DEPARTMENT OF TRANSPORTATION
National Highway Traffic Safety Administration
Docket No. NHTSA-2023-0038

Estimating the Rupture Rate and Projecting Future Ruptures for Subject Inflators in NHTSA's Proceeding Related to EA16-003

Executive Summary

This document explains how NHTSA computed its most recent estimates of the rupture rate and projected ruptures for the subject inflators in NHTSA's proceeding related to investigation EA16-003. These estimates, revised from those referenced in NHTSA's September 2023 Initial Decision, are in part informed by public comment on that Decision including through the associated Public Meeting. The agency now estimates that the rupture rate of the subject inflators is seven out of 1,349,802, or about one in every 192,829 deployments. This document also examines confidence intervals, sensitivity to sampling error, and alternative assumptions.

Background

As described in NHTSA's Initial Decision, the subject inflators are at risk of rupturing when an air bag deploys, releasing metal fragments toward vehicle occupants. Seven injuries and one fatality are known to have occurred in the U.S. from these ruptures.[1] The affected inflators were installed in approximately 51 million vehicles across 13 manufacturers.[2] Although additional manufacturing process inspections were fully implemented in 2018, the risk remains for inflators produced before this change.[3]

The following analysis quantifies the risk of future ruptures presented by the remaining subject inflators on the road by estimating:

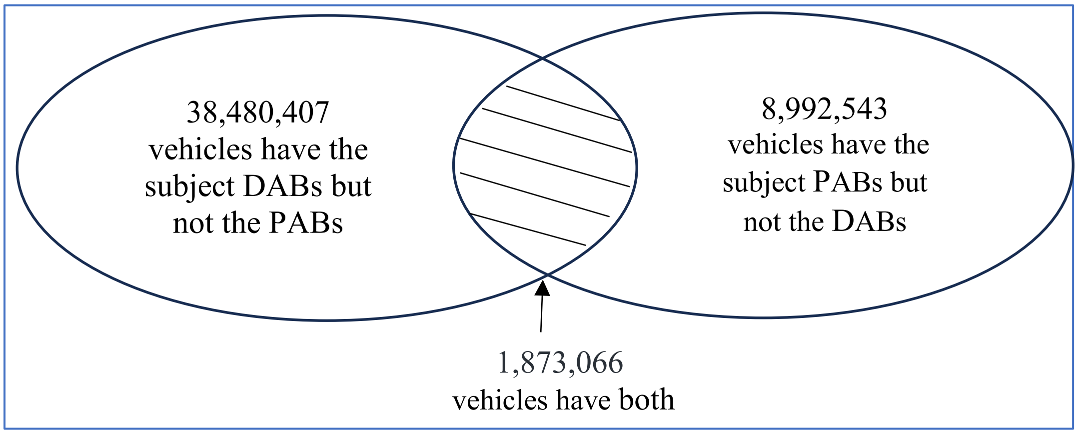
- the percentage of air bag deployments that result in rupture,
- the expected number of future ruptures that may occur, and
- the likelihood of at least 1, 2, 3, or more ruptures occurring in the future.

[1] National Highway Traffic Safety Administration, Initial Decision That Certain Frontal Driver and Passenger Air Bag Inflators Manufactured by ARC Automotive Inc. and Delphi Automotive Systems LLC Contain a Safety Defect; and Scheduling of a Public Meeting, 88 FR 62140 (Sept. 8, 2023)
[2] Since its September 2023 Initial Decision, the agency has confirmed that Jaguar Land Rover North America, LLC, has vehicles in the U.S. with the subject inflators. Those vehicles are not accounted for in this analysis.
[3] ARC completed implementation of the automated borescope process on lines producing PH7 inflators (which are passenger-side inflators) in January 2018, and then completed implementation on the remaining lines producing toroidal inflators in June 2018. The agency's September 2023 Initial Decision referenced vehicles with subject inflators built through January 2018. As such, vehicles with subject inflators built from February 2018 through June 2018 are not accounted for in this analysis.

Subject Vehicle and Inflator Populations

Approximately 51 million[4] subject air bag inflators were manufactured for approximately 150 distinct vehicle makes and models across model years 2000 to 2019. About 40 million inflators were produced for driver side air bags (DAB) while about 11 million were produced for front passenger air bags (PAB). The figure below illustrates the distribution of inflators among vehicles, where some vehicles contained subject inflators for driver air bags only, passenger air bags only, or both.

Figure 1: The Subject Vehicle Population



Only vehicles containing these inflators are considered for this analysis and are referred to as the *subject vehicle* population.

Available Data

This analysis performed by NHTSA's Mathematical Analysis Division, a division within the Office of Traffic Records and Analysis in NHTSA's National Center for Statistics and Analysis, uses data from various sources. NHTSA's crash databases, the Crash Report Sampling System (CRSS) and the Fatality Analysis Reporting System (FARS), are used to identify and estimate subject vehicles involved in crashes and count air bag deployments.

We use NHTSA's Corporate Average Fuel Economy (CAFE) models to estimate vehicle miles traveled over time.[5] These numbers are calculated using (i) an "attrition" model, expressed as a percent of an original vehicle population remaining on the road after a given number of years; and (ii) a "miles driven" model, expressed as a number of miles driven for a vehicle at a given age. These two model outputs, when multiplied together, provide a total number of miles traveled for a given vehicle each year.

---

[4] NHTSA's September 2023 Initial Decision approximates 52 million for the subject inflator population, but this estimate has been updated to 51 based on the best available information.

[5] Shaulov, M., Baskin, D., Clinton, B., Eilbert, A., Garcia-Israel, K., Green, K., Pickrell, D., Saenz, G., & Vargas, A. (2022, April). *CAFE model documentation* (Report No. DOT HS 813 281). National Highway Traffic Safety Administration.

To compute vehicle crashes per mile, we obtain total vehicle miles traveled from Federal Highway Administration's Highway Performance Monitoring System (HPMS) and compute breakdowns for cars and light trucks.[6]

Vehicle manufacturers provided data summarizing how many subject vehicle inflators were produced for each vehicle model. For example, the numbers of driver and passenger side air bag inflators produced for the 2014-2018 BMW i3 were provided for each model year.

Analysis Objectives

This analysis was initiated in response to a statement ARC made in its response to the agency's recall request letter, asserting that seven ruptures as compared to the total subject inflator population was insufficient to determine that a defect exists in the subject inflator population.[7] However, a rupture only occurs if the air bag deploys. As such, it is more appropriate and more accurate to consider the number of past field ruptures as compared to the number of past field deployments in order to determine the rate at which the subject inflators have ruptured. Determining an estimated number of past field deployments required statistical calculations, which yielded the initial analysis.

Assuming ruptures occur randomly among air bag deployments, the likelihood of a rupture occurring given that an air bag deployed is the number of ruptures observed (7) divided by the number of air bag deployments in subject vehicles to date. This "rupture rate" represents how often a rupture occurs, provided an air bag deploys.

To predict future ruptures, the rupture rate is multiplied by a forecast of future air bag deployments that are expected to occur before all subject vehicles are no longer roadworthy. For example, if the rupture rate is one in a million, and there are 1,000,000 future air bag deployments, the expected number of future ruptures is one.

Thus, the main analysis objectives are estimating the number of past deployments and predicting the number of future deployments in the subject vehicle population to predict the number of future ruptures. (Throughout this paper, the "past" refers to the time period ending on December 31, 2023, inclusive, while the "future" refers to that beginning on January 1, 2024.)

$$\text{Predicted Future Ruptures} = \frac{7}{\text{Estimated Past Deployments}} \times \text{Predicted Future Deployments}$$

While this calculation provides an estimate of the expected outcome, it does not provide information about the range of possible outcomes. The sources of uncertainty in producing estimates for past and future deployments come from both sampling error and model error. These

[6] National Center for Statistics and Analysis. (2023, December). *Traffic Safety Facts 2021: A Compilation of Motor Vehicle Traffic Crash Data* (Report No. DOT HS 813 527). National Highway Traffic Safety Administration.
[7] ARC's May 11, 2023 Response to NHTSA's Recall Request Letter, p. 2, https://static.nhtsa.gov/odi/inv/2016/INRR-EA16003-90616.pdf.

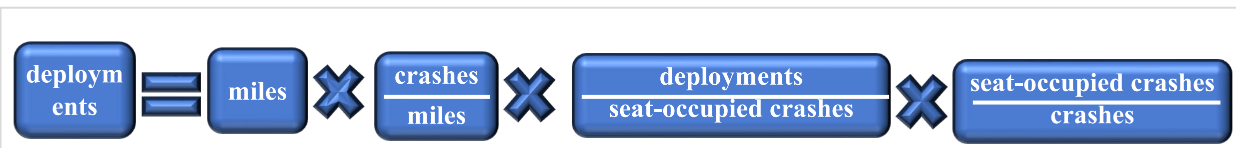
error sources and the uncertainty quantification is discussed in greater detail in the Variance Estimates section.

Analysis Overview

Air bag deployments and vehicle information (model year, make, and model) are reported on crashes recorded in CRSS and FARS. Ideally, this could lead to a direct count of past deployments, by combining the data in CRSS/FARS. However, this only provides an estimate of past deployments, and the method cannot be extended to predict future deployments. Additionally, comparable vehicle information fields are missing during early years of data reporting, so counts for early years would be unreliable. (We identify the subject vehicles in FARS and CRSS using the NHTSA Product Information Catalog and Vehicle Listing (vPIC). The predecessor to CRSS, namely the General Estimates System, does not have this information.)

We derived a method that can estimate both past and future deployments based on miles driven. Rather than directly counting deployments, deployments are computed as the product of miles driven, crashes per mile, deployments per seat-occupied-crash, and seat occupancy rates as shown in the figure below.

Figure 2: The Basic Equation for Estimating Air Bag Deployments



The CAFE models allow miles driven to be estimated for any time frame, both past and future. Thus, the total miles driven by the subject vehicle population can be estimated using these models. Combined with estimates of overall crash risk (crashes per mile) and crash severity (deployments per crash), an estimated number of deployments, both past and future, can be determined.

More formally, we estimate the number the deployments of air bags of type *a* (DAB or PAB) in vehicles of type *v* (car or light truck) in calendar year *y* between 2000 and 2058, inclusive[8] to be:

Equation 1: The Formula for Estimating Deployments

$$Deploys(a, v, y) \coloneqq Miles(a, v, y)\ CrashesPerMile(v)\ DeploysPerCrash(a, v)$$

with the terms $Miles(a, v, y)$, $CrashesPerMile(v)$, and $DeploysPerCrash(a, v)$ defined below.

[8] The affected vehicles range from MY 2000-2019, and the CAFE attrition models predict that vehicles stay on the road through age 39, hence no affected vehicle will be on the road after 2058. The "age" of a model year *m* vehicle in calendar year *y* is *y* – *m*.

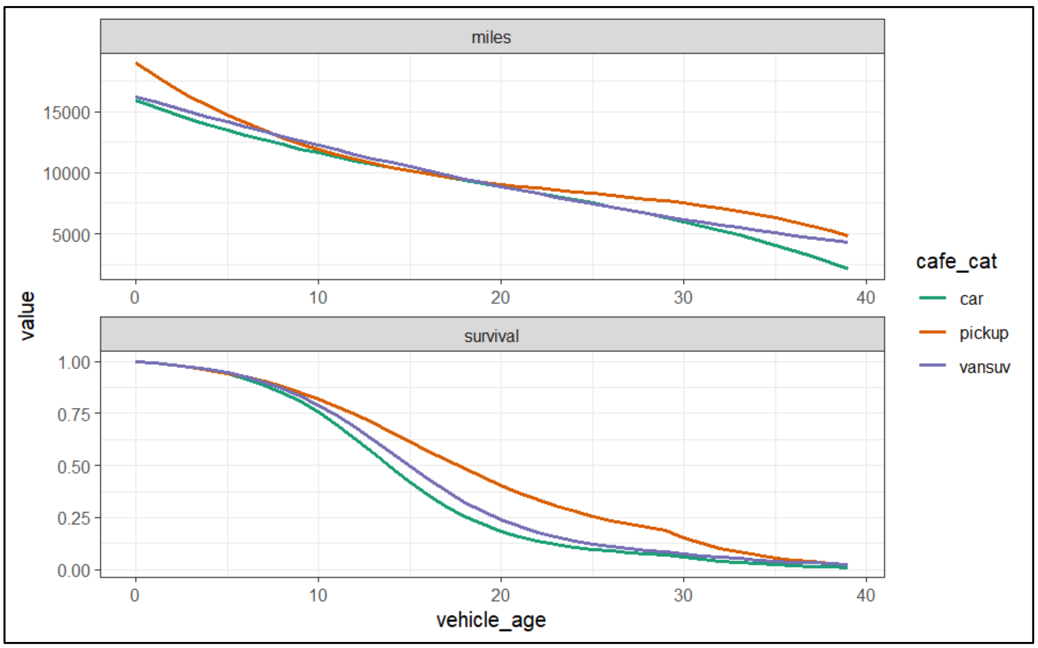
Miles Traveled

NHTSA employs various calculations to determine fuel economy regulations. Two of these calculations involve number of vehicles remaining by vehicle age, and miles traveled given a vehicle's age.

CAFE's "attrition" model estimates the number of vehicles remaining on the road after a given number of years. For example, if 100,000 model year 2004 pickup trucks were produced, only about 40,388 are expected to be on the road in 2024, at age 20 years, according to the CAFE attrition model.

CAFE's "miles driven" model estimates the average number of miles driven by a vehicle after a certain number of years. These estimates capture the effect of older vehicles being driven less often. For example, a model year 2004 pickup truck is expected to have driven about 18,964 miles in 2004, and only about 9,047 miles in 2024.

Figure 3: The CAFE Survival and Miles Driven Models



Using these models we computed the estimated miles driven by the subject vehicles in a particular calendar year by summing over each of the model years' (2000 to 2019) estimated miles driven, taking attrition into account. More formally, we estimated the miles driven *Miles(a,b,y)* by the subject vehicles of type *b* (car, van/SUV, or pickup)[9], air bag type *a* (DAB or PAB), and calendar year *y* between 2000 and 2058, inclusive via the formula

[9] We determine the vehicle type of the subject vehicles using vPIC, which reflects how manufacturer classify their own vehicles.

Equation 2: Estimating Miles Driven

$$Miles(a, b, y) \coloneqq \sum_{m=2000}^{2019} Attrition(b, y-m)\ MilesDriven(\ b, y-m)\ Production(a, b, m)$$

where

- *Attrition(b, z)* denotes the CAFE attrition model's predicted proportion[10] of vehicles of type *b* that are still registered at age *z*,
- *MilesDriven(b, z)* denotes the CAFE miles driven model's predicted # of miles driven by each registered vehicle of type *b* during the year that it is *z* years old, and
- *Production(a,b,m)* denotes the # of model year *m* subject vehicles of type *b* produced with air bags of type *a*

Doing this, and summing the miles driven by vans, SUVs, and pickups to obtain the light truck estimates, produces the following estimates of past and future miles driven[11] by the subject vehicles:

Table 1: Estimated Miles Driven by the Subject Vehicles in 2000-23 and 2024-58, by Vehicle Type and Air Bag Type

Subject vehicles	***Estimated Miles Driven in 2000-2023***	***Projected Miles Driven in 2024-2058***
Cars with DABs	2,066,199,644,112	328,811,040,149
Light trucks with DABs	5,115,617,252,323	953,558,552,169
Cars with PABs	614,202,499,602	422,763,794,778
Light trucks with PABs	595,563,650,816	585,158,011,674

A vehicle whose DAB and PAB are both at issue in this investigation contributes to both the DAB and PAB figures in Table 1.

The CAFE models reflect NHTSA's best information on the proportions of vehicles that leave the road as they age, and the decreasing miles driven by the vehicles that remain. The models are widely applicable to a range of vehicle types, like the subject vehicles.

Crashes per Mile

The expected number of vehicle crashes per mile traveled comes directly from NHTSA's Traffic Safety Facts publications. The latest Traffic Safety Facts publication at the time of writing is for 2021. Table 3, "Vehicles Involved in Crashes and Involvement Rates per VMT and per Registered Vehicle, by Vehicle Type and Crash Severity, 1975-2021", lists the crash involvement rate per 100 million vehicle miles traveled. These figures are derived from CRSS/FARS and FHWA's miles traveled.

[10] We extend the CAFE attrition and miles driven models to take the value 0 for ages < 0 and ages > 39.

[11] Although we are in 2024 at the time of this writing, we will refer to 2000-2023 as the "past" and 2024-2058 as the "future".

Although crash rates have been reported since 1975, the crash rate from 2021 was used for each analysis year. This is because crashes per mile uses data from CRSS/FARS in addition to FHWA's vehicle miles traveled. Since the CRSS sample design changed in 2016, these years are not comparable to 2015 and earlier years. The methodology for vehicle type classifications changed in 2020, meaning only 2020 and 2021 were remaining as viable years. Since 2020 was considered an outlier year due to COVID-19, 2021 was chosen as the year to represent general crash rates for all analysis years.

The resulting number of crashes per million miles is given in Table 2. These are the figures $CrashesPerMile(\text{car})$ and $CrashesPerMile(\text{light truck})$

Table 2: Crashes per Million Miles Driven in 2021, by Vehicle Type

Vehicle Type	***Crashes per Million Miles Driven in 2021***
Car	4.2268191142
Light truck	2.8031024252

As with the CAFE models, the figures in Table 2 are broadly applicable to a range of vehicle types, like the subject vehicles.

Deployments per Occupied Seat

To obtain deployments per crash, we estimated air bag deployments in subject vehicles using data from CRSS and FARS between 2017 to 2022, inclusive. We combined FARS and CRSS crashes by taking all FARS crashes and the non-fatal crashes from CRSS. All subject vehicles were identified in the crash databases using each vehicle's VIN. Each vehicle in a crash contained a record on whether the air bag deployed, the seating position of the deployment (if the seat was occupied), and make/model/model year information of the vehicle. This information allowed an estimate of the total number of occupied seats involved in crashes, and the total number of air bag deployments that occurred. This proportion, broken out by seating position and vehicle type, is air bag deployments per seat-occupied crash. The numerator and denominator of this proportion take the form of weighted totals, using the CRSS sample weights and weights of 1 for the FARS cases (as FARS is a census). Because there are unknowns in both the numerator and denominator, we limited each to cases with known information.

More formally, let D denote the dataset of all subject vehicles in (fatal) crashes in FARS in 2017-2022 together with all subject vehicles in non-fatal crashes in CRSS in the same the timeframe, and excluding motor vehicles not in transport at the time of the crash.[12] We exclude from D vehicles with no occupants that could be in the driver or right front (outboard) passenger seat.[13] There are 110,394 such vehicles in total, with 41,941 in fatal crashes and 68,453 in non-fatal

[12] Motor vehicles not in transport are either parked (often with their ignition off, preventing air bags from deployment due to a crash) or are used in a "working" capacity (e.g., for road or roadside maintenance).
[13] Of the 110,744 subject vehicles in transport in crashes during 2017-2022, 338 had no occupants. An additional 12 vehicles had some occupants but none in the driver nor right front passenger seats and none reported with unknown seating positions that could be in the driver or right front passenger seat (seating position codes 19, 98, and 99 in FARS and CRSS). We identify the right front passenger seat as seating position 13 in FARS and CRSS.

ones. On a weighted basis, these vehicles reflect the crashes of 8,466,848 subject vehicles in 2017-2022.

Let i denote a member of D, that is, a subject vehicle in a crash in 2017-2022. Let w_i take the value 1 if vehicle i was in a fatal crash and otherwise equal the CRSS sampling weight for the vehicle i. Let v denote the broader vehicle type of car versus light truck. We calculate the proportion of occupied seats that experienced an air bag deployment conditional on a crash as the weighted sum of vehicles that had an air bag deployment divided by the weighted sum of vehicles where the particular seating position is occupied. This is expressed by the following equation.

Equation 3: Estimating Deployments per Seat-Occupied Crash

$$DeploysPerSeatOccCrash(a,v) = \frac{\sum_{i \in D} w_i Veh(v,i) Deploy(a,i)}{\sum_{i \in D} w_i Veh(v,i) Occupied(a,i)}$$

where

$$Veh(v,i) := \begin{cases} 1 & \text{the vehicle type of } i \text{ is } V \\ 0 & \text{otherwise} \end{cases}$$

$$Deploy(a,i) := \begin{cases} 1 & \text{the air bag of type } a \text{ deployed in vehicle } i \\ 0 & \text{otherwise (including cases with unknown deployment status)} \end{cases}$$

$$Occupied(a,i) := \begin{cases} 1 & \text{the seating position corresponding to the air bag of type } a \text{ was occupied in vehicle } i \\ 0 & \text{otherwise (including cases where it is not known whether the seat is occupied)} \end{cases}$$

Cases where more than one person occupy a given seating position contribute exactly once to the numerator and denominator of $DeploysPerSeatOccCrash(a,V)$ if their air bag deployment codes agree, and are excluded in the rare cases of contrary indications of air bag deployment.[14]

The resulting values of $DeploysPerSeatOccCrash(a,v)$ are given in Table 3. We express the entries of the table as percentages. For instance, deployments occurred in about 7.398% of occupied car driver seats.

Table 3: Deployments per Occupied Seat in a Subject Vehicle Crash in 2017-2022

Air bag	***Vehicle type***	***Deployments per Occupied Seat in a Subject Vehicle Crash in 2017-2022***
DAB	Car	7.3982787186%
DAB	Light truck	4.5626773907%
PAB	Car	6.8804303467%
PAB	Light truck	4.2643038209%

[14] For example, vehicle 1 of CRSS case 201700350589 is a light truck with two right front passengers, one with a reported frontal air bag deployment and one with air bag deployment not reported. We excluded this case from the calculation of $DeploysPerSeatOccCrash$(PAB, light truck). A total of 53 subject vehicles had contrary DAB or PAB deployment information.

Seat Occupancy

Seat occupancy was computed in a similar manner. We identified all subject vehicles in FARS and CRSS crashes in 2017-22 from their VINs and call this set D. We computed seat occupancy as the ratio of the weighted number of occupied seats to the weighted number of occupants with known seating position. Separate estimates were computed for cars versus light trucks denoted by v, and by seating position (driver versus right front passenger), denoted by a.

Formally, we compute seat occupancy as follows.

Equation 4: Estimating Seat Occupancy

$$SeatOccupancy(a,v) \coloneqq \frac{\sum_{i\in D} w_i Veh(v,i) Occupied(a,i)}{\sum_{i\in D} w_i Veh(v,i) KnownIfOccupied(a,i)}$$

where

$$KnownIfOccupied(a,i) \coloneqq \begin{cases} 0 & \text{It is unknown whether the seat for the air bag of type } a \text{ was occupied in vehicle } i \\ 1 & \text{otherwise (including cases where the seat is occupied and unoccupied)} \end{cases}$$

The resulting values of $SeatOccupancy(a,v)$ are given in Table 4. We express the entries of the table as percentages. For instance, the drivers' seat was occupied in about 99.97% of cars.

Table 4: Seat Occupancy Subject Vehicle Crashes in 2017-2022

Air bag	***Vehicle type***	***Seat Occupancy in Subject Vehicle Crashes in 2017-2022***
DAB	Car	99.9726139280%
DAB	Light truck	99.9841941874%
PAB	Car	19.5270850951%
PAB	Light truck	20.7996605168%

Deployments per Crash

We calculate the DAB and PAB deployments per crash by multiplying the deployments per occupied seat by seat occupancy:

$$DeploysPerCrash(a,v) \coloneqq DeploysPerSeatOccCrash(a,v)\ SeatOccupancy(a,v)$$

These result in the following figures.

Table 5: Deployments per Subject Vehicle Crash in 2017-2022

Air bag	***Vehicle type***	***Deployments per Subject Vehicle Crash in 2017-2022***
DAB	Car	7.3962526206%

Air bag	*Vehicle type*	*Deployments per Subject Vehicle Crash in 2017-2022*
DAB	Light truck	4.5619562225%
PAB	Car	1.3435474887%
PAB	Light truck	0.8869607182%

Recalled Vehicles

Some vehicle manufacturers have implemented recalls for specific makes and models of the subject vehicles. This has resulted in approximately one million vehicles being recalled. This set of vehicles is excluded from the calculation of future vehicle miles traveled and future deployments.[15] However, we include all vehicles, both recalled and not, in calculating past deployments and rupture rates, as both recalled and non-recalled vehicles inform the rupture propensity.

Table 6 presents the future miles driven by the subject vehicles that have not been recalled. Comparing to Table 1, the only cell that differs is the figure for light trucks with DABs, since these are the only air bags and vehicles impacted by the recall.

Table 6: Projected Miles Driven in 2024-58 by Subject Vehicles that Have Not Been Recalled, by Vehicle Type and Air Bag Type

Subject vehicles	*Projected Miles Driven by Non-Recalled Subject Vehicles in 2024-2058*
Cars with DABs	328,811,040,149
Light trucks with DABs	866,124,504,615
Cars with PABs	422,763,794,778
Light trucks with PABs	585,158,011,674

Estimates of Deployments

We now have all the figures we need to apply Equation 1. Summing the results for cars and light trucks results in the figures in Table 7.

Table 7: Estimated Past Deployments and Projected Future Deployments in the Subject Vehicles

Air Bag	*Estimated Deployments in the Subject Vehicles During 2000-2023*	*Projected Deployments in 2024-2058 in Subject Vehicles that Have Not Been Recalled*
DAB	1,300,114.418120300	213,551.754176489
PAB	49,687.295636869	38,556.912029799
Total	**1,349,801.713757170**	**252,108.666206288**

[15] Specifically, we excluded from the future vehicle miles traveled and future deployments calculations the 994,763 vehicles recalled by GM in recall 23V-334. We did not exclude the combined 6,286 vehicles subject to other recalls from these calculations because some of those recall reports do not provide the number recalled from each model year.

In reality, the number of deployments that occur, whether in the past or future, has to take an integer value. For example, you can't have 1,300,114.418120300 DAB deployments. The reason that the figures in Table 7 take non-integer values is because they are approximations. We report them to several digits because we will be applying them to numbers that are less than one (the rupture rates).

The Main and Alternative Scenarios

Based on engineering considerations and all the information available to date, NHTSA believes the defect to be equally prevalent and the inflators equally prone to rupture, regardless of the type of air bag (DAB vs PAB), the make or model of the vehicle, plant of manufacture, or other features. As such, we would expect inflators in DABs and PABs to rupture at the same rate, on a per-deployment basis, and, according to NHTSA's Office of Defects Investigation (ODI), this is the scenario supported by the engineering evidence collected in NHTSA's investigation. Although the observed rupture rates happen to differ between airbag types, the engineering evidence supports that this is due to randomness alone. To provide additional robustness in our statistical analysis, an alternative scenario is presented where the equal rupture rate assumption is ignored, and rupture rates and projected future ruptures are estimated separately. We will refer to NHTSA's expectation that DAB and PAB inflators rupture at the same rate as the *Main Scenario*, and the assumption that they rupture at different rates as the *Alternative Scenario*.

Rupture Rate Estimates

In the Main Scenario, one would estimate the common rupture rate for DAB and PAB inflators to be the ratio of the seven total ruptures to the total past deployments from Table 7, giving 7 / 1,349,801.713757170 ≈ 0.0005185947%.

In the Alternative Scenario, one would estimate the DAB inflator rupture rate as the ratio of the six DAB inflator ruptures to the DAB deployments from Table 7, giving 6 / 1,300,114.418120300 ≈ 0.0004614978%. The PAB inflator rupture rate would be similarly calculated as 1 / 49,687.295636869 ≈ 0.0020125869%. We record these figures in Table 8. The Main Scenario assumes that driver and passenger air bag inflators rupture at the same rate, and the Alternative Scenario allows the driver and passenger air bag inflators to have different rupture rates.

Table 8: Estimated Rupture Rates, by Scenario

Air Bag	*Estimated Inflator Rupture Rate in the Main Scenario*	*Estimated Inflator Rupture Rate in the Alternative Scenario*
DAB	0.0005185947%	0.0004614978%
PAB	0.0005185947%	0.0020125869%
DABs + PABs combined	0.0005185947%	Not applicable

It does not make sense to talk about a pooled rupture rate for DAB and PAB inflators in the Alternative Scenario. While a combined rate could be calculated as a deployment-weighted average of the DAB and PAB rates, the result would depend on the mix of DAB and PAB deployments used. If we assume that these inflators rupture at different rates, then the combined rate would differ depending on the mix of DAB and PAB deployments from which it is calculated or to which it is applied. For instance, from Table 7, the weighted average of past deployments would be ((0.0004614978%)×(1,300,114.418120300) + (0.0020125869%)×(49,687.295636869)) / 1,349,801.713757170 ≈ 0.0005185947%, agreeing with the rupture rate in the Main Scenario. But the weighted average of future deployments of the same subject vehicles would be ((0.0004614978%)×(224,732.497153483) + (0.0020125869%)×(38,556.912029799)) / 263,289.409183283 ≈ 0.0006886441%. The difference stems from the fact that about 96% of past deployments involved DABs, but only about 85% of future deployments are projected to involve DABs.[16]

Table 9 also expresses the rupture rates in the form of one-in-x-deployments. For instance, the rupture rate of 0.0005185947% is equivalent to saying that ruptures occur at a rate of about one in every 192,829 deployments, since 192,829≈ 1/0.000005185947.

Table 9: Estimated Rupture Rates, by Scenario, Expressed as One-In-Every-x-Deployments

Air Bag	*Estimated Inflator Rupture Rate in the Main Scenario*	*Estimated Inflator Rupture Rate in the Alternative Scenario*
DAB	One in every 192,829 deployments	One in every 216,686 deployments
PAB	One in every 192,829 deployments	One in every 49,687 deployments
DABs + PABs combined	One in every 192,829 deployments	Not applicable

Projected Future Ruptures in the Subject Vehicles Not Recalled

As with the rupture rate estimates, we project future ruptures under both the Main and Alternative Scenarios. Each is obtained by multiplying the appropriate rupture rate by the future deployments of vehicles that have not been recalled. For instance, in the Main Scenario, we multiply the DAB inflator rupture rate of 0.0005185947% by the projected 213,551.754176489 future deployments of the DABs that have not been recalled. In the Alternative Scenario, we do likewise, but using the scenario's 0.0004614978% rupture rate. The estimated ruptures for DAB and PAB inflators combined is simply the sum of the DAB and PAB estimates. The results are given in Table 10.

Table 10: Estimated Future Ruptures in Non-Recalled Subject Vehicles

Scenario	*DAB Inflators*	*PAB Inflators*	*Both DAB & PAB Inflators*
Main	1.1074680555	0.1999540980	1.3074221535
Alternative	0.9855367398	0.7759913583	1.7615280981

[16] We conduct this illustration with all subject vehicles to demonstrate that the weighted averages differ even for the same pool of vehicles. However, as explained earlier, we will exclude the recalled vehicles from our estimated future ruptures. The share of future deployments of non-recalled vehicles that are projected to involve DABs is also about 85%.

As with deployments, the number of ruptures that occur in the future has to have an integer value. For example, you can't have 1.3074221535 DAB inflator ruptures. And as with deployments, the reason that the figures in Table 10 take non-integer values is because they reflect approximations of integer quantities. They can also be thought of as the expected numbers of future ruptures over multiple potential realizations of future deployments. That is, with ruptures occurring at a rate of about one in every 192,829 deployments, then among the estimated 252,108.666206288 future deployments of the non-recalled vehicles, we might see 1, 2, or 3 ruptures. Table 10 says that on average, we would expect to see 1.3074221535 ruptures in the non-recalled vehicles in the Main Scenario, and 1.7615280981 ruptures in the Alternative Scenario.

The Chance of At Least One, Two, Three, Etc., Future Ruptures in the Subject Vehicles Not Recalled

We can provide an additional assessment of the risk posed by the inflators by estimating the chance of at least x future ruptures occurring, where x=1, 2, 3, etc. (Of course, these future ruptures would be in addition to the seven that have already occurred).

To do this, we model ruptures as binomially distributed among deployments, with notation "Bin(N,p)" denoting a binomial distribution with N trials and probability p. That is, if we view each future deployments as the flip of a highly uneven coin, with the chance of heads equal to the rupture rate of 0.0005185947%, then the number X of ruptures among the estimated 252,109 future deployments[17] of the non-recalled vehicles is a random variable with a Bin(252,109, 0.0005185947%).[18] Applying this distribution, with analogs for the Alternative Scenario yields the figures[19] in Table 11.

Table 11: The Chance Of At Least x Future Ruptures in the Non-Recalled Vehicles

Scenario	*Chance of at least this many ruptures*	*DAB Inflators*	*PAB Inflators*	*Both*
Main	1	67.8912492193%	18.1232462757%	73.7103971993%
	2	31.4277649090%	1.7515315785%	38.5985268806%
	3	10.7099655330%	0.1147660844%	15.1402227351%
	4	2.8572767096%	0.0056782726%	4.6869885783%
	5	0.6235271186%	0.0002255174%	1.1918172966%
	6	0.1148762635%	0.0000074782%	0.2564584094%
	7	0.0182930141%	0.0000002128%	0.0477652160%
	8	0.0025635666%	0.0000000053%	0.0078358741%

[17] Here we round our estimated deployments to the nearest integer since we cannot have partial deployments.
[18] We are using the standard binomial notation Bin(n, p), where n denotes the number of trials (such as coin flips) and p denotes the probability of an outcome (heads).
[19] We could likewise calculate the chance of at least x future ruptures occurring, for any positive integer x. We stop at x=10 in this paper, as the probabilities eventually get quite small.

Scenario	*Chance of at least this many ruptures*	*DAB Inflators*	*PAB Inflators*	*Both*
	9	0.0003206782%	0.0000000001%	0.0011480668%
	10	0.0000362179%	0.0000000000%	0.0001519246%
Alternative	1	63.6146953531%	53.9757124038%	83.4673414872%
	2	26.8409815371%	18.2604626734%	53.7238233712%
	3	8.2458321041%	4.4031489921%	26.9559027383%
	4	1.9731811925%	0.8188693825%	10.8883996942%
	5	0.3852056498%	0.1235654043%	3.6516093422%
	6	0.0633911844%	0.0156642057%	1.0428390683%
	7	0.0090080949%	0.0017106365%	0.2587846967%
	8	0.0011258198%	0.0001640069%	0.0567105402%
	9	0.0001255398%	0.0000140094%	0.0111190725%
	10	0.0000126353%	0.0000010788%	0.0019715617%

Variance Estimates

The estimates that we have presented rely in part on survey data. For instance, CRSS uses a multi-stage probability sample of about 50,000 crashes annually from across the U.S. Thus our estimates of deployments, rupture rates, and future ruptures all have sampling error. We compute this error using Jackknife variance estimation.

Our composite FARS-CRSS dataset, has 67 Primary Sampling Units (PSUs) for the purpose of variance estimation, each comprising one of the 67 CRSS PSUs for variance estimation[20] with the FARS certainty PSU. Following standard practice,[21] our jackknife replicates omit one CRSS PSU at a time. Each replicate gives rise to a replicate estimate of the estimator whose variance we wish to compute (whether an estimate of deployments, a rupture rate, or an estimate of future ruptures). We combine these estimates in the standard way[22] to estimate the standard error. We estimate the covariance between past and future deployments in a similar manner. These result in the figures in Table 12.

[20] CRSS samples crashes from 60 PSUs and estimates variances using 67 PSUs. See the paper in the next footnote for details.
[21] See for example, Zhang, F., Subramanian, R., Chen, C.-L., & Noh, E. Y. (2019, April). *Crash Report Sampling System: Design Overview, Analytic Guidance, and FAQs* (Report No. DOT HS 812 688). Washington, DC: National Highway Traffic Safety Administration.
[22] Also illustrated in the aforementioned publication DOT HS 812 688.

Table 12: Standard Errors of Past Deployments, Future Deployments of Non-Recalled Vehicles, and Their Covariance

Scenario	*Air bag*	*Standard Error of Past Deployments*	*Standard Error of Future Deployments of Non-Recalled Vehicles*	*Covariance of the Past Deployments and Future Deployments of Non-Recalled Vehicles*
Main	DAB	20,781.5376674540	19,836.0547657210	2,395,714,543.325700
	PAB	5,667.4467033678	4,373.0878189530	24,727,927.876966
	DAB+PAB combined	126,070.5980010480	24,002.4273963363	3,023,451,353.251210
Alternative	DAB	120,781.5376674540	19,836.0547657210	2,395,714,543.325700
	PAB	5,667.4467033678	4,373.0878189530	24,727,927.876966
	DAB+PAB combined	126,070.5980010480	24,002.4273963363	,023,451,353.251210

Consider the bivariate random variable whose first component comprises the past deployments and second component comprises future deployments of the non-recalled vehicles. We modeled this random vector via a bivariate truncated normal distribution with variance-covariate matrix determined by Table 12.[23] We computed 95%-confidence intervals for all estimates using Monte Carlo simulations with 10,000 trials each. The results appear in the next sequence of tables.

For instance, from Table 13, a 95%-confidence interval for the past DAB deployments in the subject vehicles is 1,300,114.418120300 ± 237,913.6893573610.

Table 13: Margins of Error for Estimated Deployments with 95% confidence

Estimator	*DAB*	*PAB*	*Both*
Past deployments of all subject vehicles	237,913.6893573610	11,162.9564274228	248,286.8589788770
Future deployments of non-recalled subject vehicles	39,126.2948539718	8,634.3201667087	47,376.6559523974

Similarly, from Table 14, a 95%-confidence interval for the rupture rate in the Main Scenario is 0.0005185947% ± 0.0000985254%.

[23] We truncated the normal distributions at both ends because deployments necessarily take positive values and to ensure that the rupture rate has an expected value.

Table 14: Margins of Error for Rupture Rates with 95% confidence

Scenario	*DAB Inflators*	*PAB Inflators*	*Both*
Main	0.0000985254%	0.0000985254%	0.0000985254%
Alternative	0.0000871809%	0.0004782206%	Not applicable

We do not provide margins of error for the projected ruptures since the chance of future ruptures from Table 11 serves the same purpose of reflecting uncertainty.

Capturing Additional Uncertainty in Projections of Future Ruptures with Monte Carlo Simulation

The estimated chances of future ruptures in Table 11 assume that the rupture rate and number of future deployments are known without error. Table 13 and Table 14 estimate the uncertainty in these quantities (rupture rate and future deployments) incurred from CRSS being a sample, treating other quantities (like our inputs from the CAFE model and FHWA miles) as known without error. In this section, we use Monte Carlo simulation to incorporate additional uncertainty into the estimates from Table 11. This approach requires us to propose sampling distributions for each estimate.

The number of crashes per mile, seat occupancy, and air bag deployment rates are all survey-based estimates. Due to the large sample size of FARS and CRSS, we believe it is valid to characterize these estimates as normally distributed.[24] The mean is equal to the survey estimate, and the standard deviation is equal to the jackknife standard error. Additional care is required for the occupancy rates for driver seats, whose mean (e.g., 0.9997 for cars) and variance (e.g., 0.0001 for cars) result in a small number of normally distributed draws being greater than one. Because the number of draws greater than one was very small (less than one percent), we simply truncated them at one.

Next, we attempt to account for uncertainty in the CAFE model projections, which estimate the (i) number of vehicles that remain on the road; and (ii) the number of miles driven by those vehicles based on their model year. Standard errors for (i) and (ii) were unavailable at the time of writing. However, we can capture some uncertainty in the number of vehicles remaining on the road by characterizing them with a binomial distribution, with number of trials equal to the number of vehicles from the previous year, and probability equal to the attrition factor for that year divided by the attrition factor from the previous year (see the **Miles Traveled** section for additional details on the attrition factors).

[24]Berger, Yves G. "Rate of convergence to normal distribution for the Horvitz-Thompson estimator." *Journal of Statistical Planning and Inference* 67.2 (1998): 209-226.

Next, we present pseudo-code for the simulation. We adopt additional notation, "$NumVehicles(a, v, m, y)$," to denote the number of vehicles remaining on the road in year y with air bag type a, vehicle type v, and model year m. $N(\mu, \sigma)$ denotes the normal distribution with mean μ and standard deviation σ. $TN(\mu, \sigma, LB, UB)$ denotes the truncated normal distribution, again with mean μ and standard deviation σ, along with lower bound LB and upper bound UB. As previously, $Bin(N, p)$ denotes the binomial distribution with sample size N and probability p. We ran the simulation for 10,000 iterations, which are indexed by s in the algorithm below. Quantities that vary over the iterations are given the superscript (s). Equations with a $\sim$ symbol denote steps in which we took a random draw form a sampling distribution.

Algorithm: Monte Carlo simulation for the number of future ruptures

inputs: $Production(a,b,m)$; $Attrition(b,y-m)$; $MilesDriven(v,y-m)$

$a = DAB, PAB; v = Car, LT; b = Car, VanSUV, Pickup;\ m = 2000, \ldots, 2019; y = 2000, \ldots, 2058$

for $s = 1{:}10000$

  for $y = 2000{:}2058$

    for $m = 2000{:}2019$

      if $y = m$

        for $a = DAB, PAB; b = Car, VanSUV, Pickup$:

          $NumVehicles(a,b,y,m)^{(s)} = Production(a,b,m)$

      else if $y < m$

        for $a = DAB, PAB; b = Car, VanSUV, Pickup$:

          $NumVehicles(a,b,y,m)^{(s)} = 0$

      else

        for $a = DAB, PAB; b = Car, VanSUV, Pickup$:

$$NumVehicles(a,b,y,m)^{(s)} \sim Bin\left(NumVehicles(a,b,m,y-1)^{(s)}, \frac{Attrition(b,y-m)}{Attrition(b,(y-1)-m)}\right)$$

      end if/else

    end for loop

    for $a = DAB, PAB; b = Car, VanSUV, Pickup$:

$$Miles(a,b,y)^{(s)} = \sum_{m=2000}^{2019} MilesDriven(b,y-m) \times NumVehicles(a,b,m,y)^{(s)}$$

  end for loop

  $Miles(a,LT,y)^{(s)} = Miles(a,VanSUV,y)^{(s)} + Miles(a,Pickup,y)^{(s)}$

  $CrashesPerMile(Car)^{(s)} \sim Normal(4.2 \times 10^{-6}, 2.6 \times 10^{-7})$

  $CrashesPerMile(LT)^{(s)} \sim Normal(2.8 \times 10^{-6}, 1.4 \times 10^{-7})$

  $DeploysPerCrash(DAB,Car)^{s} \sim N(0.0740, 0.0067)$

  $DeploysPerCrash(PAB,Car)^{(s)} \sim N(0.0688, 0.0072)$

  $DeploysPerCrash(DAB,LT)^{(s)} \sim N(0.0456, 0.0042)$

  $DeploysPerCrash(PAB,LT)^{(s)} \sim N(0.0426, 0.0052)$

  $SeatOccupancy(DAB,Car)^{(s)} \sim TN(0.9997, 0.0001, 0, 1)$

  $SeatOccupancy(PAB,Car)^{(s)} \sim TN(0.1953, 0.0033, 0, 1)$

  $SeatOccupancy(DAB,LT)^{(s)} \sim TN(0.9998, 0.0001, 0, 1)$

  $SeatOccupancy(DAB,LT)^{(s)} \sim TN(0.2080, 0.0049, 0, 1)$

  for $a = DAB, PAB; V = Car, LT$::

$$PastDeploys(a,v)^{(s)} = \sum_{y=2000}^{2023} Miles(a,v,y)^{(s)} \times CrashesPerMile(v)^{(s)} \times DeploysPerCrash(a,v)^{(s)} \times SeatOccupancy(a,v)^{(s)}$$

$$FutureDeploys(a,v)^{(s)} = \sum_{y=2024}^{2058} Miles(a,v,y)^{(s)} \times CrashesPerMile(v)^{(s)} \times DeploysPerCrash(a,v)^{(s)} \times SeatOccupancy(a,v)^{(s)}$$

$$FutureRuptures^{(s)} \sim Bin\left(FutureDeploys(a,v)^{(s)}, \frac{7}{PastDeploys(a,v)^{(s)}}\right)$$

end for loop

end algorithm

Table 15 summarizes the results from the Monte Carlo simulations while also comparing those results to the main results, which treated all model input as fixed and known. (The percentages in the table are written with only two decimal places because it was the maximum possible precision after running the Monte Carlo simulation for 10,000 iterations.) The results from the two approaches are very similar because the Monte Carlo error in the number of deployments and rupture rates were relatively small, which we attribute to the large sample size of the estimates. Therefore, while it is an important exercise to try to account for every source of uncertainty in our projections, our conclusions did not appear to be sensitive to whether we did so. Both suggest that the probability of another rupture in the future is high – around 74%.

Table 15: Distribution of Future Ruptures for the Original Model and Monte Carlo Simulation. DAB: Driver Air Bag; PAB: Passenger Air Bag.

		Probability of X or More Ruptures for DAB and PAB Inflators Combined	
Scenario	***Number of Ruptures (X)***	***Original Model (from*** Table 11***)***	***Monte Carlo Simulation (10,000 iterations)***
Main: DAB and PAB inflators have same rupture rate	1	73.71%	73.32%
	2	38.60%	37.34%
	3	15.14%	14.230%
	4	4.69%	4.07%
	5	1.19%	0.94%
	6	0.26%	0.27%
	7	0.05%	0.04%
	8	0.01%	0.01%
Alternative: DAB and PAB inflators have different rupture rates	1	83.47%	83.11%
	2	53.72%	52.51%
	3	27.96%	26.08%
	4	10.89%	9.98%
	5	3.65%	3.26%
	6	1.04%	0.83%
	7	0.26%	0.15%
	8	0.06%	0.03%

Limitations

It is difficult to estimate rates of rare events precisely and project future events with precision. We have conducted three analyses to quantify uncertainty in our estimates:

- we estimated sampling error and confidence intervals to quantify the uncertainty due to sampling in FARS and CRSS.
- we conducted a Monte Carlo simulation for a more comprehensive examination of uncertainty; and
- we calculated estimates under an alternative scenario under which driver and passenger air bag inflators are believed to rupture at different rates.

In each of these analyses, we have treated the seven ruptures as known quantities, with no variation and no error, because these are known to be the totality of the ruptures that have occurred to date. We recognize that under different circumstances, it is possible that more or fewer ruptures might have occurred (if the subject vehicles had taken more or fewer trips than they did) and this would have substantively changed the estimated rupture rate. But because the seven ruptures are known, we don't vary them in our analyses.

FARS and CRSS are limited to police-reported crashes on public roads. However, we wouldn't expect many deployments in other circumstances (such as in parking lots or crashes not reported to law enforcement).

Our binomial models of ruptures assumes that ruptures constitute statistically independent events, meaning that the fact that a particular inflator ruptures (or doesn't rupture) does not impact the chance that a different inflator ruptures. This makes sense since the manufacturing defect appears to occur in a random manner.

Throughout this paper, we have treated the rupture rate as constant over time, meaning that inflators neither become more rupture prone as they age, nor less rupture prone. This would seem consistent with the nature of the defect, as the presence of debris or insufficient weld leading to the rupture would seem to be ever present (neither materializing nor vanishing over time).

The CAFE attrition model and miles driven model are based on the entire U.S. vehicle fleet. We assume the estimates for the subject vehicles resemble that of the U.S. fleet.

Estimated deployments per seat-occupied crash and seat occupancy computed rates based on known values.

Our calculations assume that the subject inflators do not deploy (or rupture) if the seat is unoccupied. Due to the prevalence of air bag suppression systems in vehicles in the U.S., we believe it is unlikely that the subject vehicles deploy frontal air bags under these circumstances. FARS and CRSS do not record air bag deployment information for unoccupied seats. Had we somehow adjusted our estimates to account for deployments with unoccupied seats, our estimated deployments (both past and future) would have increased, and our rupture rate would have decreased. It is not clear whether our projected future ruptures would have increased or decreased.

Comparison to the Analysis Supporting the Initial Decision

The September 2023 Initial Decision presented different estimates computed from a different methodology than those we have presented above. The methodology we have used in this paper reflects the consideration of points raised in several public comments to the Initial Decision. We believe the estimates presented here are more accurate because they take into account additional factors not previously incorporated.

The Initial Decision presented two estimates:

- that about 2.6 million DAB and PAB deployments occurred in the subject vehicles (this was an estimate of deployments during 2000-2023), and
- that the combined rate of ruptures to deployments was about 7 out of 2.6 million, which as explained at the Public Meeting is also stated as 0.0003%.

Based on these estimates, NHTSA also projected that about three future ruptures would occur in the subject vehicles, including both vehicles recalled and those not recalled.[25]

The methodology NHTSA used to compute these estimates was as follows. NHTSA estimated the registered vehicle years for the subject vehicles in 2000-2023 and in 2024 onwards using the 2016 CAFE attrition model. We assumed that DABs and PABs deploy in frontal crashes with a delta-V of 15 mph. We estimated that each year, about 0.4% of subject vehicles get into such crashes, using data from 2015-2016 on light trucks. Multiplying the subject vehicle registered vehicle years by the 0.4% figure yields an estimated 2.6 million deployments of the subject inflators (both DAB and PAB) during 2000-2023. We estimated the rupture rate as the ratio of the seven ruptures to the estimated 2.6 million deployments. We projected future ruptures by applying the rupture rate to the analogous estimate of future deployments.[26]

NHTSA received several public comments on these figures and the methodology used to compute them.

The comments generally fell into nine categories, summarized in the table below, along with how we addressed each.

Table 16: The Main Comments Received and How We Addressed Them

Comment: NHTSA should …	***How the comment is addressed in revised calculation***
Account for cars possibly having different deployment rates than light trucks	We compute separate deployment rates for cars and light trucks from actual crashes of the subject vehicles.
Account for older vehicles being driven less	We incorporated the CAFE miles driven model.
Use the latest CAFE model	We used the model from the 2022 Final Rule
Use more recent data to estimate deployment rates	We used data from 2017-2022 to estimate deployment rates
Account for PABs deploying less frequently than DABs	We used actual deployments from subject vehicles in crashes.
Treat recalled inflators differently	We removed recalled inflators from the projected future deployments and future ruptures.

[25] This future ruptures estimate was not posted to the public investigation file because it relied on and included information that is currently under claims of confidentiality.
[26] See the public meeting testimony in docket NHTSA-2023-0038 for additional details on this calculation.

Comment: NHTSA should …	*How the comment is addressed in revised calculation*
Include more decimal places in the estimates	We present estimates with ten decimal places.
Calculate deployments, rupture rate, and future ruptures for various subpopulations	We calculated them for DAB and PAB inflators.[27]
Be as methodologically stringent as the agency required in rejecting GM's petition for inconsequentiality in docket NHTSA-2016-0124	We added 95%-confidence intervals, reduced the degree of rounding

The new estimates differ from the old ones, as shown in Table 17.

Table 17: Revisions to the Initial Estimates

Quantity being estimated	*Initial estimate*	*Revised estimate*	*Approximate % change*	*Notes*
subject vehicle DAB and PAB deployments during 2000-2023	about 2.6 million	1,349,801.713757170	-48%	
rupture rate for DAB & PAB inflators combined	about 0.0003%	0.0005185947%	73%	
future ruptures of the subject inflators	about 3	1.3074221535	-56%	The initial estimate included vehicles that have been recalled; the revised estimate does not.

There could be several reasons for the differences. The new calculation takes a miles-based framework instead of a registered-years-based one. This allows the new estimates to take into account that older vehicles are driven less than new ones. Also, the new calculation estimates deployments per crash using actual crashes of the subject vehicles, rather than applying an engineering proxy that frontal air bags generally deploy in frontal crashes at around 15 mph delta-V. This allows the new estimates to take into account that different vehicle manufacturers may tune their air bag deployment algorithms to deploy under different types of crashes and/or at different delta-V thresholds. It also takes into account that different vehicle manufacturers may

[27] Commenters also recommended computing separate estimates for, e.g., individual vehicle manufacturers. NHTSA has no evidence to support that the manufacturing defect is more prevalent in some manufacturers' vehicles than others, and did not compute such a breakout. We computed the DAB-vs-PAB breakouts simply to examine the sensitivity of the calculation.

take different approaches to address the FMVSS 208 requirement for PAB deployments to protect small-stature individuals.

Finally, we note that there were minor revisions to the subject vehicle population since the September 2023 Initial Decision, reflected in Table 18. The revisions removed a small number of out-of-scope (non-toroidal) inflators and duplicate production figures.

Table 18: Revisions to the Subject Population

Air bag	***Production used in Initial Decision***	***Most recent production, from 2/20/2024***	***% change***
DAB	40,932,800	40,353,473	-1%
PAB	11,908,339	10,865,609	-9%
Total	**52,841,139**	**51,219,082**	**-3%**