj} * N_{inj}}{N_{noninj}} \tag{46}$$

where:

E_{all} is the effectiveness estimated by Cicchino across all crash severities,

E_{inj} is the effectiveness estimated by Cicchino for injury crashes, and E_{noninj} is the unknown effectiveness value for non-injury crashes,

N_{inj} and N_{noninj} are the number of injury and non-injury lane-change crashes in the Cicchino dataset, respectively.

Table 82. Calculation of effectiveness for non-injury crashes

From Source Data on Effectiveness (Cicchino, 2017c)				Calculated With Equation (46)
E_{all}	**E_{inj}**	**N_{inj}**	**$N_{non-inj}$**	**$E_{non-inj}$**
11%	21%	986	4447	8.8%

In a study of vehicles taken to dealerships for service, IIHS reported that 45 percent of lane maintenance warning systems were disabled (Reagan et al., 2018). A field study of GM LDW systems showed that systems with an auditory warning were turned off 71 percent of the time and haptic warning systems were only turned off 38 percent of the time (Flannagan et al., 2016). Although disabled systems certainly affect effectiveness, the proportion of systems that are disabled was already accounted for in the effectiveness reported by Cicchino (2017c), because the analysis compares real-world crash involvement rates for vehicles with and without the technology *installed* rather than for vehicles with and without the technology *enabled*. Therefore, no further adjustment was required to account for consumer disabling of systems.

C.5.3 LDW Fleet Penetration

For LDW, adjusted effectiveness for occupants in the lane-exiting vehicle, as well as in any other vehicles in the crash, was calculated based on the likelihood that the lane-exiting vehicle would be equipped with LDW technology in the crash year and the projected target year. Therefore, all penetration estimates for this countermeasure were based on the model year of the lane-exiting vehicle.

The following sources were used to estimate LDW penetration:

- Data collected by the NCAP program on the installation rate of LDW technology (NHTSA, 2018b)
- Predicted future installations (Highway Loss Data Institute, 2017)

For purposes of estimation in the projection model, it was estimated that penetration of LDW in model years (α_{MY}) prior to 2013 was 0 percent since the 2013 rate was 0.2 percent. For 2013 through 2018, model year penetration (Table 83) was determined using the LDW installation rates estimated using data collected by the NCAP program (NHTSA, 2018b).

Table 83. Penetration of LDW by vehicle model year (α_{MY})

Model Year	α_{MY} (%)
≤ 2012	0.0
2013	0.2
2014	5.6
2015	10.4
2016	10.2
2017	27.3
2018	30.1

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of LDW among vehicles in 2014 was estimated in Table 84. For projection years (2020 to 2030), overall β_{TY} for this countermeasure was approximated by the expected fleet-wide penetration predicted by the Highway Loss Data Institute (Highway Loss Data Institute, 2017) in the targeted projected years.

Table 84. Penetration of LDW in projection target years (Overall β_{TY})

Crash Year	β_{TY} (%)
2014	0.5
2020	18.0
2025	46.0
2030	69.0

C.6 FMVSS No. 138 Tire Pressure Monitoring Systems

FMVSS No. 138 requires a TPMS to be installed in all new passenger cars, trucks, and buses with a gross vehicle weight rating of 10,000 pounds or less. The final rule requires that the driver be given a warning when the tire pressure is 25 percent or more below the recommended cold inflation tire pressure (placard pressure) for at least one tire and that a TPMS malfunction indicator be installed. FMVSS No. 138 was expected to reduce the prevalence of underinflated tires, which in turn was expected to have an influence on skidding and loss of control crashes,

crashes resulting from flat tires and blowouts, and crashes that involve braking because low tire pressure can result in increased stopping distance (NHTSA, 2005).

TPMS was expected to reduce the number of skidding and loss of control crashes, as well as crashes resulting from flat tires and blowouts. However, TPMS was likely to not only reduce the number of braking-involved crashes, but also reduce the severity of the remaining (not prevented) braking-involved crashes. Therefore, FMVSS No. 138 will be implemented in the model as both a crash avoidance and a crash mitigation countermeasure, i.e., it will reduce the case weight of crashes in the target population and pseudo-cases with reduced injuries will be created for a subset of these crashes. This appendix concerns the crash avoidance portion of the effects of TPMS. The crash mitigation portion of FMVSS No. 138 is addressed in Appendix D.2.

Model parameters for this countermeasure relied on data from the Final Regulatory Impact Analysis for FMVSS No. 138 (NHTSA, 2005), as well as the subsequent evaluation of the effectiveness of the rule (Sivinski, 2012).

C.6.1 TPMS Target Population

The FMVSS No. 138 FRIA (NHTSA, 2005) identified the following target populations: skidding and loss of control crashes, crashes resulting from flat tires and blowouts, and braking-involved crashes. Based on the variables available in NASS CDS, the following categories of target population were defined for application to the model:

- Loss of control crashes: PREEVENT=2:9 for any vehicle in crash.[27]
- Crashes resulting from flat tires and blowouts: PREEVENT=1 for any vehicle in crash.
- Braking-involved crashes:[28]
    - LTVs: Crashes in which at least one LTV applied brakes and skidded:[29] MANEUVER=2:4, 8:9 and PREISTAB=2:4 for any LTV in crash.
    - Passenger Cars: Crashes in which at least one passenger car applied brakes and skidded, excluding cases that were LTV braking-involved crashes: MANEUVER=2:4, 8:9 and PREISTAB=2:4 for any passenger car in the crash.
- Passenger cars and LTVs were defined using the same definition as ESC (see Appendix C.1.1).

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[27] It is assumed that crashes involving skidding are included in the general loss of control category. The sub-type of loss of control crashes that result from flat tires and blowouts is not included here to prevent double counting of benefits. However, all other types of loss of control crashes are included in order to match the broad target population in the FRIA. Additionally, it is assumed that tire pressure could be a contributing factor for any loss of control crash, no matter the initial cause (such as vehicle failure or roadway conditions).

[28] Only crashes with skidding are expected to benefit from the improvement in braking associated with TPMS (because before the point at which the tires lose their friction capabilities, it is assumed that all potential inadequacies in braking performance are perceived and compensated for by the driver).

[29] If a crash involves both an LTV and a passenger car that used their brakes, it will be grouped with crashes in which at least one LTV braked and will be excluded from the crashes in which at least one passenger car braked, to prevent double counting of benefits. It is expected that for crashes in which both cars were braking, TPMS is more likely to have an effect (because it could improve the braking performance of both cars), and therefore, it is reasonable to group these crashes with the LTV target population which has a higher effectiveness than the passenger car target population.

C.6.2 TPMS Effectiveness

Effectiveness estimates were calculated based on the data and procedures in the FMVSS No. 138 FRIA (NHTSA, 2005) and adjusted based on the results of NHTSA's post-implementation evaluation of the effectiveness of TPMS (Sivinski, 2012). These calculations are summarized for each target population in the following sections.

Loss of Control Crashes

The FMVSS No. 138 FRIA reports that 0.77 percent of crashes are loss of control crashes with low tire pressure as a probable cause. It was also reported that in 1999, there were 10.5 million vehicles involved in injury or property damage crashes, and 413,000 vehicles involved in loss of control crashes. Based on the FRIA estimate and the crash counts in 1999, approximately 80,850 vehicles (0.77% * 10.5 million vehicles) would have been involved in loss of control crashes with low tire pressure as a probable cause, and 19.6 percent of loss of control crashes (80,850 vehicles/413,000 vehicles) were estimated to have had low tire pressure as a probable cause. Based on this estimate, 19.6 percent of loss of control crashes could potentially have been prevented by improved tire inflation. The resulting effectiveness of improved tire inflation was then calculated based on the percentage of vehicles expected to actually experience improved tire inflation due to TPMS. Post-implementation data showed that TPMS was 55.6 percent effective at preventing underinflation of 25 percent or more of placard pressure (Sivinski, 2012). Therefore, the percentage of loss-of-control crashes caused by low pressure was multiplied by 55.6 percent, to estimate effectiveness of 10.9 percent (19.6% * 55.6%). In other words, it was estimated that installation of a TPMS compliant with FMVSS No. 138 would prevent 10.9 percent of crashes in the target population of loss of control crashes.

Crashes Resulting From Flat Tires and Blowouts

The FMVSS No. 138 FRIA relied on the following estimates:

- Underinflation was involved in 20 percent of cases where a flat tire or blowout caused the crash, and
- Approximately 50 percent of the crashes caused by a flat tire or blowout, in which underinflation was involved, would be affected by improved tire inflation (while the rest would be affected by better-quality tires).

Therefore, the potential effectiveness of improved tire inflation, as applied to crashes resulting from flat tires and blowouts, was estimated to be 10 percent (20% * 50%) using the FRIA estimates, in the absence of more recent information. The potential effectiveness of improved tire inflation was then adjusted for the percentage of vehicles expected to actually experience improved tire inflation due to TPMS. Post-implementation data shows that TPMS was 55.6 percent effective at preventing underinflation (Sivinski, 2012). Therefore, the potential effectiveness was multiplied by 55.6 percent, resulting in an ultimate adjusted calculated effectiveness of 5.56 percent (10% * 55.6%). In other words, it was estimated that installation of a TPMS compliant with FMVSS No. 138 would prevent 5.56 percent of crashes in the target population of crashes resulting from flat tires and blowouts.

Braking-Involved Crashes

Based on an analysis of the average stopping distance of the existing vehicle fleet and the predicted average stopping distance of a vehicle fleet with properly inflated tires, the FMVSS No. 138 FRIA reported that 1.38 percent of all passenger car crashes and 1.36 percent of all LTV crashes could be prevented with improved tire inflation. These estimates were used in the absence of more specific estimates for the cases in the TPMS target populations. However, in order to apply this effectiveness estimate to the target population of braking involved crashes, it was necessary to convert it from a percentage of all crashes to a percentage of braking-involved crashes, using the total number of crashes and the number of braking-involved crashes (similar to the logic used for the loss of control crashes). Because this data was not provided in the FRIA, these numbers were calculated based on the baseline retrospective dataset using Equation (47) and the target population defined in Appendix C.6.1, as shown in Table 85.

$$E_{braking\ crashes} = \frac{Preventable_{all} * Total_{all}}{Total_{braking}} = \frac{Total_{preventable}}{Total_{braking}} \tag{47}$$

where:

Variable values are defined in Table 85.

Table 85. Variables used in calculation of effectiveness in Equation (47)

	Percentage of all crashes prevented [FMVSS No. 138 FRIA]	Total number of crashes [Baseline Retrospective Dataset (weighted)]	Total number of braking crashes [Baseline Retrospective Dataset (weighted)]	Crashes prevented	Effectiveness of improved inflation for braking crashes (Equation 47)
	$Preventable_{all}$	$Total_{all}$	$Total_{braking}$	$Total_{preventable}$	$E_{braking\ crashes}$
PC	1.38%	2,318,332	79,002	31,993	40.5%
LTV	1.36%	1,269,452	26,635	17,265	64.8%

The resulting potential effectiveness of improved tire inflation was then adjusted for the percentage of vehicles expected to actually experience improved tire inflation due to TPMS. Post-implementation data shows that TPMS was 55.6 percent effective at preventing underinflation (Sivinski 2012). Therefore, the effectiveness of improved inflation was multiplied by 55.6 percent, leading to a final TPMS effectiveness of 36.0 percent (64.8% * 55.6%) for LTV crashes and 22.5 percent (40.5% * 55.6%) for PC crashes.

Summary of FMVSS No. 138 Crash Avoidance Effectiveness Estimates

The effectiveness estimates calculated in the preceding sections are summarized in Table 86 and were applied to cases in the target population as a reduction in case weight.

Table 86. FMVSS No. 138 crash avoidance effectiveness estimates

Target Population	Effectiveness
Loss of control crashes	10.9%
Crashes resulting from flat tires and blowouts	5.56%
Crashes in which at least one LTV braked and skidded	36.0%
Crashes in which at least one PC and no LTV braked and skidded	22.5%

C.6.3 TPMS Penetration

The penetration of TPMS by model year, shown in Table 87, was estimated based on NHTSA estimates of installations of FMVSS No. 138-compliant systems (Simons, 2017; Simons, personal communication[30]).

Table 87. Penetration of FMVSS No. 138 by vehicle model year (α_{MY})

Model Year	α_{MY} (%)	
	PC	LTV
≤ 2004	7.7	21.4
2005	7.8	30.0
2006	21.4	30.8
2007	44.7	61.3
2008 and later	100.0	100.0

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of FMVSS No. 138 among vehicles in projection crash years was estimated in Table 88.

Table 88. Penetration of FMVSS No. 138 in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)	
	PC	LTV
2014	78.2	82.8
2020	93.1	94.6
2025	98.2	98.6
2030	99.7	99.7

[30] James F. Simons, Bowhead Logistics Solutions, LLC, Alexandria, VA, personal communication, February 2018.

Appendix D: Crash Mitigation Countermeasures

D.1 Crash Imminent Braking Component of AEB Systems

The crash prevention effects of AEB with FCW were estimated in Appendix C.2. However, it was expected that crash severity will be reduced, even in the crashes that cannot be prevented by these technologies. In the absence of specific estimates of the expected decrease in crash severity in the rear impact crashes not prevented by AEB with FCW, the potential reduction in injury severity was estimated based on the speed reduction required for crash imminent braking (CIB) systems by the terms of the March 2016 voluntary AEB commitment by U.S. manufacturers (NHTSA, 2016b). Therefore, in this analysis, the estimate of crashes *mitigated* by AEB systems was based solely on the contribution of CIB performance. As any additional information comes available, these estimates can be updated or replaced in the projection model.

D.1.1 CIB Target Population

The target population for the crash mitigating effects of the CIB component of AEB systems was the same as that for the crash prevention effects of AEB with FCW, with the exception of a more limited range of crash severity. The ranges of delta V for which CIB was estimated to be effective (i.e., the crash delta V in the target population) are listed in Table 89. Refer to C.2.1 details.

D.1.2 CIB Effectiveness

In cases where AEB with FCW fails to prevent a crash, the CIB component of AEB was expected to reduce the severity of many crashes. Estimates of its severity mitigating effectiveness were made based on the minimum crash mitigation requirements in the 2016 voluntary agreement. The crash mitigation effects were applied after the crash avoidance effects of AEB and FCW have been applied, so that they reduced the outcome severity of crashes not prevented by these countermeasures. The estimated crash mitigation effectiveness was consistent with field data that shows that effectiveness for the prevention of injury crashes was higher than overall crash prevention effectiveness.

The requirements of the March 2016 voluntary agreement indicate that CIB systems are expected to meet one of two performance targets. Option A requires a speed reduction greater than 10 mph at only 12 *or* 24 mph closing speed, while Option B calls for a speed reduction greater than 5 mph at both 12 *and* 24 mph closing speeds. In the absence of information regarding which option was likely to be more widely adopted, this countermeasure was applied in the model with a range of values that assumed closing speed reductions of at least 5 or 10 mph in rear-impact crashes with closing speeds of 12 or 24 mph. Based on the broad approximation that rear-impact delta V is about 60 percent of closing speed (Anderson et al., 2012), this required speed reduction range would translate roughly to an expected reduction in delta V of 3 to 6 mph in crashes with striking vehicle delta V of 7 to 14 mph. Therefore, average CIB effectiveness, neglecting the contribution of FCW to crash severity mitigation, might be roughly estimated on aggregate as an average delta V reduction of approximately 4.5 mph in rear-impact crashes with delta V between 7 and 14 mph. According to an estimate of the risk of moderate-to-fatal injury (MAIS 2+) in rear-impact (Kusano & Gabler 2011), a 4.5 mph reduction in delta V over the range of 7 and 14 mph would result in an average reduction in moderate-to-fatal injury risk of 45 percent for striking vehicle drivers and 38 percent for struck vehicle drivers. If it is assumed that these driver injury risks can also be applied to striking and struck vehicle passengers, they can be used to estimate the reduction in moderate-to-fatal injuries expected in vehicles with CIB, i.e., the percentage of cases in which all AIS 2+ injuries would be prevented.

Several estimates and simplifications were made in the application of this risk reduction to the current analysis. The preliminary effectiveness estimates that were made based on the following approximations are shown in Table 89:

- Given that 57.04 percent[31] of all CDS AIS2+ occupants in rear-end crashes with known delta V get their injuries in crashes where the striking-vehicle delta V was between 7 and 14 mph, the estimate that CIB prevents 45 percent of rear-impact striking injuries between 7 and 14 mph and 0 percent of injuries outside this range was equivalent to estimating that CIB prevents 57.04 percent*45 percent (25.67%) of all rear-impact striking vehicle injuries. Similarly for struck vehicles, the estimate that CIB prevents 38 percent of injuries at striking vehicle delta V between 7 and 14 mph was equivalent to estimating that CIB prevents 57.04%*38% (21.68%) of all rear-impact struck vehicle injuries. Therefore, for cases where striking vehicle delta V was unknown, the estimated injury reduction with CIB in the striking vehicle was estimated to be 25.67 percent for striking vehicle occupants and 21.68 percent for struck vehicle occupants.
- These estimates do not account for the proportion of vehicles that may be designed to meet only Option A (with a speed reduction greater than 10 mph at only 12 *or* 24 mph closing speed) or only Option B (with a speed reduction greater than 5 mph at both 12 *and* 24 mph closing speeds) in the March 2016 voluntary agreement. However, on aggregate, these estimates of the overall effectiveness of AEB systems in the mitigation of crash and injury severity in rear impacts may be conservative in that the crash mitigating effects of FCW are ignored, as are any effects of the CIB system at delta V above and below the 12 to 24 mph closing speed range.
- These estimates do not account for any negative effects of these systems, such as the potential increase in impacts to the rear of vehicles equipped with AEB systems as a result of more effective braking (Cicchino, 2016).

[31] This value was obtained via direct analysis of the baseline retrospective dataset. Among struck-vehicle and striking vehicle-occupants in rear-end crashes with MAIS2+ injuries, 57.04% sustained those injuries in crashes where the striking vehicle delta V was 7 to 14 mph.

Table 89. CIB effectiveness estimates (crashes mitigated)

Delta V of Striking Vehicle	Case Occupant Vehicle	Effectiveness (AIS 2+)
DVTOTAL≤10 km/h (6 mph) OR DVEST<10 km/h	Striking (bullet)	0
	Struck (target)	0
11 km/h≤DVTOTAL≤23 km/h (7-14mph)	Striking (bullet)	45%
	Struck (target)	38%
DVTOTAL≥24km/h (15 mph) OR DVEST>24 km/h	Striking (bullet)	0
	Struck (target)	0
Unknown	Striking (bullet)	25.67%
	Struck (target)	21.68%

Effectiveness, as implemented for mitigation of injuries with CIB, was defined as the percentage of AIS 2+ cases in the target population in which all AIS 2+ injuries in each occupant case would be deleted.

D.1.3 Relationship Between CIB and Countermeasures Dependent on Delta V

In the case-by-case method (see Section 2.6.3), each countermeasure is applied to every individual case in its target population based on case variables. Since CIB is expected to modify crash delta V, all other countermeasures that rely on crash delta V to determine effectiveness or target population were examined to understand any potential interactions.

Although FMVSS No. 301 (Fire Prevention and Crashworthiness), FMVSS No. 208 (Advanced Air Bag Update), FMVSS No. 214 (Side Impact Update), and the Side Impact Test update in NCAP 2011 all rely on delta V to identify their target populations, there was no overlap in the target populations for these countermeasures and the target population for CIB. Therefore, since there were no cases to which both the CIB countermeasure and any of these speed-dependent countermeasures were based, severity changes resulting from CIB do not need to be considered when applying these other countermeasures. Therefore, delta V changes made to cases in the CIB countermeasure have no interaction with any of the effects of the above countermeasures and no consideration needs to be given to the order in which these countermeasures are applied relative to CIB.

FMVSS No. 138 (TPMS), however, relies on delta V and has an overlapping target population with CIB. Since the delta V reduction associated with CIB could affect the effectiveness of TPMS, which was calculated as a function of delta V, CIB should be applied to cases in the projection model *before* application of TPMS. For each reduced-injury pseudo-case resulting from application of CIB, the estimated CIB-associated 4.5 mph (7.2 km/h) reduction in delta V (R_{CIB}) will be documented for use in application of the TPMS countermeasure.

D.1.4 CIB Fleet Penetration

For CIB, adjusted effectiveness for occupants in both striking and struck vehicles was calculated based on the likelihood that the striking vehicle would be equipped with AEB systems with CIB. Therefore, all penetration estimates for this countermeasure were based on the model year of the striking vehicle.

The following sources were used to estimate the penetration of AEB with CIB by model year in Table 90:

- 2013 to 2018: Data collected by the NCAP program on the installation rate of crash mitigation technology (NHTSA, 2018b).
- 2019+: March 2016 Voluntary Industry Commitment to Advance AEB Technology (NHTSA, 2016b).

For 2013 to 2018, the penetration rates estimated for FCW and CIB from NCAP data were similar since they are often concomitant technologies. An average of these values was used as a surrogate for penetration of AEB with CIB in the projection model for those model years. Based on the March 2016 AEB voluntary agreement, it was estimated that the penetration of AEB with CIB will peak in model year 2023 and be installed in 94.1 percent of vehicles. This estimate corresponds to AEB/CIB being installed in 95 percent of 99 percent of the fleet, since manufacturers of 99 percent of the fleet committed to making 95 percent of their vehicles compliant with the voluntary agreement. To estimate the penetration for 2019 and later, estimates were linearly interpolated from 2018 (the last year of NCAP data available) to 2023. It was estimated that penetration in model years prior to 2013 was negligible since the 2013 rate was estimated to be less than 1 percent.

Table 90. Penetration of AEB with CIB by vehicle model year (α_{MY})

Model Year	**α_{MY} (%)**
≤ 2012	0.0
2013	0.9
2014	5.9
2015	9.1
2016	9.9
2017	22.7
2018	40.2
2019	50.9
2020	61.7
2021	72.5
2022	83.3
2023-2030	94.1

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of AEB with CIB among vehicles in projection crash years was estimated in Table 91.

Table 91. Penetration of AEB with CIB by target crash year (overall β_{TY})

Crash Year	Overall β_{TY} (%)
2014	0.6
2020	14.4
2025	44.6
2030	72.3

D.2 FMVSS No. 138 Tire Pressure Monitoring Systems

As explained in Appendix C.6, FMVSS No. 138 was expected to reduce the number of skidding and loss of control crashes, as well as crashes resulting from flat tires and blowouts. However, even in the cases where improved braking performance was not sufficient to prevent the crash, it is likely that TPMS could reduce the severity of the remaining (not prevented) braking-involved crashes (NHTSA, 2005). Therefore, FMVSS No. 138 was implemented in the model as both a crash avoidance and a crash mitigation countermeasure. The crash avoidance portion of FMVSS No. 138 is addressed in Appendix C.6. The crash mitigation component of the countermeasure, detailed in this section, applied to all crashes that are not prevented by the crash avoidance countermeasure.

D.2.1 FMVSS No. 138 Target Population

The following target subpopulations, applicable to the crash mitigation portion of FMVSS No. 138, are defined based on the target populations identified in the FMVSS No. 138 FRIA. It should be noted that only crashes with skidding are expected to benefit from the improvement in braking associated with TPMS because before the point at which the tires lose their friction capabilities, it was assumed that all potential inadequacies in braking performance are perceived and compensated for by the driver. The following target subpopulations were defined relative to the NASS CDS variables used to code them:

- LTV: Crashes in which at least one LTV applied brakes and skidded: MANEUVER=2:4, 8:9 and PREISTAB=2:4 for any LTV in crash
- PC: Crashes in which at least one PC used brakes, excluding cases that are LTV braking-involved crashes:[32] MANEUVER=2:4, 8:9 and PREISTAB=2:4 for any PC in crash
- PC/LTV defined using the same definition as ESC (see Appendix C.1.1)

These target populations were further divided based on the following categories, using NASS CDS variables:

- Wet/dry pavement:
    - o Dry: SURCOND=1
    - o Wet: SURCOND^=1

[32] If a crash involves both an LTV and a passenger car that used their brakes, it will be grouped with crashes in which at least one LTV braked and will be excluded from the crashes in which at least one passenger car braked, to prevent double counting of benefits. It is expected that for crashes in which both cars were braking, TPMS is more likely to have an effect (because it could improve the braking performance of both cars), and therefore, it is reasonable to group these crashes with the LTV target population (which has a higher effectiveness than the passenger car target population).

- Speed limit:
  - 0-35 mph: SPLIMIT<57
  - 36-50mph: 57<SPLIMIT<81
  - 51+ mph: SPLIMIT>81

Speed limit was unknown for approximately 1.2 percent of the cases in the target population in the stepping-stone dataset. These unknown speed-limit cases were binned with the 0-35 mph cases since the majority of cases where speed limit was known fall into this case, and it was also associated with the most conservative speed reduction among the bins.

D.2.2 FMVSS No. 138 Effectiveness

Crash mitigation effectiveness estimates for braking-involved crashes were calculated based on the data and procedures in the FMVSS No. 138 FRIA. Effectiveness was estimated as the percentage of cases involving a given MAIS that would see a severity reduction or deletion of the injury. Calculated trickle-down proportions reflect the proportion of cases in which the injury severity will be reduced and in what proportion the injury will be prevented.

Effectiveness values and injury-severity trickle-down effects were estimated as a function of the roadway condition (wet and dry), roadway speed limit (0-35pmh, 36-50pmh, and 51+mph), vehicle type (PC and LTV), and delta V using a four-step process, outlined below.

Step 1: Apply Reduction in Delta V

The FMVSS No. 138 FRIA reports average reductions in delta V for the target subpopulations shown in Table 92, based on the average change in stopping distance expected to result from improved tire inflation. Separate values were reported for vehicles with and without anti-lock brakes (ABS). However, because the majority of vehicles in the projection dataset have ABS installed, only the ABS values were used in this analysis. These reductions in delta V were applied to each case in the braking-involved crash target population to estimate the expected reduced delta V with improved tire pressure among cases in each of the subpopulations defined in Appendix D.2.1. For example, each vehicle in a case involving a braking LTV on wet pavement in a 40 mph speed-limit zone would be estimated to have a 4.53 mph drop in delta V with improved tire pressure in the braking LTV (per Table 92). In cases in which there was more than one braking vehicle and each vehicle could be assigned a different delta V reduction, the highest reduction in delta V was applied to the entire case. In cases with unknown delta V, zero reduction in delta V was assigned.

For each occupant in the target population, this delta V reduction was applied to the delta V ($DV_{original}$) in the case occupant's vehicle prior to application of the TPMS countermeasure. $DV_{original}$ was based on the delta V coded in the original CDS case, and reduced by R_{CIB}, which was the reduction in delta V resulting from the application of the CIB countermeasure, as discussed on page 187. If the case was not affected by the CIB countermeasure, R_{CIB} was 0. If the severity of the case was mitigated by the CIB countermeasure, R_{CIB} was 4.5 mph (7.2 km/h).

Table 92. Average reduction in delta V from improved tire pressure (NHTSA, 2005)

Vehicle Type	Wet/Dry Pavement	Speed Limit	Weighted Average Reduction in Delta V (mph)
PC	Wet	0-35 mph	2.858
		36-50 mph	4.065
		51+ mph	5.196
	Dry	0-35 mph	2.263
		36-50 mph	3.208
		51+ mph	4.068
LTV	Wet	0-35 mph	3.185
		36-50 mph	4.530
		51+ mph	5.789
	Dry	0-35 mph	2.533
		36-50 mph	3.589
		51+ mph	4.406

Step 2: Risk of Case Injury as Function of Delta V

For the delta V in the case occupant's vehicle prior to application of the TPMS countermeasure ($DV_{original}$) and the expected delta V with improved tire pressure (DV_{TPMS}) estimated in Step 1, the risk of an injury of the severity documented in the occupant case as well as the risk of fatal injury was estimated with and without TPMS from the relationships in Table 93 and Equations (48) and (49). For example, in an occupant case with MAIS 3 injuries, the risk of MAIS 3 injuries was calculated at the original vehicle delta V in the case and at the estimated reduced delta V with improved tire pressure. The risk of fatality at each of those delta V was also calculated for each case. The injury risk probabilities in Table 93 were derived based on crashes where at least one passenger vehicle used brakes.

Table 93. Injury risk probability curves

Injury Level	Delta V	Risk-Prediction Formula
MAIS 0	Delta V≤ 35	$e^{-.0807 Delta\ V}$
	Delta V≥ 36	0
MAIS 1+	Delta V≤ 35	$0.93221 * \sin(0.0449 * Delta\ V)$
	Delta V≥ 36	100
MAIS 2+	all	$\frac{e^{0.1683 Delta\ V - 5.0345}}{1 + e^{0.1683 Delta\ V - 5.0345}}$
MAIS 3+	all	$\frac{e^{0.1292 Delta\ V - 5.5337}}{1 + e^{0.1292 Delta\ V - 5.5337}}$
MAIS 4+	all	$\frac{e^{0.1471 Delta\ V - 7.3675}}{1 + e^{0.1471 Delta\ V - 7.3675}}$
MAIS 5+	all	$\frac{e^{0.1516 Delta\ V - 7.8345}}{1 + e^{0.1516 Delta\ V - 7.8345}}$
Fatal	all	$\frac{e^{0.1524 Delta\ V - 8.2629}}{1 + e^{0.1524 Delta\ V - 8.2629}}$

$$Risk_{MAISn} = Risk_{MAISn+} - Risk_{MAISn+1} \quad (48)$$

$$Risk_{FATAL} = Risk_{FATAL} \quad (49)$$

where:
$MAIS_n$ is the estimated risk of injury of the severity n of the case injury.

Step 3: Estimation of Effectiveness

Effectiveness of improved tire pressure was estimated as a function of the risk of injury with and without improved tire pressure (Equation (50)). Effectiveness of improved tire pressure was individually calculated for each case occupant, based on that occupant's MAIS injury, the original delta V of the occupant's vehicle, and the estimated reduced delta V with improved tire pressure ($DV_{improved\ TP}$) in the braking vehicle in the crash.

$$E_{Improved\ TP} = 1 - \frac{(Risk_{MAISn}(DV_{Improved\ TP}) + Risk_{Fatal}(DV_{Improved\ TP}))}{(Risk_{MAISn}(DV_{original}) + Risk_{Fatal}(DV_{original}))} \quad (50)$$

The resulting effectiveness of improved tire inflation was then adjusted for the percentage of vehicles expected to actually experience improved tire inflation due to TPMS. Post-implementation data showed that TPMS was 55.6 percent effective at preventing underinflation (Sivinski, 2012). Therefore, the effectiveness of improved tire pressure was multiplied by 55.6 percent to estimate the effectiveness of TPMS. The final effectiveness was adjusted based on penetration of TPMS, as for all countermeasures.

Step 4: Injury Severity Trickle-Down

While the effectiveness from Step 3 (after adjustment for penetration) ultimately reflected the proportion of cases in which a given occupant's injury severity would be reduced, information from benefits evaluation for FMVSS No. 138 was used to estimate the proportion of those affected injuries that would trickle-down to each lower level of AIS severity (Equation (51)). After application of effectiveness, a pseudo-case with the same injuries as the initial case represented the proportion of cases in which FMVSS No. 138 was expected to have no effect. Additional pseudo-cases with all injuries reduced to each lower AIS level were weighted by the product of TPMS effectiveness (adjusted for penetration) and the trickle-down proportion for that AIS severity level. For example, in an occupant case that originally had MAIS 3 injuries and where TPMS penetration-adjusted effectiveness was calculated in Step 3 to be 25 percent, the proportion of those 25 percent of cases that will trickle down to MAIS 2, 1, and 0 were estimated using Equation (51). The proportion that trickle down to MAIS 2 was calculated as the risk of MAIS 2 injury with improved tire pressure (Table 93 and Equation (51)), as a proportion of the sum of the risk of MAIS 0, 1, or 2 injury.

$$Trickle-down\ Proportion_x = \left(\frac{Risk_{MAIS\ x}(w\ Improved\ TP)}{\sum_{i=MAIS_{0-1}}^{MAIS_{n-1}} Risk_{MAIS\ i}\ (w\ Improved\ TP)}\right) \qquad (51)$$

where:

x is an AIS severity level below the initial $MAIS_n$ in the original retrospective case

Trickle-down $proportion_x$ is the proportion of prevented $MAIS_n$ injuries that are expected to trickle-down to severity level x.

In each pseudo-case representing cases where the MAIS injury severity was expected to be reduced to a lower MAIS severity, each individual injury with a severity higher than the reduced case MAIS was reduced to the new MAIS severity.

D.2.3 Relationship Between TPMS and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure was applied to every individual case in its target population based on case variables. Effectiveness of TPMS was estimated as a function of the delta V of the case occupant's vehicle prior to application of TPMS. That delta V was estimated from the original delta V documented in the CDS case, and adjusted for any expected delta V reduction associated with the application CIB (R_{CIB}) as discussed on page 187. Therefore, TPMS must be applied after CIB in the model.

Since TPMS is also expected to modify crash delta V in braking-involved crashes by 2 to 6 mph, all other countermeasures that rely on crash delta V to determine effectiveness or target population were examined to understand any potential interactions.

Several countermeasures whose target populations overlap with TPMS use delta V to define their target populations: FMVSS No. 208 (Advanced Air Bag Update), FMVSS No. 214 (Side Impact Update), updates to NCAP Frontal and Side Impact Tests (NCAP Enhancement in 2011 and hypothetical future updates), and FMVSS No. 301 (Fire Prevention and Crashworthiness). These countermeasures vary in terms of the delta V variable relied on (DVTotal, DVLong, DVLat, etc.). The delta V reduction estimated in the TPMS countermeasure is applied broadly to all directions of delta V.

As a result of the reliance of these crashworthiness countermeasures on delta V, TPMS needs to be applied to the projection model prior to any of the above countermeasures so that any delta V adjustment to cases is applied prior to the determination of each countermeasure's target population. For each reduced-injury pseudo-case resulting from application of TPMS, the estimated TPMS-associated reduction in delta V (R_{TPMS}), ranging from 2 to 6 mph was documented for use in the application of each of the potentially affected countermeasures.

D.2.4 FMVSS No. 138 Penetration

Refer to Appendix C.6.3 for details on the estimated fleet penetration of FMVSS No. 138.

Appendix E: Crashworthiness Countermeasures

E.1 FMVSS No. 202 Head Restraint Upgrade

This upgrade required head restraints to be higher and closer to the head than previously mandated and to be available in front outboard positions. Head restraints were not required in rear positions, but those that were installed needed to meet height, strength and position requirements. The definition of a vehicle with a rear seat head restraint was based on the seatback height. Vehicles with rear seat seatbacks of 700 mm or greater must meet the head restraint requirements. Although a Final Rule was issued in 2004, a revised Final Rule was issued in 2007, with a revised procedure for measuring backset. The specified backset and height limits were unchanged from the 2004 Final Rule but the 2007 Final Rule required that measurements be taken with the seat at the design angle (defined in the final rule) rather than at 25 degrees, essentially reducing the average effectiveness of the update for front seat outboard occupants.

The target population and effectiveness used in the projection model were based on information from NHTSA's Final Regulatory Impact Analysis for the FMVSS No. 202 Upgrade (NHTSA, 2004) as well as on the Supplemental Final Regulatory Evaluation associated with the 2007 Final Rule (NHTSA, 2007d). Penetration estimates were based on subsequent data collected by NHTSA (Simons, 2017).

This effectiveness summary was prepared in order to apply the basic effects of FMVSS No. 202 improvements on the projection dataset. The effects, however, are not clearly shown in the current projection model results given the absence of an injury measure for the characterization of AIS 1 neck injuries. When a disability measure is incorporated into the model, this effectiveness estimate will be revisited with consideration to development of methods to calculate more targeted effectiveness estimates for subpopulations based on vehicle type (LTV or passenger car), occupant stature, etc.

E.1.1 Head Restraint Upgrade Target Population

The target population included occupants who met these inclusion criteria:

- Outboard seating positions
- Passenger vehicles
- Non-rollover cases
- Struck vehicles in rear impacts
- Documented cervical spine strain injury: AIS=640278.1

These target populations were identified in the projection model using the following NASS CDS variables and definitions:

- SEATPOS in (11, 21, 31, 41, 51, 13, 23, 33, 43, 53)
- BODYTYPE<50
- ROLLOVER=0
- Rear impact defined with the projection model's impact direction taxonomy (Table 25)

The FRIA noted that whiplash injuries can occur at low speeds and may occur in crashes that do not appear in NASS CDS: non-towaway crashes or crashes not reported to police. The resulting under-representation of lower-severity injuries in the NASS CDS source cases was addressed with upweighting procedures in the projection model to account for non-towed cases and under-reporting of low-severity crashes to the police.

E.1.2 Head Restraint Upgrade Effectiveness

Effectiveness was implemented in the projection model as the deletion of AIS 1 cervical strain injuries (AIS=640278.1).

Front Outboard Seat Positions

On average, the FRIA-estimated effect of improving front outboard restraint height and backset from their pre-upgrade fleet averages to the required dimensions in the 2004 final rule was a 3.5 percent injury reduction. This effectiveness was associated with reduction of all injury types. Since whiplash injuries were estimated to be the only injury in 60 percent of crashes in the target population and head restraints were defined to be effective only for reducing whiplash injuries, then the estimated overall effectiveness of vehicles meeting the upgraded requirements at preventing whiplash injuries was estimated in the FRIA to be 3.5%/0.6=5.83%. According to the Supplemental Final Regulatory Evaluation, the relaxation of the backset requirements in the 2007 final rule reduced this estimated effectiveness to a range between 3.83 percent and 5.83 percent, depending on the selected position of adjustable head restraint, for a weighted average estimate of 4.42 percent.

Rear Outboard Seat Positions

In rear outboard seat positions, it was estimated that only 41.7 percent of vehicles would be subject to the rear seat head restraint requirements based on the height of rear seatbacks prior to the introduction of the rule, relative to the 700 mm threshold. The overall effectiveness of height and backset improvements in injury reduction was estimated to be 12.6 percent for vehicles with initial seatback height in the targeted range. Adjusting for the frequency of whiplash injuries, effectiveness of the improvements for decreasing whiplash injury specifically was 12.6/0.6=21%. Average effectiveness across all vehicles, including those with seatback height below 700 mm was 0.417*21%=8.76%. This estimate was unchanged in the Supplemental Final Regulatory Evaluation for the 2007 Final Rule.

E.1.3 Head Restraint Upgrade Penetration

According to the Final Rule for the FMVSS No. 202 upgrade, it became mandatory for the front seat starting with vehicles manufactured on or after September 1, 2009, i.e., in MY 2010. The rule became mandatory for the rear seat a year later, i.e., starting in MY 2011. In both the front and rear seats, 80 percent compliance was required in the first year, followed by 100 percent in the next year. A survey of 14 MY2009 vehicles showed no vehicle that met both the height and backset requirements in the revised rule. Front seat penetration for MY 2010 and beyond (Table 94) was available for the front seat from NHTSA data that assumed no voluntary compliance prior to 2010 (Simons, 2017). Rear seat penetration was estimated assuming a one-year delay relative to front seat penetration.

Table 94. Penetration of head restraint upgrade by vehicle model year (α_{MY})

Model Year	α_{MY} (%) Front seat	α_{MY} (%) Rear seat
≤ 2009	0.0	0.0
2010	92.0	0.0
2011	100.0	92.0
2012 and later	100.0	100.0

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of the head restraint upgrade among vehicles in projection crash years was estimated in Table 95.

Table 95. Penetration of head restraint upgrade in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%) Front seat	Overall β_{TY} (%) Rear seat
2014	48.4	37.9
2020	79.9	74.0
2025	94.0	91.7
2030	98.7	98.1

E.2 FMVSS No. 208 Advanced Air Bag Update

The May 2000 amendment to FMVSS No. 208 to require advanced air bags and the subsequent amendment to add a high-speed belted test for the 5th percentile dummy targeted the twin goals of minimizing the risk of serious injuries caused by air bags and improving frontal crash protection for all occupants. Only the improved frontal crash protection associated with these amendments were incorporated into the current projection model.

E.2.1 Advanced Air Bag Target Population

The target population, as defined in the Final Economic Assessment in May 2000 (NHTSA, 2000), included frontal crash occupants in the categories listed below. The following list includes the NASS CDS variables used to identify the target population in the model.

Seated in Front-Outboard Positions:

- Driver: SEATPOS=11
- Passenger: SEATPOS=13

Adults by Stature:

- Age 13+
- 50th applicable occupants are 65” tall and taller
    - Where height is unknown, males are in the 50th applicable population
- 50th tests explicitly estimated to include population covered by 95th percentile male dummy (page VI-2, May 2000 FEA)
- 5th applicable occupants are shorter than 156 cm (65”)
    Where height is unknown, females are in the 5th applicable population

Delta V:

- For Phase 1 and 2 tests, target population used the test speed as the maximum delta V in the target population. Additionally, it was assumed that benefits would primarily be drawn from cases with delta V of at least 15 mph when air bags are more likely to deploy. Thus, for the 25-30 mph test, target population included all crashes with 15 mph<=delta V<30 mph. The delta V for this countermeasure was evaluated against the case delta V estimated in the original CDS case, and adjusted to reflect the expected delta V reduction (R_{TPMS}) resulting from application of TPMS in each case where it applied. The code associated with this delta V inclusion criteria was coded using NASS CDS variables (DVTOTAL, DVLONG, and DVEST) and projection model variables (R_{TPMS}):
    - 24<=(DVTOTAL – R_{TPMS})<=48 km/h or
    - 24<=(DVLONG – R_{TPMS})<=48 km/h
- The target population for the high-speed test with the 5th female was applied only to cases with (DVTOTAL – R_{TPMS}) or (DVLONG – R_{TPMS})>48 km/h.
- Where DVTOTAL and DVLONG were unavailable, DVEST was used.

The subpopulations subject to the improvements associated with each test type were established based on NHTSA review of potential test procedures (Hollowell et al., 1999) and the categorization scheme on which it was based from Stucki's ESV paper (Stucki et al., 1998). Each subpopulation was defined with NASS CDS variables, as follows:

- Rigid barrier, perpendicular
    - DOF[33]=12 & GAD1=F & SHL1 in (D, Z, Y)
- Rigid barrier, perpendicular and up to 30 degrees oblique
    - DOF=12 & GAD1=F & SHL1 in (D, Z, Y) or
    - DOF=10-2 & GAD1=F & SHL1=D & Fixed Object Contacted (OBJCONT=41:69), or
    - DOF in (10, 11, 1, 2) & GAD1=F and SHL1 in (R, L, Y, Z)
- 40 percent offset frontal, deformable barrier test
    - DOF=10-2 & SHL1 in (L, R, Y, Z), or
    - DOF=10-2 & GAD1 in (L, R) and SHL1=F
- Only belted occupants were included in the target population for belted tests and only unbelted occupants were included in the target population for unbelted tests.

Note that these divisions matched the populations used to calculate the effectiveness values in the May 2000 Final Economic Analysis for the Advanced Air Bag Rule and were different than those used currently by the agency to define oblique impacts.

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33 For DOF limitations defined in these target subpopulations, each category was coded to include cases coded with non-horizontal DOF. For example, for target subpopulations that included 12 o'clock (DOF=12), the code was written to also capture 12 o'clock impacts with non-horizontal components, i.e., DOF=12, 32, 52, 72, and 92. For more details on DOF coding of non-horizontal impacts, please refer to the NASS CDS Analytical User's Manuals (Radja, 2016).

Effectiveness was calculated with respect to fatal or MAIS 2-5 head, neck, or chest injuries, effectively further limiting the target population for both FMVSS No. 208 amendments to occupants with these injuries.

E.2.2 Advanced Air Bag Effectiveness

Effectiveness estimates for the FMVSS No. 208 amendments were based on expected injury rate reductions calculated from testing and reported in the regulatory evaluations performed prior to regulation implementation (NHTSA, 2000). Effectiveness estimates for injuries in each body region were made separately for drivers and passengers, for different body regions, and for different tests. Estimates of effectiveness for fatally injured occupants were also compared to a post-regulation evaluation (Greenwell, 2013).

Effectiveness for femur injury was 0 percent, so no change in femur injury was expected in the current analysis. No change in injury risk was expected based on chest deflection in the tests, so the effectiveness of the new rule was estimated based on the reduction of chest acceleration in tests. The reduction in head injury risk used for this analysis was the average of the reduction estimated using Prasad/Mertz and Lognormal methods.

These reduction estimates were applied to the cases in the projection model as follows. For non-fatal cases, the injury reduction values for AIS 2-6 injuries were drawn from the corresponding reported percentage reduction in MAIS 2-5 cases in the FEA (Table 96). These effectiveness estimates reflected the percentage of cases in which injuries to each corresponding body region were deleted. For example, application of a 5.9 percent effectiveness to a case in the target population for head injury reduction resulted in two pseudo-cases: one unchanged pseudo-case with a pseudo-weight of 94.1 percent of the original case weight and one pseudo-case with all AIS 2-6 injuries deleted and a pseudo-weight of 5.9 percent of the original case weight. The effectiveness estimates for each body region were applied sequentially so that a single case could be subjected to different effectiveness values for injuries in each body region.

Table 96. MAIS 2-6 injury reduction with advanced air bags
(from Table VI-5-B in May 2000 FEA, averaging head injury values drawn from Mertz/Prasad and Lognormal analyses)

Phase	Test			Head	Neck	Chest
1	5th	Unbelted rigid barrier (25 mph)*	Driver	0%	8.98 %	1.57 %
			Passenger	0%	5.36 %	2.07 %
		Belted rigid barrier (30 mph)	Driver	0%	7.40 %	0.27 %
			Passenger	0%	0.81 %	0.28 %
		Belted offset deformable barrier (25 mph)	Driver	0%	11.88 %	0%
			Passenger	5.90 %	3.44 %	0%
	50th	Unbelted rigid barrier (25 mph), perpendicular and up to 30 degrees oblique*	Driver	0%	0%	0%
			Passenger	0.25 %	0%	0%
		Belted rigid barrier (30 mph)	Driver	0%	0%	0%
			Passenger	0%	0%	0%
2	50th	Belted rigid barrier (35 mph)	Driver	0.76 %	0%	0.70 %
			Passenger	1.12 %	0%	0.10 %
5th Female Upgrade	5th	Belted rigid barrier (35 mph)	Driver	0.2%	2.4%	0.1%
			Passenger	0%	0.4%	0%

** Drawn from reduction estimates based on 20 to 30 mph rigid barrier data in Table V1-5 (Greenwell, 2013).*

For fatal cases, i.e., cases that were originally fatal before application of the model, the effectiveness estimates in Table 97 were applied to reflect the percentage of cases in which AIS 2-6 injuries to each corresponding body region would be deleted. While no direct change was made to the originally coded fatal status of the case when modeling this countermeasure, individual injuries in the case were adjusted. Since the number of fatalities in the projection datasets were calculated as a function of the coded injuries in the dataset (rather than using the originally coded fatality status) the reduction in the risk of fatality as a result of this countermeasure was captured in the projection output. Notably, the effectiveness in prevention of injuries to the body regions associated with high threat to life, head and chest, was 0 percent for many of the occupant categories in the target population. As a result, the very low estimates of injury prevention effectiveness would be expected to be equivalent to even lower estimates of effectiveness in terms of fatality prevention. For example, the 6.19 percent effectiveness in neck injury prevention for drivers in the target population for the 5th percentile dummy belted offset deformable barrier test would not result in a substantial reduction in fatality risk. These FEA-derived estimates for the effectiveness of injury prevention in each body region in Table 97 were compared to the subsequent evaluation of effectiveness in preventing fatality (Greenwell, 2013). The Greenwell study concluded that compliance with the regulation had resulted in a small (3%) but statistically insignificant reduction in overall fatality among front-seat occupants in frontal crashes. That point-estimate of effectiveness likely reflects higher effectiveness (in terms of fatality prevention) than was predicted by the pre-regulation estimates of effectiveness relative to injury prevention in single body regions among fatally injured occupants (Table 97). However, Greenwell's fatality-reduction estimates varied substantially in the post-regulation evaluation for different categories of target population, including drivers and passengers, occupants in passenger cars or LTVs and vehicles with or without advanced features such as multi-stage inflators or seat belt sensors. Therefore, although Greenwell's overall measurement of effectiveness was used to confirm that the pre-regulatory predictions of injury-reduction effectiveness estimates in fatal cases were not unreasonable, the uncertainty in those estimates was too great to use them to adjust or correct the more detailed pre-regulation estimates.

Table 97. Fatal injury reduction with advanced air bags
(from Table VI-5-A in May 2000 FEA, averaging head injury values drawn from Mertz/Prasad and Lognormal analyses)

Phase	Test			Head	Neck	Chest
1	5th	Unbelted rigid barrier (25 mph)*	Driver	0%	3.51 %	.06 %
			Passenger	0%	2.39 %	1.57 %
		Belted rigid barrier (30 mph)	Driver	0%	3.05 %	0.01 %
			Passenger	0%	0.27 %	0%
		Belted offset Deformable barrier (25 mph)	Driver	0%	6.19 %	0%
			Passenger	2.77 %	1.22 %	0%
	50th	Unbelted rigid barrier (25 mph), perpendicular and up to 30 degrees oblique*	Driver	0%	0%	0%
			Passenger	.015%	0%	0%
		Belted rigid barrier (30 mph)	Driver	0%	0%	0%
			Passenger	0%	0%	0%
2	50th	Belted rigid barrier (35 mph)	Driver	0.14 %	0%	0%
			Passenger	0.22 %	0%	0%
5th Female Upgrade	5th	Belted rigid barrier (35 mph)	Driver	1.5%	3.3%	1%
			Passenger	0%	0.5%	0%

** Drawn from reduction estimates based on 20 to 30 mph rigid barrier data in Table V1-5 (Greenwell, 2013).*

The pseudo-weights applied to cases with deleted injuries were liberal in that they essentially eliminated injuries rather than reducing them and allowing higher-severity injuries to trickle-down to lower-severity injuries. This simplification was expected to make a relatively small difference to the ultimate results given the very small effectiveness values acting on a very limited target population. Furthermore, the initial benefits estimate was described as "conservative" in that it estimated no benefit below 48 km/h other than the subsequent 5th female upgrade and neglected any additional benefits from technologies such as pretensioners. It is likely, therefore, that the simplification of injury trickle-down (which may have led to a slight overestimate of injury reduction) was balanced by other conservative estimates made in the analysis (which were expected to lead to somewhat underestimated injury reductions).

E.2.3 Relationship Between FMVSS No. 208 and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure was applied to every individual case in its target population based on case variables. The target population definition for FMVSS No. 208, as well as its effectiveness in preventing head injuries, relied on the estimated case delta V. That delta V was estimated from the original delta V documented in the

CDS case, but adjusted for the expected delta V reduction associated with the application of TPMS (R_{TPMS}) to the striking vehicle as discussed in Section D.2. Therefore, FMVSS No. 208 must be applied *after* TPMS in the model.

E.2.4 Advanced Air Bag Penetration

According to the Final Rule in May 2000 and the subsequent upgrade for the 5th female, the phase-in schedule for large manufacturers was defined as shown in Table 98.

Table 98. Regulatory phase-in schedule for FMVSS No. 208 updates

Model Year	Phase I	Phase II	5th Female
2003	0%		
2004	35%		
2005	65%		
2006	100%		
2007			
2008		35%	
2009		65%	
2010		100%	35%
2011			65%
2012			100%

Phase I and II penetrations were estimated based on these minimum phase-in requirements, under the assumption that compliance rates would increase gradually before the first year of phase-in and increase more quickly during the phase-in period. This relationship between the required phase-in and the actual adoption rates was modeled based on observed or reported rates of compliance to other FMVSS upgrades relative to phase in requirements, for standards where data was available. A similar estimate of compliance was made for the 5th female upgrade to FMVSS No. 208, relative to phase-in requirements, but was adjusted based on information from the 2006 Final Regulatory Evaluation which showed that 4 of 5 vehicles tested already met the targets that would be required starting in 2010. Based on that data, it was estimated that penetration of improvements related to the 5th female upgrade was at least 80 percent for all model years. Therefore, the penetration estimates by model year for the 5th female upgrade show the higher value of 80 percent or the penetration estimated by the same methods applied to Phase I and II penetration. The estimated penetration by model year is compared to phase-in requirements in Figure 26. Final penetration estimates used in the model for all three phases are shown in Table 99.

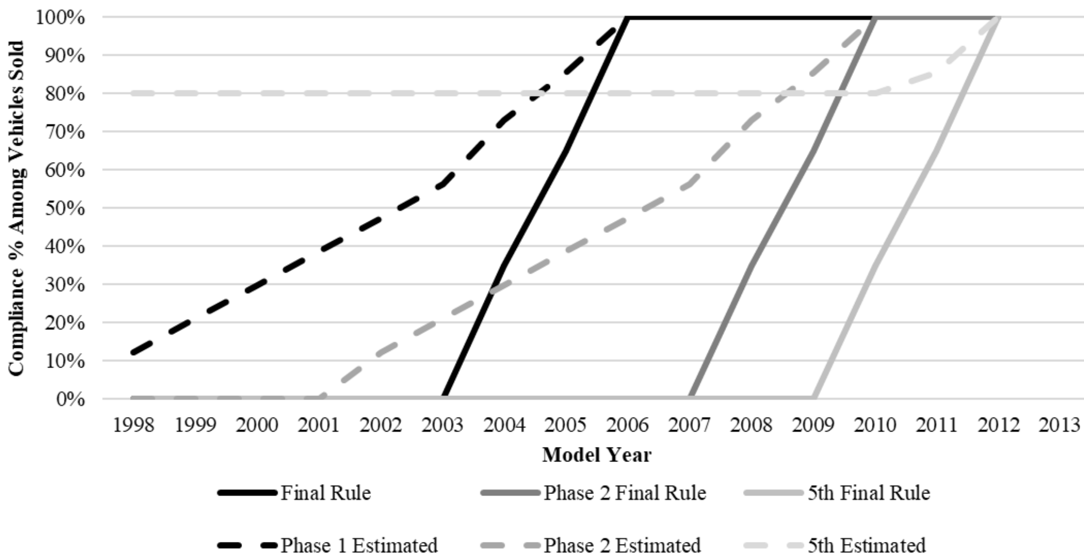

Figure 26. Estimated penetration of FMVSS No. 208 update compared with Final Rule requirements

Table 99. Penetration of FMVSS No. 208 update by model year (α_{MY})

Model Year	Phase I (%)	Phase II (%)	5th Female (%)
≤ 2004	85.0	30.0	80.0
2005	85.0	38.7	80.0
2006	100.0	47.5	80.0
2007	100.0	56.2	80.0
2008	100.0	73.0	80.0
2009	100.0	85.5	80.0
2010	100.0	100.0	80.0
2011	100.0	100.0	85.5
2012+	100.0	100.0	100.0

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of FMVSS No. 208 among vehicles in projection crash years was estimated in Table 100.

Table 100. Penetration estimate for FMVSS No. 208 by target crash year (overall β_{TY})

Crash Year	Phase I (%)	Phase II (%)	5th Female (%)
2014	98.7	80.3	86.2
2020	97.6	93.1	93.9
2025	99.9	98.1	98.0
2030	100.0	99.6	99.5

E.3 FMVSS No. 214 Side Impact Update

Estimation of the effect of the FMVSS No. 214 update that went into effect for vehicles starting with MY 2011 was based primarily on the Final Regulatory Impact Analysis for the update (NHTSA, 2007c) because it analyzed effectiveness in terms of injury, while the subsequent NHTSA evaluation was limited to analyses of fatality effectiveness. However, since the subsequent evaluation of the fatality effectiveness of FMVSS No. 214 demonstrated that FRIA-estimated effectiveness relative to fatality was overestimated (Kahane, 2014b), corresponding adjustments were made to all the FRIA-estimated injury effectiveness values used in the projection model.

E.3.1 Side Impact Update Target Population

The overall target population for the FMVSS No. 214 update was limited by the crash and occupant conditions shown in Table 101. Note that limitations on the lateral delta V in each case included in the target population were evaluated against the vehicle delta V expected after application of the TPMS countermeasure, which reduced delta V in affected pseudo-cases by a reduction of R_{TPMS}.

Target population cases also needed to meet the requirements in Table 102 for the oblique pole test target population or the requirements in Table 103 for the moving deformable barrier test target population. Occupants in the target population were further divided into subpopulations for the purpose of defining effectiveness more precisely for occupants of a given size or with specific injury characteristics. These subpopulations are defined in Table 104 to Table 106.

Table 101. Global target population limitations for FMVSS No. 214 update

Target Population Requirement	Corresponding NASS CDS Codes
Lateral component of delta V 12-25 mph	GV/|DVLAT| - R_{TPMS}=19 to 40 km/h GV/DVEST=3 (24<delta V<40)
Age 13+	OA/AGE in 13-97
Near-side outboard occupants	(GAD1=R or DOF1=1-5) and SEATPOS=13, 23, 33, 43, 53 OR (GAD1=L or DOF1=7-11) and SEATPOS=11, 21, 31, 41, 51
Rollover as first event excluded	EV/ACCSEQ=1, VEHNUM, OBJCONT in 31, 32
Impact direction & Impact angle	GAD1=R, L, and SHL1=P, Y, Z, and DOF1=1-5, 7-11

Table 102. Oblique pole test target population limitations

Target Population Requirement	Corresponding NASS CDS Codes
Front-seat occupants only (see Section E.3.2.9 for discussion of rear-seat occupants)	SEATPOS in (11, 13)
Vehicle-to-pole, or vehicle-to-tree impacts	OBJCONT1 in (41, 42, 45, 50, 51, 52, 53) *Includes: small tree, large tree, breakaway pole, small pole, medium pole, large pole, unknown size pole*
2-3 o'clock and 9-10 o'clock impacts (limited based on width of bag required in 214 tests)	DOF1=2-3, 9-10 *Alternative definition in footnote 33 on page V-19 of FRIA appears to be global, while pole-test applicability more limited*
Complete ejections excluded	OA/Ejection^=1
GVWR (Gross Vehicle Weight Rating)	<10,000 lbs

Table 103. MDB test target population limitations

Target Population Requirement	Corresponding NASS CDS Codes
Front-seat occupants only	SEATPOS in (11, 13)
Vehicle-to-other vehicle or roadside objects	OBJCONT1 in (1-11, 43-44, 46-49, 54-59, 64, 68-71, 77-78) *Includes: vehicle, bush, embankment, guardrails, concrete or traffic barriers, fence, wall, building, bridge, other/unknown fixed objects, vehicle not in transport, train/railway vehicle, disconnected trailer*
2-3 o'clock and 9-10 o'clock impacts (limited based on width of bag required in 214 tests)	DOF1=2-3, 9-10 *Alternative definition in footnote 33 on page V-19 of FRIA appears to be global, while pole-test applicability more limited*
Complete ejections excluded[34]	OA/Ejection^=1
GVWR	<10,000 lbs

[34] As discussed in Appendix C.3.2, the application of SSF creates pseudo-cases in which rollovers and ejections are added to or removed from existing cases in the model. The pseudo-cases in which an ejection is added by the application of SSF will be excluded from the 214 target population. The pseudo-cases in which an ejection is deleted by the application of SSF will not be excluded from the 214 target population based on ejection status (but they could be excluded based on other target population limitations).

Table 104. Occupant subpopulations by size

	50th Occupant Subpopulation (for tests with 50th percentile male ATD)	**5th Occupant Subpopulation (for tests with 5th percentile female ATD)**
Height	>=65 inches [NASS CDS HEIGHT>=165]	<65 inches [NASS CDS HEIGHT<165]
If height unknown	Male [NASS CDS SEX=1]	Female [NASS CDS SEX in (2:6)]
If height and sex unknown	Estimated effectiveness based on 50th percentile test results	

Table 105. Occupant subpopulations by head impact source

Head contact source	**Side Impact Type**	**Corresponding NASS CDS Codes (INJSOU)**
Head-to-pole	Vehicle-to-pole	INJSOU=598
Head-to-striking vehicle	Vehicle-to-vehicle	INJSOU in (501-514)
Head-to-vehicle interior components	Vehicle-to-pole or Vehicle-to-vehicle	INJSOU ^in (451:551, 598:697) and INJSOU^="." *Excludes: injury sources exterior to the vehicle compartment, as well as fire in vehicle, flying glass, other noncontact, air bag exhaust gases, same occupant contact, other occupant contact, and injuries with unknown source or unknown vehicle or object.*

Table 106. Occupant subpopulations by other (non-head) injury regions

Injury Region	**Definition (AIS Injury Codes)**
Chest	AIS Body Region=4
Abdomen	AIS Body Region=5
Pelvis	AIS codes: 8506xx (hip), 851808 (femur head fracture), 851810 (intertrochanteric femur fracture), 851812 (femur neck fracture), 8526xx (pelvis fracture), 8528xx (sacroilium fracture), 8530xx (Symphysis pubis separation), 8304xx (sciatic nerve)

E.3.2 Side Impact Update Effectiveness

Effectiveness estimates for subpopulations of the target populations are shown in Table 107. Effectiveness estimates were calculated based on the data and procedures in the Final Regulatory Impact Analysis for the FMVSS No. 214 update (NHTSA, 2007b), and adjusted according to the results of a subsequent evaluation that showed that effectiveness estimates in the FRIA were overestimated (Kahane, 2014a). Since the evaluation analysis was focused on fatality and did not specifically analyze effectiveness in injury cases, the percentage magnitude of the overestimate determined in fatal cases was applied as a correction to the injury-specific effectiveness estimates developed based on FRIA results.

For each target subpopulation in Table 107, see the referenced report section or table number for a detailed summary of the uncorrected FMVSS No. 214 effectiveness for that target subpopulation, including estimates of trickle-down of injury severity. For each of the target subpopulations in the tables below, effectiveness was estimated as the percentage of cases involving a given injury that would see a severity reduction or deletion of the injury. Calculated trickle-down proportions reflect the proportion of cases in which the injury severity would be reduced and in what proportion the injury would be prevented. For example, in an occupant case with an AIS 3 chest injury in the target population for the 50th occupant subpopulation for the pole test, Table 107 shows that effectiveness is 4.9 percent. Table 108 shows that of the 4.9 percent of cases expected to see an injury reduction, 50 percent would be reduced to an AIS 2 chest injury and 50 percent reduced to an AIS 0 or 1 injury.[35] Application of this countermeasure to a case with weight of 100 would lead to replacement of the case with three pseudo-cases. This simple example assumes that the original retrospective NASS CDS case was not compliant with the FMVSS No. 214 update ($\alpha'=0$) but that it would be in the projection year ($\beta=100$). In one of the resulting pseudo-cases, with a case weight of 95.1 (100-4.9), all other case parameters would be unchanged and there would still be an AIS 3 chest injury. In a second pseudo-case, with a weight of 2.45 (4.9x0.5), the only difference from the original case parameters would be replacement of the AIS 3 chest injury with an AIS 2 chest injury. In the third pseudo-case, with a weight of 2.45, the chest injury would be deleted.

[35] In the current version of the model, harm measures are not estimated for AIS 1 injuries and injuries that trickle down to AIS 1 are assumed to be prevented. In future versions of the model that include harm estimation for AIS 1 injuries such as whiplash associated injuries and mild traumatic brain injury, AIS 1 injuries will be retained for harm analysis.

Table 107. Uncorrected effectiveness by target population for FMVSS No. 214 update

	Side-Impact Type	By Body Region		Applicable occupant subpopulation: 50th	Applicable occupant subpopulation: 5th
214-Applicable	Vehicle impact with pole or tree	Head	*Pole/Tree source*	See Appendix E.3.2.1 E=f(injury source and delta V)	
			Interior source		
		Chest		Table 108 AIS 3: E=4.9% AIS 4+: E=10.5%	E=0
		Abdomen		Table 109 AIS 3: E=94.8% AIS 4+: E=99.3%	E=0
		Pelvis		Table 110 AIS 2: E=26.2% AIS 3+: E=19.4%	Table 111 AIS 2+: E=20.1%
	Vehicle-to-vehicle impact	Head	*Striking vehicle source*	See Appendix E.3.2.1 E=f(impact type, injury source and delta V)	
			Interior source		
		Chest		Table 112 AIS 3: E=19.1% AIS 4+: E=31.0%	Table 113 AIS 3: E=25.5% AIS 4+: E=26.5%
		Abdomen		Table 114 AIS 3: E=80.0% AIS 4+: E=80.9%	E=0
		Pelvis		Table 115 AIS 2: E=54.2% AIS 3+: E=41.3%	Table 116 AIS 2+: E=95.7%
	Far-side occupants	*All body regions*		E=0 See discussion in Appendix E.3.2.8	
	Rear seat (regardless of impact partner)	Head	*Striking vehicle source*	E=0 See discussion in Appendix E.3.2.9	
			Interior source		
		Chest			
		Abdomen			
		Pelvis			

After calculating the uncorrected effectiveness that applied to a given case as summarized in Table 107, correction factors were applied to the case-specific uncorrected effectiveness. These correction factors accounted for the overestimation demonstrated by a subsequent evaluation of the FMVSS No. 214 update (Kahane, 2014a). The evaluation showed that the FRIA effectiveness in fatal cases in vehicles with curtain and torso air bags (which make up the majority of vehicles compliant with the updated FMVSS No. 214) was only 31.3 percent, 14 percent lower than the 36.4 percent predicted in the FRIA. In the absence of a specific post-implementation evaluation of the accuracy of the injury effectiveness estimates in the FRIA or of effectiveness in specific impact types, a 13.7 percent correction was applied to the effectiveness of all cases in the FMVSS No. 214 target population. This correction was implemented by multiplying effectiveness in each of these cases by 0.863.

E.3.2.1 Effectiveness and Injury Trickle-Down for Head Injuries

Effectiveness of the side impact update for head injury was the same for occupants represented by the 5th and 50th occupant subpopulations. Uncorrected effectiveness values and injury-severity trickle-down effects were estimated as a function of the head injury source and the delta V using a four-step process, described below. Effectiveness was corrected based on Kahane's subsequent evaluation of real-world effectiveness after applying all four steps.

Step 1: HIC With/Without Air Bag Estimated by Delta V for Each Head Impact Source

Based on the head injury surface and the lateral component of the delta V in a given case, expected HIC (Head Injury Criterion) with and without an FMVSS No. 214-compliant air bag was determined using the equations in Figure 27 to Figure 29. Lateral component of delta V was based on the original estimate in the CDS case, reduced for pseudo-cases affected by TPMS by the estimated magnitude of delta V reduction (R_{TPMS}).

Head impact to pole (FRIA Appendix XI):

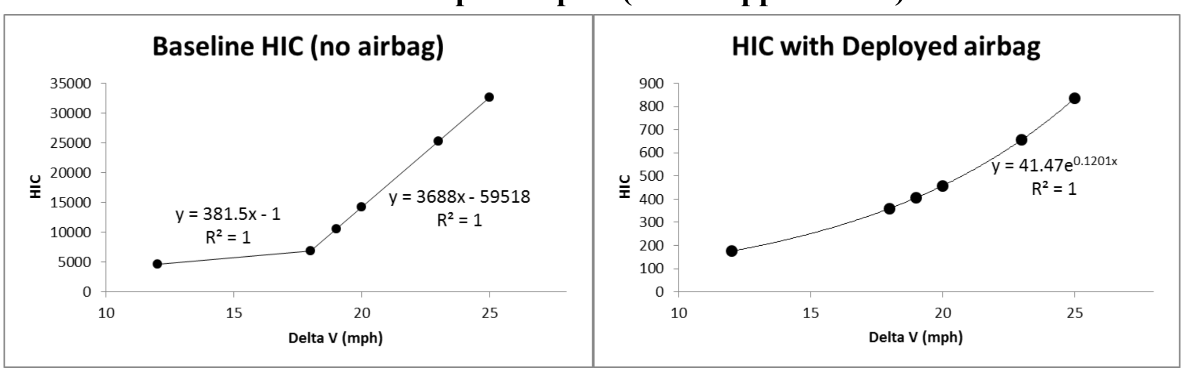

Figure 27. Estimated relationship between delta V and HIC in head-to-pole impacts

Head-to-vehicle-interior impact (FRIA Appendix XI):

Note that these relationships apply in both vehicle-to-pole and vehicle-to-vehicle crashes.

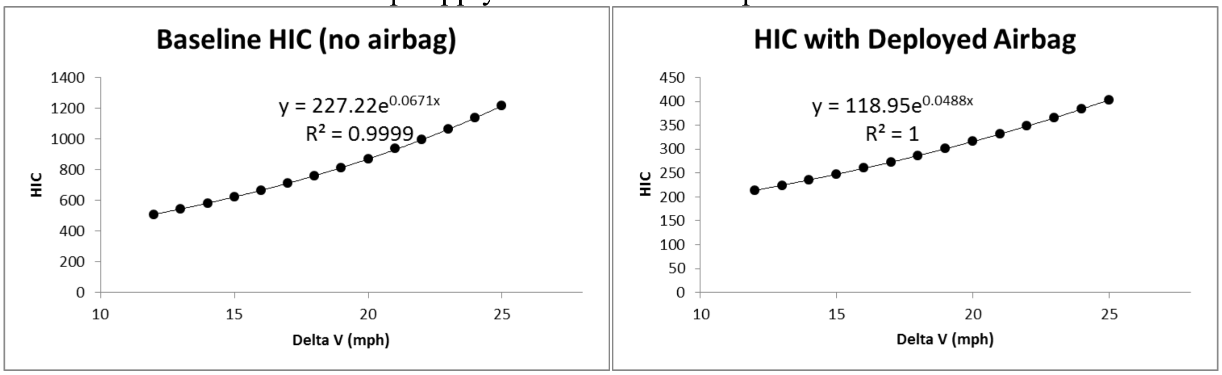

Figure 28. Estimated relationship between delta V and HIC in head-to-interior impacts

Head-to-striking-vehicle impact (FRIA Appendix XI):

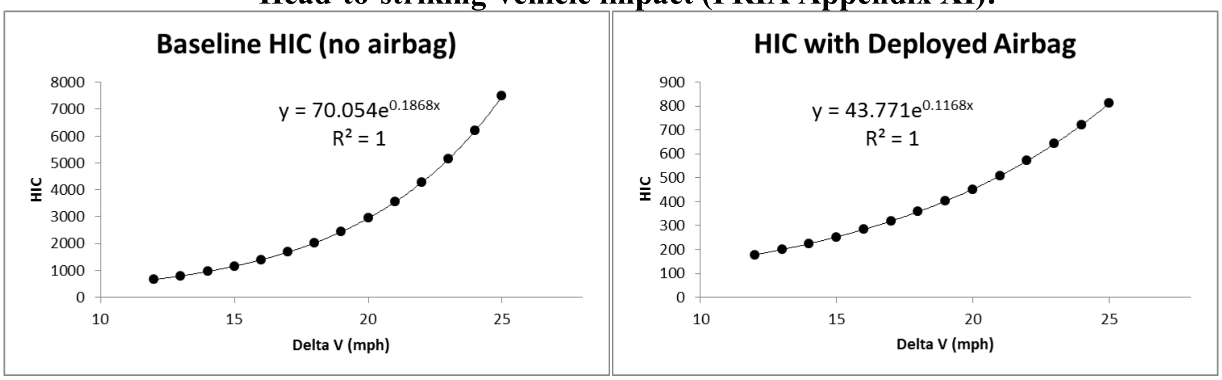

Figure 29. Estimated relationship between delta V and HIC in head-to-striking-vehicle impacts

Step 2: Risk of Case Injury as Function of HIC

For the expected HIC with and without an air bag (HIC_{bag} and HIC_{nobag}) estimated in step 1, the risk of a head injury of the severity documented in the occupant case as well as the risk of fatal injury was estimated with and without an air bag from the relationships in Figure 30 and Equations (52) and (53).

$$
\begin{array}{ll}
\text{AIS 1+:} & [1 + \exp((1.54 + 200/HIC) - 0.0065 \text{ x } HIC)]^{-1} \\
\text{AIS 2+:} & [1 + \exp((2.49 + 200/HIC) - 0.00483 \text{ x } HIC)]^{-1} \\
\text{AIS 3+:} & [1 + \exp((3.39 + 200/HIC) - 0.00372 \text{ x } HIC)]^{-1} \\
\text{AIS 4+:} & [1 + \exp((4.9 + 200/HIC) - 0.00351 \text{ x } HIC)]^{-1} \\
\text{AIS 5+:} & [1 + \exp((7.82 + 200/HIC) - 0.00429 \text{ x } HIC)]^{-1} \\
\text{Fatal:} & [1 + \exp((12.24 + 200/HIC) - 0.00565 \text{ x } HIC)]^{-1}
\end{array}
$$

Figure 30. Head injury risk as function of HIC

$$Risk_{AISn} = Risk_{AISn+} - Risk_{AISn+1} \quad (52)$$

$$Risk_{FATAL} = Risk_{FATAL} \quad (53)$$

where:

$Risk_{AISn}$ is the estimated risk of injury of the severity n of the case head injury.

Step 3: Estimation of Effectiveness

Effectiveness was estimated as a function of the risk of injury with and without an FMVSS air bag (Equation (54)).

$$E = 1 - \frac{(Risk_{AISn}(HIC_{bag}) + Risk_{Fatal}(HIC_{bag}))}{(Risk_{AISn}(HIC_{no\ bag}) + Risk_{Fatal}(HIC_{no\ bag}))} \quad (54)$$

Note that this relationship is a function of the risk of fatal injury as well as of the risk of the head injury severity actually sustained in the original retrospective case. The inclusion of fatal risk was necessary since in head-to-pole and head-to-vehicle injuries, all injuries are expected to be fatal at some delta Vs. At these delta Vs, effectiveness would appear to be 0 at all injury levels since there is no way of definitively determining whether an individual head injury was fatal (even when a case is fatal). The inclusion of the fatal injury risk component of the calculation will have little effect mathematically on cases that are not fatal and cases that do not involve head-to-pole and head-to-vehicle contact. Effectiveness for cases in those categories that are *not* fatal may not be accurate but is expected to be better estimated with Equation (54) than by assigning an effectiveness of zero, which would result if fatal injury risk were not included in the estimate.

Step 4: Injury Severity Trickle-Down

While the effectiveness from Step 3 (after adjustment for penetration) ultimately reflects the proportion of the time that a given occupant's head injury severity will be reduced, information from benefits evaluation for the FMVSS No. 214 update could be used to estimate the proportion of those affected injuries that would trickle-down to each lower level of AIS severity (Equation (55)). After application of effectiveness, a pseudo-case with the same injuries as the initial case represents the proportion of the time that the 214 update is expected to have no effect. Additional pseudo-cases with head injuries reduced to each lower AIS level were weighted by the product of effectiveness (adjusted for penetration) and the trickle-down proportion for that AIS severity level.

$$Trickle-down\ Proportion_x = \left(\frac{Risk_{AIS\ x}(w/\ airbag)}{\sum_{i=AIS_{0-1}}^{AIS_{n-1}} Risk_{AIS\ i}\ (w/\ airbag)} \right) \quad (55)$$

where:

x is an AIS severity level below the initial AIS_n in the original retrospective case

Trickle-down proportion$_x$ is the proportion of prevented AIS_n injuries that are expected to trickle-down to severity level x.

E.3.2.2 Effectiveness and Injury Trickle-Down for Pole CHEST Injuries

Estimated AIS 4+ effectiveness was applied to AIS 4 and 5 and fatal cases (as discussed on page V-57 of the FMVSS No. 214 FRIA). For occupants represented by testing with the 5th dummy, results were equivocal (chest deflection did not show a clear improvement with thorax bags, but lower spine acceleration did) so, as in the FRIA, this analysis assumed thorax bags were not effective at preventing chest injuries for 5th size occupants in vehicle-to-pole/tree crashes in front near-side seating positions.

Table 108. Effectiveness and trickle-down proportions for pole chest injuries for 50th subpopulation (based on data from FRIA V-49)

	E	Trickle-down proportion to lower AIS Injuries		
		AIS 3	**AIS 2**	**AIS 0-1**
AIS 4+	10.52%	31.90%	34.05%	32.82%
AIS 3	4.92%		50.00%	50.00%
AIS 0-2	0%			

E.3.2.3 Effectiveness and Injury Trickle-Down for Pole ABDOMEN Injuries

For the 5th dummy, no abdomen criterion was included in the updated rule so no effectiveness was estimated.

Table 109. Effectiveness and trickle-down proportions for pole abdomen injuries for 50th subpopulation (based on data from FRIA V-55)

	E	Trickle-down proportion to lower AIS Injuries		
		AIS 3	**AIS 2**	**AIS 0-1**
AIS 4+	99.27%	3.48%	48.26%	48.26%
AIS 3	94.76%		50.00%	50.00%
AIS 0-2	0%			

E.3.2.4 Effectiveness and Injury Trickle-Down for Pole PELVIS Injuries

The target population for pole pelvis injuries for both 50th and 5th occupant subpopulations was zero, so no benefits were calculated in the FRIA, but calculations will apply to any applicable target population in the projection model.

Table 110. Effectiveness and trickle-down proportions for pole pelvis injuries for 50th occupant subpopulation (based on data from FRIA V-58a)

	E	Trickle-down proportion to lower AIS Injuries	
		AIS 2	AIS 0-1
AIS 3+	19.36%	6.12%	93.88%
AIS 2	26.22%		100.00%
AIS 0-1	0%		

Table 111. Effectiveness and trickle-down proportions for pole pelvis injuries for 50th occupant subpopulation (based on data from FRIA V-59)

	E	Trickle-down proportion to lower AIS Injuries	
		AIS 2	AIS 0-1
AIS 2+	20.14%		100.00%
AIS 0-1	0%		

E.3.2.5 Effectiveness and Injury Trickle-Down for Vehicle-to-Vehicle CHEST Injuries

Table 112. Effectiveness and trickle-down proportions for vehicle-to-vehicle chest injuries for 50th occupant subpopulation (based on data from FRIA V-81)

	E	Trickle-down proportion to lower AIS Injuries		
		AIS 3	AIS 2	AIS 0-1
AIS 4+	30.99%	23.68%	38.16%	34.44%
AIS 3	19.05%		50.00%	50.00%
AIS 0-2	0%			

Table 113. Effectiveness and trickle-down proportions for vehicle-to-vehicle chest injuries for 5th occupant subpopulation (based on data from FRIA V-85)

	E	Trickle-down proportion to lower AIS Injuries		
		AIS 3	AIS 2	AIS 0-1
AIS 4+	26.50%	3.31%	48.34%	47.77%
AIS 3	25.47%		50.00%	50.00%
AIS 0-2	0%			

It remains an open question whether the effectiveness estimates for the 5th occupant subpopulation apply to front-seat or rear-seat occupants. While it appeared from the FRIA chapter preliminaries that the target population was limited to the front seat, the tested values appear to have been estimated using a rear-seat dummy.

E.3.2.6 Effectiveness and Injury Trickle-Down for Vehicle-to-Vehicle ABDOMEN Injuries

Benefits were not calculated for AIS 4+ injuries in the FRIA because the target population was zero, but effectiveness estimates were made and can be applied to any applicable target population in the projection model.

For the 5th dummy tests, no abdomen injury criterion is in the updated rule, so no effectiveness was estimated.

Table 114. Effectiveness and trickle-down proportions for vehicle-to-vehicle abdomen injuries for 50th occupant subpopulation (based on table in FRIA footnote 87, on page V-80)

	E	Trickle-down proportion to lower AIS Injuries		
		AIS 3	**AIS 2**	**AIS 0-1**
AIS 4+	80.86%	0.99%	49.51%	49.51%
AIS 3	80.03%		50.00%	50.00%
AIS 0-2	0%			

E.3.2.7 Effectiveness and Injury Trickle-Down for Vehicle-to-Vehicle PELVIS Injuries

Note that although data was available to calculate AIS 2 injuries, benefits were only calculated in the FRIA for AIS 3+. The projection model used the source data in the FRIA to calculate effectiveness for AIS 2 injuries as well as AIS 3+ injuries.

Table 115. Effectiveness and trickle-down proportions for vehicle-to-vehicle pelvis injuries for 50th occupant subpopulation (based on FRIA page V-81)

	E	Trickle-down proportion to lower AIS Injuries	
		AIS 2	**AIS 0-1**
AIS 3+	41.31%	2.96%	97.04%
AIS 2	54.15%		100.00%
AIS 0-1	0%		

For the 5th occupant subpopulation, only effectiveness at the AIS 3+ level was provided in the FRIA, without supporting test data that could be used to develop AIS 2 effectiveness. Therefore, the same effectiveness was assumed for AIS 2 and AIS 3+ injuries. Trickle-down for AIS 2 and AIS 3+ injuries was estimated to be evenly distributed between AIS 2 and AIS 0-1.

Table 116. Effectiveness and trickle-down proportions for vehicle-to-vehicle pelvis injuries for 5th occupant subpopulation (based on FRIA page V-81)

	E	Trickle-down proportion to lower AIS Injuries	
		AIS 2	AIS 0-1
AIS 2+	95.70%		100.00%
AIS 0-1	0%		

It remains an open question whether the effectiveness estimates for the 5th occupant subpopulation apply to front seat or rear-seat occupants. While it appeared from the FRIA chapter preliminaries that the target population was limited to the front seat, the tested values appear to have been estimated using a rear seat dummy.

E.3.2.8 Effectiveness Estimation for Far-Side Occupants

Although NHTSA initially estimated that torso and head air bags would reduce far-side fatality by an estimated 24 percent (Kahane, 2007), an updated analysis showed that far-side fatality reduction with head and torso bags was likely less than the original estimate (Kahane, 2014a). In fact, different methods of analyzing the data did not consistently confirm definite improvement for far-side occupants with side air bags with the highest effectiveness identified for vehicles and seating positions where it would be expected to be lowest. Additionally, research engineers and a peer-reviewer who worked on these evaluations of the update did not expect it to be effective in far side impacts. Therefore, this analysis does not predict any injury reduction for far-side occupants as a result of FMVSS No. 214.

E.3.2.9 Effectiveness Estimation for Rear-Seat Occupants

Several open questions remain regarding the application of effectiveness for rear-seat occupants. Until resolved, rear-seat effectiveness for FMVSS No. 214 updates in the model has been set to zero.

Globally: It needs to be confirmed that the same impact target direction can be used in the rear seat as in the front seat (PDOF 2-3 and 9-10).

Head injuries: The FRIA indicated that it was assumed that curtain air bags were big enough to protect against occupants represented by a 5th percentile female test dummy in impacts with PDOF of 2-3 and 9-10 o'clock. Benefits for rear-seat occupants in pole crashes appeared to have been based on effectiveness in head-to-interior test results from FRIA Table V-30. Remaining questions include the following:

- Is it reasonable to assume that effectiveness for rear-seat occupants in vehicle-to-vehicle crashes can be based on effectiveness in head-to-interior results from FRIA Table V-30?
- Does rear seat target population include the 50th occupant subpopulation or only 5th?

Chest injuries: Since all dummies in rear-seating positions reported in FRIA testing met requirements, no benefits were estimated for the chest and it was expected that manufacturers would not include a thorax bag in the rear seat. Therefore, it was estimated that effectiveness for rear seat chest injuries in the projection model would be zero.

Abdomen: There were no injuries in the FRIA target population so no benefit estimate was made. It is proposed that if there are relevant injuries in the projection model target population, the following data in the FRIA could be used to estimate effectiveness for rear-seat occupants: Table V-90 & footnote #87 (AIS 3 and AIS 4+ effectiveness for 50th male dummy in vehicle-to-vehicle/others side crashes). No estimate could be made for 5th-applicable occupant subpopulation because no risk curves were available.

Pelvis: From page V-95 in the FRIA, it appeared that pelvis effectiveness estimates were applied to both the 50th and 5th-applicable occupant subpopulations. Note that benefits seem to have been reduced given an assumed 75 percent passing rate for existing vehicles. It also appears that effectiveness for the 5th occupant subpopulation of 92.28 percent was multiplied by 25 percent and applied to the combined 5th and 50th occupant subpopulations. For application to the projection model, it needs to be confirmed whether the effectiveness associated with the 5th occupant subpopulation should be applied to whole population, and whether an adjustment needs to be made to the effectiveness to reflect the 75 percent passing rate.

E.3.3 Relationship Between FMVSS No. 214 and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure was applied to every individual case in its target population based on case variables. The target population definition for FMVSS No. 214, as well as its effectiveness in preventing head injuries, relied on the estimated delta V of the side-struck vehicle. That delta V was estimated from the original delta V documented in the CDS case but adjusted for the expected delta V reduction associated with the application of TPMS (R_{TPMS}) to the striking vehicle. Therefore, FMVSS No. 214 must be applied after TPMS in the model.

The FMVSS No. 214 target population is dependent on the ejection status of occupants. Since the SSF countermeasure can produce pseudo-cases with ejection introduced to cases whose parent cases did not involve ejection, FMVSS No. 214 must be applied *after* SSF in the model.

E.3.4 Side Impact Update Penetration

In most other countermeasures in the model, data on penetration was needed to estimate the likelihood that a case occupant had the countermeasure available in the original crash (α'), as well as the likelihood that the countermeasure would be available in the projected target year crash (β_{TY}). For application of the side impact update, however, the presence of side impact air bags compliant with the update was estimated in each retrospective case using the data in the supplemental air bag data in the original retrospective NASS CDS case.

<u>For cases where the original retrospective case already had head and thorax air bags</u>, it was assumed that a future projected version of the case would also have the countermeasure and no change in outcome would be expected. Effectiveness was set to zero for these cases.

<u>For cases where the original retrospective cases did not have head and thorax air bags</u>, the relevant effectiveness from Appendix E.3.2 was adjusted using Equation (7) in this report,

setting α'_{MY} to zero since it was known that the occupant did not have the countermeasure available. The penetration for the target projection year (β_{TY}) was calculated as for all countermeasures using Equation (18), with α_{MY} set to 0 since it was known that the original case did not have the countermeasure available.

For cases where air bag availability was unknown in the original retrospective case, penetration for the target projection year (β_{TY}) was calculated as for all countermeasures using Equation (18). However, the β^*_{NOCM} component in Equation (18) was calculated differently for this countermeasure than as defined in Equation (17). Instead it was calculated as shown in the following equation (Equation (56)), as a function of average values of penetration in the stepping-stone dataset, rather than as a function of overall penetration estimated from fleet penetration.

$$\beta^*_{NoCM} = \frac{Overall\ \beta_{TY} - Average\ \alpha_{Retro}}{1 - Average\ \alpha_{Retro}} \tag{56}$$

For countermeasures like those used to address FMVSS No. 214 crash conditions, where the presence of the countermeasure is known in some cases, *Average* α_{retro} in this expression is estimated with the higher of:

- The percentage of countermeasure-compliant cases in the MY2005+ stepping-stone dataset, i.e., cases with head and thorax air bags, or
- Overall α – (Percentage of stepping-stone dataset with documented CM present), where overall α is calculated as in other countermeasures, summed by model year, as a product of the fleet penetration by model year and the percentage of the MY2005+ fleet expected to be in the given model year.

Note that the estimation of penetration parameters for cases where air bag availability was unknown in the retrospective case relied on α, rather than on α' as was used for other countermeasures.

Estimation of the average fleet-wide penetration of compliance with the update by model year (α_{MY}) was still needed for calculation of estimated overall penetration in the projection target years (Overall β_{TY}). The penetration of side impact air bags (combination bags or window curtains) by model year, shown in Table 117, was based on NHTSA's estimates of installation of FMVSS No. 214-compliant systems in passenger cars and LTVs (Simons, 2017; Simons, personal communication[36]). For each model year, a combined α value was calculated based on the proportion of PCs and LTVs among vehicle sales.

[36] James F. Simons, Bowhead Logistics Solutions, LLC, Alexandria, VA, personal communication, February 2018.

Table 117. Penetration of FMVSS No. 214 air bags by model year (α_{MY})

Model Year	Sales Proportion (%)		α_{PC} (%)	α_{LTV} (%)	α_{MY} (%)
	PC	LTV			
≤ 2004	48.1	51.9	26.6	16.5	21.3
2005	50.5	49.5	31.0	20.0	25.6
2006	52.9	47.1	44.1	27.9	36.5
2007	52.9	47.1	59.9	33.1	47.3
2008	52.7	47.3	78.9	46.5	63.6
2009	60.5	39.5	93.1	60.7	80.3
2010	54.5	45.5	96.3	79.4	88.6
2011	47.8	52.2	99.3	86.7	92.7
2012	55.0	45.0	100.0	90.6	95.8
2013	54.1	45.9	100.0	92.2	96.4
2014	49.2	50.8	100.0	94.9	97.4
2015	46.8	53.2	98.6	94.9	96.6
2016	42.0	58.0	100.0	96.2	97.8
2017+	Estimated to be 100.0				

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of FMVSS No. 214 air bags among vehicles in projection crash years was estimated in Table 118.

Table 118. Penetration of FMVSS No. 214 air bags in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)
2014	72.5
2020	88.9
2025	96.3
2030	99.1

E.4 FMVSS No. 216 Roof Strength Upgrade

According to the Final Regulatory Impact Analysis, the FMVSS No. 216 Upgrade Roof Crush Resistance Final Rule modified the test procedures such that vehicles <=6,000 lbs GVWR would meet roof strength test requirements with application of force up to 3 times the vehicle's unloaded weight prior to head contact with the representation of a 50th percentile male or 5 inches of platen travel, whichever comes first (NHTSA, 2009). Previously, the requirement involved application of force up to 1.5 times the vehicle's weight. The test is conducted on the passenger and driver sides. Vehicles with 6000 lbs<GVWR<=10,000lb (previously not subject to testing) must meet the requirements at 1.5 times the vehicle's unloaded weight.

The primary source for effectiveness estimates for this countermeasure was the Final Regulatory Impact Analysis, FMVSS No. 216 Upgrade Roof Crush Resistance (NHTSA, 2009). Target population studies were used to define the parameters of the included target population (Austin et al., 2003; Strashny, 2007).

E.4.1 Roof Strength Target Population

The target population included cases defined by the following NASS CDS variables:

- Non-convertible light duty vehicles
  - NASS CDS body type in (2:49)
- Roof-involved rollover, excluding no roll, ¼ turn, and unknown number of turns
  - ROLLOVER in (2:98)
- Belted, outboard seated occupants (including rear seat)
  - SEATPOS in (11, 13, 21, 23, 31, 33)
  - CHTYPE in (1:8) or MANUSE in (2:8, 12:18)
- Occupants with vertical intrusion of a roof component over their seating position, where a roof component includes the roof itself, roof side rails, front (windshield) and back (backlight) headers, A and B pillars, the sun visor, as well as any roof console, sunroof components, or roll-bar.
  - INCOMP1-10 in (6, 7, 13, 14, 16, 19)
  - CDRIR1-10=vertical
  - INLOC1-10 in (11, 13, 21, 23, 31, 33) (outboard seat positions)

Cases with the following characteristics were deleted from the target population, as they were in NHTSA's benefit analysis:

- Vehicles that experienced a collision with a fixed object (other than a bush, embankment, ditch, culvert, or the ground) to the top of the vehicle. These were identified in the code using the following NASS CDS variables.
  - GADEV1=T and OBJCONT in (41:42, 45, 47:52, 54:59, 62, 64)

Injuries included in the target population were limited to head, neck, and face injury from a vertically intruding roof component into the occupant's seating position. These injuries were identified using NASS CDS injury codes:

- REGION90 in (1, 2, 3) or REGION90=6 and STRUSPEC=02
- INJSOU in (3, 53, 54, 103, 104, 201, 202, 203, 204, 205, 206, 207, 208, 251)

As in previous analyses,[37] it was not specifically confirmed that the injury source matched the intruding component. It was sufficient to identify vertical intrusion over the occupant's seating position and one of the above injury sources.

Children were excluded from previous analyses by Austin and Strashny primarily based on the recommendation that children 12 and under be seated in the rear seat. Secondarily, pre-crash headroom for children had not been estimated (Austin et al., 2003; Strashny, 2007; Austin, personal communication[35]). It is unclear if children were excluded from FRIA calculations. Children were not excluded from the target population in the projection model.

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[37] Rory Austin, Division Chief, Office of Behavioral Research, National Center for Statistics and Analysis, National Highway Traffic Safety Administration, personal communication, January 13, 2017.

In the FRIA, fully ejected occupants were excluded from the target population since 80 percent of fully ejected occupants sustained their most serious injury (MAIS) outside the vehicle. However, since the projection model targets changes to specific injuries sustained inside the vehicle, ejection cases were not excluded. Only injuries sustained outside of the vehicle were excluded.

As discussed in Appendix E.4.3, the application of SSF to the model prior to the application of the roof strength countermeasure created pseudo-cases in which rollovers were added to or removed from existing cases in the model. The resulting SSF pseudo-cases were treated as follows in the roof strength target population:

- SSF pseudo-cases in which a rollover and a roof-contact head injury were added were coded to fall in the FMVSS No. 216 target population. An analysis of the retrospective baseline dataset determined that the average roof intrusion experienced by occupants in side impact crashes with a subsequent rollover was approximately 14 cm. Based on this data, it was estimated that occupants for which a pseudo-roof-contact head injury was added experienced vertical intrusion of a roof component equal to 14 cm.
- Cases in which a rollover was added, but no roof-contact injury was added, were coded not to fall in the FMVSS No. 216 target population.

E.4.2 Roof Strength Effectiveness

Effectiveness was calculated for each injury in the target population as a function of the AIS severity of the injury and the magnitude of the intrusion at the location of the case occupant. Intrusion magnitudes for NASS CDS cases were obtained directly from NCSA.[38]

For each occupant case, the expected reduction in intrusion at that seat position with the upgrade was estimated using the equations on page 43 of the FRIA (Equations (57) and (58)). These equations were based on a strength weight ratio (SWR) of 3 times vehicle weight for GVWR<=6,000 lb and 1.5 times vehicle weight for GVWR>6,000 lb.

For GVWR<=6,000 lb: $$y = -0.000004x^3 + 0.0016x^2 + 0.1148x + 0.7692 \quad (57)$$

For GVWR>6,000 lb: $$y = -0.000005x^3 + 0.0020x^2 - 0.0435x + 1.813 \quad (58)$$

where:
y=intrusion prevented (in mm),
x=baseline intrusion in original case (in mm), and
x-y=expected intrusion after reduction (in mm).

For each injury in the target population, the probability of an injury of at least the severity of that injury was estimated as a function of intrusion (i) according to the injury risk equations derived from those used in the benefit calculations on page 45 of the FRIA (Equations (59) to (63)). Injury risk was estimated for intrusion *i,* calculated at the baseline intrusion (x) as well as at the expected reduced intrusion (x-y).

[38] Gregory A. Radja, National Center for Statistics and Analysis, National Highway Traffic Safety Administration, personal communication, February 21, 2017.

$$p(AIS\ 2+) = 1 - \phi(2.21 - 0.075 \times i) \tag{59}$$

$$p(AIS\ 3+) = 1 - \phi(2.81 - 0.075 \times i) \tag{60}$$

$$p(AIS\ 4+) = 1 - \phi(3.06 - 0.075 \times i) \tag{61}$$

$$p(AIS\ 5+) = 1 - \phi(3.18 - 0.075 \times i) \tag{62}$$

$$p(AIS\ 6) = 1 - \phi(3.24 - 0.075 \times i) \tag{63}$$

where:
Φ() is the standard normal cumulative distribution, and
I=intrusion in inches.

Effectiveness for a given injury of a specified severity *n* can then be calculated using Equation (64) as a function of the probability of an injury of at least that severity at baseline intrusion (p(i=x)) and at reduced intrusion (p(i=x-y)).

$$E = 1 - \frac{p_{i=x-y}(AIS\ n+)}{p_{i=x}(AIS\ n+)} \tag{64}$$

In practical terms, weights for the resulting pseudo-cases that accounted for the percentage of injuries at the given severity level that remained unchanged, as well as the percentage of injuries that trickled down to each lower-severity level, are shown in Table 119.

Table 119. Multipliers for effectiveness in roof crush trickle-down analysis where p(AIS n) is estimated as a function of the reduced intrusion

		Injury in Pseudo-Case					
		No Injury	**AIS 2**	**AIS 3**	**AIS 4**	**AIS 5**	**AIS 6**
Original Injury	AIS 2	E	1-E				
	AIS 3	$E * \frac{1-p(AIS\ 2)}{1-p(AIS\ 3+)}$	$E * \frac{p(AIS\ 2)}{1-p(AIS\ 3+)}$	1-E			
	AIS 4	$E * \frac{1-p(AIS\ 2+)}{1-p(AIS\ 4+)}$	$E * \frac{p(AIS\ 2)}{1-p(AIS\ 4+)}$	$E * \frac{p(AIS\ 3)}{1-p(AIS\ 4+)}$	1-E		
	AIS 5	$E * \frac{1-p(AIS\ 2+)}{1-p(AIS\ 5+)}$	$E * \frac{p(AIS\ 2)}{1-p(AIS\ 5+)}$	$E * \frac{p(AIS\ 3)}{1-p(AIS\ 5+)}$	$E * \frac{p(AIS\ 4)}{1-p(AIS\ 5+)}$	1-E	
	AIS 6	$E * \frac{1-p(AIS\ 2+)}{1-p(AIS\ 6)}$	$E * \frac{p(AIS\ 2)}{1-p(AIS\ 6)}$	$E * \frac{p(AIS\ 3)}{1-p(AIS\ 6)}$	$E * \frac{p(AIS\ 4)}{1-p(AIS\ 6)}$	$E * \frac{p(AIS\ 5)}{1-p(AIS\ 6)}$	1-E

For example, for an AIS 3 injury in the target population with 8” of intrusion in the original case for a vehicle <=GVWR of 6,000 lb.:

Original intrusion: $\boldsymbol{x = 203\ mm = 8''}$
Intrusion prevented: $\boldsymbol{y = 56.6\ mm = 2.23''}$
Reduced intrusion: $\boldsymbol{x - y = 5.77''}$
p(AIS 3+) @ 8”: $1 - \phi(2.81 - 0.075 \times i) = 0.01355$
p(AIS 3+) @ 5.77”: $1 - \phi(2.81 - 0.075 \times i) = 0.00872$
p(AIS 2+) @ 5.77”: $1 - \phi(2.21 - 0.075 \times i) = 0.03776$
p(AIS 2) @ 5.77”: $\text{p(AIS 2 +)} - \text{p(AIS 3+)} = 0.02904$
$E = 1 - \frac{p_{i=x-y}(AIS\ n+)}{p_{i=x}(AIS\ n+)} = 1 - \frac{0.00872}{0.01355} = 0.3565$
Weights for resulting pseudo-cases:
with AIS 3 injury (unchanged): weight = w*(1-E) = w*0.6435
with AIS 2 injury (reduced): weight = w*E*(p(AIS 2))/(1-p(AIS 3+)) = w*0.0105
with no injury or AIS 1 injury: weight = w*E*(1-p(AIS 2+))/(1-p(AIS 3+)) = w*0.3461

E.4.3 Relationship Between Roof Strength and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure is applied to every individual case in its target population based on case variables. As discussed in Appendix C.3.3, the application of SSF creates pseudo-cases in which rollovers are added to or removed from existing cases in the model. These changes have the potential to move a case into, or out of, the target population for the roof strength countermeasure. Therefore, the SSF countermeasure must be applied before the roof strength countermeasure in the model. The target population definition in the roof strength countermeasure specifically addresses criteria for inclusion of the SSF rollover pseudo-cases in the roof strength countermeasure.

E.4.4 Roof Strength Penetration

The penetration of roof strength upgrades by model year for 2005 to 2016, shown in Table 120, was estimated based on NHTSA’s estimates of installation of FMVSS No. 216-compliant systems in passenger cars and LTVs (Simons, 2017; Simons, personal communication[39]). For 2017 and later, α_{MY} was estimated to be 100 percent for PCs. For LTVs, α_{MY} was linearly extrapolated from 2012 to 2016 data.

[39] James F. Simons, Bowhead Logistics Solutions, LLC, Alexandria, VA, personal communication, February 2018.

Table 120. Penetration of roof strength upgrade (α_{MY})

Model Year	α_{MY} (%)	
	PCs	**LTVs**
≤ 2011	18.0	29.0
2012	25.5	29.0
2013	72.1	37.1
2014	89.2	49.1
2015	95.8	64.5
2016	98.6	76.7
2017	100.0	87.9
2018+	100.0	100.0

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of the roof strength upgrade among vehicles in projection crash years was estimated in Table 121.

Table 121. Penetration of roof strength upgrade in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)	
	PCs	**LTVs**
2014	30.0	31.3
2020	64.6	57.3
2025	86.1	79.8
2030	96.3	93.6

E.5 NCAP 2011 Enhancement (Frontal and Side Impact Tests)

NCAP frontal and side impact test procedures were enhanced for 2011 model year vehicles, starting in calendar year 2010. In their 2015 ESV paper, Park et al. tracked the progression of measured injury risk estimates in NCAP testing by body region for each of the components of the updated NCAP procedures. For this model countermeasure, the change in the ESV-reported injury risk values in the frontal rigid barrier test, the MDB test, and the pole test were each used to estimate the "effectiveness" of the NCAP 2011 update. In reality, this effectiveness estimate did not really evaluate the isolated effect of the NCAP update, but it captured all improvements made during that period for any reason. Since all these changes, regardless of motivation, will have an effect on future safety, no effort was made to exclude improvements that were not motivated by the NCAP update. However, for simplicity and consistency with terminology for other countermeasures, the sum effect of all observed changes was identified as the "effectiveness" of NCAP 2011.

The Park et al. study compared NCAP test results for MY 2011 and MY 2014/2015 vehicles. However, it should be noted that updates to frontal and side impact regulations were also being phased in during that period. For the frontal test, the phase-in for the increase in test speed for the 5th female in the FMVSS No. 208 rigid barrier was not fully phased-in until 2012. For the MDB and pole tests, the phase-in for updates to FMVSS No. 214 was not complete until 2013. This overlap in the NCAP comparison period and the phase-in periods for the FMVSS updates meant there was a potential for double-counting the improvements made to meet the FMVSS requirements and the improvements captured by enhanced NCAP testing. However, review of

NCAP 2011 test results showed that MY 2011 vehicles met the FMVSS No. 208 and 214 requirements in the large majority of 2011 enhanced NCAP tests. This result supported that nearly all improvement in enhanced NCAP testing between 2011 and 2015 was beyond that estimated in the effectiveness estimates for FMVSS No. 208 and 214 updates in the projection analysis. Therefore, for the purpose of the projection model, the effectiveness of FMVSS updates and the improvement of enhanced NCAP results were applied independently in the projection model, under the assumption that double-counting of improvement from these countermeasures would be negligible.

E.5.1 NCAP 2011 Target Population

NCAP testing applies to vehicles up to 10,000 pounds GVWR, so all CDS-eligible vehicles were included in the overall target population. The target populations for each individual NCAP test were defined as follows.

E.5.1.1 Frontal Rigid Barrier Test

Impact type:

- Target population limited to perpendicular frontal impacts based on the strategy used to estimate benefits for rigid barrier testing in FMVSS No. 208 (NHTSA, 2000), and
- Defined using NASS CDS variables: DOF 11-1 (and 31, 51, etc.) & GAD1=F & SHL1=D, Z, Y.

Right front passenger:[40]

- Defined using NASS CDS variable SEATPOS=13 only.

Occupants relevant to 5th dummy:

- Limited to adults age 13+, and
- Since improvements made to protect the 5th female in the right front seat would likely also affect taller occupants and there were no test results available for a 50th ATD, the target population for occupants relevant to the 5th dummy included occupants of all heights in the right front seat position.

Belted:

- Belted occupants only, and
- Although it was possible that unbelted occupants would also benefit from improvements, no estimates of effectiveness were available for unbelted occupants.

[40] Park's unpaired analysis of MY 2011 versus MY 2014-2015 vehicles showed that the driver, on average, had no statistically significant improvement in combined injury probability. While some injury regions appeared to decrease in risk, others had small increases in injury risk. For the purpose of this interim analysis, no change to frontal protection in the driver seat position was estimated as a result of the NCAP 2011 frontal enhancement.

Delta V:

- All crashes with delta V of 35 mph or less were included in the target population. While the estimated injury reductions may not apply at much lower severity and injury reductions would also occur at higher severities, this target population limitation matched the strategy used to estimate benefits for rigid barrier testing in FMVSS No. 208 (NHTSA, 2000).
- The delta V estimate made in each original source case using NASS CDS reconstruction variables (DVTOTAL, DVLONG, DVEST, and BEV) was adjusted based on the reduction expected with the application of TPMS (model variable: R_{TPMS}). This adjustment was coded as follows:
  - (DVTOTAL – R_{TPMS}) or (DVLONG – R_{TPMS})<=56.3 km/h, or
  - BEV – R_{TPMS}<=56.3 km/h, or
  - DVEST in (1-4), as well as those coded as unknown, since the large majority of crashes have a delta V less than 56.3 km/h.

E.5.1.2 MDB Test

Impact type: Impact type limitations were based on those used in the benefits estimation for FMVSS No. 214, since those tests are run at impact angles that are similar to the NCAP MDB test. The increased impact speed in NCAP testing is not expected to change the delta V target population used for the FMVSS No. 214 analysis, since that range was based on the estimated typical side impact deployment thresholds and the delta V at which side air bags would be expected to bottom-out, rather than on test speed. Inclusion criteria for the target population were defined as follows:

- Lateral component of delta V 12-25 mph, based on estimates made in the original CDS case, adjusted for expected reduction after application of TPMS,
- Cases with rollover as first event excluded,
- Side impacts identified using NASS CDS variables: GAD1=R, L, and SHL1=P, Y, Z, and DOF1=2-3, 9-10, and
- Impact partner identified as vehicle-to-vehicle or other roadside object using the NASS CDS variable OBJCONT1=1-11, 43-44, 46-49, 54-59, 64, 68-71, 77-78.

Occupants: Occupants included in the target population for the NCAP MDB test, based on the limitations included in the FMVSS No. 214 MDB target population, were defined as follows:

- Nearside outboard occupants only, in the front seat and first rear seat (note that NCAP typically reports to consumers that the ratings for the driver and left rear passenger apply to the front and rear passengers on the right side of the vehicle also),
- Not limited by belt use,

- Complete ejections excluded using the NASS CDS variable OA/Ejection^=1,[41]
- Only occupants age 13+, and
- Although the NCAP test uses a 50th percentile dummy in the driver's seat and a 5th percentile dummy in the rear seat, adult occupants of all heights were included in the target population in both seat positions. Target populations in the modeled countermeasure were only separated for occupants of heights corresponding to different dummies if effectiveness results were available for both dummies.

E.5.1.3 Pole Test

Impact type: Target population limitations on impact type were based on those used in benefits estimation for the pole test in FMVSS No. 214, and were defined in the model as follows:

- Lateral component of delta V 12-25 mph, based on estimates made in each original NASS CDS source case, adjusted for expected speed reduction with application of TPMS,
- Rollover as first event excluded,
- Side impacts, defined using NASS CDS variables: GAD1=R, L, and SHL1=P, Y, Z, and DOF1=2-3, 9-10, and
- Vehicle-to-pole, or vehicle-to-tree impacts identified using the NASS CDS variable OBJCONT1=41, 42, 45, 50, 51, 52, 53.

Occupants: Occupants included in the target population for the NCAP pole test, based on the limitations included in the FMVSS No. 214 MDB target population, were defined as follows:

- Drivers and right front passengers, identified using the NASS CDS variable SEATPOS in (11, 13) (while the NCAP tests are not performed on the passenger side, NCAP typically reports to consumers that the ratings for the driver apply to the front passenger on the right side of the vehicle also),
- Nearside outboard occupants only,
- Not limited by belt use,
- Only occupants age 13+,
- In the absence of test results for a 50th ATD, included occupants of all heights in the target population for the 5th female dummy, and
- Complete ejections excluded using the NASS CDS variable OA/Ejection^=1.

[41] As discussed in Section A.3.2, the application of SSF creates pseudo-cases in which rollovers and ejections are added to or removed from existing cases in the model. The pseudo-cases in which an ejection is added by the application of SSF will be excluded from the MDB population. The pseudo-cases in which an ejection is deleted by the application of SSF will not be excluded from the MDB population based on ejection status (but they could be excluded based on another target population limitation).

E.5.2 NCAP 2011 Effectiveness

The percentage improvement in average injury risk per body region from 2011 to 2014/2015 was used as an estimate of effectiveness for each test mode.

The effectiveness estimates are tabulated by body region for the 2011 updated NCAP frontal rigid barrier test in Table 122. Effectiveness estimates by test mode and seat position for the enhanced NCAP side MDB and pole tests are found in Table 123 to Table 125. "Combined" estimates of injury probability in each table are drawn from Park et al.'s calculated values of the risk of injury in any body region.

Table 122. Average probability of AIS 3+ injury by body region for front passengers in frontal NCAP test (Park et al., 2015) (along with calculated percentage change from 2011 to 2014/2015)

	2011	**2014/2015**	**Change**	**Percentage Improvement Effectiveness**
Head	0.015	0.009	0.60%	40.0%
Neck	0.104	0.082	2.20%	21.2%
Chest	0.018	0.015	0.30%	16.7%
Leg	0.022	0.015	0.70%	31.8%
Combined	0.151	0.117	3.40%	22.5%

Table 123. Average probability of AIS 3+ injury by body region for drivers in side MDB NCAP test (Park et al., 2015) (along with calculated percentage change from 2011 to 2014/2015)

	2011	**2014/2015**	**Change**	**Percentage**
Head	0.001	0.001	0.00%	0.0%
Chest	0.07	0.04	3.00%	42.9%
Abdomen	0.027	0.014	1.30%	48.1%
Pelvis	0.006	0.003	0.30%	50.0%
Combined	0.099	0.0057	9.33%	94.2%

Table 124. Average probability of AIS 3+ injury by body region for rear passengers in side MDB NCAP test (Park et al., 2015) (along with calculated percentage change from 2011 to 2014/2015)

	2011	2014/2015	Change	Percentage
Head	0.009	0.007	0.20%	22.2%
Pelvis	0.079	0.04	3.90%	49.4%
Combined	0.087	0.047	4.00%	46.0%

Table 125. Average probability of AIS 3+ injury by body region for driver in side pole NCAP test (Park et al., 2015) (along with calculated percentage change from 2011 to 2014/2015)

	2011	2014/2015	Change	Percentage
Head	0.024	0.014	1.00%	41.7%
Pelvis	0.117	0.05	6.70%	57.3%
Combined	0.137	0.063	7.40%	54.0%

The test mode effectiveness estimates reflect a percentage improvement in the risk of injury to a given body region. For example, a test procedure demonstrating a 20 percent improvement in AIS 3+ head injury risk is expected to reduce head injuries such that there are expected to be 20 percent fewer occupants with AIS 3+ head injury in the target population.

There is no information available to estimate the trickle-down effects of preventing AIS 3+ injuries. In the case of AIS 5 head injuries, for example, it is unknown how many are likely to be reduced to AIS 4 or AIS 3 injuries. Therefore, it was estimated that for a given body region effectiveness reflects the percentage of all occupants with AIS 3+ injuries in that body region whose injuries would be reduced to AIS 2 severity. This approximation is conservative in that it neglects the possibility that some injuries may be reduced to an AIS 1 level or prevented altogether. It also neglects trickle-down of AIS 5 or 4 injuries to the AIS 4 or 3 severity level.

Body regions for applying each effectiveness estimate were estimated broadly (Table 126), potentially covering more injuries than specifically covered by injury risk curves. Future consideration should be given to further refinement of these targeted injury regions.

Table 126. Definition of body regions for effectiveness estimates

	AIS-Coded Definition of Body Region
Head	REGION90=1
Neck	REGION90=3 or REGION90=6 and STRUSPEC=02
Chest	REGION90=4
Abdomen	REGION90=5
Leg	REGION90=8
Pelvis	AIS codes: 8506xx (hip), 851808 (femur head fracture), 851810 (intertrochanteric femur fracture), 851812 (femur neck fracture), 8526xx (pelvis fracture), 8528xx (sacroilium fracture), 8530xx (Symphysis pubis separation), 8304xx (sciatic nerve)

E.5.3 Relationship Between NCAP 2011 and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure is applied to every individual case in its target population based on case variables. The target population for the improvements associated with the NCAP enhancements made in 2011 relies on the estimated delta V of the struck vehicle. That delta V is estimated from the original delta V documented in the CDS case but adjusted for the expected delta V reduction associated with the application of TPMS (R_{TPMS}) to the striking vehicle as discussed in Appendix D.2. Therefore, NCAP 2011 must be applied *after* TPMS in the model.

The NCAP 2011 target population is dependent on the ejection status of occupants. Since the SSF countermeasure can produce pseudo-cases with ejection introduced to cases whose parent cases did not involve ejection, the NCAP 2011 countermeasure must be applied *after* SSF in the model.

E.5.4 NCAP 2011 Penetration

Although it is probable that some vehicle models continued to improve after 2014/2015, when only 42 percent of vehicles had a 5-star rating, the 2014/2015 level of performance was used as the “final” performance level for improvements in response to the 2011 NCAP enhancement.

Vehicle improvements in enhanced NCAP tests occurred incrementally between 2011 and 2015. Penetration for enhanced NCAP was defined somewhat differently than for other more discrete countermeasures since the introduction of enhanced NCAP improvements into the fleet was a function of both gradual decreases in injury risk reflected by improving test scores between 2011 and 2015, as well as the gradual increase in the percentage of the fleet covered or described by the NCAP test results. Therefore, the estimation of penetration involved:

(1) Estimating the maximum “penetration” of the decreased injury risk measured in enhanced NCAP between MY 2011 and 2015, i.e., the percentage of MY 2015 and later vehicles to which the average 2011 to 2015 performance improvement applies, and
(2) Estimating the rate of incremental magnitude of those decreases in injury risk for model years between 2011 and 2015.

Values for maximum penetration and incremental penetration were estimated as follows:

Maximum penetration: Published estimates on past coverage of the fleet by NCAP testing indicated that approximately 81 to 87 percent of the vehicle fleet was rated annually by NCAP (Hershman, 2001; NHTSA, 2011c; NHTSA, 2012). According to personal communication with the NCAP team,[42] the percentage of the new vehicle fleet tested using enhanced NCAP based on projected sales volume increased from 63 percent in 2011 to 88 percent in 2015. Therefore, for the purpose of the projection model, it was estimated that the average improvement in tested vehicles between 2011 and 2014/15 reflected average performance improvements in about 85 percent of vehicles in the fleet in MY 2015 and later. Therefore, the maximum “penetration” of

[42] Jennifer N. Dang, National Center for Statistics and Analysis, National Highway Traffic Safety Administration, personal communication, March 2017.

average NCAP-measured improvements (relative to 2011 performance) was estimated to be 85 percent.

Incremental penetration: For the purpose of the projection model, the combined improvement in test performance and increase in coverage of the fleet by NCAP testing between 2011 and 2015 was approximated by linear incremental "penetration" of enhanced NCAP-associated changes each year between 2011 and 2015. The resulting penetration estimates by model year are shown in Table 127.

Table 127. Estimated incremental penetration of improvements associated with NCAP 2011 update (α_{MY})

Model Year	α_{MY} (%)
2011 and earlier	0
2012	21
2013	43
2014	64
2015 and later	85

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of improvements in passenger safety associated with the NCAP 2011 update among vehicles in projection crash years was estimated in Table 128.

Table 128. Penetration of improvements in passenger safety associated with NCAP 2011 update in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)
2014	11.6
2020	48.0
2025	70.3
2030	81.1

E.6 FMVSS No. 226 Ejection Mitigation Update

New ejection performance requirements were introduced to reduce partial or complete ejection through side windows in vehicle crashes (NHTSA, 2011b). According to the Final Regulatory Impact Analysis for the new requirements in 2011, it was believed that curtain air bags would be used to pass the test. The primary source for target population and effectiveness estimates was the Final Regulatory Impact Analysis for FMVSS No. 226 Ejection Mitigation (NHTSA, 2011a), and Kahane's post-implementation evaluation of fatality effectiveness (Kahane, 2014a).

E.6.1 Ejection Mitigation Target Population

The basic target population includes seriously injured occupants in rollovers or side planar crashes (or both), ejected through side windows in rows 1 to 3 or the cargo area behind the second row.

Basic overall requirements for an occupant to be in target population, with corresponding NASS CDS variables:

- Occupant in rows 1-3: SEATPOS in (11:39),
- Non-convertible light-duty vehicle: BODYTYPE in (2:49),
- Completely or partially ejected occupant: EJECTION in (1:3), and
- Occupant ejected through 226-relevant window: EJCTMED in (3, 4, U) and EJCTAREA in (2:5, 8).

Exclusions:

- Occupant in FMVSS No. 214 target population as defined in Table 101,
- Occupant belted AND completely ejected (indicative of potentially intractable severity), identified using the following NASS CDS variables: CHTYPE in (1:8) or MANUSE in (2:8, 12:18) and EJECTION=1.

Effectiveness was assigned to different subpopulations within the target population based on the following variables, which will be defined in detail in this summary.

Fatal:

- Fatal
- Not fatal

Impact type:

- Rollover without side impact
- Side impact without rollover
- Side impact with subsequent rollover

Belt use:

- Belted/child restraint
- Unbelted/no child restraint

Delta V of side impact:

- 12-25 mph
- Not 12-25 mph

Age:

- 0-12
- 13+

Ejection degree:

- Partial ejection
- Complete ejection

E.6.1.1 Definition of Variables Needed to Identify Target Population and Subpopulations

Fatality: Fatality status in each case is determined based on the fatality status of the occupant in the original NASS CDS case as well as on the reduced probability of fatality given the countermeasures that have already been applied in earlier stages of the model. Cases with a probability of fatality (using the attributable fatality method) of less than 1 percent after application of other countermeasures are classified as not fatal (fatal226=0) for the application of this countermeasure. All other cases with non-negligible probability of fatality will be separated into two pseudo-cases (one fatal and one not fatal) prior to application of this countermeasure using the methods described in Section 2.7.1.1.

Vehicle type: A binary variable (VehTP) for cases where the vehicle type was in the target population for FMVSS No. 226 was assigned to each case based on the NASS CDS variable BODYTYPE (Table 129).

Table 129. FMVSS No. 226 vehicle type definition for target population

CDS Variable BODYTYPE	FMVSS No. 226 Relevant Vehicle Type Model variable: VehTP
2-49	1
All others	0

Relevant seat position: Occupants were coded as being in a seat position in the target population (i.e., occupant rows 1-3) with the model variable SeatTP as defined in the table below. Occupants in unknown seat positions were distributed between relevant and non-relevant seat positions proportional to the distribution of occupants in the dataset with known seat positions in the first three rows as calculated in Table 130. Instead of a binary variable, SeatTP is set to 0.9984 in cases where seat position is unknown, since 99.84 percent of weighted occupants with known seat position were seated in the first three rows among cases in the baseline retrospective dataset.

Table 130. FMVSS No. 226 seat position definition for target population

Variable	FMVSS No. 226 Relevant Seat Position Model variable: SeatTP
SEATPOS=11:39	1
SEATPOS=U.	0.9984
All others	0

Ejection status: For inclusion into the target population, all occupants coded with complete ejection, partial ejection, or ejected with degree unknown were set to EjectTP=1 (Table 131). For assignment to a subpopulation of partial or completely ejected occupants, those with unknown ejection degree were distributed between the partial and complete groups according to the frequency of complete versus partial ejections in cases where it was known. Among ejection cases in the current baseline retrospective dataset, 55.88 percent of weighted occupant cases where degree of ejection was known were complete ejection cases (Table 132).

Table 131. FMVSS No. 226 ejection definition for target population

Variable EJECTION	FMVSS No. 226 Relevant Ejection Model variable: EjectTP
1 – complete	1
2 – partial	1
3 – degree unknown	1
All others	0

Table 132. FMVSS No. 226 degree of ejection definition for target population

Variable EJECTION	Subpopulation Variable Model variable: CompleteEjct
1 – complete	1
2 – partial	0
3 – degree unknown	0.5588

Ejection through 226-applicable window: For inclusion in the target population, occupants must be ejected through a side window in rows 1 to 3 or the cargo area behind the second row. Based on review of the Preliminary Regulatory Impact Analysis (PRIA), Final Regulatory Impact Analysis, and NASS CDS coding manual, there was considerable ambiguity in the binning of occupants by ejection route. The definition of the categories to be used in the projection model is described in Table 133. Categories with RouteTP=1 indicate cases to be included in the target population and RouteTP=0 indicates those excluded from the target population. Categories where ejection area or medium were unknown are listed with a percentage that corresponds to the distribution of these variables among known cases. The percentage of cases with unknown parameters that are in the target population was estimated to match the percentage of cases with known parameters that were in the defined target population. Based on glazing ejection cases in the baseline retrospective dataset, 79.97 percent of weighted cases with known ejection area were documented as being ejected through an ejection area in the target population. Among ejection cases through windows in the target population, 84.67 percent were through glazing areas and were therefore in the target population for ejection medium.

Table 133. FMVSS No. 226 ejection route definition for target population

	FMVSS No. 226 Relevant Ejection Route Model variable: RouteTP		
NASS CDS Variable EJCTMED	**3 – Fixed Glazing 4 – Nonfixed Glazing**	**0,1,2,5,8,**	**U – Unknown**
NASS CDS Variable EJCTAREA			
1 – Windshield	0	0	0
2 – Left front	1	0	0.8467
3 – Right front	1	0	0.8467
4 – Left rear	1	0	0.8467
5 – Right rear	1	0	0.8467
6 – Rear	0	0	0
7 – Roof	0	0	0
8 – Other area	1	0	0.8467
9 – Unknown if ejected	0	0	0
99 – Unknown area	0.7997	0	0.7997*0.8467

Global FMVSS No. 226 target population variable (TP226): As shown in Equation (65), a single variable (TP226) was used to flag cases that met the basic inclusion criteria for FMVSS No. 226. This variable value ranged from 0 (for cases that were definitely not in the target population) to 1 (for cases that were definitely in the target population). This variable took on a value between 0 and 1 for cases where one or more of the target population requirements was unknown, reflecting the estimated probability that the case was in the target population.

$$TP226 = VehTP \times SeatTP \times EjectTP \times RouteTP \tag{65}$$

where:
TP226 is an indicator variable corresponding to the probability that the case is in the target population,
VehTP is defined in Table 129,
SeatTP is defined in Table 130,
Eject TP is defined in Table 131, and
RouteTP is defined in Table 133.

Crash types – rollover: According to the FRIA, rollover crashes included crashes where rotation about the vehicle longitudinal axis occurred during the crash sequence, regardless of whether or not a planar impact or rotation about some other vehicle axis occurred. End-over-end crashes (without longitudinal axis rotation) were excluded. These criteria were coded using the NASS CDS variable EV/OJBCONT=Rollover Overturn.

Crash types – side impact: According to the FRIA, planar side crashes were defined by using primary or first area of damage as a surrogate for impact direction. For this study, GAD1 in (R, L) was defined as a side impact, coded using the NASS CDS variable EV/GAD1EV in (R, L).

Delta V of side impact: A binary variable was coded for cases where side impact delta V was between 12 and 25 mph (Table 134). Delta V was coded as in the countermeasure for FMVSS No. 214, using NASS CDS variables: GV/DVLAT=19 to 40 km/h or GV/DVEST=3 (24<delta V<40). Cases in the delta V target population range were assigned a value of 1 for the model's delta V target population variable LATDeltaV. Cases where delta V was unknown were assigned a value that corresponded to the percentage of ejected occupants in the baseline retrospective dataset with known lateral delta V who were within the targeted delta V range.

Table 134. FMVSS No. 226 lateral delta V definition for target population

	Subpopulation Variable Model variable: LATDeltaV
12-25 mph	1
Not 12-25 mph	0
Unknown if 12-25 mph	0.3261

Inclusion of rollover/side impact crashes: For the purpose of this analysis, three categories of crashes were included in the target population (coded as a function of the NASS CDS variables: ACCSEQ, OBJCONT, GADEV1):

- Rollover without side impact,
- Side impact without rollover, and
- Side impact with subsequent rollover.

In 214 target population: Cases included in the FMVSS No. 214 target population were excluded from the current target population.

Belted complete ejections: As in the FRIA (page 55), completely ejected belted occupants in rollover crashes were excluded from the target population, based on the assumption that the rollover was very violent given the structure failure required to allow ejection of belted occupants, i.e., these rollovers were assumed to be catastrophic. Only cases where ejection status and belt use were known were included in this group, so no distributed variables were used to estimate this value.

Note also that the FRIA reasoned that a similar percentage of complete ejection unbelted fatalities were also likely to be associated with catastrophic crashes. Based on the ratio of such belted cases, it was estimated that 2.3 percent of completely ejected unbelted fatalities should be excluded from the target population. In the current analysis, this 2.3 percent adjustment for completely ejected unbelted fatalities was made as an adjustment in effectiveness rather than in the target population. See the next page.

Age: Age was used to define a subpopulation of the target population for application of variable effectiveness (Table 135).

Table 135. Age subpopulation variable

	Subpopulation Variable Model variable: Adult
Age<13	0
Age≥13	1

Restraint use: Restraint use was defined as a variable (Belted) to identify a subpopulation of the target population for application of variable effectiveness. When restraint use was unknown, this variable was assigned a value of 0.3636 to reflect the proportion of ejected occupants in the baseline retrospective target population with known restraint use who were determined to be restrained (Table 136).

Table 136. Restraint use subpopulation variable

NASS CDS variables	Subpopulation Variable Model variable: Belted
CHTYPE=1-8 MANUSE=2-8, 12-18 ABELTUSE=1	1
MANUSE=0-1	0
Belt/restraint use unknown	0.3636

Pseudo-cases created by the application of SSF: As discussed in Appendix E.6.3, the application of SSF creates pseudo-cases in which rollovers and ejections are added to or removed from existing cases in the model. The resulting pseudo-cases created by the application of SSF could have a different FMVSS No. 226 target population status than their parent cases prior to the application of SSF. The assignment of subpopulation variables to the SSF pseudo-cases is summarized in Table 137.

Table 137. Pseudo-cases created by the application of SSF

<table>
<tr><th colspan="2">Possible pseudo-cases created by application of SSF</th><th rowspan="2">Impact on the case's inclusion in FMVSS No. 226 target population and subpopulation variables (Defined in terms of model variables)</th></tr>
<tr><th>Rollover added or removed?</th><th>Ejection added or removed?</th></tr>
<tr><td>No change</td><td>No change</td><td>No change from parent case</td></tr>
<tr><td>Rollover added</td><td>No change</td><td>Crash category=Side impact with subsequent rollover</td></tr>
<tr><td>Rollover added</td><td>Ejection added</td><td>EjctTP=1
CompleteEjct=1
RouteTP=0.7997*0.8467
Crash category=Side impact with subsequent rollover</td></tr>
<tr><td>Rollover removed</td><td>Ejection removed (if ejection occurred)</td><td>EjctTP=0
CompleteEjct=0
Crash category=Side impact without rollover</td></tr>
</table>

Final definition of FMVSS No. 226 subpopulations: The variables defined above were used to categorize cases into subpopulations for the purpose of applying effectiveness values that were available for different types of cases and occupants in the target population (Table 138).

Table 138. Subpopulations of target population

Rollover, no side impacts
Side impacts followed by rollovers, excluding 12-25 mph
Side impacts, w/ subsequent rollovers, 12-25 mph
Side impacts, no rollovers, 12-25 mph
Side impacts, no rollovers, children (0-12 yrs), partial and complete, 12-25 mph

These subpopulations were further broken down by belt use, by degree of ejection, and by injury severity (serious injury versus fatal injury) so that an effectiveness estimate (E) can be applied to each subpopulation. An occupant may fall in one of these target populations or be probabilistically distributed among them based on the distributed variables Complete and Belted.

E.6.2 Ejection Mitigation Effectiveness

Based on the assumptions laid out in the FRIA (page 64), effectiveness estimates were drawn from Tables IV-63 and IV-65 in the FRIA, which were estimated using the weighted risk of ejection method. Where there was contradiction between the values discussed in the text and the values reported in the tables, the tabulated values were used. Effectiveness estimates for each target subpopulation (B=Belted, U=Unbelted, P=Partially Ejected, C=Completely Ejected), are compiled in Table 139 for serious injury cases and in Table 140 for fatal cases. These estimates are "uncorrected" in that they have not yet been adjusted according to the correction factors determined from Kahane's evaluation (2014a).

Table 139. Uncorrected effectiveness for serious injury cases

Restraint Use	Ejection	Belted	Complete	System Effectiveness
Rollover, no side impacts:				
Belted (B*)	Partial ejection (P*)	1	0	55 % (BP*)
Belted	Complete ejection (C*)	1	1	0 % (BC*)
Unbelted (U*)	Partial ejection	0	0	50 % (UP*)
Unbelted	Complete ejection	0	1	43 % (UC*)
Side impacts, no rollovers, 12-25 mph:				
Belted	Partial ejection	1	0	49 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	49 % (UP)
Unbelted	Complete ejection	0	1	36 % (UC)
Side impacts, no rollovers, children (0-12 yrs), partial and complete, 12-25 mph:				
Belted	Partial ejection	1	0	49 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	49 % (UP)
Unbelted	Complete ejection	0	1	36 % (UC)
Side impacts followed by rollovers, excluding 12-25 mph:				
Belted	Partial ejection	1	0	30 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	28 % (UP)
Unbelted	Complete ejection	0	1	20 % (UC)
Side impacts, w/ subsequent rollovers, 12-25 mph:				
Belted	Partial ejection	1	0	34 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	31 % (UP)
Unbelted	Complete ejection	0	1	23 % (UC)

** B=belted, U=unbelted, P=partial ejection, C=complete ejection.*

Table 140. Uncorrected effectiveness for fatal cases
(Note that values from FRIA appear to be calculated based on 89% sensor effectiveness rather than FRIA-reported 81%)

Restraint Use	Ejection	Belted	Complete	System Effectiveness
Rollover, no side impacts:				
Belted (B*)	Partial ejection (P*)	1	0	44 % (BP*)
Belted	Complete ejection (C*)	1	1	0 % (BC*)
Unbelted (U*)	Partial ejection	0	0	40 % (UP*)
Unbelted	Complete ejection	0	1	50 % (UC*)
Side impacts, no rollovers, 12-25 mph:				
Belted	Partial ejection	1	0	49 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	49 % (UP)
Unbelted	Complete ejection	0	1	83 % (UC)
Side impacts, no rollovers, children (0-12 yrs), partial and complete, 12-25 mph:				
Belted	Partial ejection	1	0	49 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	49 % (UP)
Unbelted	Complete ejection	0	1	83 % (UC)
Side impacts followed by rollovers, excluding 12-25 mph:				
Belted	Partial ejection	1	0	34 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	31 % (UP)
Unbelted	Complete ejection	0	1	53 % (UC)
Side impacts, w/ subsequent rollovers, 12-25 mph:				
Belted	Partial ejection	1	0	32 % (BP)
Belted	Complete ejection	1	1	0 % (BC)
Unbelted	Partial ejection	0	0	29 % (UP)
Unbelted	Complete ejection	0	1	50 % (UC)

** B=belted, U=unbelted, P=partial ejection, C=complete ejection.*

The subsequent retrospective NHTSA evaluation of rollover curtain effectiveness analyzed fatality risk of front-seat occupants in first-event rollovers in FARS (Kahane, 2014a), concluding an estimated 41.3 percent fatality risk reduction with rollover curtains in this group. This post-implementation estimate was compared to the pre-implementation prediction in the FRIA by examining the FRIA effectiveness estimates for fatalities in rollovers without side impact (Table 140), which were disaggregated by belt use and ejection status (partial versus complete). The proportion of fatally injured rollover occupants in each bin was estimated using the baseline retrospective dataset. In the retrospective dataset, 20.7 percent of fatally injured occupants in rollover crashes without side impact were belted. Among those belted fatality cases, 10.8 percent were complete ejections and 32.6 percent were partial ejections. Among unbelted fatality cases, 75.5 percent of unbelted cases were complete ejections and 7.6 percent were partial ejections. The resulting aggregate FRIA estimate for effectiveness of rollover curtains in fatal rollover cases without side impact would be 35.3 percent, calculated using Equation (66). The retrospectively determined 41.3 percent fatality risk reduction was 16.9 percent higher than this aggregate pre-implementation prediction**.**

$$E_{Fatal,Rollover} = (Prop_{BP} \times E_{BP}) + (Prop_{BC} \times E_{BC}) + (Prop_{UP} \times E_{UP}) + (Prop_{UC} \times E_{UC}) \tag{66}$$

where, e.g.,

$E_{Fatal,Rollover}$ is the estimated effectiveness for fatal rollover cases,

$Prop_{BP}$ is proportion of fatal rollover cases that are Belted, Partial ejection, and

E_{BP} is FRIA-estimated effectiveness in Belted, Partial ejection fatal rollover cases

The retrospective evaluation effectiveness, based on post-implementation crash data, is expected to be more realistic than the effectiveness estimates made in advance of the implementation of the FMVSS No. 226 Upgrade. Although the 41.3 percent effectiveness estimated retrospectively for fatal front-seat occupants in first-event rollovers was not derived from an identical target population as the aggregate 35.3 percent estimated for fatal rollovers without side impact in the FRIA, the two populations are similar enough that the effectiveness for the sub-populations within the fatal, rollover without side impact group in the model were each increased by 16.9 percent to reflect this post-evaluation analysis.

No post-implementation effectiveness data was available for comparison to the pre-implementation estimates for non-fatal cases, or for fatal cases with side impact. In the absence of specific data for these target populations, the 16.9 percent increase calculated for fatal rollovers without side impact was applied to all occupants in the target population for this countermeasure. In other words, the effectiveness estimates for each group in Table 139 and Table 140 were adjusted by multiplying them by 1.169.

E.6.2.1 Application of Effectiveness

For cases categorized as ***non-fatal*** (FATAL226=0), the effectiveness values reported for serious injury (Table 139) were multiplied by 1.169.

As defined for this countermeasure, effectiveness reflects the likelihood that an occupant's serious injuries would be prevented by the countermeasure. The effectiveness is applied to the occupant rather than to individual injuries. Since the effectiveness estimates incorporate the expected change in injury risk for an ejected occupant versus an occupant who is kept in the vehicle, the effectiveness is applied to all an ejected occupant's serious injuries regardless of the source of those injuries.

In the projection model, the severity of injury in each case is important. Therefore, the effectiveness estimate was applied to each AIS 3+ injury in the case, reflecting the probability that all AIS 3+ injuries would be reduced to AIS 2 severity by the countermeasure. In the absence of specific estimates of the effectiveness of FMVSS No. 226 countermeasures in the reduction of AIS 2 injuries, it was estimated that the AIS 3+ effectiveness estimates would also apply to AIS 2 injuries and represent the proportion of injuries that would be reduced from AIS 2 to a lower severity. In the current version of the model, this injury reduction was achieved by deleting AIS 2 injuries.

In summary, for each *non-fatal* case, the effectiveness values in Table 139 were multiplied by 1.16 and used to proportionally divide the case into two pseudo-cases: one with injuries unchanged, and the other with all original AIS 3+ injuries reduced to AIS 2 severity and all original AIS 2 injuries deleted.

For cases categorized as *fatal* (FATAL226=1), the effectiveness values reported for fatality (Table 140) were multiplied by 1.169. In the FRIA, these effectiveness values estimated the probability that an occupant's fatality would be prevented. In the projection model, the specific injury reduction in a case is more useful than the conversion rate from fatal to non-fatal, since this effect is difficult to interpret when several countermeasures are applied. Therefore, the effectiveness for fatal cases in the projection model was interpreted to represent the probability that all that occupant's AIS 3+ injuries would be reduced to severity of AIS 2 and all original AIS 2 injuries would be deleted.

The effectiveness value from Table 139 or Table 140 applied to a specific case is dependent on its crash category (side impact, no rollover, delta V, etc.), the model variables Belted, EjectDeg, and deltaV, and on the global target population variable TP226. To accommodate cases that were assigned a probabilistic (non-binary) value for Belted, EjectDeg, DeltaV, or TP226 because of missing case information, case-specific effectiveness was calculated as a function of these variables as well as the effectiveness values tabulated in Table 139 and Table 140 adjusted by the factor of 1.169. Additionally, case-specific effectiveness for unbelted fatal cases with complete ejection were reduced by 2.3 percent by multiplying by 0.977 to reflect the FRIA estimate that crashes would be so catastrophic that injuries would be intractable in that percentage of such crashes.

For cases in the "Rollover, no side impact" category, case-specific effectiveness was independent of delta V, and was calculated using Equation (67).

$$\begin{aligned} E_{226} = TP226 \times \big[& Belted \times Complete \times E_{BC} + Belted \times (1 - Complete) \times E_{BP} \\ & + (1 - Belted) \times Complete \times E_{UC} \\ & \times \big((1 - Fatal226) + \ 0.977 \times Fatal226\big) + (1 - Belted) \\ & \times (1 - Complete) \times E_{UP} \big] \end{aligned} \tag{67}$$

where:
E_{226} is the estimated effectiveness,
Belted, Complete, and Fatal226 are model variables for target population categories, and E_{BC}, E_{BP}, E_{UC}, E_{UP} are effectiveness estimates for occupants who are belted (B), unbelted (U), completely ejected (C), or partially ejected (P).

For cases with side impact where delta V is known and is between 12 and 25 mph, i.e., LatDeltaV=1, Equation (68) is used. For cases with side impact where delta V is known and is not between 12 and 25 mph, i.e., LatDeltaV=0, Equation (69) is used. For side impact cases where delta V is unknown and a probabilistic value has been estimated for the likelihood of delta V falling between 12 and 25 mph, then both Equation (68) and Equation (69) are calculated, and the results are summed in Equation (70).

$$E_{226,1} = LatDeltaV \times TP226 \times \left[Belted \times Complete \times E_{BC} + Belted \times (1 - Complete) \times E_{BP} + (1 - Belted) \times Complete \times E_{UC} \times \left((1 - Fatal226) + 0.977 \times Fatal226\right) + (1 - Belted) \times (1 - Complete) \times E_{UP}\right] \quad (68)$$

where:

$E_{226,1}$ is the effectiveness for a case in the 12-25 mph delta V range.

$$E_{226,2} = (1 - LatDeltaV) \times TP226 \times \left[Belted \times Complete \times E_{BC} + Belted \times (1 - Complete) \times E_{BP} + (1 - Belted) \times Complete \times E_{UC} \times \left((1 - Fatal226) + 0.977 \times Fatal226\right) + (1 - Belted) \times (1 - Complete) \times E_{UP}\right] \quad (69)$$

where:

$E_{226,2}$ is the effectiveness for a case not in the 12-25 mph delta V range.

Since a case with unknown lateral delta V (where 0<LatDeltaV<1) may or may not be within the 12 and 25 mph range, the estimated effectiveness is the sum of the two effectiveness estimates above. This summation (Equation (70)) can be applied to all cases.

$$E_{226} = E_{226,1} + E_{226,2} \quad (70)$$

where:

$E_{226,1}$ and $E_{226,2}$ are the effectiveness values estimated in Equations (68) and (69).

E.6.3 Relationship Between Ejection Mitigation and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure is applied to every individual case in its target population based on case variables. As discussed in Appendix C.3.3, the application of SSF creates pseudo-cases in which rollovers are added to or removed from existing cases in the model, and some of those rollovers also involve ejection and ejection injuries. These changes have the potential to move a case into, or out of, the target population for ejection mitigation. Therefore, the SSF countermeasure must be applied *before* the ejection mitigation countermeasure in the model. The target population definition in the ejection mitigation countermeasure specifically addresses criteria for inclusion of the SSF rollover pseudo-cases.

E.6.4 Ejection Mitigation Penetration

The penetration of side impact air bags and rollover sensors by model year (α_{MY}) up to 2016, shown in Table 141, was estimated based on NHTSA's estimates of installation of FMVSS No. 226-compliant systems in passenger cars and LTVs (Simons, 2017; Simons, personal communication[43]). For each model year, a combined α value was calculated based on the proportion of PCs and LTVs among vehicle sales. For 2017 and later, α_{MY} was estimated to be 100 percent based on the compliance requirement in the FMVSS No. 226 Final Rule (NHTSA, 2011b).

[43] James F. Simons, Bowhead Logistics Solutions, LLC, Alexandria, VA, personal communication, February 2018.

Table 141. Penetration of FMVSS No. 226 by model year (α_{MY})

Model Year	Proportion of sales		α_{PC} (%)	α_{LTV} (%)	α_{MY} (%)
	PC	LTV			
≤ 2004	48.1	51.9	0.0	4.5	2.3
2005	50.5	49.5	0.7	10.7	5.6
2006	52.9	47.1	1.4	20	10.2
2007	52.9	47.1	1.3	37.8	18.5
2008	52.7	47.3	2.9	55.4	27.8
2009	60.5	39.5	1.9	63.6	26.3
2010	54.5	45.5	7.6	78.5	39.8
2011	47.8	52.2	13.7	78.8	47.7
2012	55.0	45.0	12.9	78.3	42.3
2013	54.1	45.9	15.7	83.9	47.0
2014	49.2	50.8	28.2	88.7	58.9
2015	46.8	53.2	60.5	93.4	78.0
2016	42.0	58.0	70.8	96.6	85.8
2017-2030					100.0

Using Equation (14) and the vehicle age distributions in Appendix A, the penetration of FMVSS No. 226 among vehicles in projected crash years was estimated in Table 142.

Table 142. Penetration of FMVSS No. 226 Upgrade in projection target years (β_{TY})

Crash Year	Overall β_{TY} (%)
2014	32.2
2020	62.7
2025	83.8
2030	95.2

E.7 FMVSS No. 301 Rear Impact Upgrade

Although the FMVSS No. 301 rear impact upgrade finalized in 2003 was targeted at reducing fires associated with rear impact, the improvements made to meet the new requirements were expected to reduce occupant compartment intrusion and injuries as well. For the projection model, the fire-reducing benefits of the upgrade were estimated based on the Final Regulatory Evaluation (NHTSA, 2003b) and on NCSA's post implementation evaluation of the upgrade (Pai, 2014). The additional reduction in crash injury that was associated with the structural improvements needed to reduce fires was quantified in a study by Viano and Parenteau (2016) by comparing the rate of AIS 4+ injury in rear-impacted vehicles in model years before and after the revision of FMVSS No. 301. As noted by those authors, the cause of the injury rate reduction could be attributed to other safety improvements (such as seat structure changes to improve retention in the seat) as well as to the FMVSS No. 301 upgrade. However, since no other crashworthiness countermeasures involving high-speed rear impact were applied to the projection model for vehicle model years during the FMVSS No. 301 phase-in period, this global comparison of injury risk in vehicles before and after the phase-in is appropriate and does not introduce any double-counting of improvements: this method simply combines the effects of all rear impact crashworthiness improvements contemporaneous with the FMVSS No. 301 phase-in period, regardless of whether they were motivated by the required upgrade.

In this summary, the target populations and effectiveness for fire prevention and crash injury reduction are described separately, but it was assumed that the phase-in period is the same for both effects included in the projection model.

E.7.1 Fire Prevention Target Population

According to the Final Regulatory Evaluation for the FMVSS No. 301 Upgrade (NHTSA, 2003b), the following cases were included in the target population for fire prevention improvements:

- Multi-vehicle crashes, where a passenger vehicle is struck in the rear by another passenger vehicle and catches on fire. This population was defined, using NASS CDS variables, as follows:
  - Rear impact: NASS CDS variable GAD1=B.
  - Multi-vehicle: NASS CDS variable VEHFORMS>1.
  - The FRE excluded larger-than-passenger-vehicle striking vehicles but noted this choice was conservative. For the purpose of the projection model, truck impacts were included.
  - The FRE made an adjustment for cases in which a fuel leak in the struck vehicle could result in fire in the striking vehicle. In the projection model, fire in striking vehicle was only included in the target population if there was also a fire in the struck vehicle. The corresponding NASS CDS variables were FIRE in (1, 2) for vehicle with GAD1=B.
- Although the FRE defines target population as cases in which the fire was the cause of death or injury, it appears this percentage was estimated rather than drawn from case data. Since non-fatal burn injuries were mostly minor and not typically the maximum injury, these were not included in the FRE benefits. No exclusion was made in the projection model, however, because all burn injuries were deleted from the case. GVWR<=10k pounds (NASS CDS variable WGTCDTR<3).
- No specific delta V is recommended for the target population in the FRE but the analysis suggested that only tests "like" the proposed test would be covered. Based on an approximation that the test represented a delta V of "about" 20-30 mph, the FRE indicated that countermeasures "might have been effective" in delta V crashes "slightly" different than this range, estimating that only 40 percent to 70 percent of burn cases in the target population would be similar enough to benefit from the revised standard. Therefore, for the purpose of the projection model, it was estimated that cases where the struck vehicle's total or longitudinal delta V or estimated delta V was between 15 and 35 mph were within the target population of the countermeasure. For cases where delta V was unknown, it was estimated that 55 percent (mid-point of the range from 40% to 70%) were within the target population.
- The threshold total or longitudinal delta V for inclusion in the FMVSS No. 301 countermeasure target population was a function of the delta V variables in the original NASS CDS source case as well as the estimated delta V reduction (R_{TPMS}) associated with the application of the TPMS countermeasure:

- DVEST in (3, 4) or
- 24<DVTOTAL - RTPMS<56 or
- 24<DVLONG - RTPMS<56

E.7.2 Fire Prevention Effectiveness

Although the FRE assumed benefit only for those whose death was attributed to fire, the current application assumes that prevention of the fire would lead to the deletion of all burn-related injuries (based on AIS codes corresponding to burns).

The FRE analyzed fire cases in crash databases to determine the percentage of rear impact fire cases that were similar to the test setup in the revised FMVSS No. 301 test. Benefits were based on 50 percent to 75 percent effectiveness of the improvements, estimated based on the risk of fire in vehicles meeting the improved standard compared to those not meeting the improved standard.

A follow-up analysis in 2014 (based on FARS cases, Polk registration data, and information on vehicle models that were certified to meet rear impact upgrade requirements in each model year) refined the NHTSA estimate to 50 to 65 percent fire-reduction effectiveness for the rear impact estimate (Pai, 2014).

The estimated effectiveness for fire prevention in the projection model was based on NHTSA's 2014 estimate of effectiveness of 50 to 65 percent, with effectiveness of 57.5 percent assigned to cases in the target population with known delta V. For cases with unknown delta V, but otherwise in the target population, the effectiveness estimate was reduced to 55 percent of the original estimate to reflect the finding (discussed in the target population section) that 40 to 70 percent of all cases would be "similar enough" to the regulatory test to benefit from the improvements. The resulting effectiveness in cases where delta V was unknown was 31.6 percent (0.55 * 0.575 = 0.316).

E.7.3 Rear Impact Crashworthiness Target Population

The target population for crashworthiness improvements associated with FMVSS No. 301 was slightly different than the one used for fire prevention:

- Crashworthiness effects were applied only to the struck vehicle in car-to-car rear impacts.
- As in Viano and Parenteau, relevant rear impacts included the following (with the NASS CDS variables used to code them):
  - Principal impact location rear (GAD1=B).
  - Rollovers excluded (ROLLOVER=0).
- No limitations regarding the striking vehicle.
- The FMVSS No. 301 FRIA indicated that the test represented a delta V of "about" 20 to 30 mph. According to supplemental data in Viano and Parenteau's study, average injury effectiveness was relatively low when averaged across the 15 to 30 mph delta V bin compared to the effectiveness calculated for all cases with delta V of 15 mph and greater, suggesting low effectiveness at the lower speeds in the 15 to 30 mph range and greater effectiveness at higher speeds. The Viano delta V ranges were based on total, rather than longitudinal delta V. Therefore, the target population for FMVSS No. 301

crashworthiness improvements was limited to struck vehicles in which the total delta V was estimated to be 20 mph or greater.

- The threshold total or longitudinal delta V for inclusion in the FMVSS No. 301 target population was a function of the NASS CDS delta V variables in the original source case as well as the estimated delta V reduction (R_{TPMS}) associated with the application of the TPMS countermeasure.
    - DVTOTAL – R_{TPMS}>32 or
    - DVLONG – R_{TPMS}>32 or
    - DVEST in (4, 5)
- Viano's supplemental data showed that approximately 18 to 23 percent of cases with known delta V were documented with delta V of 15 mph or greater. For the purpose of this model, it is roughly estimated that approximately half of these crashes had delta V of 20 mph or greater. Therefore, for rear impact cases with unknown delta V, it was estimated as a placeholder that approximately 10 percent of cases with unknown delta V would be in the target population.

E.7.4 Rear Impact Crashworthiness Effectiveness

Viano and Parenteau reported on the reduction of MAIS 4+ cases from model years preceding the FMVSS No. 301 upgrade to model years after the FMVSS No. 301 upgrade. Effectiveness estimated based on their analysis was interpreted to correspond to the reduction of AIS 4 to 6 injuries (in fatal or non-fatal cases) to AIS 3. No reduction was made to AIS 3 injuries in this countermeasure, although adjustments to lower-severity injuries would be reasonable to consider in the future.

The injury reductions reported by Viano and Parenteau were complicated by the relatively small number of late MY vehicles in the dataset and by severe injuries in these vehicles. The reduction in severe (or worse) injury among all rear impact occupants in the target population was estimated to be 70.2 percent. When limited to cases where known delta V was 15 mph or greater, the severe injury reduction was 69.4 percent. In the absence of an estimate specifically based on cases in the 20+ mph delta V target population, an effectiveness of 70 percent was estimated for the target population used in the projection model.

It should be noted that the injury reduction reflected in this effectiveness estimate cannot be definitively attributed to improvements made to meet FMVSS No. 301 requirements. Therefore, application of this effectiveness should be considered as an overall improvement in rear impact protection during this period, rather than a necessarily direct benefit of FMVSS No. 301.

E.7.5 Relationship Between FMVSS No. 301 and Other Countermeasures

In the case-by-case method (see Section 2.6.3), each countermeasure is applied to every individual case in its target population based on case variables. The target population for the improvements made relative to FMVSS No. 301 relies on the estimated delta V of the struck vehicle. That delta V was estimated from the original delta V documented in the CDS case but adjusted for the expected delta V reduction associated with the application of TPMS (R_{TPMS}) to the striking vehicle as discussed in Section D.2. Therefore, FMVSS No. 301 must be applied *after* TPMS in the model.

E.7.6 Rear Impact Update Penetration

The penetration of vehicle changes made to meet the requirements of FMVSS No. 301 were assumed to correspond to both the fire-reduction benefits as well as the crashworthiness benefits of the improvements.

The required phase-in period for the FMVSS No. 301 upgrade spanned from 2007 to 2009. A post-implementation assessment of the FMVSS No. 301 upgrade reported on certification percentages of actual implementation of the rule (Pai, 2014), shown in Table 143.

Table 143. FMVSS No. 301 compliance rates (Pai, 2014)

Model Year	Certified percentage of vehicles actually compliant (%)
2006	18.23
2007	57.40
2008	82.93
2009	100

Pai also used test data on vehicles with MY 2005 and earlier to estimate that sales-weighted compliance prior to this time was 39.9 percent for vehicles weighing less than 3,500 pounds, and higher for heavier vehicles. The final estimates of penetration by model year used in the projection model was therefore as shown in Table 144.

Table 144. Penetration of FMVSS No. 301 upgrade by model year (α_{MY})

Model Year	α_{MY} (%)
2006 and earlier	39.9
2007	57.4
2008	82.9
2009+	100

Using Equation (14) and the vehicle age distribution data in Appendix A, the penetration of FMVSS No. 301 compliance among vehicles in projection crash years was estimated in Table 145.

Table 145. Penetration of FMVSS No. 301 upgrade in projection target years (overall β_{TY})

Crash Year	Overall β_{TY} (%)
2014	82.4
2020	94.2
2025	98.4
2030	99.7

Appendix F: Program and Infrastructure Countermeasures

F.1 Roadway Rumble Strips

Rumble strips alert inattentive drivers, using vibration and sound, when their vehicles leave the travel lane. This countermeasure applies the effects of both shoulder/edge line rumble strips and centerline rumble strips.

F.1.1 Rumble Strips Target Population

The Transportation Research Board's National Cooperative Highway Research Program Report 641: Guidance for the Design and Application of Shoulder and Centerline Rumble Strips (Torbic, 2009) includes an evaluation of the safety effectiveness of rumble strips based on the frequency of targeted crashes before and after their implementation. Based on this report, the target population for rumble strips and associated coding parameters in the projection model are defined below.

Centerline rumble strip target crashes*:* head-on and sideswipe opposite direction crashes:

- NASS CDS variable ACCTYPE in (50-53, 64-67)

Shoulder rumble strip target crashes: single vehicle run off the road crashes:

- NASS CDS variable ACCTYPE in (1, 6)

Roadway type: Per the Federal Highway Administration, two-lane roadways have had relatively limited use of rumble strips historically (compared to freeways, on which rumble strips are more common), but these types of roadways show the highest reductions in crash frequency with rumble strips (Himes & McGee, 2016). Therefore, while the NCHRP report includes results for other roadway types, the application to the projection model will be limited to urban and rural two-lane roadways. There are no NASS CDS variables to distinguish urban and rural crash locations; however, by limiting to two-lane roadways, it is reasonable to roughly separate urban and rural by speed limit. Based on a brief review of speed limit practices across multiple States, a 45 mph division was used for the projection model. It was pragmatically approximated that two lane roads with a speed limit greater than or equal to 45 mph (72 km/h) are rural or exurban roads, and two lane roads with a speed limit lower than 45 mph are urban roads. The corresponding NASS CDS variables to define the two target subpopulations were as follows:

- Urban two-lane roads: (TRAFFLOW in (1, 2) and LANES=1) or (TRAFFLOW=0 and LANES=2) AND SPLIMIT<72
- Rural two-lane roads: (TRAFFLOW in (1, 2) and LANES=1) or (TRAFFLOW=0 and LANES=2) AND SPLIMIT>=72

Exclusions: It is noted that rumble strips likely have little benefit in situations where the vehicle is making an intentional maneuver, such as an evasive maneuver or passing another vehicle, or in situations of vehicle failure or control loss, so these cases were excluded. Additionally, rumble strips are generally not present at intersections or other junctions, so these crashes were excluded as well. These exclusions were coded using the following NASS CDS variables:

- Vehicle failure: PREEVENT in (1-4)
- Control loss: PREEVENT in (5-9)
- Intentional maneuver: PREMOVE in (6, 8-12, 14-16)
- Intersections and junctions: RELINTER in (1:4)

F.1.2 Rumble Strips Effectiveness

NCHRP estimated the following safety effectiveness of rumble strips (Table 146). These effectiveness estimates are defined relative to crash prevention, correspond to the reduction of the case weight of any case in the target population.

Table 146. Safety effectiveness of rumble strips

Rumble Strip Type	Roadway Type	Crash Type	Crash Reduction (Effectiveness)
Centerline rumble strips	Urban two-lane roads	All target crashes	40%
		Fatal/injury target crashes	64%
	Rural two-lane roads	All target crashes	30%
		Fatal/injury target crashes	44%
Shoulder rumble strips	Rural two-lane roads	All target crashes	15%
		Fatal/injury target crashes	29%

To apply these estimates to non-injury crashes as well as to fatal/injury crashes, effectiveness estimates were calculated for non-injury crashes using Equation (72). The relative proportions of fatal/injury target crashes to non-injury target crashes were drawn from the crash statistics provided in the NCHRP report (Tables 22, 59, 60). These statistics are shown in Table 147, along with the resulting effectiveness estimates for non-injury crashes.

By the definition of effectiveness:

$$E_{all} = \frac{E_{non-inj} * Total_{non-inj} + E_{inj} * Total_{inj}}{Total_{non-inj} + Total_{inj}} \tag{71}$$

where:

E_{inj}, $E_{non-inj}$, E_{all} is the effectiveness (in injury cases, non-injury cases, and in all cases), and Total is the number of injury or non-injury crashes in NCHRP crash statistics.

That relationship can be rearranged to isolate the effectiveness specifically in non-injury cases:

$$E_{non-inj} = \frac{E_{all} * (Total_{non-inj} + Total_{inj}) - E_{inj} * Total_{inj}}{Total_{non-inj}} \tag{72}$$

Table 147. *Effectiveness estimate calculation for non-injury crashes*

Rumble Strip Type	Roadway Type	From Source Data on Effectiveness (NCHRP)				Calculated With Equation (72)
		E_{all}	E_{inj}	$Total_{inj}$	$Total_{non-inj}$	$E_{non-inj}$
Centerline rumble strips	Urban two-lane roads	40	64	90	79	13%
	Rural two-lane roads	30	44	559	518	15%
Shoulder rumble strips	Rural two-lane roads	15	29	868	1058	4%

In summary, the effectiveness values in Table 148 were applied to cases in each target subpopulation in the projection model. The effectiveness value was applied to all vehicles and occupants in a given crash. Injury crashes were defined as crashes in which at least one occupant in one vehicle was listed as having at least one AIS 1+ injury.

Table 148. *Effectiveness of rumble strips for application to projection model*

Rumble Strip Type	Roadway Type	Effectiveness in Injury/Fatality Cases (Eff_{inj})	Effectiveness in Non-Injury Cases ($Eff_{non-inj}$)
Centerline rumble strips	Urban two-lane roads	64%	13%
	Rural two-lane roads	44%	15%
Shoulder rumble strips	Rural two-lane roads	29%	4%

F.1.3 Rumble Strips Penetration

Penetration, as applied to infrastructure improvements in the projection model, is an estimate of the rate of installation of the countermeasure on roadways in the target population. For rumble strips, estimated penetration by crash year is an estimate of the percentage of potential crashes in the defined target population that could be expected to occur at sites with rumble strips installed. There is no data available on historical rumble strip installation, nor on expected future installation rates. Therefore, very rough estimates were made based on provisional assumptions about past and future adoption of rumble strips using values that can be updated as more definitive information comes available.

FHWA includes rumble strips on two-lane roads in its list of proven safety countermeasures and recommends that Federal, State, and local governments consider rumble strips when administering highway projects. FHWA's Decision Support Guide for the Installation of Shoulder and Center Line Rumble Strips on Non-Freeways includes three approaches for identifying roadways for the installation of rumble strips (Himes & McGee, 2016). The systemic safety approach identifies roadways with high risk factors associated with target crashes, the high crash corridor safety approach identifies roadways with above-average crash frequencies, and the systematic approach focuses on installing rumble strips system-wide, often while completing other projects, unless there is a reason for exception. Previous support for rumble strip installation was included in the NCHRP Report 641 in 2009 and an FHWA Technical Advisory in 2011.

Although rumble strips would ideally be implemented in high-frequency crash areas, in addition to being implemented system-wide, installation is often limited by other considerations.[44] For example, installation can be limited by road width or by road surface materials that are unable to handle a milled rumble. Rumble strips may also not be placed in locations where installation may leave inadequate room for cyclists or near residences because of noise concerns. Centerline rumble strips may not be installed in passing lanes. Due to lack of specific information on installation, it was therefore estimated for the purpose of the projection model that rumble strips would be installed using a systematic approach on a proportion of existing roads when they undergo substantial construction, such as asphalt resurfacing, rather than at particularly high-risk locations. Two-lane asphalt roads are typically resurfaced every 15 years.[45] Therefore, as a preliminary estimate of increased rumble strip implementation for the purpose of the projection model, it was estimated as a starting point that:

(1) Installation of rumble strips stayed relatively constant prior to the publication of the 2009 NCHRP Report 641.
(2) Installation of rumble strips over 2009 levels began increasing at a constant rate in 2010 and will continue at this constant rate in the future.
(3) Each year, 1/15 of all roads will be resurfaced on average.
(4) In rural locations, an estimated 4 percent of these resurfacing projects will include the addition of shoulder rumble strips in the near future, but the rate will slow to 2 percent by 2025 as the result of complicating factors such as road width and bike lane installation on the remaining roads.
(5) Rural centerline rumble strips will be included in approximately 2 percent of resurfacing projects.
(6) In urban locations, an estimated 1 percent of these resurfacing projects will include the addition of centerline rumble strips.

The resulting estimated penetration is shown in Table 149.

[44] Cathy Satterfield, Federal Highway Administration, personal communication, May 2018.
[45] Mark Spears, EHM&T, New Albany, OH, personal communication, August 2017.

Table 149. Penetration of rumble strips on two-lane roadways over 2009 levels (β_{TY} and α_{CY})

Crash Year	α_{CY} for 2009–2030 and Overall β_{TY} for 2014, 2020, 2025, 2030 (%)		
	Rural Shoulder Rumble Strips	Rural Centerline Rumble Strips	Urban Centerline Rumble Strips
≤ 2009	0.00	0.00	0.00
2010	0.27	0.13	0.07
2011	0.53	0.27	0.13
2012	0.80	0.40	0.20
2013	1.07	0.53	0.27
2014	1.33	0.67	0.33
2015	1.60	0.80	0.40
2016	1.87	0.93	0.47
2017	2.13	1.07	0.53
2018	2.40	1.20	0.60
2019	2.67	1.33	0.67
2020	2.93	1.47	0.73
2021	3.20	1.60	0.80
2022	3.47	1.73	0.87
2023	3.73	1.87	0.93
2024	4.00	2.00	1.00
2025	4.13	2.13	1.07
2026	4.27	2.27	1.13
2027	4.40	2.40	1.20
2028	4.53	2.53	1.27
2029	4.67	2.67	1.33
2030	4.80	2.80	1.40

F.2 Maximum Speed Limit Increases

Driving speed is a key factor in road safety, affecting both the likelihood and the severity of a crash (Aarts & van Schagen, 2006). Since the 1995 repeal of the national maximum speed limit of 65 mph on rural interstates, States have been raising their maximum speed limits leading to an increase in average driving speeds. It has been estimated that 18,000-33,000 fatalities between 1995 and 2013 can be attributed to State speed limit increases (Farmer, 2017b). Presently, 19 States have a maximum speed limit of 75 mph or greater as seen in Figure 31 (IIHS, 2019). There have been 22 +5 mph increases in individual States since 2007 and expressed interest in future increases by at least 11 States.

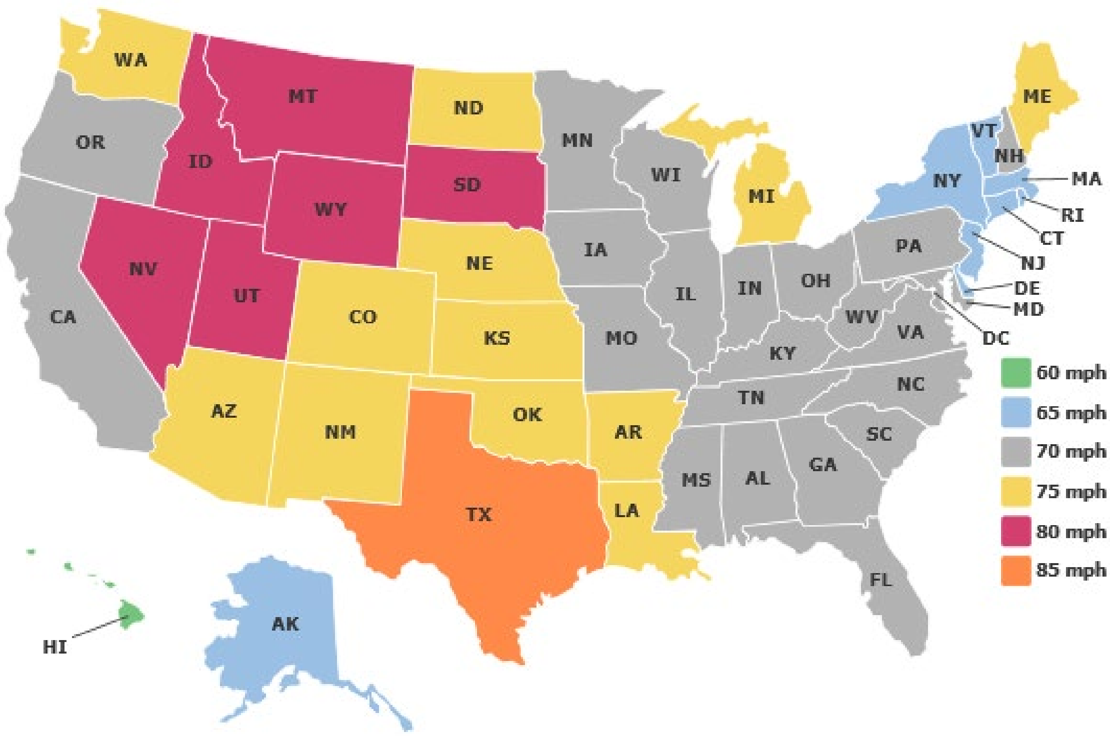

Figure 31. Maximum speed limits by State as of April 2019 (IIHS, 2019)

F.2.1 Maximum Speed Limit Increases Target Population

When a State increases the maximum speed limit, the roads that get a posted increase are historically rural highways defined as multiple-lane, limited-access highways with restricted access via exit and entrance ramps (IIHS, 2019). These roads are selected due to their relatively low traffic and minimal speed fluctuations when compared to arterial, urban highways. Additionally, arterial roadways encompass many intersections, residential areas, and school zones and therefore, would not be suitable for an increase to a State's maximum speed limit in the future.

The target population for speed limit increases was defined as occupants in injury and fatal crashes occurring on rural highways, identified using the following NASS CDS variables:

- GV/TRAFFLOW=1 (divided, no barrier),
- GV/LANES>1 (at least two lanes),
- GV/SPLIMIT>96 (speed limit ≥ 60 mph),
- GV/TRAFCONT^ in (1:8) (no traffic signals), and
- ACC/AAIS>0 (injury crashes).

F.2.2 Maximum Speed Limit Increases Anti-Effectiveness

When the speed limit is increased, the mean driving speed also increases. A logarithmic model of this relationship was developed for the model (Figure 32), using the observed mean speeds based on posted speed limits on rural highways reported in the literature (Parker, 1997; Skszek, 2004;

Kockelman, 2006; Mannering, 2007; Retting & Cheung, 2008; Hu, 2017). A log model was selected because human behavior with regard to driving speed has been noted to be logarithmic and for any given road, there is a maximum speed at which drivers are comfortable regardless of the posted speed limit. The best fit log model provided an R^2 value of 86 percent. Mean speeds for common speed limits on rural highways, estimated using the relationship defined in Figure 32, are summarized in Table 150.

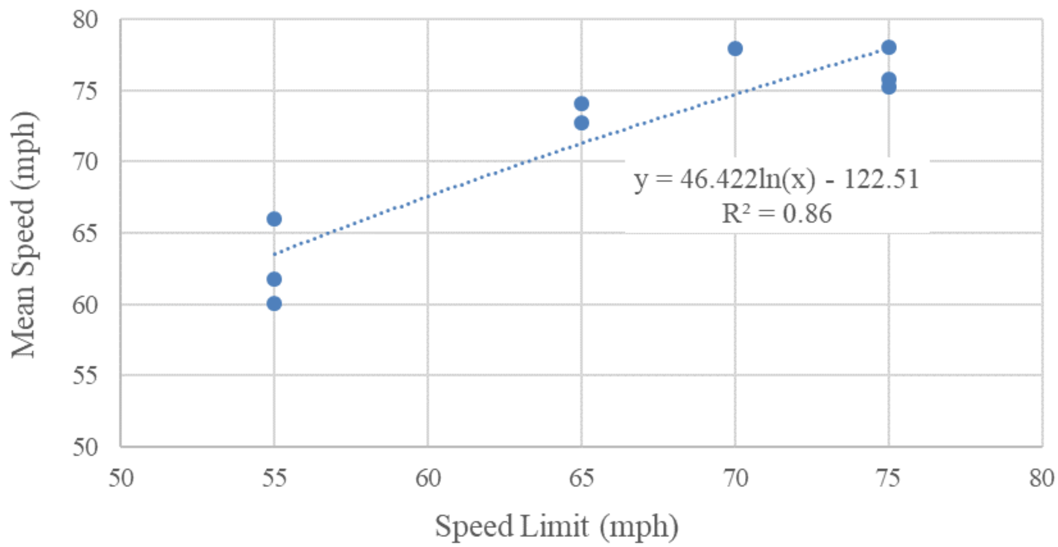

Figure 32. Mean speed on a rural highway based on speed limit

Table 150. Estimated mean speed for common speed limits on rural interstates

Speed Limit (mph)	Mean Speed (mph)
60	67.6
65	71.3
70	74.7
75	77.9
80	80.9
85	83.7

The increase in mean speed due to higher speed limit results in more fatal and non-fatal injury crashes. The relationship between a change in mean speed and the subsequent crash increase has been modeled by Elvik (2013), with the effect on crashes varying with the initial speed limit. Elvik's mathematical models are defined in Equations (73) and (74) for fatal and injury crashes. Table 151 summarizes the resulting predicted effect of +5 mph change on a rural interstate.

$$F = \left(\left(\frac{x_2}{x_1}\right)^{4.234} - 1\right) \tag{73}$$

where:

F is the percentage increase in fatal crashes when the mean speed increases from x_1 to x_2.

$$I = \left(e^{0.0548(x_2 - x_1)} - 1\right) \tag{74}$$

where:

I is the percentage increase in non-fatal injury crashes when the mean speed increases from x_1 to x_2.

Table 151. Expected increase in crashes with a speed limit increase on a rural interstate

	Speed Limit Increase (mph)	Mean Speed Increase (mph)	% Increase in Crashes	
			Fatal	**Non-fatal Injury**
+5 mph	60 to 65	67.6 to 71.3	25	22
	65 to 70	71.3 to 74.7	22	20
	70 to 75	74.7 to 77.9	19	19
	75 to 80	77.9 to 80.9	17	18
	80 to 85	80.9 to 83.7	15	17

For coding purposes in the projection model, a simplified estimate was developed for crash increases independent of the initial speed limit using data from 2005 and 2009. The first step was to assign each State a weight term (Equation (75)) that corresponded to the ratio of fatal and non-fatal injury crashes occurring in that State over those occurring nationally. Crash data from 2009, summarized in Table 152 (Nelli et al., 2014), was used to calculate the weight term because it was the most recent year for which State-by-State data was available. For States where the number of annual non-fatal injury accidents was incomplete, the values were estimated using a regression based on the State-specific number of fatal accidents, licensed drivers, and vehicle miles traveled (R^2=0.98). Italicized values in Table 152 are regression-based estimates.

$$Weight = \frac{(Fatal + NonFatalInjury)_{state}}{(Fatal + NonFatalInjury)_{US}} = \frac{(Fatal + NonFatalInjury)_{state}}{1{,}890{,}989} \tag{75}$$

where:

Weight is proportional to the number of injury and fatality crashes in a given State in 2009, and Fatal and NonFatalInjury are counts of the 2009 number of injury cases of each type in a given State.

Table 152. Number of crashes by type and State in 2009

State	Fatal	Non-fatal Injury	Total	Weight	State	Fatal	Non-fatal Injury	Total	Weight
AL	775	25,415	26,190	0.0138	MT	208	5,793	6,001	0.0032
AK	64	*615*	679	0.0004	NE	205	12,212	12,417	0.0066
AZ	807	*33,805*	34,612	0.0183	NV	243	*9,496*	9,739	0.0052
AR	529	19,486	20,015	0.0106	NH	110	*6,163*	6,273	0.0033
CA	2,805	163,524	166,329	0.0880	NJ	545	67,394	67,939	0.0359
CO	599	32,201	32,800	0.0173	NM	319	13,137	13,456	0.0071
CT	214	25,738	25,952	0.0137	NY	1,060	133,888	134,948	0.0714
DE	96	4,946	5,042	0.0027	NC	1,234	69,394	70,628	0.0373
FL	2,371	125,681	128,052	0.0677	ND	116	2,450	2,566	0.0014
GA	1,349	81,730	83,079	0.0439	OH	945	73,290	74,235	0.0393
HI	109	*3,824*	3,933	0.0021	OK	738	*42,510*	43,248	0.0229
ID	226	*6,803*	7,029	0.0037	OR	377	*17,754*	18,131	0.0096
IL	832	63,383	64,215	0.0340	PA	1,143	61,776	62,919	0.0333
IN	632	33,786	34,418	0.0182	RI	83	*2,918*	3,001	0.0016
IA	338	14,434	14,772	0.0078	SC	817	31,086	31,903	0.0169
KS	350	13,927	14,277	0.0076	SD	131	*3,483*	3,614	0.0019
KY	730	25,036	25,766	0.0136	TN	989	*47,786*	48,775	0.0258
LA	729	45,335	46,064	0.0244	TX	2,793	155,044	157,837	0.0835
ME	159	*6,412*	6,571	0.0035	UT	258	19,424	19,682	0.0104
MD	516	32,358	32,874	0.0174	VT	74	*2,601*	2,675	0.0014
MA	334	*45,558*	45,892	0.0243	VA	694	44,284	44,978	0.0238
MI	836	53,550	54,386	0.0288	WA	462	35,789	36,251	0.0192
MN	371	22,159	22,530	0.0119	WV	356	*10,030*	10,386	0.0055
MS	700	*40,363*	41,063	0.0217	WI	495	31,085	31,580	0.0167
MO	786	37,005	37,791	0.0200	WY	116	3,360	3,476	0.0018

For each State, Equations (73) and (74) were used to calculate the potential percentage increase in crashes due to a +5 mph increase over the 2005 State speed limit. A +5 mph change was selected because approximately 90 percent of the State speed limit increases since the repeal of the national maximum speed limit have been of this magnitude. The remaining 10 percent were +10 mph changes which were treated as two +5 mph increases. Each State's potential crash increase was multiplied by the weight term and the weighted increases for all 50 States were summed to estimate increases in crashes due to any 5 mph increase in State maximum speed limit. Table 153 summarizes this process. For example, Alabama's maximum speed limit in 2005 was 70 mph. A potential +5 mph increase to 75 mph in this State was estimated to result in a 19 percent increase in both fatal and non-fatal injury crashes based on Equations (73) and (74). Alabama's contribution to a national increase in fatal and injury crashes was calculated by multiplying its 0.0138 weight by 19, which corresponds to an estimated 0.2622 percent increase in the total national number of fatal and injury crashes as a result of a +5 mph increase in Alabama.

To calculate a national increase, the weighted increases for all 50 States were summed. On average, a +5 mph increase in State maximum speed limit was estimated to increase fatal and non-fatal injury crashes on rural highways by 19.5 percent, and 19.1 percent, respectively. Since the national estimated percentage increase in fatal and non-fatal injury crashes are within 0.4 percentage points of each other, the projection model applies an effectiveness corresponding to a mean 19.3 percent increase for all crashes in the injury-crash target population due to 5 mph increases in State maximum speed limits.

Table 153. Estimated crash increases associated with +5 mph speed limit increase

State	Weight (% of 2009 crashes)	2005 Max Limit (mph)	Potential % Crash Increase		Weighted Crash Increase	
			Fatal	Injury	Fatal	Injury
AL	1.38	70	19	19	0.2622	0.2622
AK	0.04	65	22	20	0.0088	0.0080
AZ	1.83	75	17	18	0.3111	0.3294
AR	1.06	70	19	19	0.2014	0.2014
CA	8.80	70	19	19	1.6720	1.6720
CO	1.73	75	17	18	0.2941	0.3114
CT	1.37	65	22	20	0.3014	0.2740
DE	0.27	65	22	20	0.0594	0.0540
FL	6.77	70	19	19	1.4894	1.3540
GA	4.39	70	19	19	0.8341	0.8341
HI	0.21	60	25	22	0.0525	0.0462
ID	0.37	75	17	18	0.0629	0.0666
IL	3.40	65	22	20	0.7480	0.6800
IN	1.82	70	19	19	0.3458	0.3458
IO	0.78	70	19	19	0.1482	0.1482
KS	0.76	70	19	19	0.1444	0.1444
KY	1.36	65	22	20	0.2992	0.2720
LA	2.44	70	19	19	0.4636	0.4636
ME	0.35	65	22	20	0.0770	0.0700
MD	1.74	65	22	20	0.3828	0.3480
MA	2.43	65	22	20	0.5346	0.4860
MI	2.88	70	19	19	0.5472	0.5472
MN	1.19	70	19	19	0.2261	0.2261
MS	2.17	70	19	19	0.4123	0.4123
MO	2.00	70	19	19	0.3800	0.3800
MT	0.32	75	17	18	0.0544	0.0576
NE	0.66	75	17	18	0.1122	0.1188
NV	0.52	75	17	18	0.0884	0.0936
NH	0.33	65	22	20	0.0726	0.0660
NJ	3.59	65	22	20	0.7898	0.7180
NM	0.71	75	17	18	0.1207	0.1278
NY	7.14	65	22	20	1.5708	1.4280
NC	3.73	70	19	19	0.7087	0.7087
ND	0.14	75	17	18	0.0238	0.0252
OH	3.93	65	22	20	0.8646	0.7860
OK	2.29	75	17	18	0.3893	0.4122
OR	0.96	70	19	19	0.1824	0.1824
PA	3.33	65	22	20	0.7326	0.6660
RI	0.16	65	22	20	0.0352	0.0320
SC	1.69	70	19	19	0.3211	0.3211
SD	0.19	75	17	18	0.0323	0.0342
TN	2.58	70	19	19	0.4902	0.4902
TX	8.35	80	15	17	1.2525	1.4195
UT	1.04	75	17	18	0.1768	0.1872
VT	0.14	65	22	20	0.0308	0.0280
VA	2.38	65	22	20	0.5236	0.4760
WA	1.92	70	19	19	0.3648	0.3648
WV	0.55	70	19	19	0.1045	0.1045
WI	1.67	65	22	20	0.3674	0.3340
WY	0.18	75	17	18	0.0306	0.0324
				Total	19.5%	19.1%

F.2.3 Maximum Speed Limit Increases Penetration

Because the source CDS cases for the model were not sampled to be representative by State, overall penetration was estimated nationally, rather than on a State-by-State basis. This national penetration was essentially an estimate of the percentage of U.S. crashes in a given year that occur in States that have enacted a +5 mph maximum speed limit increase since 2005. From January 1, 2005, to December 31, 2018, there were 22 increases in State maximum speed limits in individual States. Since the national "penetration" resulting from a State speed limit increase will not be the same for each State (e.g., a +5 mph increase in California has a much greater effect on average national crash safety than a +5 mph increase in Rhode Island), national penetration has been estimated by multiplying the number of +5 mph speed limit increases by the State weight in Table 152. Figure 33 indicates the timing and the impact of each State's speed limit increases on national penetration using 2005 as a baseline. For example, the step labeled KY in 2007 represents Kentucky's 2007 65-to-70 mph increase, weighted by 1.36 percent from Table 152. In 2012 Maine increased the max speed to 75 mph from 65 mph, effectively two +5 mph changes. The penetration increase in 2012 due to Maine is 2×0.35%=0.7%.

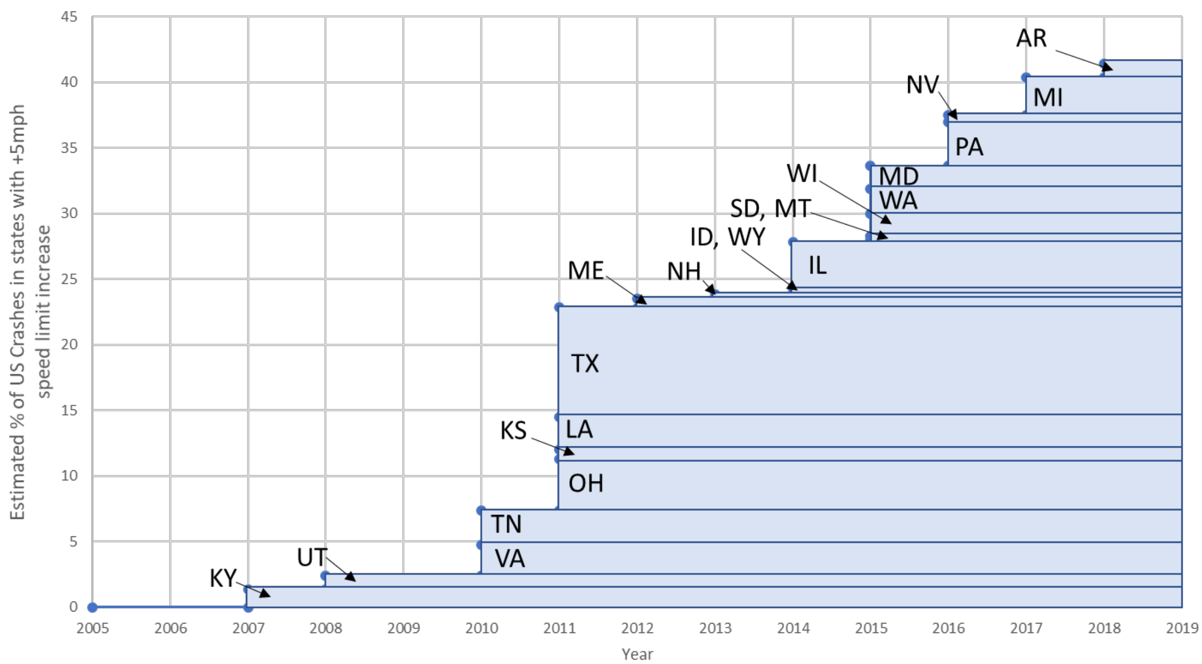

Figure 33. +5 mph speed limit increases weighted by State over 2005 levels

Since several States currently have pending legislation or lobbyist groups advocating for higher maximum speed limits, it is expected that additional increases will occur. Future penetration was estimated by assuming that overall national penetration, calculated based on State weights, will continue to increase at the same rate until reaching a plateau. The plateau was estimated under the approximation that half of the States with State maximum limits under 75 mph in 2018 will have one +5 mph increase, resulting in an estimate of 36 percentage points of continued penetration beyond current levels (Table 154). The estimate for future penetration was developed by placing a linear best-fit line through the weighted pre-2019 data from Figure 33 up to the estimated plateau, 36 percentage points higher than current rates (Table 154).

Table 154. Estimated additional penetration after 2018

States with speed limits <75 mph in 2018	Weight
AL	0.0138
AK	0.0004
CA	0.0880
CT	0.0137
DE	0.0027
FL	0.0677
GA	0.0439
HI	0.0021
IL	0.0340
IN	0.0182
IA	0.0078
KY	0.0136
MD	0.0174
MA	0.0243
MN	0.0119
MS	0.0217
MO	0.0200
NH	0.0033
NJ	0.0359
NY	0.0714
NC	0.0373
OH	0.0393
OR	0.0096
PA	0.0333
RI	0.0016
SC	0.0169
TN	0.0258
VT	0.0014
VA	0.0238
WV	0.0055
WI	0.0167
% of U.S. crashes in States with maximum speed limit <75 mph: sum	**0.72 (72%)**
Estimated penetration increase: 0.5 (sum)	**0.36 (36%)**

Based on the known speed limit changes since 2005, the rate of increases since 2005, and projected speed limit increases, estimated penetration (% of crashes in the target population affected by the speed limit increase) is plotted in Figure 34. Specific penetration values from Figure 34 used for the projection model are summarized in Table 155.

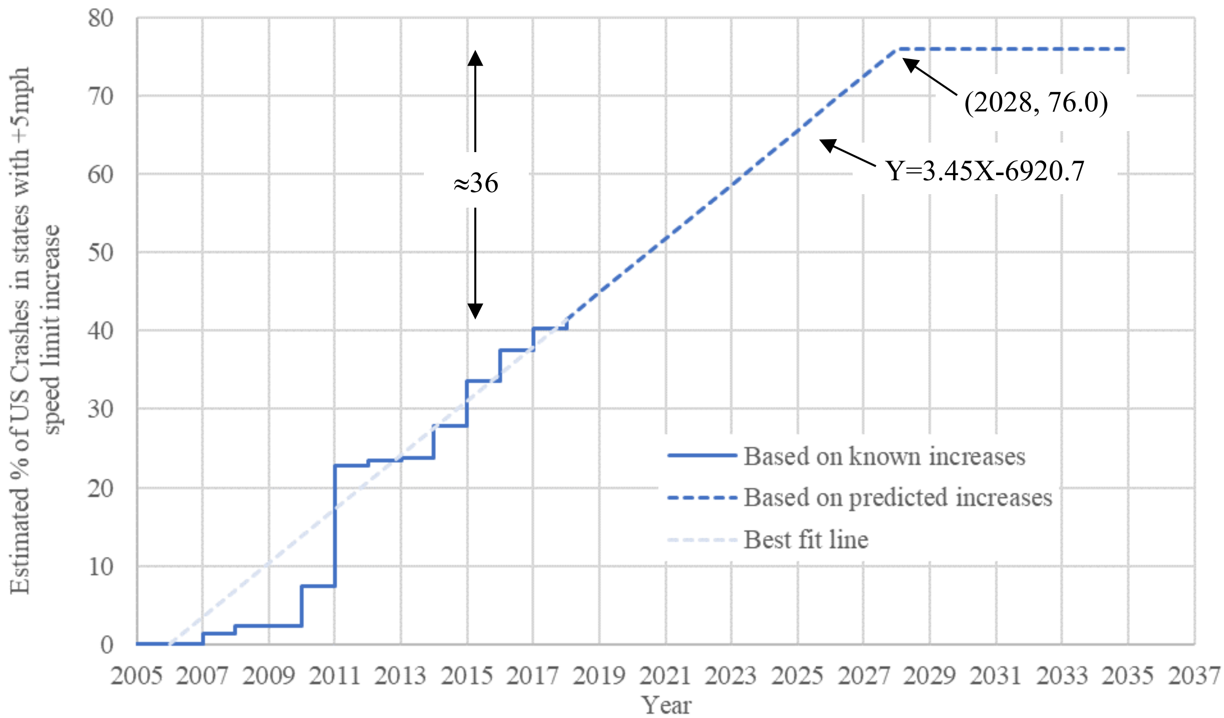

Figure 34. Estimated penetration for maximum State speed limit increases over 2005 levels by crash year

Table 155. Penetration of maximum State speed limit increases over 2005 levels (β_{TY} and α_{CY})

Crash Year	α_{CY} for 2009-2015 and Overall β_{TY} for 2014, 2020, 2025, 2030 (%)
≤ 2005	0.0
2006	0.0
2007	1.4
2008	2.4
2009	2.4
2010	7.4
2011	22.8
2012	23.5
2013	23.8
2014	27.8
2015	33.6
2020	48.3
2025	65.6
2030	76.0

F.3 Cable Median Barriers

Cross-median crashes, often referred to as cross-overs, are among the most injurious and fatal crashes occurring on highways. The number of these crashes can be minimized by installing a median barrier. The installation of tension cable median barriers on rural interstates, as seen in Figure 35, has been increasing since the 1990s (Ray et al., 2009). CMBs function by redirecting a striking vehicle by elastically stretching the cables, minimizing the forces on the vehicle and its occupants. During a crash, the kinetic energy of the vehicle is absorbed by deformation of the posts and stretching of the cables. This type of median barrier is an advantageous choice due to its low installation costs, reduced impact forces, and better visibility when compared to solid barriers (Russo et al., 2016). Cable median barriers significantly reduce cross-over crashes compared to no barrier when placed correctly in the median to engage with the vehicle without over-ride or under-ride. They also reduce injuries when compared to crashes with concrete or guard rail barriers. However, CMBs do increase single vehicle, property-damage-only crashes when compared to no barrier.

Figure 35. Example of a cable median barrier

F.3.1 Cable Median Barrier Target Population

The installation of CMBs affect two types of crashes, identified as follows:

- Multi-vehicle cross-over crashes where a vehicle departs the road on the left side and collides with a vehicle in the oncoming lane, and
- Single-vehicle crashes where the vehicle departs the left side of the road and strikes a fixed object.

The target population for both types of crashes is expected to be limited to those occurring on rural divided highways with speed limits greater than or equal to 55 mph.

Effectiveness was estimated separately for each of these target populations, which were identified in the projection model as follows. For both target populations, crashes in the target population were limited using the following NASS CDS variables:

- GV/TRAFFLOW=1 (divided, no barrier)
- GV/LANES>1 (at least two lanes)
- GV/SPLIMIT>88 (speed limit ≥ 55 mph)
- GV/TRAFCONT^ in (1:8) (no traffic signals)

The cross-over target population was identified using the following NASS CDS variables:

- ACC/VEHFORMS>1, and
- GV/PREEVENT=62 (vehicle encroaching into lane from opposite direction over left lane line)

The single-vehicle target population was identified using the following NASS CDS variables:

- GV/ACCTYPE in (6-10), and
- GV/OBJCONT1 or OBJCONT2 in (31, 32, 36, 38, 39, 41:45, 50:53, 57, 60, 61, 64, 68, and 69)

F.3.2 Cable Median Barrier Effectiveness

CMBs are effective at preventing most cross-overs and reducing the number of occupants who suffer disabling injuries. However, CMBs increase the number of low-severity injuries and non-injury crashes. Therefore, the effectiveness of CMBs varies based on the type of crash.

F.3.2.1 Effectiveness in cross-over crashes

Cable median barriers prevent approximately 94 percent of cross-over crashes (Ray et al., 2009; Villwock et al., 2010; Chitturi et al., 2011). Therefore, effectiveness of 94 percent was applied to all cases in the target population. Since effectiveness reflects prevention of the crash, case weight in each target population crash was multiplied by ($1-E_{adj}$), where E_{adj} was the effectiveness adjusted for penetration.

It is acknowledged that some of the cross-over crashes in the future will become single-vehicle crashes into structures in the median with implementation of CMB. This expected increase in single-vehicle crashes was accounted for by upweighting some categories of crashes in the single-vehicle target population, as discussed below.

F.3.2.2 Effectiveness in single-vehicle crashes

Since some vehicles that depart the left side of the road will come to a rest mid-median, the presence of any barrier will increase police-reported single vehicle crashes of this type by about 70 percent (Ray et al., 2009; Villwock et al., 2010; Chitturi et al., 2011). However, 70 to 88 percent of those police-reported single vehicle crashes on rural highways with a CMB will be low-severity PDO crashes (Ray et al., 2009; Villwock et al., 2010; Chitturi et al., 2011).

The distribution of injury severity expected after the installation of a CMB has been estimated in the literature (Shankar et al., 1996; Hu & Donnell, 2010). Using the KABCO scale, the percentage of occupants killed or with incapacitating injuries decreases with the installation of a CMB, while the percentage of occupants with less severe or no injuries increase (Table 156).

Therefore, the effect of cable median barriers on single vehicle crashes was applied in two steps:

1. The percentages of single vehicle crashes with severe injuries, less severe injuries, and no injuries was shifted after application of CMB in the model.
2. Overall, a 70 percent increase in single vehicle crashes was applied due to the presence of the barrier.

Table 156. Estimated distribution of KABCO injury severities for single vehicle crashes on rural highways

KABCO category	Percentage of occupants by injury severity based on median type (%)	
	No Barrier	CMB
K (Killed)	0.6	0.5
A (Incapacitating)	14.8	1.0
B (Non-Incapacitating)	5.1	5.4
C (Pain complaint)	11.5	13.9
O (No injury)	68.0	79.2
Total	100	100

Since the projection model adjusts occupant cases in the NASS CDS database, which uses MAIS for occupant injury severity, Table 156 was converted using the KABCO/MAIS translator supplied by Blincoe et al. (2015). The resulting occupant injury severity broken down by MAIS is in Table 157.

Table 157. Estimated distribution of MAIS injury severities for single vehicle crashes on rural highways

Fatality	MAIS	Percentage of occupants by injury severity based on median type (%)	
		No Barrier	CMB
Fatal	Any MAIS	0.66	0.50
Not Fatal	5	0.27	0.03
Not Fatal	4	0.79	0.20
Not Fatal	3	2.17	0.47
Not Fatal	2	4.51	2.10
Not Fatal	1	32.4	28.3
Not Fatal	0	59.2	68.4
	Total	100	100

Effectiveness, defined as the percentage reduction in cases at each MAIS level when going from no barrier to a CMB on a rural highway, is shown in Table 158. Effectiveness accounts for the redistribution of case injury severity (reduction of higher-severity cases and increase in lower-severity cases), and an overall 70 percent increase in single vehicle crashes. For example, the percentage of occupant cases in this target population with MAIS 0 injuries increased from 59.2 percent with no barrier to 68.4 percent with a CMB. Additionally, there was an estimated approximate 70 percent increase in single vehicle crashes overall (Ray et al., 2009; Villwock et al., 2010; Chitturi et al., 2011), which ultimately resulted in an estimated 96.4 percent increase in MAIS 0 injury cases in the single-vehicle target population when a CMB was installed. Based on this method, the frequency of more serious injury cases was expected to decrease, while MAIS 0 and 1 cases would increase, resulting in negative effectiveness for these lower severity levels.

Table 158. Overall effectiveness of CMB when compared to no barrier

MAIS	Percentage of occupant injuries based on median type		70% increase (1.7×CMB)	Effectiveness % (Reduction from "No Barrier")
	No Barrier	CMB		
3+	3.89	1.20	2.04	47.6%
2	4.51	2.10	3.56	21.1%
1	32.4	28.3	48.1	-48.5%
0	59.2	68.4	116.3	-96.4%
Total	100	100	170	

For case occupants in the CMB single-vehicle crash target population, CMB effectiveness was assigned based on the MAIS in the crash. For example, a crash in which the maximum injury in any vehicle was an AIS 2 was assigned an effectiveness of 21.1 percent, reflecting a 21.1 percent reduction in crashes of this severity.

It is assumed that the estimated effectiveness of CMB as applied to the projection model was conservative. This assumption is primarily because the studies used to develop these estimations were based on all police reported, single vehicle crashes on a stretch of rural highway, including crashes where the vehicle left either the left or right side of the roadway. However, the projection model applied this countermeasure to a much more narrowly defined population which only included single vehicle crashes where a vehicle left the left side of the road.

F.3.3 Cable Median Barrier Penetration

The FHWA estimated that there were approximately 31,000 miles of rural highway in the United States (FHWA, 2014). The installation of CMBs along these highways is increasing due to their crash and cost effectiveness. In 2005 there was an estimated 1,900 miles of cable median barrier in the United States (Ray et al., 2009). Penetration of CMBs was defined as the likelihood that a crash along a rural highway would occur along a stretch of road with cable barrier. It was roughly estimated as (1,900/31,000) = 6.1% for 2005. In 2010 the NCHRP report 711 examined the use of CMB in 37 States and the participating States reported approximately 4,800 miles of cable barrier (Marzougui et al., 2012). Considering that the participating States make up 91 percent of the land area in the United States (Blank, 2012), the penetration for 2010 was estimated as (4,800/(.91*31,000))=17.0%. Assuming that cable median barrier installation continues at the same rate, the penetration of this countermeasure along rural highways was linearly modeled using Equation (76). Assuming the penetration of CMB along rural highways is approximately equivalent to the penetration of CMB at the locations of crashes in the target population, the percentage of crashes on rural highways likely exposed to cable median barrier is estimated by year in Figure 36. The estimated penetration of CMB by crash year used in the projection model is reported in Table 159.

$$Penetration = 2.1772(Year) - 4359.2 \tag{76}$$

where:

Penetration is the annual penetration of CMB estimated for the projection model, estimated for a given crash year.

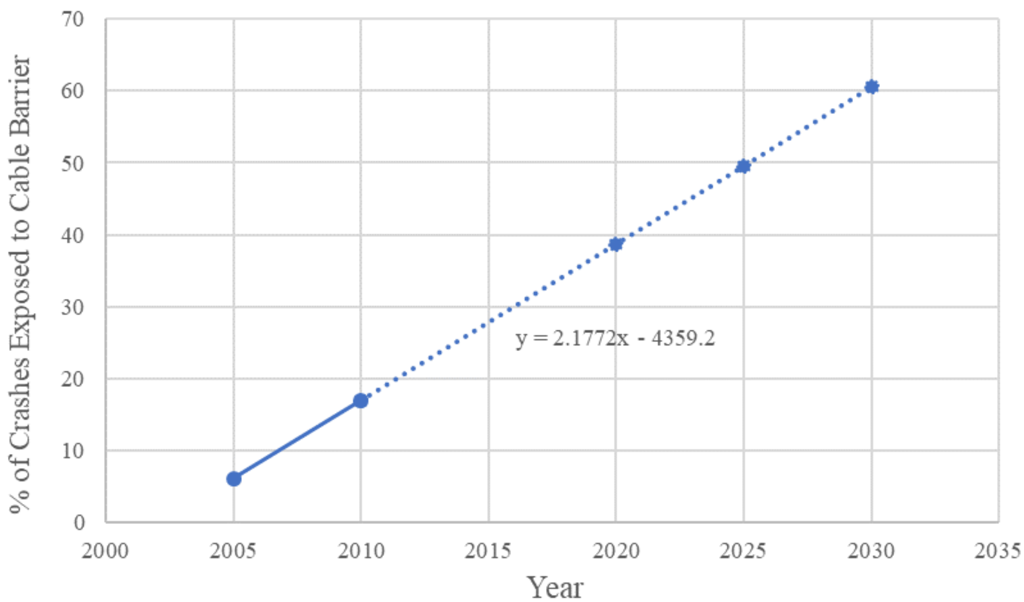

Figure 36. Percentage of crashes on rural highways estimated to have CMB

Table 159. Penetration of CMB (β_{TY} and α_{CY})

Crash Year	α_{CY} for 2004-2015 and Overall β_{TY} for 2014, 2020, 2025, 2030
2004	3.9
2005	6.1
2006	8.3
2007	10.4
2008	12.6
2009	14.8
2010	17.0
2011	19.1
2012	21.3
2013	23.5
2014	25.7
2015	27.9
2020	38.7
2025	49.6
2030	60.5

F.4 Red Light Cameras

Red light cameras are intended to increase compliance with traffic signals, which is expected to reduce intersection-related crashes (specifically, red-light-running crashes). There have been numerous studies of red light cameras over the past 20 years. Table 160 summarizes the key results of a literature review, focusing on studies that:

- Include safety outcomes, i.e., crash or injury rates versus only red light violations,
- Are broad, in terms of location and/or study time period, and
- Account for spillover effects and/or regression to the mean.

While there appears to be reasonable consistency in the results for the effectiveness of red light cameras in preventing right-angle crashes, the results for rear-end crashes vary substantially in terms of both magnitude and direction. Because even the direction of the effect is unclear, i.e., whether red light cameras increase or decrease rear-end crashes, rear-end crashes were not adjusted for the effectiveness of red light cameras in the current version of the projection model. However, should more definitive information become available in the future, it will be possible to either increase or decrease the rear-end crashes in the projection model.

Table 160. Red light camera literature review

Study	Method	Results (Changes With Red Light Cameras)
Aeron-Thomas and Hess (2005)	-Literature review of quasi-controlled trials and controlled before-after studies of red light cameras, with before-and-after periods of at least one year each -Before-and-after data extracted and rate ratios calculated for each study -Rate ratios were pooled to give an overall estimate, using a generic inverse variance method and a random-effects model -Studies were grouped according to the extent to which they adjusted for regression to the mean and spillover effects	8 percent and 7 percent decreases in total crashes (for partially adjusted and fully adjusted studies, respectively) 13 percent and 29 percent decreases in total casualty crashes (for partially adjusted and fully adjusted studies, respectively) 14 percent decrease in right-angle casualty crashes (for partially adjusted studies) 18 percent decrease in rear-end casualty crashes (for partially adjusted studies)
Council et al. (2005)	-Empirical Bayes before-and-after approach -Crash outcomes obtained from State crash data -Data from 7 jurisdictions at 132 treatment sites (across multiple States)	24.6 percent decrease in right-angle crashes 15.7 percent decrease in right-angle injury crashes 14.9 percent increase in rear-end crashes 24.0 percent increase in rear-end injury crashes $50,000 overall crash reduction benefit per site year
Erke (2009)	-Meta-analysis of studies on intersection crashes with enough information to compute effect estimates and statistical weights -Log-odds method used for effect estimates -Studies were evaluated according to the extent to which they adjusted for regression to the mean and spillover effects	15 percent increase in overall crashes 13 percent increase in injury crashes 43 percent increase in rear-end crashes 10 percent decrease in right-angle crashes
Hu and Cicchino (2017) *	-Data from 117 large U.S. cities (across States) collected from 1992 to 2014 -Compared 57 cities that initiated camera programs during 1992 to 2014 and 33 cities without cameras to examine effects of activating camera programs. -Compared 14 cities that removed cameras 2010 to 2014 to 29 regionally matched cities with continuous camera programs -Poisson regression was used to examine the relationship between fatal crash rates and the activation of red light cameras -Crash data obtained from FARS	-When cameras were activated: 21.3 percent decrease in fatal red-light-running crashes 14.2 percent decrease in fatal crashes -When cameras were deactivated: 30.1 percent increase in fatal red-light-running crashes 16.1 percent increase in fatal crashes

** The target population is defined in terms of "red-light-running crashes." Because CDS lacks information on causation, these crashes cannot be directly identified in the projection model.*

F.4.1 Red Light Camera Target Population

Ideally, the target population for red light cameras would be defined specifically as red-light-running crashes. However, NASS CDS does not include any variables that specify whether a vehicle ran a red light, so red-light-running crashes could not be directly identified in the projection model. Since this limitation was also true of other crash datasets, many studies defined the target population as right-angle intersection crashes because these crashes are most likely to be attributed to red-light-running and are most likely to benefit from red light cameras. Based on a review of the target populations used in the literature on red light cameras (Retting & Kyrychenko, 2002; Council et al., 2005; Washington & Shin, 2007), the following target population definition and corresponding NASS CDS variables were used in the projection model:

- Right-angle crashes[46] (broadside crashes involving two vehicles travelling at right angles to each other before the crash): ACCTYPE in (86:91),
- Intersection crash: RELINTER=2 for any vehicle in the crash, and
- Signalized intersection: TRAFCONT=1.

The target population defined above was consistent with the target population identified in the Council et al. study (2005) that was used to define effectiveness in the following section.

F.4.2 Red Light Camera Effectiveness

The results from the Council et al. study (2005) were used in this analysis because these authors reported the effectiveness of red light cameras on all right-angle crashes, as well as injury-only right angle crashes. This specificity allowed for a more detailed application of effectiveness to injury and non-injury crashes separately for a target population that could be defined for NASS CDS cases in the projection model. The results were reasonably consistent with the results of the other studies from Table 160.

To apply Council's estimates to both fatal/injury crashes and non-injury crashes, effectiveness estimates were calculated for non-injury crashes using Equation (77) and the relative proportions of fatal/injury target crashes to non-injury target crashes, which were obtained from the crash statistics provided in the Council report. These statistics are shown in Table 161, along with the resulting effectiveness estimates for non-injury crashes.

[46] LTAP crashes are not included because left-turn crashes do not typically involve red-light-running (Retting & Kyrychenko, 2002).

By the definition of effectiveness:

$$E_{all} = \frac{E_{non-inj} * Total_{non-inj} + E_{inj} * Total_{inj}}{Total_{non-inj} + Total_{inj}} \tag{77}$$

where:
E is the effectiveness (in injury cases, non-injury cases, and in all cases), and
Total is the number of injury or non-injury crashes in NCHRP crash statistics.

That relationship can be rearranged to isolate the effectiveness specifically in non-injury cases:

$$E_{non-inj} = \frac{E_{all} * (Total_{non-inj} + Total_{inj}) - E_{inj} * Total_{inj}}{Total_{non-inj}} \tag{78}$$

Table 161. Effectiveness estimate calculation for non-injury crashes

From Source Data on Effectiveness Council et al., (2005)				Calculated With Equation (78)
E_{all}	**E_{inj}**	**$Total_{inj}$**	**$Total_{non-inj}$**	**$Eff_{non-inj}$**
24.6%	15.7%	351	1291	27.0%

In summary, the effectiveness values in Table 162 were applied to cases in each target subpopulation in the projection model. Injury crashes were defined as crashes in which at least one occupant in one vehicle was listed as having at least one AIS 1+ injury.

Table 162. Effectiveness of red light camera for application to projection model

Target population	Sub-population	Effectiveness
Right-angle intersection crashes	Injury crashes	15.7%
	Non-injury crashes	27.0%

F.4.3 Red Light Camera Penetration

The "penetration" of red light cameras was estimated based on the average percentage of the U.S. population who live in communities with red light camera programs, using trends in the number of U.S. communities with red light camera programs and population data. It was approximated that the percentage of the population who lives in red light camera communities corresponds to the percentage of intersection exposures that occur at intersections that include red light cameras. This exposure percentage is analogous to the penetration (β) used in other countermeasures, and it can be used to estimate the likelihood that an intersection crash in the retrospective dataset occurred at an intersection with red light cameras or whether red light cameras would be expected to be present for a crash in the future projection dataset.

There were no available projections for the number of red light camera programs in the future, but IIHS has reported the number of U.S. communities with red light camera programs each year through 2017, as shown in Table 163 (IIHS, 2018). As of 2018 there existed pending legislation in at least eight States to restrict automated enforcement and pending legislation in five States to allow automated enforcement (Goble, 2018). Therefore, it was assumed that while new red light camera programs would likely continue to be initiated, more red light camera programs would be discontinued than initiated each year. Based on this assumption, it was estimated that the number of communities with red light camera programs would continue to decrease at the 2012 to 2017 rate until the number reaches half of the 2012 peak value. This estimated projection is shown in the shaded cells in Table 163. After the number of communities with red light cameras decreases to half the peak number in 2025, it is estimated, for lack of other data, that communities of various sizes will start and discontinue red light camera programs over time, and therefore this percentage will remain approximately constant after 2025.

Table 163. Number of U.S. communities with red light camera programs by year

Year	Number of U.S. Communities With Red Light Camera Programs
2004	94
2005	115
2006	155
2007	243
2008	380
2009	440
2010	491
2011	530
2012	533
2013	528
2014	516
2015	467
2016	458
2017	430
2018	409.4
2019	388.8
2020	368.2
2021	347.6
2022	327.0
2023	306.4
2024	285.8
2025	266.5
2026	266.5
2027	266.5
2028	266.5
2029	266.5
2030	266.5

To estimate penetration of red light cameras for application in the projection model, it was necessary to convert the number of communities with red light camera programs into an estimate of exposure, estimated in this case by the percentage of the population who live in communities with red light camera programs. The percentage of the U.S. population represented by each single community with a red-light camera program was calculated using the average population of U.S. communities with red light camera programs and the total U.S. population:

1. Using the 2018 Automated Traffic Enforcement State Surveys (NHTSA, 2018a), the average population of all jurisdictions (cities, counties, or municipalities) that reported both red light camera usage and population data was calculated as approximately 209,304 people per jurisdiction.
2. The total U.S. population in 2017 was estimated as 325,719,178 by the Census Bureau (Census Bureau, 2019b).
3. Therefore, it was estimated that the average community using red light cameras represented approximately 0.064 percent (209,304/325,719,178) of the U.S. population, in 2017.

Multiplying this percentage (0.064%) by the number of communities with red light camera programs provided the percentage of the U.S. population expected to live in communities with red light camera programs each year, as shown in Table 164. The decreasing penetration from 2012 through 2030 can result in a negative adjusted effectiveness for a given case since, for example, a 2011 crash in the target population would be *less* likely to have an available red-light camera in 2020 to 2030 than at the time of the original crash.

Table 164. Penetration of red light cameras (β_{TY} and α_{CY})

Crash Year	α_{CY} for 2004-2030 and Overall β_{TY} for 2014, 2020, 2025, 2030 (%)
2004	6.0
2005	7.4
2006	10.0
2007	15.6
2008	24.4
2009	28.3
2010	31.6
2011	34.1
2012	34.3
2013	33.9
2014	33.2
2015	30.0
2016	29.4
2017	27.6
2018	26.3
2019	25.0
2020	23.7
2021	22.3
2022	21.0
2023	19.7
2024	18.4
2025	17.1
2026	17.1
2027	17.1
2028	17.1
2029	17.1
2030	17.1

Interaction with roundabouts countermeasure: Red light cameras will not be installed in intersections in the future that are designed as roundabouts. The roundabouts countermeasure is not included in the evaluation version of the model, since penetration was determined to be essentially unchanged from the retrospective period to the evaluation period. However, the roundabouts countermeasure can be applied optionally in versions that project into the future. In runs of the model that include the optional roundabouts countermeasure, this interaction between red light cameras and roundabouts is addressed by reducing the penetration of the red-light countermeasure by the hypothesized penetration of roundabouts (Equation (79)). For example, a hypothesized 5 percent penetration of roundabouts among intersections in 2030 would reduce the 17.1 percent penetration of red light cameras by 5 percent to 16.2 percent. Note that this broad adjustment does not account for the likelihood that red light cameras and roundabouts would be installed preferentially in certain locations, such as urban locations or intersections with a history of high-frequency crashes.

$$\beta_{TY/RedLIght\ Cameras\ (reduced)} = \beta_{TY/RedLight\ Cameras} \times (1 - \beta_{TY/Roundabouts}) \qquad (79)$$

where:

$\beta_{TY/Roundabouts}$ *is the penetration of roundabouts in versions of the model that include roundabouts.*

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