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Evaluation of Electronic Stability Control: FMVSS No. 126, an Update

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16. Abstract This report evaluates the effectiveness of electronic stability control (ESC) in mitigating single-vehicle, first-event rollover crashes. NHTSA mandated ESC standard equipment in certain light vehicles manufactured on or after September 1, 2011, by Federal Motor Vehicle Safety Standard (FMVSS) No.126, <i>Electronic stability control systems</i> . The study used National Automotive Sampling System (NASS) General Estimate System (GES) data from 2013 to 2015 to compare outcomes for similar vehicles with and without ESC. This research estimated a logistic regression model that found that a vehicle with ESC is 51.6 percent less likely on average to be in a single-vehicle, first-event rollover crash than a vehicle without ESC if all other variables remain fixed. Considering effectiveness, we saw an overall first-event, single-vehicle rollover crash relative risk reduction of 47.7 percent on the grouping of vehicles with ESC and vehicles without ESC, accounting for the effect of passenger vehicle body type and travel speed. The reduction is statistically significant at alpha level 0.05. These conclusions align with prior evaluations of ESC that found a reduction in first-event rollover crashes due to the technology.			
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Executive Summary

The primary benefit of electronic stability control (ESC) is its ability to help drivers maintain control of their vehicle in critical situations, thereby reducing the risk of crashes, especially those involving rollovers and loss of control. Occupants of vehicles departing the roadway face an increased risk of rollover and fatal injury. From 1982 to 2021, single-vehicle rollover fatalities accounted for about 25 percent of all passenger vehicle (PV) occupant fatalities in NHTSA's Fatality Analysis Reporting System (FARS).

To mitigate these fatalities NHTSA mandated ESC as standard equipment in certain light vehicles manufactured on or after September 1, 2012, by Federal Motor Vehicle Safety Standard (FMVSS) No. 126 *Electronic stability control systems* for light vehicles. ESC effectiveness was evaluated most recently in 2014, but that evaluation only considered fatal crash data; earlier evaluations had small sample sizes of vehicles with ESC. This report evaluates ESC's effectiveness in mitigating single-vehicle, first-event rollover crashes. The study uses the National Automotive Sampling System (NASS) General Estimate System (GES) data from 2013 to 2015 for reasons described in the Data System section.

This analysis shows ESC had a statistically significant effect on reducing single-vehicle, first-event rollover crashes from 2013 to 2015. The study's fitted logistic regression model shows that:

- Holding travel speed and PV body type constant, the odds of getting in a single-vehicle, first-event rollover crash for vehicles with ESC ($x_1 = 1$) over the odds of getting in a single-vehicle, first-event rollover crash for vehicles without ESC ($x_1 = 0$) is $\exp(-0.6621)=0.5118$. In terms of percentage change, we can say that the odds of involvement in a first-event rollover crash for PVs with ESC are 51.6 percent lower than the odds for PVs without ESC.
- The coefficient for PV body type says that, holding ESC presence and travel speed at a fixed value, when comparing passenger cars (PCs) to light trucks and vans (LTVs), we will see a 73.4-percent increase in the odds of LTVs being in a single-vehicle, first-event rollover crash since $\exp(0.5502)=1.7336$.
- The coefficient for travel speed says that, holding ESC presence and PV body type at a fixed value, we will see a 4.7-percent increase in the odds of being in a single-vehicle, first-event rollover crash for each 1-mph increase in travel speed since $\exp(0.0459)=1.047$.

The evaluation division used relative risk to estimate effectiveness rather than the odds ratio because relative risk tells us how an intervention changes risk; the odds ratio determines association between two variables (George et al., 2020). This posed the problem of counting the population of vehicles of interest for the exposure denominator. So, we used GES to fit a log binomial model to estimate the relative risk and thus the effectiveness of ESC. Considering effectiveness, we found an overall first-event, single-vehicle rollover crash relative risk reduction of 47.7 percent of vehicles with ESC versus those without ESC, adjusting for the effect of PV body type and travel speed. This reduction is statistically significant at alpha level .05. These conclusions align with prior evaluations of ESC that found a significant reduction in first-event rollover crashes due to the technology (Kahane, 2014). While previous estimates showed a significant reduction, they cannot be directly compared to the new estimate due to

methodological differences. We compared an ESC effectiveness estimate for fatal crashes only; while greater, the estimate was not significantly different than the overall crash population estimate at alpha level .05.

This report estimates the effectiveness of equipping vehicles with ESC, as mandated by FMVSS No. 126. It does not determine whether the ESC system on a particular vehicle met or exceeded the performance level required by FMVSS No. 126. Therefore, this research did not evaluate the effectiveness of FMVSS No. 126, but rather the effectiveness of ESC systems in general.

Background

ESC enhances a driver's ability to maintain control in various driving situations. ESC systems use automatic computer-controlled braking of individual wheels to assist the driver in maintaining control in critical driving situations. When the system senses a loss of control -- like losing directional stability at the rear wheels or directional control at the front wheels -- it applies braking force to one or more wheels or reduces engine output to assist the driver. Often the driver is unaware of system intervention. The primary benefit of ESC is its ability to help a driver maintain control of the vehicle in a critical situation, thereby reducing the risk of a crash, especially one involving a rollover and loss of control. The likelihood of a rollover and fatality increase when a driver loses control.

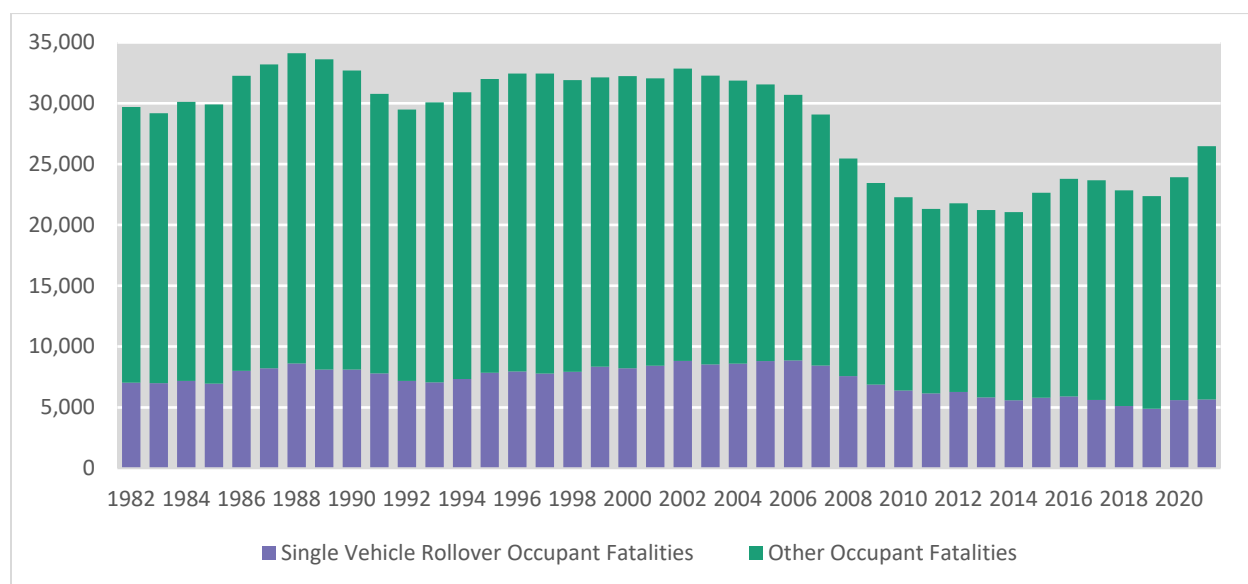


Figure 1. Passenger vehicle occupant fatalities by crash type, 1982-2021

Source: FARS 1982-2021.

Historically, single-vehicle rollover fatalities accounted for about 25 percent of all passenger vehicle occupant fatalities, as shown in Figure 1. To minimize single-vehicle crashes primarily due to loss-of-control, NHTSA mandated ESC systems as standard equipment on certain light vehicles manufactured on or after September 1, 2011, by FMVSS No. 126, *Electronic stability control systems* (71 FR 54712; Docket No. NHTSA-2006-25801). The final rule requires passenger cars, multipurpose passenger vehicles, trucks, and buses with gross vehicle weight ratings of 4,536 kg (10,000 lb) or less have ESC systems that meet the requirements in FMVSS No. 126.

During its final regulatory impact analysis, NHTSA's Regulatory Analysis Division found ESC to be highly effective in preventing single-vehicle, loss-of-control, run-off-the-road crashes, of which a significant portion are rollover crashes. NHTSA found ESC reduces some multivehicle crashes (NHTSA, 2007). NHTSA's Evaluation Division evaluated the safety effectiveness of ESC most recently in 2014. The 2014 evaluation used fatal data only and prior evaluations were based on small sample sizes of vehicles with ESC.

When trying to evaluate a vehicle's safety equipment it's ideal to isolate the vehicle differences to the presence of the safety technology, all else remaining constant. For example, we wouldn't want to examine a particular make/model combination if in 2011 the manufacturer added *both* ESC and some other crash avoidance technology simultaneously. The effectiveness in mitigating rollovers could be related to the other crash avoidance technology. As much as possible, we want the only difference between make/models to be the presence or absence of ESC. So, NHTSA identified 136 make/models that switched to ESC without other concurrent safety or body changes and focused on the years surrounding the MY make/model switched to standard ESC systems for the entire make/model fleet.

We compared make/models of PCs and LTVs with ESC as standard equipment with earlier versions of similar make/models without ESC. Thus, we compared only vehicles in which: (1) the percentage of factory-installed equipment for "stability control" systems increased from 0 to 100 percent in Wards' Automotive Yearbook or (2) ESC is listed as standard in all vehicles in that model line for particular MYs, and not available at all for previous MYs in a NHTSA *Buying a Safer Car* booklet (Dang, 2007). We excluded vehicles with ESC as optional equipment from the analysis because we could not determine which vehicles had ESC and which did not.

We compared models that had factory-installed ESC as a standard feature with earlier versions of identical models because those models remained the same (e.g., same generation chassis) during the pre- and post-ESC years. In other words, for each vehicle listed in Table A-1, we compared the same vehicle before and after ESC was introduced (Dang, 2007). Luxury vehicles transitioned to having ESC as standard equipment ahead of non-luxury brands. So, prior evaluations compared more of these luxury vehicles, and the luxury models in the study are older than some other vehicles considered.

The 2011 and 2014 reports used NHTSA's FARS data on fatal crashes to estimate the effectiveness of ESC (Sivinski, 2011; Kahane, 2014). Since the analysis included only vehicle models that transitioned from "ESC not available" to "ESC standard" in the analysis, estimates were based on a small sample size. ESC effectiveness was measured by the difference in the ratio of crashes predicted to be affected by ESC (single-vehicle crashes, rollovers, etc.), to control crashes in vehicles with and without ESC. A control crash included crashes in which a vehicle was (1) stopped, parked, backing up, entering or leaving a parking space before the crash, or traveling at a speed less than 10 mph; (2) struck in the rear by another vehicle; or (3) a non-culpable party in a multivehicle crash on a dry road (Kahane 2014). The current analysis takes a slightly different approach by removing the culpability aspect, using fatal in addition to non-fatal crash data, and fitting logistic and log binomial regression models. It aims to determine the effectiveness of ESC in mitigating single-vehicle, first-event rollover crashes. This analysis used the risk ratio to determine effectiveness rather than the odds ratio because relative risk tells us how an intervention changes risk; the odds ratio determines association between two variables (George et al., 2020). We opted for a binomial logistic regression model to estimate the risk ratio. While previous estimates showed significant reductions, they cannot be directly compared to the new estimate due to methodological differences.

Data and Methodology

Data System

This analysis used NHTSA's NASS GES data for the analysis. GES is a nationally representative sample of all police-reported motor vehicle crashes. NASS GES is designed to provide statistical information to monitor large scale trends on the general characteristics of the Nation's police-reported traffic crashes (Mynatt & Radja, 2013). We used crash years 2013 to 2015. These represent the last 3 years of the NASS GES before NHTSA transitioned to the Crash Report Sampling System. The goal was to capture the most vehicles of interest during the time after the standard's final compliance date. Starting with the crash year 2016 and using the Crash Report Sampling System would've resulted in low counts of older MY vehicles of interest.

The NASS GES gets its data from a nationally representative probability sample selected from the more than 5 million police-reported crashes that occur annually. These crashes include those that result in fatality (K) or injury (A, B, C) and those involving major property damage (O) (NHTSA, 2019).¹ Table 1 shows the estimated total police-reported crashes by severity over the study period 2013 to 2015.

Table 1. Estimated total police-reported crashes by severity, 2013-2015

Year	Crash Severity							
	Fatal (K)		Injury (A, B, C)		Property Damage (O)		Total	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
2013	30,202	0.5	1,591,016	28.0	4,065,673	71.5	5,686,891	100.0
2014	30,056	0.5	1,647,726	27.2	4,386,502	72.3	6,064,284	100.0
2015	32,538	0.5	1,715,394	27.2	4,548,203	72.2	6,296,134	100.0

Sources: FARS 2013-2015 Final, NASS GES 2013-2015.

Vehicles of Interest and Variables

NHTSA's Office of Vehicle Safety Compliance identified 136 vehicles of interest. The vehicles examined in this study transitioned from not having ESC to having ESC. We grouped the years before and after the change for the vehicles identified and compared those two groups. These are the same vehicles that NHTSA used in the 2014 analysis. The goal is to compare like-to-like and isolate ESC as the difference. The identified vehicles spanned from MY 1996 to 2013. A detailed list of the make/models compared is in Table A-1. These groupings serve as the predictor variable "ESC presence."

ESC Presence

We used the following NASS GES variables to derive ESC presence and find vehicles of interest: vehicle make (MAKE), vehicle model (MODEL), vehicle model year (MOD_YEAR), VIN-decoded vehicle trim (VINTRIM_T), VIN-decoded drive type (DRIVETYP), VIN-decoded cab configuration (TKCAB), and VIN-decoded number of doors (DOORS).

¹ Known as the KABCO scale.

Passenger Vehicle Type

The National Center for Statistics and Analysis (2023) defines PVs as motor vehicles with gross vehicle weight ratings of 10,000 lb or less and include passenger cars and light trucks (SUVs, pickups, and vans). We used the auxiliary variable for body type, A_BODY. The analysis only considers attributes one through four, representing passenger cars, light truck-pickups, light truck-utilities, and light truck-vans. The passenger cars make up one group and the light truck elements make up the LTV group for PV type.

Vehicle Travel Speed

This data element records the investigating officer's reported travel speed of the vehicle prior to the crash.

Driver Age

This data element identifies the driver's age at the time of the crash, in years, with respect to the last birthday. The imputed data element has the same definition and data element values as age.

Driver Sex

This data element identifies the sex of the driver in the crash. The imputed data element has the same definition and data element values as sex.

Crash Groupings

We grouped vehicles by their crash type and then considered single-vehicle crashes where GES showed the first harmful event is a rollover or where GES reported the most harmful event was a rollover and the first harmful event was contact with a tripping mechanism such as a curb or ditch. These are the crashes ESC stands to prevent. This is also the most we can isolate outside influences on the vehicle. We considered all other crashes "not a crash of interest." These groupings serve as the response variable.

We used the following NASS GES variables to derive crash type: pre-event movement (P_CRASH1), initial contact point (IMPACT1), number of motor vehicles in transport (VE_FORMS), roadway surface condition (VSURCOND), first harmful event (HARM_EV), travel speed (TRAV_SP), and manner of collision (MAN_COLL).

Statistical Methods

Logistic Regression Model

We used SAS Viya software's SURVEYLOGISTIC and LOGISTIC procedures to determine the relationship between ESC and single-vehicle, first-event rollover crashes.² We assigned the variable *weight* to the WEIGHT option. We assigned variables *psu* and *psustrata* to the CLUSTER and STRATA options. For the weighted frequencies we used PROC SURVEYFREQ with the same variables. We also considered other predictor variables like PV type, vehicle travel speed, driver age, and sex.

² SAS Institute Inc., Cary, NC. www.sas.com/en_us/software/viya.html

$y_i = \text{crash type} \begin{cases} 0 & \text{not a crash of interest} \\ 1 & \text{single – vehicle, first – event rollover crash} \end{cases}$

$x_{1i} = \text{ESC presence} \begin{cases} 0 & \text{vehicle with ESC} \\ 1 & \text{vehicle without ESC} \end{cases}$

$x_{2i} = \text{passenger vehicle type} \begin{cases} 0 & \text{passenger car} \\ 1 & \text{light truck, van, or SUV} \end{cases}$

$x_{3i} = \text{vehicle travel speed} \{0 – 151 \text{ mph}\}$

$x_{4i} = \text{driver age} \{0 – 120 \text{ years}\}$

$x_{5i} = \text{driver sex} \begin{cases} 1 & \text{male} \\ 2 & \text{female} \end{cases}$

Our goal is to understand the relationship between the predictor variables (ESC, PV type, travel speed, driver age, driver sex) and a vehicle's crash type. The crash groups are mutually exclusive, as are the PV types and ESC groups.

$$H_0: \boldsymbol{\beta} = 0 \text{ or } H_0: \beta_1 = \beta_2 = \dots = \beta_5 = 0$$

$$H_A: \boldsymbol{\beta} \neq 0, \text{ at least one of the betas is not zero}$$

The null hypothesis states all coefficients in the model are equal to zero, or that none of the predictor variables (ESC, PV type, travel speed, driver age, driver sex) have a statistically significant relationship with the vehicle crash type. The alternative hypothesis states that not every parameter is equal to zero, or that one or more of the predictor variables has a statistically significant relationship with the vehicle crash type.

Logistic regression uses a method known as maximum likelihood estimation to find an equation of the following form:

$$\log\left(\frac{p(X)}{1 - p(X)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \quad (1)$$

where:

- X_j : The j^{th} predictor variable
- β_j : The coefficient estimate for the j^{th} predictor variable

The Logistic Regression Model section of this report summarizes the strength of association between presence of ESC, PV type, driver sex, driver age, or travel speed, and involvement in a single-vehicle, first-event rollover crash. SAS's PROC SURVEYLOGISTIC treats missing values as if they are *missing completely at random*. The odds ratio is a measure of how strongly a single-vehicle, first-event rollover crash is associated with ESC presence, PV body type, and travel speed. The odds ratio is symmetric in the predictors and we're indicating correlation rather than causation.

Effectiveness

We used R's *svyglm* and *svydesign* from the survey package to fit a log binomial regression model to the survey design (R Core Team, 2024; Lumley, 2004, 2010; Lumley et al., 2024). We used the variable *weight* in the *weight* argument. We used *psu* and *psustrat* in the *id* and *strata* arguments. We used the predictor variables selected in the logistic regression model to fit a log binomial model to estimate the risk ratio for vehicles with and without ESC.

Our goal is to estimate the relative risk between ESC presence adjusted for the predictor variables selected in the logistic regression model. The crash groups are mutually exclusive, as are the predictor variable groups. The null hypothesis states that there will be no association between ESC presence or other predictors and the crash outcome, meaning that the risk ratio will equal 1.0. If the study data provides evidence against the null hypothesis, then this hypothesis can be rejected, and we conclude there is an association between ESC presence and the crash outcome.

Log binomial regression uses a method known as maximum likelihood estimation to find an equation of the following form:

$$\log(p(X)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \quad (2)$$

where:

- X_j : The j^{th} predictor variable
- β_j : The coefficient estimate for the j^{th} predictor variable

With logistic regression, the left-hand side is the log of the odds, whereas in log-binomial regression it is the log of the probability. Exponentiating a regression coefficient in logistic regression results in an odds ratio. Similarly, exponentiating a regression coefficient in log-binomial regression results in a risk ratio (RR) (Nahhas, 2024). RR is a measure of the risk of a certain event happening (single-vehicle, first-event rollover) in one group (vehicles without ESC) compared to the risk of the same event happening in another group (vehicles with ESC). By risk, we mean the probability of a single-vehicle, first-event rollover in the group of vehicles without ESC compared to the probability of a single-vehicle, first-event rollover in the group of vehicles with ESC.

We use the RR to determine the effectiveness (E). Effectiveness tells you the extent to which the risk of an adverse outcome is reduced by an intervention by the following formula:

$$E = 1 - RR \quad (3)$$

In this case we're interested in how the risk of a single-vehicle, first-event rollover crash is reduced by ESC.

Results

The analysis uses crash years 2013 to 2015. We only considered vehicles from MYs 1997 to 2013, a detailed list of the vehicles we used is in Table A-1. Of the 136 models, 2 required VIN information to determine ESC presence, and we excluded them from the analysis. Three make/model combinations weren't captured in the GES data. We excluded nine make/models from the study because only one of the two groups was present: for example, finding eight 2007 Dodge Caravans without ESC and zero 2008 or 2009 Dodge Caravans with ESC in the GES. We considered 122 PV models, consisting of 120 separate make/model codes.

Exploratory Data Analysis

First, we fit a model considering only the ESC presence and PV type to examine the relationship between these variables and crash type. ESC presence and PV type are significant in the model at alpha level .05. Additionally, the percent concordance (agreement of the actual and fitted values) of this model is low (47.5), so we considered other independent variables for the model to provide a better prediction for crash type. We fit further models by adding additional independent variables. To fit a model, SAS omits observations with a missing value on any variable considered. For each model SAS uses a different subset of the target vehicles. Driver age and sex were not significant in the model with ESC and PV groups. Details of these attempted fit models are in Appendix A.

Descriptive Statistics

A breakdown of the analysis dataset by vehicle body type and ESC presence is shown in Table 2.

Table 2. Weighted vehicle estimates and (standard error) by body type and ESC group, analysis dataset

ESC Group	Passenger Cars	Light Trucks and Vans	Total
Without ESC	440,007 (60,508)	364,087 (51,179)	804,094 (110,495)
With ESC	449,335 (59,943)	315,035 (44,211)	764,370 (102,713)
Total	889,342 (119,644)	679,122 (94,757)	1,568,464 (212,147)

Logistic Regression Model

Next, we considered vehicle travel speed (variable name TRAV_SP). Of the vehicles identified, more than half (51%) had missing values for TRAV_SP. This left 1,568,464 vehicles to consider in the analysis. The breakdown of vehicles is in Tables 2 and 3.

$$y_i = \text{crash type} \begin{cases} 0 & \text{not a crash of interest} \\ 1 & \text{single – vehicle first – event rollover crash} \end{cases}$$

$$x_{1i} = \text{ESC presence} \begin{cases} 0 & \text{vehicle without ESC} \\ 1 & \text{vehicle with ESC} \end{cases}$$

$$x_{2i} = \text{passenger vehicle type} \begin{cases} 0 & \text{passenger car} \\ 1 & \text{light truck, van, or SUV} \end{cases}$$

$$x_{3i} = \text{vehicle travel speed} \{0 - 151 \text{ mph}\}$$

Referring to equation (1) we get:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = -6.21 - 0.66\mathbf{X}_1 + 0.55\mathbf{X}_2 + 0.046\mathbf{X}_3 \quad (1a)$$

These values come from the parameter estimate column of the Analysis of Maximum Likelihood Estimates SAS output in the Appendix, which is summarized in Table 5. Equation 1a is the fit logistic regression model representing the chance of single-vehicle, first-event rollover crash involvement based on ESC presence, PV type, and vehicle travel speed.

Table 3 shows consistently lower estimated counts of single-vehicle, first-event rollover crashes for vehicles with ESC than those without in all injury types.

Table 3. Driver injury severity by crash type estimates and (standard error), by ESC presence, analysis dataset

Injury Type	Single-vehicle, First-event Rollover Crash		Other Crash	
	Without ESC	With ESC	Without ESC	With ESC
No Apparent Injury (O)	4,756.8 (1,443)	2,778 (531.6)	630,529 (89,636)	612,215 (85,685)
Possible Injury (C)	1,340.7 (603.1)	485.6 (226.2)	83,744 (10,983)	81,813.7 (10,719)
Suspected Minor Injury (B)	1,860.8 (634.6)	415.9 (199.2)	49,647.2 (7,054)	45,950.2 (7,581)
Suspected Serious Injury (A)	1,165.1 (433.8)	207 (94.9)	16,120 (2,635)	9,712.9 (2,004)
Fatal Injury (K)	38.9 (34.97)	0 (0)	2,080.4 (759.0)	1,284.1 (439.7)
Injured, Severity Unknown (U)	252.9 (240.95)	0 (0)	6,499.6 (3,481)	5,880.8 (2,621)
Unknown	339.4 (176.5)	21.6 (21.6)	5,719.4 (1,614)	3,605.8 (880.9)
Total	9,754.6 (2,584)	3,907.9 (685.3)	794,339 (108,847)	760,462 (102,383)

Table 4. Logistic regression model coefficients and confidence intervals

Model	β	Std. Error	t	Sig.	$\exp(\beta)$	95% CI for $\exp(\beta)$	
						Lower	Upper
Intercept	-6.2058	0.3337	-18.60	<0.0001	0.0020		
ESC Group	-0.6621	0.2401	-2.76	0.0080	0.516	0.319	0.835
PV Body Type	0.5502	0.2700	2.04	0.0466	1.734	1.009	2.980

Travel Speed	0.0459	0.00403	11.39	<0.0001	1.047	1.039	1.056
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Dependent variable: Crash type.

The Wald test for testing the statistical significance of the explanatory variables shows that not every parameter is equal to zero, suggesting that one or more of the predictor variables has a statistically significant relationship with the vehicle crash type. A significant two-way interaction means that the effect of one variable depends on the level of another variable, and vice versa. There was no significant interaction in the final model.

Refer to equation (1a) or Table 4 and see that $\beta_1 = -0.6621$. So, the estimated odds of involvement in a single-vehicle, first-event rollover crash multiplied by $e^{\hat{\beta}_1} = e^{-0.6621} = 0.5158$ comparing a vehicle without ESC to one with ESC; that is, there is a 51.6-percent decrease in odds. Reminder x_1 can only be two values: without ESC ($x_1 = 0$) and with ESC ($x_1 = 1$). To illustrate, a PC without ESC traveling at 55 mph ($x_1 = 0, x_2 = 0, x_3 = 55$) has $\hat{p}(x) = 0.02462$, and odds = $\frac{0.02462}{0.97538} = 0.02524$. At $x_1 = 1$ (vehicle with ESC) and holding x_2 and x_3 constant from above you can check that $\hat{p}(x) = 0.01285$ and odds = $\frac{0.01285}{0.98715} = 0.01302$. However, this is a 51.6-percent decrease; that is, $0.01302 = 0.02524(0.516)$.

Refer to equation (1a) or Table 4 and see that $\beta_2 = 0.5502$. So, the estimated odds of involvement in a single-vehicle, first-event rollover crash multiplied by $e^{\hat{\beta}_2} = e^{0.5502} = 1.7336$ comparing a PC to an LTV, which is a 73-percent increase. Reminder, x_2 can only be two values: PC ($x_2 = 0$) and LTV ($x_2 = 1$). To illustrate, a PC without ESC traveling at 55 mph ($x_1 = 0, x_2 = 0, x_3 = 55$) has $\hat{p}(x) = 0.02462$, and odds = $\frac{0.02462}{0.97538} = 0.02524$. At $x_2 = 1$ (LTV) and holding x_1 and x_3 from above you can check that $\hat{p}(x) = 0.04192$ and odds = $\frac{0.04192}{0.95808} = 0.04375$. However, this is a 73.4-percent increase; that is, $0.04375 = 0.02524(1.734)$.

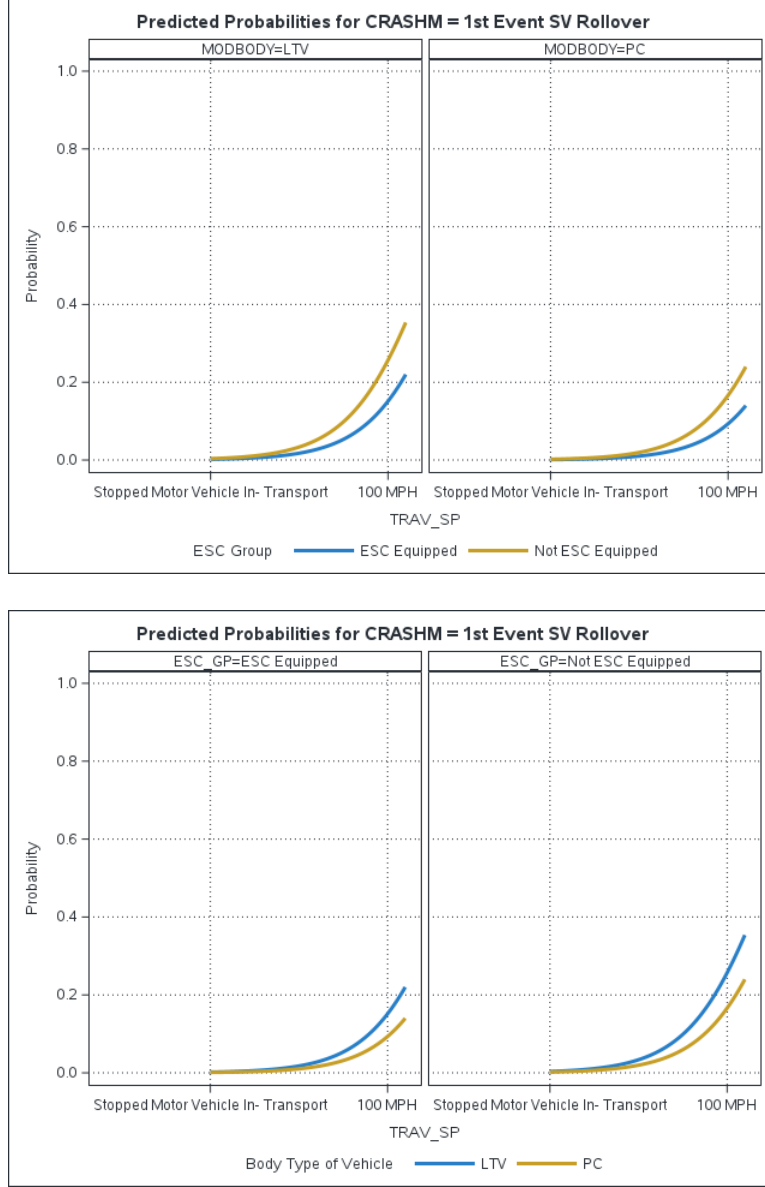


Figure 2. Predicted probabilities for first-event single-vehicle rollover by PV type and ESC presence

Refer to equation (1a) or Table 4 and see that $\beta_3 = 0.0459$. So, the estimated odds of involvement in a single-vehicle, first-event rollover crash multiplied by $e^{\hat{\beta}_3} = e^{0.0459} = 1.047$ for each mph increase in travel speed; that is there is a 4.7-percent increase. To illustrate, an LTV with ESC traveling at 25 mph ($x_1 = 1, x_2 = 1, x_3 = 25$) has $\hat{p}(x) = 0.005656$, and odds = $\frac{0.005656}{0.99434} = 0.00569$. Increasing travel speed 1 mph at $x_3 = 26 = 25 + 1$, and holding x_1 and x_2 from above you can check that $\hat{p}(x) = 0.005921$ and odds = $\frac{0.005921}{0.99408} = 0.00596$. However, this is a 4.7-percent increase; that is, $0.00596 = 0.00569(e^{0.0459}) = 0.00569(1.047)$. Figure 2 shows this relationship between increased speed and increased odds of first-event rollover crash if all other variables remain fixed. This figure also shows LTVs at higher odds of first-event, single-vehicle rollover crashes than PCs. Additionally, the vehicles without ESC are at higher

odds of first-event rollover crashes than those with ESC. All the relationships described are shown in Figure 2, which displays the predicted probability of being in a single-vehicle, first-event rollover crash with respect to the predictor variables and values.

Effectiveness

This analysis seeks to determine the relative risk reduction due to a safety countermeasure, which we call effectiveness. The goal of this analysis is to estimate the effectiveness of ESC. We considered the same 1,568,464 drivers from the logistic regression analysis.

$$y_i = \text{crash type} \begin{cases} 0 & \text{not a crash of interest} \\ 1 & \text{single vehicle first – event rollover crash} \end{cases}$$

$$x_{1i} = \text{ESC presence} \begin{cases} 1 & \text{vehicle without ESC} \\ 2 & \text{vehicle with ESC} \end{cases}$$

$$x_{2i} = \text{passenger vehicle type} \begin{cases} 0 & \text{passenger car} \\ 1 & \text{light truck, van, or SUV} \end{cases}$$

$$x_{3i} = \text{vehicle travel speed } \{0 - 151 \text{ mph}\}$$

Referring to equation 2, we get:

$$\log(p(X)) = -5.52 - 0.65X_1 + 0.537X_2 + 0.044X_3 \quad (2a)$$

These values come from the coefficient estimate column of the R output available in the R Output for Effectiveness Calculations section and summarized in Table 5. Equation 2a is the fit log-binomial regression model representing the chance of single-vehicle, first-event rollover crash involvement based on ESC presence.

Table 5. Log binomial regression model coefficients and confidence intervals

Model	β	Std. Error	t	Sig.	$\exp(\beta)$	95% CI for $\exp(\beta)$	
						Lower	Upper
Intercept	-5.5219	0.4589	-12.034	<0.0001	0.0040	0.00158	0.0101
ESC Group	-0.6475	0.2337	-2.771	0.00828	0.5233	0.3266	0.8386
PV Body Type	0.5370	0.2596	2.068	0.04480	1.7109	1.0131	2.889
Travel Speed	0.0444	0.003745	11.863	<0.0001	1.0454	1.0376	1.0534

Dependent variable: Crash type.

We now use the above values with equation (2a) and calculate:

$$RR = e^{\beta_1} = e^{-0.6475} = 0.5233$$

Referring to equation 3:

$$E = 1 - RR = 1 - 0.5233 = 0.4767$$

Therefore, the introduction of FMVSS No. 126 provides an overall single-vehicle, first-event rollover crash relative risk reduction of 47.7 percent with respect to the grouping of vehicles with ESC and vehicles without ESC.

From the R output above a 95 percent confidence interval for the relative risk is (.3266, .8386). Therefore, a 95 percent confidence interval for the effectiveness estimate of ESC is a 16.14- to 67.34-percent reduction in single-vehicle, first-event rollover crashes compared to vehicles without ESC. Since one is not included in the effectiveness estimate confidence interval, at alpha level .05 we find our estimate statistically significant. The null hypothesis can be rejected, and we conclude there is an association between ESC presence and the crash outcome.

We estimated the effectiveness of ESC for nonfatal and fatal crashes separately to see if they are different. We used the 2013 to 2015 FARS for the fatal crash population. While the ESC effectiveness estimate appears higher in FARS than the estimates for GES, the estimates weren't statistically significantly different, as shown in Figure 3 by the overlapping confidence intervals. Referring to equations 2a and 3 to estimate effectiveness, note the confidence interval around $\hat{\beta}_1$ is symmetric but this doesn't translate to a symmetric interval around $E = 1 - e^{\hat{\beta}_1}$.

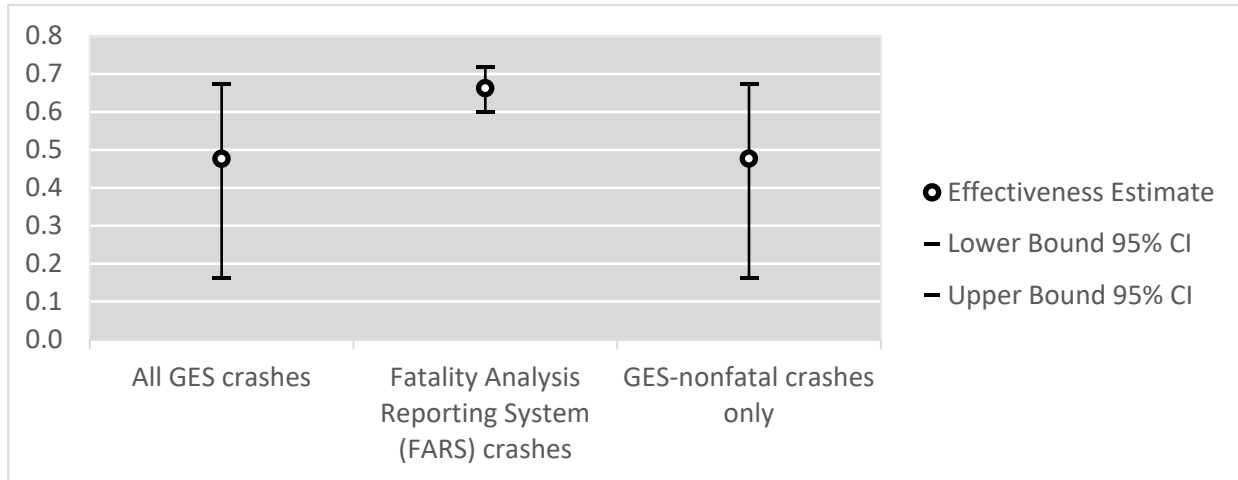


Figure 3. ESC effectiveness estimates and 95 percent confidence interval by crash data system

Conclusions

This analysis showed that ESC, mandated by FMVSS No. 126, is statistically significantly more likely to reduce first-event, single-vehicle rollover crashes, as shown in the data from 2013 to 2015. The logistic regression model fit showed comparing a vehicle without ESC to a vehicle with ESC there was a 51.6-percent decrease in the odds of a vehicle with ESC being in a single-vehicle, first-event rollover crash, holding other variables constant. The model also showed a 73-percent increase in the odds of an LTV being in a single-vehicle, first-event rollover crash compared to a PC if all other variables remain fixed.

Considering another statistic, effectiveness, we saw an overall first-event, single-vehicle rollover crash relative risk reduction of 47.7 percent with respect to the grouping of vehicles with ESC and vehicles without ESC, accounting for the effect of PV body type and travel speed. The reduction is statistically significant at alpha level .05. These conclusions align with prior evaluations of ESC that found a reduction in first-event rollover crashes due to the technology.

A Note on Odds Ratio Versus Risk Ratio

Historically, the methods for estimating effectiveness varied. Some evaluations used the odds ratio to estimate effectiveness; others used the risk ratio. We chose to fit a logistic regression model to identify indicator variables associated with first-event rollover single-vehicle crashes and examine that relationship. This posed the problem of counting the population of vehicles of interest for the exposure denominator. So, we fit a second log binomial model with the same variables estimating the risk ratio for the survey data in the GES. For this study the relative risk is the ratio of the probability of a first-event, single-vehicle rollover crash in the ESC group to the probability of the same crash in the vehicles without ESC. The odds ratio is the ratio of the odds of a first-event rollover single-vehicle crash in the ESC group versus the odds of the same crash in the vehicles without ESC. The alternative to being in a single-vehicle, first-event rollover crash in this case is being in another type of police reported crash. Although the relationship between the odds ratio and risk ratio is complex, when the outcome is rare (typically less than 10%) the odds is close in value to risk, and the odds ratio and risk ratio can be used interchangeably (Ranganathan et al., 2015).

From the SAS output in the Appendix (SAS Output for Selected Model), the odds ratio estimate is 0.516 with a 95 percent confidence interval (.319, .835). Looking again at the Appendix (R Output for Effectiveness Calculations) the risk ratio estimate is 0.523 with a 95 percent confidence interval (.327, .839). Examining first-event rollover single-vehicle crashes as the event of interest offers the opportunity to use either estimate interchangeably in estimating the effectiveness of ESC in mitigating these crashes. Had we selected the odds ratio our estimate would be represented by a 95 percent confidence interval of .165 to .681. Rather than the risk-ratio-based effectiveness we presented with a 95 percent confidence interval of .161 to .673.

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Limitations

Our crash groupings rely on input variables. However, our model focused on the crashes ESC stands to prevent the most, single-vehicle, first-event rollover crashes. Table 6 shows a summary of the crash types in the analysis dataset.

Table 6. Crash types in the analysis dataset

Crash Type	Estimate (Standard Error)	Percentage
Two-vehicle first-event rollover	91.8 (52.5)	0.01
Single-vehicle, first-event rollover	13,662.5 (2,951)	0.9
Stopped, parked, backing up, entering or leaving a parking space, traveling less than 10 mph, struck in the rear by another vehicle	991,431.2 (110,867)	63.2
Multi-vehicle	158,236.0 (31,583)	10.1
Pedestrian or pedalcyclist	66,519.1 (19,959)	4.2
Struck another vehicle in the rear	178,501.6 (32,889)	11.4
Other single-vehicle	160,021.8 (32,959)	10.2

Note: Percentages may not total 100 due to rounding.

The vehicle assignments primarily used crash report-based variables. Some vehicles required further detail and we used the VINtelligence-based pre-decoded variables in addition to the crash report-based variables.³ For example, VINtelligence and the information from the crash report do not always match. If the VIN-based and crash report-based variables don't align, and we needed both to assign ESC presence to this vehicle, this observation was likely excluded from the study.

Ideally, we'd like to consider a variable representing the mass or weight of a vehicle. Similarly, NHTSA is interested in exploring the effect of ESC accounting for the mass from added occupants or cargo. Curb weight varies greatly within make/model type. Without writing a VIN decode program a programmer cannot assign these values to vehicles for analysis. This information is not available in a pre-existing VIN decode program like VINtelligence or vPIC. We had to exclude two of the make/models included in the 2014 analysis for this VIN decode issue. Without writing a decode program these vehicles cannot be teased out of the GES database.

Fifty percent of the travel speed data was unknown and excluded from the models. The sample dataset and vehicle of interest grouping were large enough for a model, but more known values would be ideal.

SAS's PROC SURVEYLOGISTIC treats missing values as if they are *missing completely at random*. Missing data in a survey for any reason, such as nonresponse, can compromise the quality of the results. For example, if all of one State didn't report vehicle travel speed our survey estimates might be biased and cannot accurately represent the survey population. We inspected missing values for all study variables and have no reason to conclude that they weren't

³ VINtelligence, R.L. Polk & Co.

missing completely at random. A larger sample leads to a smaller variance. Therefore, our estimates are conservative but could underestimate the variance of the estimated coefficients.

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Appendix A

Table A-1 shows a complete list of the make/models used for the analysis, their National Crime Information Center (NCIC) codes and MYs are included in each ESC grouping. It also shows the make/models that were used in the 2014 analysis, but we excluded from this update with reasons for omission. For a detailed description of the original vehicles evaluated in 2007, the foundation of this list, see *Statistical Analysis of the Effectiveness of Electronic Stability Control (ESC) Systems – Final Report* (Dang, 2007).

Table A-1. Make/models used in regression model

NCIC Code	Make/Model	Low/No ESC MYs	Std/High ESC MYs
2403	Jeep Wrangler 2 Door	2005-2006	2007-2008
2404	Jeep Grand Cherokee	2004-2005	2006-2007
2405	Jeep Liberty	2004-2005	2006-2007
6051	Chrysler 300	2003-2004	2005-2006
6054	Chrysler Pacifica	2005-2006	2007-2008
6441	Chrysler Town & Country	2006-2007	2008-2009
7025	Dodge Caliber	2010	2012
7026	Dodge Avenger	2009-2010	2011-2012
7422	Dodge Durango	2004-2005	2006-2007
7482	Dodge Ram 1500	2007-2008	2009-2010
12003	Ford Mustang	2008-2009	2010-2011
12017	Ford Taurus	2007-2008	2009-2010
12021	Ford 500	2007	
12023	Ford Fusion	2007-2008	2009-2010
12037	Ford Focus	2008-2009	2010-2011
12401	Ford Explorer	2003-2004	2005-2006
12402	Ford Escape	2006-2007	2008-2009
12422	Ford Expedition	2005-2006	2007-2008
12473	Ford Explorer Sport Trac	2004-2005	2007-2008
12481	Ford F-150	2007-2008	2009-2010
13001	Lincoln Town Car	2008-2009	2010-2011
13013	Lincoln MKZ	2007-2008	2009-2010
13421	Lincoln Navigator	2001-2002	2003-2004
14017	Mercury Sable	2008	2009
14021	Mercury Milan	2009	2010
14402	Mercury Mariner	2006-2007	2008-2009
18022	Buick Lacrosse	2008-2009	2010-2011
18023	Buick Lucerne	2007-2008	2009-2010
18402	Buick Rainier	2004-2005	2006-2007
19014	Cadillac Seville	1997-1998	1999-2000
20002	Chevrolet Impala	2008-2009	2010-2011
20004	Chevrolet Corvette	1998-1999	2001-2002
20023	Chevrolet HHR	2006-2007	2009-2010
20403	Chevrolet Trailblazer	2004-2005	2006-2007

NCIC Code	Make/Model	Low/No ESC MYs	Std/High ESC MYs
20404	Chevrolet Equinox	2005-2006	2007-2008
20421	Chevrolet Tahoe	2004-2005	2006-2007
20473	Chevrolet Colorado	2011	2012
20481	Chevrolet Silverado 2 Door & Extended Cab	2007-2008	2009-2010
20481	Chevrolet Silverado Crew Cab	2006-2007	2008-2009
20482	Chevrolet Avalanche	2004-2005	2006-2007
22403	Pontiac Torrent	2006	2007
23401	GMC Envoy	2004-2005	2006-2007
23421	GMC Yukon Denali & Yukon Denali XL	2001-2002	2003-2004
23472	GMC Canyon	2011	2012
24401	Saturn Vue	2006-2007	2008-2009
32043	Audi A4	1999-2000	2002-2003
32044	Audi A8	1998-1999	2001-2002
32045	Audi TT	2000	2001
34034	BMW 300	1998-1999	2000-2001
34035	BMW 500	1997-1998	1999-2000
34037	BMW 700	1996-1997	1998-1999
34039	BMW Z3	1998-1999	2000-2001
35039	Nissan Maxima	2006-2007	2008-2009
35043	Nissan Sentra	2010-2011	2012-2013
35047	Nissan Altima	2008-2009	2010-2011
35049	Nissan Murano	2006-2007	2009-2010
35050	Nissan Versa	2010-2011	2012-2013
35401	Nissan Pathfinder	2003-2004	2005-2006
35402	Nissan Xterra	2003-2004	2006-2007
35443	Nissan Quest	2008-2009	2011-2012
35472	Nissan Frontier	2009-2010	2011-2012
35481	Nissan Titan	2008-2009	2010-2011
37039	Honda Fit	2009-2010	2011-2012
37402	Honda CR-V	2003-2004	2005-2006
37403	Honda Element	2004-2005	2006-2007
37421	Honda Pilot	2003-2004	2005-2006
37441	Honda Odyssey	2003-2004	2005-2006
38421	Isuzu Ascender	2004-2005	2006-2007
39032	Jaguar XJ sedan	1998-1999	2000-2001
41050	Mazda 6	2007-2008	2009-2010
41051	Mazda 3	2008-2009	2011-2012
41402	Mazda Tribute	2006-2007	2008-2009
42042	Mercedes C	1998-1999	2000-2001
42043	Mercedes S	1997-1998	1999-2000

NCIC Code	Make/Model	Low/No ESC MYs	Std/High ESC MYs
42044	Mercedes SL	1997-1998	1999-2000
42045	Mercedes SLK	1999-2000	2001-2002
42047	Mercedes CLK	1998	1999
42048	Mercedes E	1997-1998	1999-2000
42401	Mercedes ML	1998	1999
47035	Saab 9-3	2001-2002	2003-2004
48034	Subaru Legacy	2007-2008	2009-2010
48038	Subaru Impreza	2007-2008	2009-2010
48045	Subaru Outback	2007-2008	2009-2010
48401	Subaru Forester	2007-2008	2009-2010
49032	Toyota Corolla	2008-2009	2010-2011
49040	Toyota Camry excluding Hybrids	2008-2009	2010-2011
49046	Toyota Prius	2008-2009	2010-2011
49047	Toyota Matrix	2007-2008	2010-2011
49050	Scion tC	2007-2008	2009-2010
49051	Toyota Yaris	2008-2009	2010-2011
49052	Scion xD	2008-2009	2010-2011
49401	Toyota 4Runner	1999-2000	2001-2002
49402	Toyota RAV4	2002-2003	2004-2005
49421	Toyota Land Cruiser	1999-2000	2001-2002
49472	Toyota Tacoma	2010-2011	2012-2013
49482	Toyota Tundra	2006-2007	2008-2009
51046	Volvo 40 Series	2004-2005	2006-2007
52034	Mitsubishi Galant	2008-2009	2010-2011
52046	Mitsubishi Lancer	2008-2009	2010-2011
52047	Mitsubishi Outlander	2005-2006	2007-2008
52401	Mitsubishi Montero	2001-2002	2003-2004
52402	Mitsubishi Endeavor FWD	2006-2007	2008, 2010
52402	Mitsubishi Endeavor AWD	2005-2006	2007-2008
53040	Suzuki SX4	2008-2009	2010-2011
53404	Suzuki Grand Vitara	2004-2005	2006-2007
53405	Suzuki XL7	2005-2006	2007-2008
54036	Acura RL	1998-1999	2000-2001
54421	Acura MDX	2001-2002	2003-2004
55033	Hyundai Sonata	2004-2005	2006-2007
55036	Hyundai Accent	2010-2011	2012-2013
55401	Hyundai Santa Fe	2005-2006	2007-2008
58032	Infiniti Q45	2000-2001	2002-2003
59032	Lexus LS	1997-1998	1999-2000
59034	Lexus GS	1997-1998	1999-2000
59401	Lexus RX	1999-2000	2001-2002

NCIC Code	Make/Model	Low/No ESC MYs	Std/High ESC MYs
59421	Lexus LX	1998-1999	2000-2001
62421	Land Rover Range Rover	2001-2002	2003-2004
63032	Kia Rio	2010-2011	2012-2013
63034	Kia Optima	2004-2005	2007-2008
63402	Kia Sorento	2005-2006	2007-2008
63441	Kia Sedona	2005-2006	2007-2008

Make/Models Missing From Data			
7462	Sprinter 2500	2002-2003	2004-2005
39031	Jaguar XK coupe	1998-1999	2000-2001
42046	Mercedes CL	1998	1999
Make/Models Excluded Because Need VIN to Identify			
54035	Acura TL	2001-2003	2002-2004
20037	Chevrolet Malibu	2007-2008	2009-2010
Make/Models Excluded Due to Only One Group of ESC Present in Data			
30442	VW Eurovan	1999-2000	2001-2002
Make/Models Excluded Due to Only One Group Present in Known Travel Speed Dataset			
7442	Dodge Caravan	2006-2007	2008-2009
19421	Cadillac Escalade 4x4	1999-2000	2002-2003
23481	GMC Sierra 2 Door & Extended Cab	2007-2008	2009-2010
23481	GMC Sierra Crew Cab	2006-2007	2008-2009
37035	Honda S2000	2004-2005	2006-2007
45031	Porsche 911	1998-1999	2000-2001
47401	Saab 9-7X	2005	2006-2007
59033	Lexus SC	2000-2001	2002-2003

Figure 4 shows a distribution of MY of the vehicles considered.

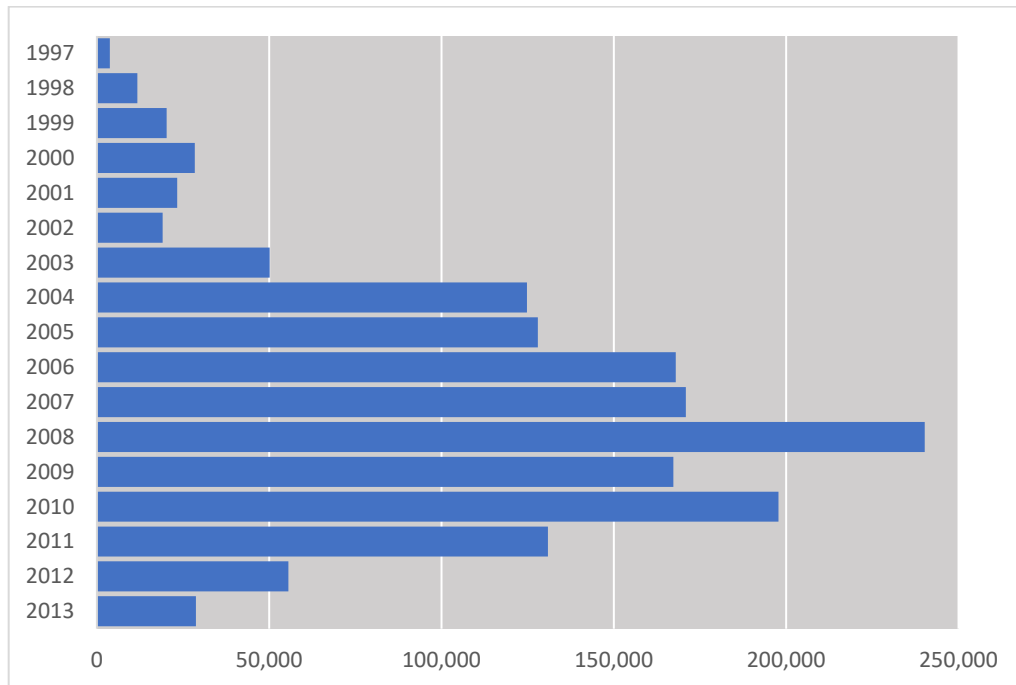


Figure 4. Analysis PVs of interest by vehicle MY

SAS Output for Selected Model

Crash of Interest with Travel Speed – Missing at Random The SURVEYLOGISTIC Procedure

Domain analysis for domain Person Type=Driver of a Motor Vehicle In-Transport

Domain Summary	
Number of Observations	25,504
Number of Observations in Domain	25,504
Sum of Weights in Domain	3,217,817.5

Model Information		
Data Set	WORK.FINALMA	
Response Variable	CRASHM	Crash Type
Number of Response Levels	2	
Stratum Variable	PSUSTRAT	PSU Stratum
Number of Strata	14	
Cluster Variable	PSU_VAR	
Number of Clusters	67	
Weight Variable	WEIGHT	Case Weight
Model	Binary Logit	
Optimization Technique	Fisher's Scoring	
Variance Adjustment	Degrees of Freedom (DF)	

Variance Estimation	
Method	Taylor Series
Variance Adjustment	Degrees of Freedom (DF)

Number of Observations Read	25,504
Number of Observations Used	12,535

Sum of Weights Read	3,217,817
Sum of Weights Used	1,568,464

Response Profile			
Ordered Value	CRASHM	Total Frequency	Total Weight
1	1st Event SV Rollover	217	13,662.5
2	Not a Crash of Interest	12,318	1,554,801.5

Probability Modeled is CRASHM='1st Event SV Rollover'.

Note: 12,969 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information		
Class	Value	Design Variables
ESC_GP	ESC Equipped	1
	Not ESC Equipped	0
MODBODY	LTV	1
	PC	0

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	156,815.90	138,287.44
SC	156,828.17	138,336.51
-2 Log L	156,813.90	138,279.44

Testing Global Null Hypothesis: BETA=0				
Test	F Value	Num DF	Den DF	Pr > F
Note: Second-order Rao-Scott design correction 0.3532 applied to the likelihood ratio test.				
Likelihood Ratio	29.90	2.2170	117.50	<.0001
Wald	57.75	3	51	<.0001

Type 3 Analysis of Effects				
Effect	F Value	Num DF	Den DF	Pr > F
ESC_GP	7.60	1	53	0.0080
MODBODY	4.15	1	53	0.0466
TRAV_SP	129.78	1	53	<.0001

Analysis of Maximum Likelihood Estimates							
Parameter		Estimate	Standard Error	t Value	Pr > t	Exp(Est)	Label
NOTE: The degrees of freedom for the t tests is 53.							
Intercept		-6.2058	0.3337	-18.60	<.0001	0.002	Intercept: CRASHM=1 st Event SV Rollover
ESC_GP	ESC Equipped	-0.6621	0.2401	-2.76	0.0080	0.516	ESC Group ESC Equipped
MODBODY	LTV	0.5502	0.2700	2.04	0.0466	1.734	Body Type of Vehicle LTV
TRAV_SP		0.0459	0.00403	11.39	<.0001	1.047	Travel Speed

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	76.3	Somers' D	0.584
Percent Discordant	17.9	Gamma	0.620
Percent Tied	5.8	Tau-a	0.020
Pairs	2,673,006	c	0.792

Odds Ratio Estimates and t Confidence Intervals				
Effect	Unit	Estimate	95% Confidence Limits	
ESC_GP ESC Equipped vs Not ESC Equipped	1.0000	0.516	0.319	0.835
MODBODY LTV vs PC	1.0000	1.734	1.009	2.980
TRAV_SP	1.0000	1.047	1.039	1.056
Note: The degrees of freedom in computing the confidence limits is 53.				

R Output for Effectiveness Calculations

```
Call:
svyglm(formula = CRASHM ~ ESC_GP + MODBODY + TRAV_SP, design = GESdata_sd,
family = quasibinomial(link = "log"))

Survey design:
svydesign(id = ~PSU, weights = ~WEIGHT, strata = ~PSUSTRAT, data = GESdata)

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.521856    0.458852  -12.034 3.38e-15 ***
ESC_GP      -0.647543    0.233662   -2.771  0.00828 **
MODBODY      0.537008    0.259635    2.068  0.04480 *
TRAV_SP      0.044431    0.003745   11.863 5.39e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasibinomial family taken to be 0.7963863)

Number of Fisher Scoring iterations: 8

> exp(fit2$coefficients)
(Intercept)      ESC_GP      MODBODY      TRAV_SP
0.003998422 0.523329855 1.710879979 1.045433189
> exp(confint(fit2))
              2.5 %      97.5 %
(Intercept) 0.001583913 0.0100936
ESC_GP      0.326575862 0.8386233
MODBODY     1.013129369 2.8891772
TRAV_SP     1.037561380 1.0533647
```

SAS Code

Crash Group of Interest Assignment

```
ELSE IF VE_FORMS=1 AND HARM_EV = 1 THEN CRGRP="1EV SV ROLL";
ELSE IF VE_FORMS=1 AND HARM_EV in (33,34,38,41,44,48,53,54,58,72) AND
M_HARM=1 THEN CRGRP="1EV SV ROLL";
```

Models

```
PROC SURVEYLOGISTIC DATA=FINALMa;
  WHERE (PER_TYP=1);
  TITLE "Simple Crash of Interest Model";
/*exclude unknown crashes and only consider drivers
goal is to determine if being in a vehicle with ESC
effects odds of being in a crash of interest*/
  FORMAT CRASHM CRASHM. ESC_GP ESCFMT. MODBODY BODY.;
  WEIGHT WEIGHT;
  MODEL CRASHM=ESC_GP MODBODY/EXPB PARMLABEL;
RUN;

PROC SURVEYLOGISTIC DATA=FINALMa;
  WHERE (PER_TYP=1);
  TITLE "Crash of Interest with Age";
  WEIGHT WEIGHT;
  FORMAT CRASHM CRASHM. ESC_GP ESCFMT. MODBODY BODY.;
  MODEL CRASHM=ESC_GP MODBODY /*AGE*/ AGE_IM/ EXPB PARMLABEL;
```

```

/*0.1099 P VALUE FOR AGE IN MODEL*/
/*0.1336 P VALUE FOR IMPUTED AGE IN MODEL*/
RUN;
PROC SURVEYLOGISTIC DATA=FINALMa;
    WHERE (PER_TYP=1);
    FORMAT CRASHM CRASHM. ESC_GP ESCFMT. MODBODY BODY.;
    TITLE "Crash of Interest with Sex";
    WEIGHT WEIGHT;
    MODEL CRASHM=ESC_GP MODBODY /*SEX*/ SEX_IM/ EXPB PARMLABEL;
/*0.6487 P VALUE FOR SEX IN THE MODEL*/
/*0.6424 P VALUE FOR IMPUTED SEX IN THE MODEL*/
RUN;

PROC SURVEYLOGISTIC DATA=FINALMa;
    WHERE (PER_TYP=1 );
    FORMAT CRASHM CRASHM. ESC_GP ESCFMT. MODBODY BODY.;
    TITLE "Crash of Interest with Travel Speed";
    WEIGHT WEIGHT;
    MODEL CRASHM (EVENT='1st Event SV Rollover')
        =ESC_GP MODBODY TRAV_SP
        /*ESC_GP*TRAV_SP*/ /*MODBODY*TRAV_SP*/ /*ESC_GP*MODBODY*/
EXPB PARMLABEL;
    OUTPUT OUT=PRED P=PHAT LOWER=LCL UPPER=UCL;
RUN;
PROC LOGISTIC DATA=FINALMa ;
    WHERE (PER_TYP=1 );
    FORMAT CRASHM CRASHM. ESC_GP ESCFMT. MODBODY BODY.;
    TITLE "Crash of Interest with Travel Speed - Effect Plots";
    CLASS CRASHM ESC_GP MODBODY;
    WEIGHT WEIGHT;
    MODEL CRASHM (EVENT='1st Event SV Rollover')
        =ESC_GP MODBODY TRAV_SP/ EXPB PARMLABEL;
    EFFECTPLOT / AT(MODBODY=ALL) NOOBS;
    EFFECTPLOT SLICEFIT(SLICEBY=MODBODY PLOTBY=ESC_GP) / NOOBS;
RUN;

```

The output, code, and data analysis for this paper were generated using SAS software. (SAS Institute Inc., Cary, NC).

R Code for Effectiveness

```

#GES ALL data logistic regression model inspection
logfitall2 <-svyglm(CRASHM ~ ESC_GP + MODBODY+TRAV_SP, design=GESdata_sd,
family = "binomial")
summary(logfitall2 )
exp(logfitall2$coefficients)
exp(confint(logfitall2))

#log binomial All GES data with Travel Speed Effectiveness Estimate
fit2 <- svyglm(CRASHM ~ ESC_GP+ MODBODY + TRAV_SP, design=GESdata_sd,
family=quasibinomial (link="log"))

```



```
summary(fit2)
exp(fit2$coefficients)
exp(confint(fit2))
```

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U.S. Department
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**National Highway
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Administration**

