

An Assessment of the Effects of Passenger Vehicle Weight and Size on Accident and Fatality Risk Based on Data for 1991 through 2007 Model Year Vehicles

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ABSTRACT

Quantifying the independent effects of vehicle weight and size on overall vehicle safety is necessary in order to assess the risks and benefits of vehicle weight reduction. This paper describes the results of one-stage and two-stage logistic regression analyses of the effects of passenger vehicle weight, wheelbase, track, and footprint on fatalities per accident, accidents per exposure (e.g., vehicle-miles-traveled), and fatalities per exposure using national and multi-state traffic accident and exposure databases. The analyses were accomplished in two phases. The first phase used 1995 through 2000 calendar year data for 1991 through 1999 model year vehicles. The second phase used 2002 through 2008 calendar year data for 2000 through 2007 model year vehicles. The overall fatalities per exposure results tend to confirm the one-stage results previously reported by NHTSA, however the new two-stage results provide additional insight into the independent effects of weight reduction and size reduction on vehicle crash involvement, crashworthiness and crash compatibility. The sensitivity of the results to various databases, variables, and assumptions was also investigated. The results from both phases indicated that the estimated overall effects of passenger vehicle weight reduction (while holding vehicle size constant) on fatalities are small in comparison to other variables and may not be statistically significant depending on various key assumptions (e.g., controlling for changes in wheelbase and track versus changes in footprint, and the type of induced-exposure data that are used), and this is due to small or opposing effects of these variables on crash involvement, crashworthiness and crash compatibility.

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INTRODUCTION

Quantifying the independent effects of light passenger vehicle weight and size on overall vehicle safety is necessary in order to assess the risks and benefits of vehicle weight reduction on crashworthiness, crash compatibility, and crash involvement and other vehicle design goals such as fuel economy. The National Highway Traffic Safety Administration (NHTSA¹), Dynamic Research, Inc. (DRI), Lawrence Berkley National Laboratory (LBNL) and other researchers have been investigating the effects of weight and

size on vehicle safety for many years, using both statistical analysis of accident data and computer simulations based on predictive models (e.g., [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15]²). This research and understanding of the effects of weight and size on safety has evolved from the initial assumption that vehicle weight and size are not independent and therefore have one-and-the-same effect on safety,³ to the need to treat vehicle weight and size as independent vehicle parameters⁴ that may have different independent effects on vehicle accident and fatality rates.⁵

¹ Acronyms are listed in the Definitions/Abbreviations section at the end of this paper.

² [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15] provide only a partial list of relevant scientific literature since 1997, listed in chronological order. See also US Federal Dockets NHTSA-2003-16318 and NHTSA-2010-0152. A brief chronology of the NHTSA and DRI analyses is provided in Ref [13].

³ For example, Joks, Massie, and Pichler (1998) wrote that "some researchers consider a distinction of weight and size unnecessary" [16, p 15]; and Crandall and Graham (1989) explained that "'Weight' is chosen as the independent variable in these investigations because it is both easily measured and strongly correlated with other vehicle attributes such as wheel-base, track, 'size' in general, hood length, trunk size, and engine displacement" [17, p 110].

⁴ For example, vehicles can be designed to be relatively heavier or lighter, depending on shape, features, structure, materials, drivetrain and many other variables, but with the same wheelbase and track.

⁵ O'Neill, Joks, and Haddon explained in 1974 that mass and size had different effects on crashworthiness for theoretical reasons and concluded that "For vehicles using the same roads these relationships suggest a crashworthiness design concept for inter-vehicular crashes that regards increases in vehicle size as primarily protective, and increase in vehicle weight as primarily hostile, indicating the desirability of relatively sizable but not heavy vehicles." [18, p 368].

Results based on this new understanding are reflected in the adoption of vehicle “footprint”⁶ based fuel economy standards in the US (e.g., [19,20]).

This paper describes the results of one-stage and two-stage weighted logistic regression (i.e., case-by-case) analyses of the effects of passenger vehicle weight, wheelbase, track, and footprint on fatalities per accident, accidents per exposure (e.g., vehicle miles traveled), and fatalities per exposure using national and multi-state traffic accident and exposure databases. This analysis considers all fatalities in the crash to represent a societal viewpoint, rather than just “occupant” fatalities which represents a self-protection viewpoint. The analyses were accomplished in two phases. The first phase used 1995 through 2000 calendar year data for 1991 through 1999 model year vehicles, the results of which were described in detail in [12]. The second phase used 2002 through 2008 calendar year data for 2000 through 2007 model year vehicles, preliminary results of which were described in detail in [13-14]. The results from the second phase have been updated based on the latest available data from the NHTSA (as of April 2012).

BASIC METHODOLOGY

The basic methodology used herein was originally developed by NHTSA as described in [1]. This methodology has been subsequently revised, extended, and refined, often independently and in parallel, by both NHTSA and DRI.

Accident and Fatality Risk Models

DRI has assumed that the effects of vehicle weight and size and other factors on accident and fatality risk can be expressed in terms of the following two-stage process, where details of the individual stages are described in later sections:

$$\underbrace{\log\left(\frac{F}{E}\right)}_{\text{Measure of overall fatality risk}} = \underbrace{\log\left(\frac{F}{A}\right)}_{\text{Measure of crashworthiness \& crash compatibility}} + \underbrace{\log\left(\frac{A}{E}\right)}_{\text{Measure of crash involvement}} \quad (1)$$

where “ F ” represents the total number of fatalities in the accident (corresponding to a societal viewpoint), “ A ” represents the number of accidents, and “ E ” represents the exposure (e.g., vehicle registration years or vehicle miles traveled of exposure) and “ $\log(x)$ ” is the natural logarithm of “ x ”. This model is justified because crash related fatalities can only occur if there is a crash, and crashes can only occur if vehicles are being driven on the road and therefore exposed

to potential crash conditions. The “ F/A ” ratio in Eq. (1) is therefore the relative risk of fatality per crash, which is a measure of “crashworthiness” and “crash compatibility.” The “ A/E ” ratio is the number of crashes relative to exposure (e.g., “ E ” is vehicle miles traveled), which is a measure of “crash involvement”.

It was further assumed that each of the terms in Eq. (1) can be expressed as a linear combination of accident, vehicle, and driver factors as follows:

$$\log\left(\frac{F}{E}\right) = \beta_{F/E,0} + \sum_{i=1} \beta_{F/E,i} x_i + \varepsilon_{F/E} \quad (2)$$

$$\log\left(\frac{F}{A}\right) = \beta_{F/A,0} + \sum_{i=1} \beta_{F/A,i} x_i + \varepsilon_{F/A} \quad (3)$$

$$\log\left(\frac{A}{E}\right) = \beta_{A/E,0} + \sum_{i=1} \beta_{A/E,i} x_i + \varepsilon_{A/E} \quad (4)$$

where x_i are weight and size and other control variables that are assumed to be related to the probability of crash occurrence or outcome, β_i are model coefficients with values that are unknown and to be estimated,⁷ and where the β_i are related as follows:

$$\beta_{F/E,i} = \beta_{F/A,i} + \beta_{A/E,i} \quad \text{for } i = 0, 1, 2, \dots \quad (5)$$

Vehicle weight and size variables

Vehicle weight and size were quantified in terms of curb weight (CURBWT, lbs), wheelbase (WHEELBAS, in), and the average of the front and rear track (TRAKWDTH, in) for the purpose of this analysis. These vehicle parameters were chosen because they are typically the most commonly available measures of vehicle weight, length, and width at the vehicle make-model-year and body type level of detail. The rationale for these parameters is that vehicle mass, length, and width have different effects on vehicle crashworthiness (e.g., as observed in [21]); and that vehicle mass, wheelbase, and track are separate terms in the rigid body dynamic equations of motion related to driver control (e.g., [22]) and therefore have different effects on crash involvement.

In addition, depending on the candidate vehicle weight and size model, the following vehicle parameters were derived from the basic vehicle parameters:

⁶Vehicle “Footprint” is defined as the product of the vehicle wheelbase and track. Footprint has units of area.

⁷Logistic regression analysis estimates the coefficient values for the log-odds ratio (e.g., $\log(F/(F-E))$) instead of the log of the rate on the left hand side of Eqs. (2-3). It is assumed throughout this analysis that $F \ll A \ll E$ and therefore the log-odds ratio and log of the rate are approximately the same (e.g., $\log(F/(F-E)) \approx \log(F/E)$). See footnote 22 in [4].

$$\text{UNDRWT00} = \begin{cases} \frac{\text{CURBWT} - W_0}{100 \text{ lbs}} & \text{if CURBWT} < W_0 \\ 0 & \text{if CURBWT} \geq W_0 \end{cases} \quad (6)$$

$$\text{OVERWT00} = \begin{cases} 0 & \text{if CURBWT} < W_0 \\ \frac{\text{CURBWT} - W_0}{100 \text{ lbs}} & \text{if CURBWT} \geq W_0 \end{cases} \quad (7)$$

$$\text{LBS00} = \frac{\text{CURBWT}}{100 \text{ lbs}} \quad (8)$$

$$\text{FOOTPRNT} = \frac{\text{WHEELBAS} \times \text{TRAKWDTH}}{144 \text{ in}^2} \quad (9)$$

where FOOTPRNT is the measure of the vehicle footprint (i.e., wheelbase times track) in square feet, and the other derived parameters are dimensionless. UNDRWT00 and OVERWT00 are used to define a two-piece linear curb weight model with a change in slope at W_0 , the value of which depends on the vehicle type and model year epoch. The two-piece model was introduced in the 2003 NHTSA report in order to model trends observed in aggregated fatality rates versus curb weight bin. The vehicle footprint is of interest as a single measure of vehicle size and a metric used in US fuel economy regulations.

Other control variables

There are many driver, vehicle, and environmental factors that can also affect accident and fatality risk besides vehicle weight and size. For consistency and comparability, these factors were controlled for using the same control variables that were used in the NHTSA analyses. These included, for example, nine different variables to describe the driver age (as a piecewise linear function) and sex; variables for the vehicle body type and subtype (e.g., 2-door vehicle, Sport Utility Vehicle (SUV)) and equipment (e.g., antilock brake system (ABS), electronic stability control (ESC), airbags); environmental variables such as night time, rural road; and variables for vehicle age and calendar year which may be related to vehicle usage and long term trends.

These variables were selected because they are a relatively parsimonious set of variables that can be assumed to describe or are associated with the main effects of the vehicle, driver and environment on accident and fatality risk, and they are available or derivable from the coded FARS, state accident data, and induced-exposure data that were used in this analysis. For example, there may be other vehicle technologies such as warning systems and seat belt

pretensioners that may also have an effect on accident and fatality risk, but these technologies are typically bundled with other vehicle technologies such as ESC or curtain airbags that are controlled for in the analysis. Likewise, control variables for the driver age and sex are assumed to represent other driver factors such as driver experience, skill, seat-belt use, impairment, and risk-taking in general, as well as the weight, stature, and injury tolerance of the driver. Environmental variables such as "rural road" also address factors such as emergency medical response time, etc.

Data

The data used in this analysis comprise fatal and reported accident data, vehicle registration data, annual mileage data, and vehicle parameter data. The data used for the two phases are summarized in Table 1. These data were used to construct three datasets comprising individual cases for vehicles involved in fatal crashes, vehicles involved in non-fatal crashes, and induced-exposure cases. The subject vehicle type, curb weight, wheelbase, track and control variables (e.g., driver age, night, rural road, road surface condition) were determined for each of these cases. The vehicle type, curb weight, wheelbase, track, and other equipment (e.g., ABS, ESC, airbags) were determined for each of the subject vehicles based on the vehicle identification number (VIN) recorded in the databases. The crash type (e.g., rollover) was also determined for each fatal and non-fatal crash case.⁸

Table 1 also lists the vehicle types and crash types that were used in the analysis. The Phase I vehicle and crash types are defined in [4], which are similar to but not exactly the same as earlier DRI reports (e.g., [2,3]). The Phase II vehicle and crash types correspond to the most recent NHTSA reports [9,15], as well as the LNBL reports [10,11].

The subject vehicle types for Phase I were passenger cars and light trucks and vans (LTVs). The rationale for treating these vehicle types separately is that passenger cars and LTVs are subject to different safety, fuel economy, and emissions regulations, due to possible differences in vehicle use, and therefore various factors that may have different effects on the passenger car and LTV fatality risk. As a result there are also differences in the control variables that are used in the regression analyses of these different vehicle types.

The LTV vehicle types for Phase II were further subdivided into truck-based LTVs as one group, and minivans and cross-over utility vehicles (CUVs) as another group. The rationale for this subdivision was that the minivans and CUVs had more passenger car type design features and intended use, compared to the truck-based LTVs.

⁸For the Phase II analysis DRI used fatal and induced-exposure data that was extracted and reduced from the FARS and state accident databases by NHTSA and was downloaded from NHTSA's [ftp://ftp.nhtsa.dot.gov/CAFE](http://ftp.nhtsa.dot.gov/CAFE) website. DRI independently extracted and reduced the non-fatal accident data from the state accident databases, as well as the fatal and induced-exposure data from the FARS and state accident databases for the Phase I analysis.

Table 1. Summary of Major Differences in Phase I and II Data

Attribute	Phase I	Phase II
Calendar Years	1995 - 2000	2002 - 2008
Model Years	1991 - 1999	2000 - 2007
Fatal Data	FARS data reduced by DRI	FARS data reduced by NHTSA (farscs24.sas7bdat, farsstop.sas7bdat)*
Reported Accident Data States	<u>8 States:</u> (FL,IL,MD,MO,NC,NM,OH,PA) reduced by DRI	<u>10 States:</u> (FL,KS,KY,MD,MI,MO,NE,PA,WA,WY) reduced by DRI
Induced-Exposure Data States	<u>8 States:</u> (FL,IL,MD,MO,NC,NM,OH,PA) reduced by DRI	<u>13 States:</u> (AL,FL,KS,KY,MD,MI,MO,NE,NJ,PA,WA,WI,WY) reduced by NHTSA (stcs2_6.sas7bdat, ststop_6.sas7bdat)*
Vehicle Types	<u>2 Vehicle Types:</u> 1) Passenger Cars, 2) Light Trucks and Vans (LTVs)	<u>3 Vehicle Types:</u> 1) Passenger Cars, 2) Truck-Based LTVs (TBLTVs) excl. vans, 3) Minivans and CUVs
Crash Types	<u>6 Crash Types:</u> 1) Rollovers, 2) Hit object, 3) Ped/bike/motorcycle (MC), 4) Hit heavy truck, 5) Hit PC 6) Hit LTV	<u>9 Crash Types:</u> 1) Rollovers, 2) Hit object, 3) Ped/bike/MC, 4) Hit heavy truck, 5) Hit light PC, CUV or Minivan 6) Hit heavy PC, CUV or Minivan 7) Hit light TBLTV 8) Hit heavy TBLTV 9) Other

* The name of the datafile which can be downloaded from NHTSA's <ftp://ftp.nhtsa.dot.gov/CAFE> website.

Fatal accident data

Fatal data for all US traffic crashes were obtained from the NHTSA Fatality Analysis Reporting System (FARS) [23]. FARS data comprise a census of all fatal traffic crashes in the US, which is compiled on an annual basis. Cases for vehicles involved in fatal accidents were then extracted from the FARS data files for comparison with cases with the same

human, vehicle, and environmental coded variables among the non-fatal accident data files and induced-exposure data files in order to estimate the effects of weight and size reduction on fatalities per accident and fatalities per exposure using logistic regression analysis.

Reported accident data

Reported accident data from various (i.e., 8 or 10) states, depending on data suitability and availability, were obtained from the NHTSA State Data System [24]. The criteria for state accident data suitability included having the first 10 characters of the vehicle identification number recorded in the state accident data files, which was needed in order to determine the various vehicle type, parameters, and equipment; and the ability to determine the values for the crash type and other control variables from the state specific data coding schemes. Cases for vehicles involved in non-fatal accidents were then extracted from these state data files for comparison with the corresponding (as described above) fatal data and induced-exposure data in order to estimate the effects of weight and size reduction on fatalities per accident and accidents per exposure using logistic regression analysis.

Exposure data

Exposure data is also needed in order to estimate the effects various factors have on the probability of an accident or fatality occurring. Crash exposure is commonly measured in terms of the number of vehicle-registration years (VRY) or the number of vehicle miles traveled (VMT).

One VRY represents one vehicle registered for one calendar year. For a group of vehicles in a given time period (comprising whole calendar years), the VRY is the number of vehicles registered in each calendar year, summed over a range of calendar years in the time period. VRY is often used because it can potentially be accurately determined from state motor vehicle registration/licensing rolls.

The VMT for one vehicle in a given time period would be the total distance traveled in miles in the time period. For a group of vehicles in a given time period, the VMT is the sum of the VMT for each vehicle in the group of vehicles. VMT may be more representative of vehicle crash exposure, but is often not directly available and is typically estimated based on sampled data from various sources (e.g., maintenance and repair odometer readings, self-reported survey data).

Vehicle registration and VMT data

Vehicle registration data providing the number of specific make-model-year-body type (MMYB) vehicles registered on July 1 of each calendar year⁹ in each of the 50 states plus the District of Columbia were obtained from R.L. Polk [25]. This data was used to determine the number of vehicle-registration years and to estimate the number of vehicle miles travel exposure for the MMYB vehicles in the fatal and reported accident databases. The number of vehicle

⁹The number of registered vehicles can change daily or weekly. Polk registration data provides a census of vehicles registered on July 1st of any given calendar year.

miles traveled for each MMYB vehicle in a given calendar year estimated by multiplying the number registered vehicles by the assumed annual miles traveled. The assumed annual miles traveled depended on the vehicle type or MMYB and the vehicle age (depending on the analysis phase), as described in [4,9].

Induced-exposure data

A limitation of the vehicle-based VRY and VMT exposure data is that these data do not directly provide information about who is driving the exposed vehicles and the environmental conditions in which they are being driven. Therefore an “induced-exposure” database was constructed using a subset of the reported accident data from the various states in order to extend the vehicle-based VRY and VMT exposure data to include information about the exposed vehicle drivers and environmental conditions. This subset was selected based on certain criteria in order to approximate a representative sample of all (not just crash involved) drivers and conditions for which the MMYB vehicles are being driven. Each of these cases were then weighted by either VRY or VMT at the MMYB level of detail in order to obtain a nationally representative exposure database suitable for comparison to the extracted fatal and non-fatal accident cases. This weighting procedure is described in detail in [4,9].

The challenge is how to select a representative sample of all drivers and conditions for which the MMYB vehicles are being driven. One possible criterion is to use “non-culpable vehicles” involved in two-vehicle crashes, where the fault has been assigned to the driver of the other vehicle based on the coded information on who was at fault available in the state accident data files (e.g., the other vehicle driver was charged with a violation and the “non-culpable” vehicle driver was not charged with a violation) [4,9]. Another possible criterion is to use “stopped vehicles” involved in two-vehicle crashes, where the stopped vehicle was legally stopped, and typically rear-ended [1]. The key assumption in both of these criteria are that the “non-culpable” or “stopped vehicle” driver was involved in the crash merely by chance (e.g., they were hit because they were blamelessly there), and are therefore randomly sampled from the population of all drivers with equal probability.

A possible disadvantage of the “non-culpable vehicle” induced-exposure criterion is that some drivers may be better able to avoid a collision than other drivers (i.e., due to experience or skill) even if they were not culpable, and therefore such drivers may be underrepresented in the resulting “non-culpable vehicle” induced-exposure database.

A possible disadvantage of the “stopped vehicle” induced-exposure criteria is that it is more restrictive and results in fewer induced-exposure cases, which may result in larger confidence intervals for the results.

Both criteria have the advantage that no other suitable exposure data have been found to date that better represent exposure for all drivers and conditions.

Vehicle parameter data

Vehicle parameter data was obtained from various sources, e.g., [26,27,28] as described in [2,3,9].

Model Coefficient Estimation Methods

The objective of this analysis was to estimate the effects of vehicle weight and size reduction on accidents and fatalities. This generally involves estimating values for the β_i model coefficients in Equations (2), (3), and/or (4) that best fit the available data. This has been accomplished in the past and in the present analysis using a variety of linear and logistic regression methods. These methods are briefly described along with the advantages and disadvantages of each approach.

Linear regression of aggregated data

The initial 1997 NHTSA and 2002 DRI reports [1,2] primarily used multi-variable linear regression analysis of aggregated data to estimate the values for the model coefficients (β_i).¹⁰ This generally involved aggregating the fatality and induced-exposure data into “bins” (e.g., for a given MMYB and calendar year), computing the fatality rates for the bins, and estimating the model coefficients using a weighted least squares regression of the binned data.

One advantage of using multi-variable linear regression is that the statistical methods are well developed and the estimates can be solved using linear algebraic methods [29]. The resulting estimates have the property that they are “Best Linear Unbiased Estimates” for the given data, and the confidence intervals can also be readily calculated, provided the basic assumptions about the data are valid.

The disadvantage of using the aggregated linear regression method is that substantial information is lost in the data aggregation process. The aggregated data comprise average values for the weight, size, and control variables (e.g., driver age), however information about the variability and correlation of the data variables within the bin are lost.

Therefore, the aggregated linear method was not used in the current analysis or in the 2004 and subsequent DRI reports.

Logistic regression of disaggregated data

The current analysis uses logistic regression methods to determine the maximum likelihood estimates (designated here as b_i) of the model coefficients (β_i) using disaggregated data (i.e., each case is treated individually) [30]. The advantage of this method is that the estimates are based on all of the available data (i.e., no information is lost), which helps to mitigate the possible effects of multicollinearity and model

¹⁰The 2003 DRI report also used a two-step aggregated linear regression analysis to estimate the effects of vehicle weight and size on the induced-exposure sampling (i.e., IE/VRY stage). This approach was replaced with a weighted logistic regression method in the 2004 and 2005 DRI reports.

over-parameterization (i.e., a large number of model coefficients).

Multicollinearity and model over-parameterization are undesirable because the estimates may become unreliable. One measure of this effect is the “Variance Inflation Factor” (VIF), which was computed for each regression. VIF values are by definition greater than or equal to 1, with larger values indicating that more multicollinearity is present. Some guidelines for VIF are as follows:

- Allison “*begins to get concerned*” with VIF values greater than 2.5 [33, p 50].
- Menard suggests that VIF values greater than 5 is a “*cause for concern*” and a VIF value greater than 10 “*almost certainly indicates a serious collinearity problem*” [34, p 76].

However, O'Brien offers a contrary view that “*Values of the VIF of 10, 20, 40, or even higher do not, by themselves, discount the results of regression analyses*” [35].

The logistic regression method also determines the standard errors of the estimates. These standard errors are the basis for the Wald Chi-Square statistic used for significance testing, but they do not include all sources of uncertainty in the results. Therefore these logistic regression standard errors are used to estimate a “lower bounds” for the 95% confidence interval of the estimates.

All of the logistic regressions were accomplished using both specialized Fortran software [31] and the SPSS (Statistical Package for the Social Sciences) “LOGISTIC REGRESSION” procedure [32]. The results from these two implementations were compared and found to be in very close agreement.

One-stage regression

The effects of weight and size on fatalities per exposure (e.g., VMT) according to the model in Eq. (2) were estimated using logistic regression analysis. The inputs to the regression are the fatal and induced-exposure datasets, comprising individual fatal cases and induced-exposure cases. Each fatal vehicle case was weighted by the number of fatalities in the crash, and each induced-exposure case was weighted by the VRY or VMT allocated to the induced-exposure case. This regression is referred to as a one-stage regression because the relationship between the two datasets (exposure and fatalities) is modeled by a single equation, resulting in a single set of maximum likelihood estimates for the model coefficients (i.e., $\beta_{F/E,i}$).

The 95% confidence intervals for the Phase II one-stage regressions were computed using the “jackknife” method described in pages 77-79 the 2011 NHTSA report [9]. In summary this method involved estimating the uncertainty in

the regression results due to FARS and induced-exposure based errors. This was accomplished by partitioning the fatal cases into 10 fatal subsamples based on the last digit of the FARS case number, and partitioning the induced-exposure data into 11 different subsamples based on the state from which the cases were derived.¹¹ Then the regression coefficients were re-estimated with one of the data subsamples removed (e.g., FARS cases with case numbers ending in a “1”, induced-exposure cases from Florida) and then calculating a “pseudo estimate” corresponding to an estimate based on only the removed data. Pseudo estimates were computed for each of the 10 fatal case subsamples and 11 induced-exposure case subsamples. The FARS based standard error was estimated based on 10 pseudo estimates with FARS data removed based on the last digit of the case number. The induced-exposure based standard error was estimated based on 11 pseudo estimates with data from one or more states removed.¹² The resulting 95% confidence interval was then calculated according to the following equation [9]:

$$95\% \text{ CI} = \pm t_{v,0.025} \sqrt{\frac{s_F^2}{10} + C^2 \frac{s_E^2}{11}} \quad (10)$$

where s_F is the standard deviation of the 10 FARS pseudo estimates, s_E is the standard deviation of the 11 induced-exposure pseudo estimates, $C=0.8718$ is a finite population correction, and the number of degrees-of-freedom “ v ” is assumed to be 10 and $t_{v,0.025}=2.262$.

Two-stage regression

The effects of weight and size on fatalities per accident, accidents per exposure, and fatalities per exposure were estimated using a “simultaneous three-way” two-stage logistic regression method first described in [3]. This method estimates the coefficients for the three Eqs. (2), (3) and (4) simultaneously such that the constraint Eq. (5) is also satisfied.

Ideally the fatalities per exposure results ($b_{F/E,i}$) using the two-stage method would be the same as the results using the one-stage method, however differences in the results have been observed. These differences may be due to factors that affect the reported accident involvement frequency (e.g., accident reporting thresholds which may vary from state to state) which have not been controlled for. Therefore the simultaneous three-way method was extended in [12] to support “internal control variables.” Internal control variables are similar to other variables in Eqs. (3) and (4) but are defined such that $\beta_{F/E,i}=0$ and $\beta_{F/A,i} = -\beta_{A/E,i}$ and therefore do

¹¹Data from Kansas, Nebraska, and Wyoming were combined into one subsample for this analysis. See [9].

¹²NHTSA constructed the induced-exposure data sets with “one or more states” removed directly from the non-publicly available state data using the method described in Section 2.6 of [9]. This method included combining exposure data for some low volume vehicles and dropping some fatal cases without corresponding exposure data. DRI was unable to reproduce NHTSA’s special handling of low volume vehicles using the publicly available induced-exposure data files. Therefore DRI used an alternative approach to approximate the NHTSA method using only the publicly available induced-exposure and fatal data. This included removing fatal cases with no corresponding induced-exposure at the make-model-body type-MY-CY level of detail from the data sets with “one or more states” removed.

not appear in Eq. (2). With this extension it was then possible to include additional control variables such as state and calendar year in the intermediate stages of the model, but not in the overall F/A model, in order to improve the overall fit to the data and agreement with the one-stage F/A results.

RESULTS

Results for each phase were obtained for the candidate models listed in Table 2. These models represent different combinations of wheelbase and track versus footprint, and stopped-vehicle versus non-culpable vehicle induced-exposure. The models with wheelbase and track are more directly related to vehicle design parameters, whereas the models with footprint are related to footprint based fuel economy standards. The different induced-exposure types were considered in order to assess possible effects this may have on the results. Note that Model D corresponds to the “baseline” model in the 2011 and 2012 NHTSA reports, and Models A, B, and C correspond to the “alternative” models 1, 3, and 2 in [15].

Table 2. Candidate Models

Model Designation	Vehicle Size Variables	Induced-Exposure Type
A	Wheelbase and Track	Stopped-Vehicle
B	Wheelbase and Track	Non-Culpable Vehicle
C	Footprint	Stopped-Vehicle
D*	Footprint	Non-Culpable Vehicle

*NHTSA 2011 and 2012 baseline model.

Phase I Results

The Phase I analysis used the methods and data to best reproduce and extend the results in the 2003 and 2010 NHTSA reports [4,8] to the extent possible.¹³ This involved estimating the change in fatalities compared to a baseline number of fatalities using logistic regressions of 1995 through 2000 calendar year data for 1991 through 1999 model year vehicles as indicated in Table 1. This was accomplished for all combinations of two vehicle types (passenger cars, LTVs), two weight groups, and six crash types defined in [4]. The passenger car regressions were based only on data for 4-door non-police cars and VRY exposure. The LTV regressions used VMT exposure. The baseline number of fatalities in each category is also from [4]. The estimated total change in fatalities for each vehicle type

and weight group is then the sum of the changes for all six crash types. The relative changes in fatalities were then determined by dividing the changes in fatalities by the corresponding baseline number of fatalities and converting the resulting values to percentages.

The effects of wheelbase, track, and footprint reduction were also scaled to approximately correspond to an “equivalent” 100 lb weight reduction.¹⁴ This was done so the relative effects of each weight and size term could be compared on an equal basis, and the total effect of the weight and size reductions would be somewhat independent of the number of weight and size reduction terms in the model. For example, it was found in [3] that a 100 lb weight reduction in passenger cars was also associated with a 1.01 in wheelbase and 0.34 in track reduction. The corresponding footprint reduction values are from [8]. These equivalent values, which are different for passenger cars and LTVs, are indicated in the legends of Figures 1, 2, 3, 4.¹⁵

One-stage results

The effects of weight and size reduction on overall fatalities were estimated using one-stage regressions of fatalities per exposure (F/E). For example, it was estimated using candidate Model B with data for only 4-door non-police cars that a 100 pound reduction in curb weight in cars weighing less than 2,950 lbs would result in an increase of 411 (± 90)¹⁶ fatalities, compared to 13,608 baseline fatalities. It was also estimated that a 1.01 inch wheelbase reduction would decrease fatalities by 52 (± 72) and a 0.34 in track reduction would increase fatalities by 257 (± 44). These results are not significantly different from NHTSA's results reported in Table 2-2 of [8]. These and other one-stage results for models B and D are tabulated on pages G.d-12, G.f-12, H.d-12, H.f-12 in Appendix G and H of [12].¹⁷ In addition, all of the VIF values for the regressions with curb weight, wheelbase and track were less than 6.6, and the VIF values for the regressions with curb weight and footprint were less than 6.8.

Two-stage results

The effects of weight and size reduction on crashworthiness, crash compatibility and crash involvement were estimated using simultaneous three-way two-stage regressions of fatalities per accident (F/A), accidents per exposure (A/E) and fatalities per exposure (F/E). The two-

¹³This included using the same control variables. One known remaining difference is that NHTSA used accident data from Utah, which was not available to DRI. DRI had previously used data from New Mexico in the 2002 through 2005 DRI analyses which NHTSA did not use, and these data from New Mexico were also used in the Phase I analysis in order to compensate for not having data from Utah. The fatal and induced-exposure data were also independently reduced by NHTSA and DRI.

¹⁴The term “equivalent” refers to the change in vehicle wheelbase, track or footprint associated with, on average, a change in vehicle weight, due to the correlation that may exist between each of these size parameters and weight. This correlation and corresponding equivalent size and weight reduction values may be different for different types of vehicles and different model year epochs. The equivalent values for passenger car and LTV wheelbase and track in the Phase I analysis were determined in using linear regressions of the respective vehicle size parameter vs. weight (see Table 3.8 in [3]).

¹⁵Figures 1, 2, 3, 4, 5, 6, 7, 8, 9 and Tables 3, 4, 5, 6, 7 are located at the end of this paper due to their large size.

¹⁶Numbers in parentheses are ± 2 logistic regression standard errors, which do not include all sources of uncertainty.

¹⁷Ref [12] and the appendices also contain detailed regression results and comparisons to corresponding NHTSA results to the extent that they were available.

stage model results, which have been normalized by the baseline numbers of fatalities, are illustrated in [Figures 1, 2, 3, 4](#).

Each figure illustrates the results for Models A through D for a given vehicle type and weight group. Each figure has three rows of vertical bar graphs. The top row illustrates the percentage change in fatalities due to crashworthiness and crash compatibility (i.e., F/A); the middle row illustrates the percentage change in fatalities due to crash involvement (i.e., A/E); and the bottom row illustrates the percentage change in fatalities due to both effects combined (i.e., F/E). Within each row there are several vertical shaded bars for each candidate model. The two or three narrow bars illustrate the independent effects of weight and size reduction on fatalities. The cyan colored bar on the left illustrates the effect of weight reduction. The yellow and magenta bars in the middle and right illustrate the effects of wheelbase and track reduction. The orange bar also on the right illustrates the effect of footprint reduction. Each of these shaded bars has two “I” shaped error bars. The smaller blue error bars represent the point estimate ± 2 uncorrected standard errors, and the larger green error bars represent the point estimate ± 2 corrected standard errors. The uncorrected two-stage standard errors are from the “three-way” logistic regressions, which under represent the uncertainty in the results because each data record was used in the logistic regression twice. Therefore to better approximate the uncertainty in the results the corrected two-stage standard errors have been scaled to match the standard errors of the one-stage results. The wider blue bar illustrates the combined effect of weight and size reduction on fatalities, which is the numerical sum of the narrow bars.

More detailed results for Models B and D are tabulated in Appendices J and K (e.g., pages J.d-14 and J.d-15) of [12].

The differences between the two-stage and one-stage results were generally found to be small and not statistically significant.

Sensitivity results

In addition to the results for the four candidate models reported herein, the sensitivity of the results to other changes in the data and methods were also investigated. These sensitivity results are illustrated in Figures 3 through 33 in [12]. Figures 32 and 33 indicate, for example, that the results are also sensitive to the differences in the crash types as defined in the 1997 and 2003 NHTSA reports.

Phase II Results

The Phase II analysis used methods similar to the Phase I analysis with more recent data to reproduce and extend the results in the 2011 and 2012 NHTSA reports [9,15]. This analysis involved estimating the change in fatalities

compared to a baseline number of fatalities using logistic regressions of 2002 through 2008 calendar year data for 2000 through 2007 model year vehicles as indicated in [Table 1](#). Example regression results for passenger car collisions with a truck-based LTV weighing 4,150 lbs or more using Model D are listed in [Table 3](#). This was accomplished for all combinations of three vehicle types (passenger cars, truck-based LTVs, and minivans and CUVs), weight groups, and nine crash types defined in [9]. The baseline number of fatalities in each category is from [15]. The estimated total change in fatalities for each vehicle type and weight group is then the sum of the changes for all nine crash types.¹⁸ The relative changes in fatalities were then determined by dividing the changes in fatalities by the corresponding baseline number of fatalities and converting the resulting values to a percentage.

New wheelbase, track, and footprint reduction values corresponding to a 100 lb weight reduction were also computed for the three vehicle types based on the newer data as well. These values are listed in the second column of [Table 4](#).

One-stage results

The effects of weight and size reduction on fatalities per VMT were estimated using one-stage regressions. Example results for passenger car collisions with a truck-based LTV weighing 4,150 lbs or more using Model D are listed in the last four columns of [Table 3](#), corresponding to the regression coefficients listed in the first column of the table. These results list the estimated logistic regression point-estimate and standard error, followed by the 95% jackknife confidence interval, and variance inflation factor. The point-estimates are in very close agreement with the results reported in Section 3.2 of the 2012 NHTSA report [15]. The results are considered statistically significant if the magnitude of the point estimate is greater than the 95% confidence interval. This logistic regression result was based on 3,622 fatal cases representing 4,256 fatalities, and 1,242,083 non-culpable vehicle induced-exposure cases representing 3.9 trillion VMT. The deviance statistic¹⁹ for this regression, which is a measure of the model fit similar to the sum-of-squares of the residuals for linear regression models, is 110,552.

The overall one-stage results for Models A through D with all nine crash types combined are listed in [Tables 4, 5, 6, 7](#). These results list the one-stage logistic regression point estimates and standard errors, and jackknife confidence intervals that account for FARS and induce-exposure based sampling errors. The jackknife confidence intervals may not include other sources of uncertainty, such as the accuracy of the VMT data at the MMYB level of detail.

¹⁸Kahane used two different methods to estimate the total fatalities, the results of which were listed in Tables 3-5 and 3-8 of [15]. The results presented herein correspond to the results in [Table 3, 4, 5](#), which were described as the “Volpe Model Coefficients.”

¹⁹The deviance is minus 2 times the natural logarithm of the likelihood ratio (e.g., Eq. 1.9 in [30]).