

**Unveiling Regulatory Operations: A Data Set of the Determinants, Process, and Outcomes of Product Defect Investigations by the U.S. Automotive Safety Regulator**

**Forthcoming in *Manufacturing & Service Operations Management (M&SOM)***

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<sup>1</sup> Vivek is the corresponding author. This article is an offshoot of Vivek's doctoral dissertation. Vivek thanks Neetu Astvansh, Ramesh Bhat, and Ishan Srivastava for collecting part of the data. Last, this manuscript has reached fruition because of the developmental, decisive, and considerate AE. So, Hoorsana and Vivek bow down to the AE in gratitude.

## Unveiling Regulatory Operations: A Data Set of the Determinants, Process, and Outcomes of Product Defect Investigations by the U.S. Automotive Safety Regulator

### Abstract

**Problem Definition.** The paucity of data on governmental regulatory agencies' product safety defect investigations has restricted our knowledge about (1) the determinants of a regulator's decisions to open or close an investigation, (2) the process it follows between opening and closing of an investigation, and (3) the outcomes of the investigation when it is closed.

**Methodology/Results.** The authors view a safety regulator's opening and closing of a product defect investigation as a decision of interest to the OM discipline. This data paper describes a rich, novel, and hand-collected data set of all investigations that the National Highway Traffic Safety Administration (NHTSA)—the U.S. regulator for automobile safety—opened and closed against 187 manufacturers between 2009 and 2021. The authors provide two Microsoft Excel data files, one capturing data for the investigations opened and the other for the investigations closed. The data files enable researchers to address three sets of research questions. First, researchers can use the "Data on Investigations Opened" file to model the determinants of a regulator's opening of a product defect investigation. Second, researchers can mine the textual variables from both files to identify the steps involved in the investigation process. They can also use the process variables included in the data to investigate the regulator's efficiency in opening and closing investigations. Third, researchers can use the "Data on Investigations Closed" file to better understand when and why a regulator closes an investigation and the outcomes of the closed investigations.

**Managerial Implications.** The data files can also be valuable to nonacademic stakeholders (e.g., governmental organizations and regulators, journalists, liability lawyers, politicians, and safety advocates). The authors provide an open-access website that simplifies the use of the data for a nonacademic audience and allows them to draw insights from the data via graphs and tables.

*Keywords:* public policy, regulatory agency, product defect investigation, decision-making process

### 1. Introduction

Operations management (OM) academics have extensively researched a manufacturer's investigation of a product safety defect. This research falls under the rubric of product recall and, more broadly, product quality management (see Tables OS1-OS6 in the online supplement for a summary of this research). While examining a *manufacturer's* investigation and the concomitant product recalls has significantly contributed to OM theory and practice, studying a product safety *regulator's* investigation of safety defects can help develop and test organizational theories outside the typical setting of for-profit organizations (Astvansh et al. 2024b; Cho et al. 2021; Helper et al. 2021; Kaplan 2021). More concretely, OM academics can develop and/or test theories on (1) the determinants of a regulator's decision to open or close an investigation, (2) the regulator's process unfolding between its opening and closing of an

investigation, and (3) the outcomes of the investigation, observed at the time of closing (Ball et al. 2022).

A product safety regulator aims to keep people safe from unsafe products in categories that fall under its jurisdiction. For example, the U.S. National Highway Traffic Safety Administration (NHTSA) aims to “save lives, prevent injuries, and reduce economic costs due to road traffic crashes, through education, research, safety standards and enforcement activity” (NHTSA 2023). Broadly, the process by which a regulator achieves this aim includes (1) receiving reports from product users or product manufacturers about incidents where a product user has been harmed<sup>2</sup>, (2) testing new products for compliance with the product-safety standards<sup>3</sup>, (3) determining whether the product has a safety defect or is noncompliant with standards, and (4) deciding what to do next, including whether to mandate a product recall (Astvansh et al. 2022; Ball et al. 2022; Eilert et al. 2017).

The regulator faces a dilemma in its decisions to open and close investigations. On the one hand, it is short on human resources and analytical capability (NHTSA 2015; U.S. Department of Transportation 2023). Therefore, it must choose which set of incident reports to focus on and when to open an investigation to prevent wasting resources or pressuring the manufacturer into initiating a premature product recall. On the other hand, the longer the regulator waits to open an investigation, the greater the product users’ exposure to an allegedly unsafe product, raising doubts over the regulator’s efficiency and effectiveness (U.S. Department of Transportation 2023; U.S. Government Accountability Office 2011). This dilemma presents an opportunity for OM academics and practitioners to develop theory and empirical evidence on the regulator’s decision-making process.

Some prior studies (e.g., Borah and Tellis 2016; Liu et al. 2017) have mentioned anecdotes of the regulator’s process, providing academics and practitioners a teaser of the process and the available regulatory data. Other studies have gone a step forward and used parts of the data (e.g., Astvansh and

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<sup>2</sup> Harm ranges from injury to a crash (in the case of automobiles) or fire to fatality, suggesting a continuum of severity.

<sup>3</sup> For example, the NHTSA’s Office of Defect Investigations (ODI) receives the reports, analyzes them, and makes these data publicly available ([https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/14895\\_odi\\_defectsrecallspublicdoc\\_110520-v6a-tag.pdf](https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/14895_odi_defectsrecallspublicdoc_110520-v6a-tag.pdf)). The NHTSA’s Office of Vehicle Safety and Compliance (OVSC) tests new vehicles for the compliance with the Federal Motor Vehicle Safety Standards ([https://www.nhtsa.gov/sites/nhtsa.gov/files/ovsc\\_mission.pdf](https://www.nhtsa.gov/sites/nhtsa.gov/files/ovsc_mission.pdf)).

Eshghi 2023; Astvansh et al. 2022; Colak and Bray 2016). However, the focus has exclusively been on regulatory investigations and inspections *that lead to a recall* (Ball et al. 2018 is a welcome exception). Therefore, what is lacking is a concerted effort to develop theory and provide empirical evidence on the complete regulatory decision-making process and its outcomes. We attribute the lack of research on the regulatory decision-making process, at least partly, to the paucity of data describing the process.

We aim to remove this paucity by providing a hand-collected, rich, and novel data set on *all* product defect investigations opened and closed by the NHTSA between January 1, 2009, and May 31, 2021. The novelty of our data files emerges through the three tasks we perform. First, our data files include regulator-specified text on each investigation at the time of the opening and at the time of the closing. The text helps glean process variables, bookended by the opening and closing events. Second, our files cover *all* stages of a regulatory investigation (e.g., preliminary investigation, engineering analysis). We link these stages to complaint and early warning reporting (EWR) variables, thus opening the black box of what drives the regulator to escalate an investigation. Third, our data files cover investigations that did *not* result in a recall, thus enabling users of our data files to avoid sample selection and develop theories on all types of regulatory investigations.

We have collected this data set exclusively for a data paper for the *Manufacturing & Service Operations (M&SOM)*. We follow the prior data papers that *M&SOM* has published (Astvansh et al. 2022; Manary and Willems 2022; Shen et al. 2020; Sun et al. 2021) to structure our data files and this article. We provide two Microsoft Excel data files, which include data on the characteristics of 628 investigations the NHTSA opened and 577 investigations the NHTSA closed during our observation period. These investigations involved 187 distinct automotive manufacturers. For each investigation, we collected all the information available in the PDF files that the NHTSA uploads on its website at the time of opening (named “opening resume” by the NHTSA) or closing (i.e., “closing resume”) the investigation. This information appears as columns in our data files and, to our knowledge, is novel and forms the primary contribution of our article (see §2 of the online supplement for a discussion on related data used or provided in the extant literature).

We created additional columns/variables by linking variables in our data files to (1) the Standard & Poor's Compustat, (2) the Center for Research in Security Prices (CRSP), (3) the NHTSA's three publicly available data files (recalls,<sup>4</sup> investigations,<sup>5</sup> and complaints<sup>6</sup>), (4) early warning reporting (EWR) data sets<sup>7</sup>, and (5) the data from manufacturers' recall safety or noncompliance reports (Astvansh et al. 2022). While the EWR data sets are novel, the variables imported from Compustat, CRSP, and NHTSA's three data files are not novel and are provided to facilitate the usability of our data files. Last, we created a website (<https://unveiling-regulatory-operations.streamlit.app/>) that allows users to examine the statistical distribution and time trends of the variables in our data files via tables and graphs.

Our data files allow academics to research the determinants, process, and outcomes of a regulator's opening and closing of an investigation. Such research can help discover similarities and/or differences between a government agency's processes and that of a (for-profit) business, and thus contribute to relevant theories such as the problem-solving perspective (Cantor and Macdonald 2009; Choo 2014; Ni and Huang 2018), and organizational learning theory (Cyert and March 2015; Greve 1998; Haunschild and Rhee 2004).

Our data files can also be of value to various nonacademic stakeholders, such as the U.S. federal government, the NHTSA, journalists, liability lawyers, and consumer safety advocates. The U.S. Department of Transportation's audits in 2015 and 2023 reported deficiencies in the NHTSA's process of receiving and mining harm-incident reports (U.S. Department of Transportation 2015b, 2023). Similarly, journalists, liability lawyers, and safety advocates have critiqued the NHTSA for being slow in its investigation process based on anecdotal evidence (LaReau 2019; Plungis 2018). Our data files allow stakeholders to provide data-driven evidence for the NHTSA's efficiency, or the lack thereof.

## 2. Related Literature

Academics have researched product-safety defects for long. Tables OS1, OS2, and OS3

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<sup>4</sup> [https://www-odi.nhtsa.dot.gov/downloads/folders/Recalls/FLAT\\_RCL.zip](https://www-odi.nhtsa.dot.gov/downloads/folders/Recalls/FLAT_RCL.zip)

<sup>5</sup> [https://static.nhtsa.gov/odi/ffdd/inv/FLAT\\_INV.zip](https://static.nhtsa.gov/odi/ffdd/inv/FLAT_INV.zip)

<sup>6</sup> [https://static.nhtsa.gov/odi/ffdd/cmpl/FLAT\\_CMPL.zip](https://static.nhtsa.gov/odi/ffdd/cmpl/FLAT_CMPL.zip)

<sup>7</sup> <https://www.nhtsa.gov/vehicle-manufacturers/early-warning-reporting>

summarize the multidisciplinary empirical research on the determinants, processes, and outcomes of product safety defects in the automotive industry, respectively.<sup>8</sup> This research falls under the narrower, substantive topic of product recall and the broader, theoretical domain of product quality management.

The articles in Table OS1 consider a broad set of determinants of product safety defects. Such determinants exist at (1) product level (e.g., luxury versus functional products, innovation radicalness), (2) brand or firm level (e.g., firm size, reputation, production volume, financial leverage, and debt), (3) consumer level (e.g., content of consumer complaints, perceived brand reliability), and (4) the interplay of the firm and external parties (e.g., distance between manufacturer and suppliers, supply chain network characteristics, industry unionization, and lobbying spending). Research summarized in Table OS2 examines the characteristics of the process, beginning with the discovery and investigation of a defect to the initiation and implementation of a product recall (e.g., investigation opening to recall time, and defect discovery to recall time). Last, research on the outcomes (Table OS3) has considered—among others—the recalling firm’s financial (e.g., sales and abnormal stock returns) and marketing (e.g., advertising spending, engagement with the firm’s social media posts) outcomes.

A consistent theme among these articles is the focus on the manufacturers of defective products. As Tables OS1 and OS3 suggest, this focus has produced valuable theoretical and managerial insights about the determinants and outcomes of product safety defects. However, researchers have paid little attention to the process and operations underlying the discovery and investigation of safety defects. This lack of attention is understandable because a safety defect can be discovered and investigated not only by product manufacturers, but also by product safety regulators—an entity whose role has been overlooked in the existing literature. The distinction between manufacturer and regulator as the investigator is critical because a manufacturer is a for-profit organization. In contrast, a regulator is a nonprofit, governmental organization, whose aim is to protect the public from unsafe products. The two types of organizations

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<sup>8</sup> Because our data set is on automotive safety defects, we limit our first set of tables to research in the automotive context. However, the themes and implications discussed in this section are generalizable to safety defects across product categories. Tables OS4, OS5, and OS6 provide a summary of the empirical research on the determinants, processes, and outcomes of safety defects in nonautomobile contexts, respectively.

differ in the incentives that drive whether, when, how, and why they investigate unsafe products (Astvansh et al. 2024b). Indeed, while a manufacturer would prefer to report fewer investigations, a regulator is evaluated more favorably if it opens more investigations (Plungis 2018).

The fundamental differences in the manufacturers' and the regulator's incentives and goals mean that research on the regulator's role is vital in presenting a complete and accurate overview of the determinants, process, and outcomes of product safety defects. In addition, these differences serve as a roadmap to test whether organizational theories (e.g., those of knowledge, failure, and learning)—which extant research has tested to explain *business* operations—also explain *regulatory* operations. Studying regulatory operations can not only help develop and test theory, but also yield consequential practical implications by shaping regulatory decisions, which in turn would impact product manufacturers. Our data set helps provide the means for this roadmap.

### 3. Context

#### 3.1. NHTSA and its roles and responsibilities

Safety defects in a product are an unfortunate reality. While the product manufacturer strives to detect all defects before selling the product to a user, safety defects are often discovered during the course of usage and, often, when a user experiences an incident where they perceive their safety is threatened. The user may report the safety incident to the manufacturer, the retailer, their insurance company, or others via social media (Astvansh et al. 2024). In the ideal world, one would expect the manufacturer—the entity owning the legal liability for the unsafe product—to be responsive and responsible (Hora et al. 2011). That is, the manufacturer would promptly recall the unsafe products and provide a remedy (e.g., replace or repair the unsafe product, or refund the purchase). In parallel, the manufacturer would identify the source of the problem, devise a solution, and implement it in the product units currently being manufactured and/or designed. However, the manufacturer's decision is far more complex, and the potential for product liability lawsuits makes the decision trickier (Astvansh et al. 2024a). Consequently, consumers might stay unaware of unsafe products.

The solution to this problem is the product safety regulator. A regulator is created by federal or

state laws, which grant the regulator powers and establish their responsibilities. For example, the NHTSA is an agency of the U.S. federal government and a part of the U.S. Department of Transportation. It was created on September 9, 1966, when President Lyndon Johnson signed the National Traffic and Motor Vehicle Safety Act and the Highway Safety Act into law. A regulator's mission is to protect people from unsafe products in all categories falling under its jurisdiction. Regulators achieve this mission by creating safety standards and regulations and enforcing them through premarket approval and/or postmarket surveillance (Ball et al. 2017; Cavazos et al. 2015). For instance, the FDA must approve moderate- to high-risk medical products before firms can market these products in the United States (i.e., premarket approval). In addition, FDA inspectors regularly visit manufacturing facilities to check their adherence to quality standards (Ball et al. 2017).

In contrast to the FDA, the NHTSA undertakes only postmarket surveillance, for which the primary catalyst is the reports of safety incidents (NHTSA calls them *consumer complaints*) where consumers believe their safety is threatened (Bray et al. 2019; Magno 2011). The NHTSA shares these reports with the manufacturer and makes them available on its website. In addition, Title 49 of the Code of Federal Regulations Part 579 requires that automobile manufacturers submit to the NHTSA quarterly early warning reporting (EWR) data for each vehicle year, make, and model combination. The EWR data provides "Death & Injury Record" and "Property Damage Records." The former reports the date, location, number of deaths, number of injuries, and the allegedly defective components for each incident. The latter names the component(s) alleged to have caused the property damage (Astvansh et al. 2024a). That is, the EWR data are harm data and not complaints data.

We note two additional differences between the NHTSA's complaints data and a manufacturer's EWR data. First, the unit of observation in the NHTSA's complaints data is a complaint. In contrast, the manufacturer's EWR data are aggregated quarterly and at the vehicle make-model-year level. Notwithstanding this difference, if a harm incident involving a manufacturer's vehicles leads to a complaint filed to the NHTSA, the complaint and the concomitant harm will feature in the NHTSA's complaints data, while the harm will likely feature in the manufacturer's EWR data for that quarter. We

thus expect the complaints and EWR data to overlap. Second, whereas the NHTSA receives complaints data in real-time from the public, it receives the EWR data at least one quarter after the harm occurred. Regardless, the NHTSA uses both the complaints and the EWR data as inputs to its investigation process, which we describe next.

### 3.2. The NHTSA's investigation process

The process of discovering a potential defect in a vehicle includes discrete events, each with a specific date. The events include (1) the date of the earliest safety-incident report the NHTSA received, (2) the date when (and if) the NHTSA opened an investigation, (3) the date when (and if) the NHTSA closed the investigation, and (4) the date when (and if) one or more automotive manufacturers initiated recalls. Figure 1 outlines these events and their corresponding dates in our data files.

**Figure 1. Events in the NHTSA's investigation process**

Note: Text in italics is the variable's name in our data files.

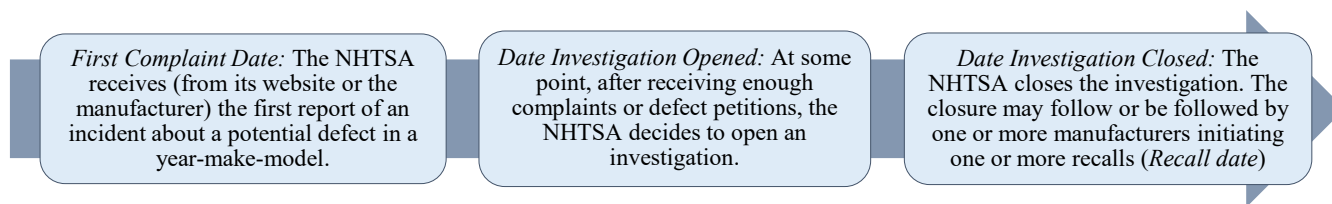
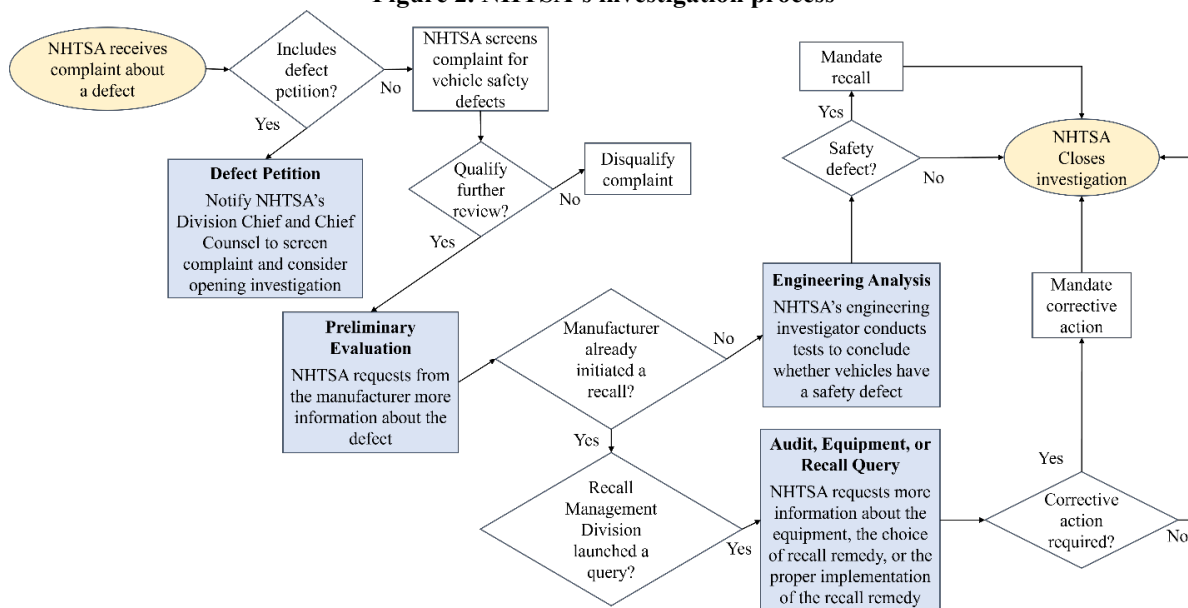


Figure 2 summarizes the NHTSA's process to investigate a safety defect. The process often begins when the NHTSA receives a complaint about a safety incident, and ends when the NHTSA closes the investigation. Figure 2 highlights (in blue-colored boxes) the six types of investigations the NHTSA can open. When the NHTSA receives a complaint about a safety incident, it screens the complaint to determine (1) whether it meets the criteria for a defect petition, and (2) whether it indeed reports an incident that is potentially related to a vehicle safety defect (NHTSA 2019). If the complaint meets the criteria for a defect petition, the NHTSA escalates the complaint to its divisional chiefs so that they can consider the direct launch of an investigation. If the complaint does not qualify as a defect petition but describes a vehicle safety defect, the NHTSA assigns the complaint a *severity level* (NHTSA 2020).

The NHTSA's severity level is a product of two characteristics: (1) whether the driver can detect the defect (three levels: not considered, reasonable detectability, and none or poor detectability) and (2)

the severity of the potential harm (three levels: minor, moderate, and major/severe). The NHTSA infers the levels of these two characteristics and assigns the complaint a severity level that varies from 1 (lowest) to 5 (highest) (NHTSA 2020). The NHTSA escalates complaints with a severity level of 5 as a cause for launching a Preliminary Evaluation (PE). It compiles complaints with severity levels between 1 and 4 and gathers more information from the complainer, its internal databases, the manufacturer's EWR data, or other third-party sources. This compilation leads the NHTSA to decide whether to launch a PE (NHTSA 2019).

**Figure 2. NHTSA's investigation process**



A PE involves the NHTSA formally requesting more information about the alleged defect from the manufacturer. If the manufacturer initiates a recall related to the focal defect after the NHTSA opens the PE, the NHTSA may close the PE. If the manufacturer initiated a recall *before* the NHTSA opened a PE, the NHTSA may close the PE and open an audit query, an equipment query, or a recall query. These queries are meant to investigate (1) potentially inadequate remedies, (2) installation of potentially defective components during recall repair, and/or (3) low recall completion rate (Stout 2015). In other words, such audits aim to investigate whether the manufacturer complied with the vehicle safety standards, and whether the manufacturer's remedy process met the expected level of completion. Last, the NHTSA may close a PE after upgrading it to an *Engineering Analysis* (EA). An EA involves the

investigator conducting engineering tests on the allegedly defective vehicles. If the EA concludes that the vehicles have a safety defect, the NHTSA can mandate the manufacturer to initiate a recall.

#### 4. Data Collection and Dataset Description

Next, we explain our procedure for collecting data and constructing our data files. Table OS7 in the online supplement is the data dictionary, which lists the data type/format, computation method and formula, and source for the variables included in our data files. In addition, Table OS8 lists all the variables included in our data files, organized by their sources.

##### 4.1. Data retrieval

The NHTSA identifies each investigation with a unique Investigation ID, such as PE09001. We downloaded the NHTSA investigations data file (`flat_inv.txt`) on May 31, 2022, and retained a list of all unique investigation IDs associated with the investigations opened or closed since January 1, 2009 (we chose this date to be consistent with Astvansh et al. [2022]). We found 690 distinct investigation IDs. Next, we concatenated each Investigation ID to <https://www.nhtsa.gov/recalls?nhtsaId=>, and accessed the NHTSA's PDF files for each investigation.

Of the 690 distinct Investigation IDs, we found the opening or closing resume PDF files for 650 investigations: (1) 555 investigations opened *and* closed, (2) 73 opened *but not* closed, and (3) 22 only closed during our observation period. We downloaded<sup>9</sup> 1,205 opening and closing resume PDF files: 628 opening resumes, and 577 closing resumes.

The raw data from these PDF files serve as the basis for our data files. Because most of these PDF files are images, we used the optical character recognition (OCR) feature in Adobe Acrobat Pro software program so that we could select the text, copy it, and paste it into an Excel file. We copied and pasted the data from 100 PDF files to Excel files ourselves to familiarize ourselves with any errors or potential mistakes that the research assistants (RAs) could make. We reviewed the results and found some

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<sup>9</sup> We coded a Python scraper to automate the download, but the NHTSA website blocked our scraper after it downloaded a few files. We thus hired research assistants to download the files manually. Also, we used the Internet Archive Wayback Machine (<https://archive.org/>) to search for files that were not available on the website when we searched.

redundant blank spaces in the values (e.g., 1,000 was pasted as 1, 000) but no error in the actual values. So, we wrote software code to remove these redundant blank space characters.

Next, we wrote instructions for RAs. We hired four RAs and distributed the remaining investigation IDs among them. We first asked each RA to copy-and-paste (and not type at all) data from 50 PDF files so we could check them for errors. We were pleased that the only errors were in the blank space characters. After the data for all 1,205 files were collected, we randomly picked 400 rows from the Excel files. We assigned 100 of these randomly picked rows to an RA and asked them to check for errors. Each coauthor read another 100 rows. Thus, we manually checked nearly 50% of all rows for errors. We found no errors. We attribute the absence of any errors to our strict instruction that RAs will copy and paste and not type anything in the Excel files.

#### **4.2. Data set construction**

We used the NHTSA's *opening* resume PDF files as the basis for creating our "Data on Investigations Opened" Excel file. This Excel file has four sheets. Sheet #1—named Characteristics of Inv Data—includes 628 non-header rows, each representing an opened investigation, and 60 columns describing the characteristics of each investigation *at the time of its opening*.<sup>10</sup> Sheet #3—named, Complaints at Opening—includes 16,985 non-header rows representing the complaints that led to the opening of at least one investigation and 10 columns describing their characteristics. Sheets #2 and #4 are the dictionaries for sheets #1 and #3.

We used the NHTSA's *closing* resume PDF files to create our "Data on Investigations Closed" Excel file, the second of our two data files. This Excel file has six sheets. Sheet #1—named Characteristics of Closed Inv Data—includes 577 non-header rows, each representing a closed investigation, and 62 columns describing the characteristics of each investigation *at the time of its closing*. Sheet #3—named, Complaints at Closing—includes 30,271 non-header rows representing the complaints the NHTSA received before closing the investigations, and 11 columns describing these complaints.

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<sup>10</sup> Of these 60 columns, five overlap with the fields in the NHTSA's investigation data file (flat\_inv.txt).

Lastly, Sheet #5—named, Outcomes of Inv— includes 1,196 non-header rows representing the outcomes of the 577 closed investigations, and 38 columns stating the characteristics of such *outcomes*. Sheets #2, #4, and #6 are the dictionaries for sheets #1, #3, and #5.

Next, we briefly describe how we extracted the raw values from the opening and closing resume PDF files using PE09001, the first investigation in our data files, as an example. We also describe how we used these values and other data files to create additional variables. Figure OS1 in the online supplement summarizes our data retrieval and data set construction procedure.

**4.2.1. The “Characteristics of Opened Inv” and “Characteristics of Closed Inv” sheet**

Consider the opening resume of PE09001 as an example. The opening resume file comprises three sections: (1) a top, (2) a table in the middle, and (3) a bottom (see Figure 3.A).

**Figure 3: Screenshot of the NHTSA website for the opening and closing resumes of PE09001**

3.A. Opening resume of PE09001

3.B. Closing resume of PE09001

The top section provides values of the following eight columns of the “Characteristics of Opened Inv” sheet: *Investigation ID*, *Date Investigation Opened*, *Principal Investigator*, *Subject*, *Manufacturer*, *Products*, *Population Raw*, and *Problem Description*. The top section of *some* opening resumes (e.g., investigation DP10005) includes three additional values: *Prompted By*, describing what or who prompted

the investigation, and the names of the investigation's *Reviewer* and *Approver*.

The top section of the closing resume of PE09001 (see Figure 3.B) provides the values of the same eleven columns in the “Characteristics of Closed Inv” sheet, plus the column *Date Investigation Closed*. The values of several of these columns differ at the time of opening and closing of investigations, indicating the change in the NHTSA's level of information between the times it opens and closes an investigation. For instance, while the defect that led to the investigation PE09001 was initially suspected in the model-year 2008 of Blue Bird Vision, the investigation later expanded to include model years 2006 and 2007, resulting in a substantial broadening of the scope.

The middle sections of the opening and closing resume PDF files comprise a table—named “Failure Report Summary”—with seven rows and four columns. These tables specify the count of complaints, and reports of fires/crashes, injuries, fatalities, and “other” failure reports received by the NHTSA, the manufacturer, and the two parties (removing the overlap) at the time of opening or closing the investigation. The tables also specify the number of injuries and fatalities involved in the incidents that led to these complaints and reports. Last, the tables are followed by a description of the reports classified as “other.” The “Failure Report Summary” tables provide the values of columns L through AG of the “Characteristics of Opened Inv” sheet, and columns M through AH of the “Characteristics of Closed Inv” sheet.

The bottom section of the opening and closing resumes populate the columns *Action*, *Engineer*, *Divisional Chief*, *Office Director*, and *Summary*. Last, we used the opening or closing resume PDF files' name to populate the column *File Name*.

We used the values of the columns extracted from the opening and closing resume PDF files to add more variables to our data sets in three ways: by (1) mining the content of the textual variables to create new variables, (2) combining the existing variables to create new variables, and (3) using the existing variables to merge our data with other relevant data sets. We describe below the creation and addition of these variables. Please refer to Table OS7 for a detailed description of these variables.

We created the variable *Population* by retaining only the integer value in the *Population Raw*

column. Next, we used the value from the first two characters of the *Investigation ID* column, to create a new variable, *Investigation Type*. We also subtracted *Date Investigation Closed* from *Date Investigation Opened*, to compute the *Investigation Opening to Closing* time for all closed investigations.

Next, we used latent Dirichlet allocation (LDA) topic modeling to discover topics from the textual content of the *Problem Description* variable. Before building our LDA model, we preprocessed and cleaned the textual data by lowering the text case, expanding contractions, removing unwanted characters, and stop words, and tokenizing, part-of-speech tagging, and lemmatizing the text (Berger and Packard 2021). Further, we removed the lemmas in a *Problem Description* with term frequency, inverse document frequency (TFIDF) scores lower than the 20<sup>th</sup> percentile of the scores (Blei and Lafferty 2009) and thus increased the accuracy of our topic model. We chose the optimal number of topics by calculating the topic coherence scores for 1 to 100 topics and choosing the number 17, which produced the highest topic coherence score before the curve flattened and dropped. Next, we used the results from our trained LDA model to create three variables: *Problem Description Dominant Topic ID*, *Problem Description Dominant Topic Percentage*, and *Problem Description Dominant Topic Keywords*. In addition, we created *Problem Description Sentiment*—the compound sentiment score of the textual content of the *Problem Description* column calculated using the Valence Aware Dictionary and Sentiment Reasoner (VADER). We followed the same procedure to create four similar variables from the textual content of the *Summary* variable.

We used the name of the automotive manufacturer involved in each investigation (i.e., the *Manufacturer* column) to add five firm-level identifiers for publicly traded firms in the United States: *GVKEY*, *TIC*, *CUSIP*, *PERMNO*, and *PERMCO*. We also added the manufacturer's four-digit Standard Industrial Classification (SIC) code, and six-digit North American Industry Classification System (NAICS) code. The unique identifiers allow researchers to merge our data with other data sources (e.g., Compustat) for the publicly traded firms in our data set.

Last, we merged our data with the EWR data at the vehicle year-make-model level. We used the merged data to count and aggregate these numbers up to the quarter of the year in which the investigation was opened or closed, resulting in the creation of four other variables.

#### 4.2.2. The “Complaints at Opening” and “Complaints at Closing” sheets

We assessed the *Summary* column in the “Characteristics of Opened Inv” and “Characteristics of Closed Inv” sheets to extract the unique NHTSA-specified identification number for the complaints associated with the investigation at the time of its opening and closing. For each investigation with a *Summary* section that lists complaint identification numbers, we provide all such *Complaint IDs*, and the *No. Complaint IDs* mentioned in the summary.

We used our *Complaint ID* column, which is the equivalent of the *ODINO* field in the NHTSA’s complaints data file (*flat\_cmpl.txt*) to extract the *Complaint Date*, *Complainer Type*, the names of *Components* and *Make-Model-Years* reported in the complaint, and *Complaint Description*. All these variables are available in NHTSA’s data file. The novelty is in linking these complaints and their characteristics to the associated NHTSA investigations.

Next, we sorted the complaints associated with each investigation based on *Complaint Date* to create *First Complaint Date* (i.e., the date the NHTSA received the first complaint about an alleged defect). Thereafter, we subtracted *Date Investigation Opened* from *First Complaint Date* to create *First Complaint to Investigation Opening*. This variable indicates NHTSA’s efficiency in opening an investigation. For the closed investigations, we also subtracted *Date Investigation Opened* from *First Complaint Date* to create *First Complaint to Investigation Closing*.

#### 4.2.3. The “Outcomes of Inv” sheet

We merged our data with the NHTSA’s investigations data file on *Investigation IDs*, to identify the outcomes of the closed investigations in our data set and create our “Outcomes of Inv” sheet. Of the 577 investigations closed, 268 did not result in any recall, whereas the remaining 309 yielded at least one recall (223 leading to exactly one recall, and 86 leading to more than one recall). We count the unique recalls resulting from each investigation, to create the variable *No. NHTSA Campaign Numbers*. The total number of unique recalls resulting from the closed investigations in our data is 914.

Next, we merged our “Outcomes of Inv” sheet with NHTSA’s recall data file (*flat\_rcl.txt*), to

extract the characteristics of the recalls resulting from the closed investigations in our data. We retained 13 variables from the original NHTSA recall data file, including the *NHTSA Campaign Number*, *Recall Date*, and *Owner Notification Date*. We created *Investigation Closing to Recall* by subtracting *Recall Date* from *Date Investigation Closed*. Similarly, we created *Recall to Owner Notification* by subtracting the *Owner Notification Date* from the *Recall Date*.

We also merged our “Outcomes of Inv” sheet with EWR data at the vehicle year-make-model level. This merge allowed us to count the product-damage incidents, and the number of injuries and deaths for a specific make-model-year up to the quarter of the year in which it initiated the recall, resulting in the creation of four more variables.

Last, we used the unique *NHTSA Campaign Number* to merge our data set with the data from manufacturers’ recall safety or noncompliance reports, provided by Astvansh et al. (2022). We retained three variables from Astvansh et al.’s (2022) data file: *Manufacturer Awareness Date*, *Manufacturer Awareness to Recall* (their *Time\_to\_Recall* variable, denoting the time elapsed between the date when the manufacturer becomes aware of a defect, and *Recall Date*), and *Supplier Mentioned*. Researchers can compare the *Manufacturer Awareness to Recall* variable, to the process-time variables in our data set, such as *First Complaint to Investigation Opening*, or *Investigation Opening to Closing*, and thus compare the process efficiency of the NHTSA and manufacturers in dealing with a safety or noncompliance issue.

## 5. Descriptive statistics and data exploration

We report summary statistics and use graphs to explore the structure and trends for a select number of variables in our data files. The summary statistics and graphs provide an overview of our data. We also explain our website that enables researchers and managers to further explore the characteristics of our data via additional tables and graphs.

### 5.1. Insights from the number of harm incidents reported to the manufacturer and the NHTSA

We begin by assessing the summary statistics of the numeric variables in the two sheets of our “Data on Investigations Opened” file (see columns II–V of Table 1). We focus on the average counts of the various types of failures reported to the NHTSA and to the manufacturer before the NHTSA opens an

investigation. For each type of failure, the average number reported to the NHTSA at the time of opening of an investigation is much lower than the average number reported to the manufacturer. For example, Table 1 reports that the average number of harm-incident reports received by the NHTSA is 44, whereas the average for the manufacturer is 222. A two-sample with unequal variance  $t$ -test reveals a statistically significant difference between these counts ( $t = -4.29, p < .000$ ). Indeed, Figure 4 depicts that the average number of complaints reported to the manufacturer far exceeds the average number of complaints reported to the NHTSA every year, except the year 2016. This imbalance is consistent with the intuition that when vehicle owners experience a harm incident, they are more likely to report the incident to the dealer or the manufacturer, rather than the safety regulator. Further, few owners may be aware of the NHTSA's existence, and among those aware, fewer would know that they can report the incident to the NHTSA and the channel by which they can report.

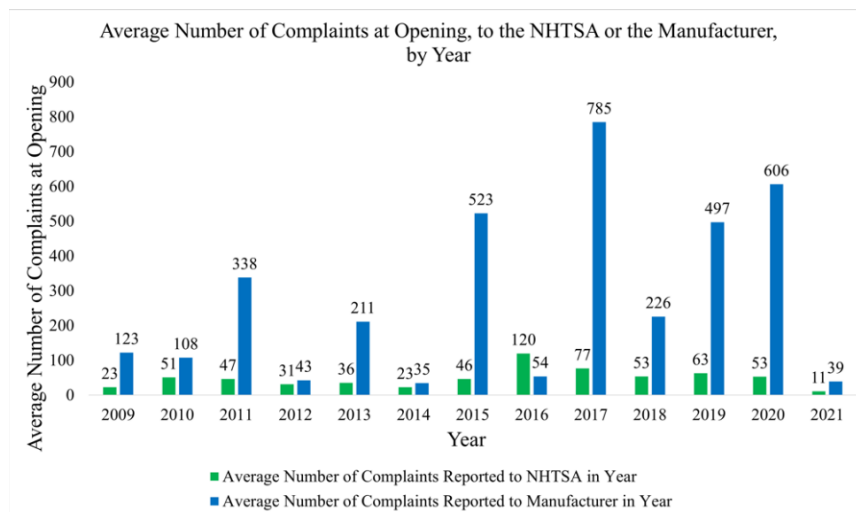
Next, we examine the summary statistics of the numeric variables in the three sheets of our "Data on Investigations Closed" file (see columns VI-IX of Table 1). Again, the average counts of each failure reported to the NHTSA at the time of closing the investigation is lower than the average reported to the manufacturer. This imbalance at the time of opening and at the time of closing suggests that the NHTSA's counts are systematically downward biased and, thus, *not* an accurate measure of the extent of harm caused. Consequently, the NHTSA must rely more on the EWR data from manufacturers rather than solely on the incident reports it receives from owners/consumers.

**Table 1. Descriptive statistics of numeric columns**

	<i>Data on Investigations Opened</i>				<i>Data on Investigations Closed</i>			
	Mean	SD	Mean for PEs	Mean for EAs	Mean	SD	Mean for PEs	Mean for EAs
	II	III	IV	V	VI	VII	VIII	IX
Population (number of vehicles affected)	3584106	57062121	193730	799508	3851418	59536069	252014	474786
No. Complaints Reported to NHTSA	44	131	33	105	93	269	74	184
No. Complaints Reported to Manufacturer	222	537	136	325	253	740	224	422
No. Complaints Reported	306	1609	93	694	331	883	287	586
No. Crashes and Fires Reported to NHTSA	2	14	2	3	3	20	2	7
No. Crashes and Fires Reported to Manufacturer	21	149	40	11	11	123	4	17
No. Crashes and Fires Reported	21	153	31	15	13	141	5	22
No. Injury Incidents Reported to NHTSA	1	2	1	1	1	3	1	2
No. Injury Incidents Reported to Manufacturer	2	8	1	3	2	11	1	7
No. Injury Incidents Reported	2	9	1	4	3	13	2	8

No. Injuries Reported to NHTSA	1	5	1	4	3	8	2	7
No. Injuries Reported to Manufacturer	5	14	4	7	6	22	4	16
No. Injuries Reported	6	15	4	10	8	26	6	21
No. Fatality Incidents Reported to NHTSA	.05	.29	.05	.07	.05	.43	.04	.13
No. Fatality Incidents Reported to Manufacturer	.09	.92	.03	.15	.13	2	.06	.55
No. Fatality Incidents Reported	.1	.95	.04	.18	.14	2	.08	.55
No. Fatalities Reported to NHTSA	.09	.41	.08	.3	.47	2	.25	3.5
No. Fatalities Reported to Manufacturer	.30	2	.09	.71	1	5	.44	12
No. Fatalities Reported	.34	2	.09	.86	1	7	.5	15
No. Other Types of Failures Reported to NHTSA	13	76	9	4	12	66	5	10
No. Other Types of Failures Reported to Manufacturer	1918	5944	865	2877	3048	10497	2276	8109
No. Other Types of Failures Reported	1493	5147	500	2820	2954	10438	2230	7920
Problem Description Sentiment	-.3	.4	-.4	-.3	-.3	.4	-.4	-.3
Summary Sentiment	-.7	.5	-.8	-.8	-.7	.6	-.7	-.7
No. Product Damage Reports Up to Quarter	6443	13239	3904	10000	3398	9701	2204	6323
No. Deaths Incidents Up to Quarter	16	31	12	25	7	21	5	15
No. Injury Incidents Up to Quarter	200	533	123	384	102	299	72	183
No. Injury and Death Reports Up to Quarter	66229	208689	34560	133087	33957	119203	18719	60128
No. Complaint IDs	471	446	523	445	897	757	921	1163
First Complaint to Investigation Opening	1735	1008	1820	1964.2				
First Complaint to Investigation Closing					2467	1223	1875	3147
Investigation Opening to Closing					320	282	203	539
Investigation Closing to Recall					-164	242	-3	-66
Recall to Owner Notification Date					26	137	72	86
Manufacturer Awareness to Recall					579	646	481	785
No. NHTSA Campaign Numbers					20	32	2	1
Recall Size					95976	403060	144592	608140
Recall Scope					9	15	9	10
No. Distinct Manufacturers of Recalled Products					1.06	0	1	1
No. Product Damage Reports Up to Quarter of Recall					1139.7	5368	996	7693
No. Deaths Incidents Up to Quarter of Recall					2	10	3	13
No. Injury Incidents Up to Quarter of Recall					35	153	47	213
No. Injury and Death Reports Up to Quarter of Recall					10814	67567	9622	84977

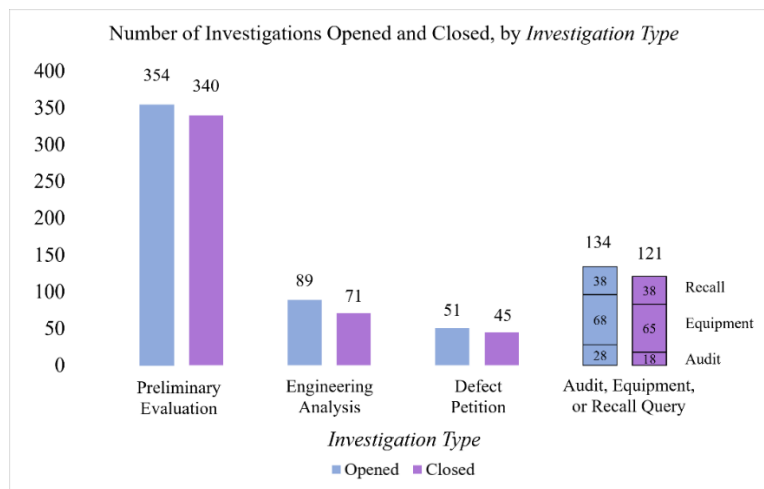
**Figure 4. Total number of complaints reported to the NHTSA and the manufacturer at the time of opening, by year**



## 5.2. Insights from the number of investigations the NHTSA opened and closed

Figure 5 provides the counts—by investigation type—of the 628 investigations the NHTSA opened, and the count of the 577 investigations the NHTSA closed. As §3.2 described and consistent with intuition, the lion’s share belongs to preliminary evaluation ( $354 \div 628 = 56.4\%$  for opened investigations and  $340 \div 577 = 58.9\%$  for closed), followed by engineering analysis ( $89 \div 628 = 14.2\%$  for opened and  $71 \div 577 = 12.3\%$  for closed). Table 1 reports the average values of all numeric variables in our data files for these two major types of investigations. Users of our data can uncover additional informative trends by comparing these values for preliminary evaluations and engineering analyses.

**Figure 5. The number of investigations opened and closed by the NHTSA, by *Investigation Type***



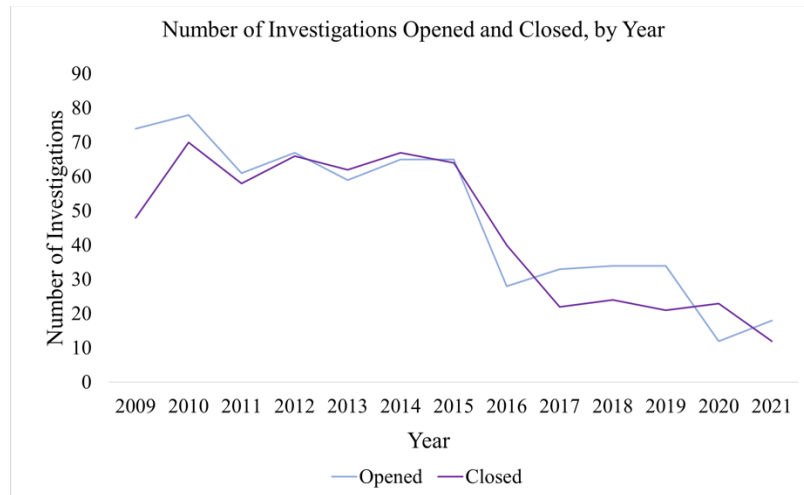
The other four types of investigations are less common. Therefore, we suggest users of our data files exercise caution in using the data for these four types lest their model overfits the data and captures noise instead of true evidence. Users could combine the less frequent investigation types based on an appropriate theory.

Figure 6 depicts the number of investigations the NHTSA opened and closed, by year. We highlight three insights. First, the count of investigations opened dropped substantially in 2016 (from 65 in 2015 to merely 28 in 2016) and it remained at this relatively low level until 2019. This trend supports *Consumer Reports*' conjecture that the count may be related to the former U.S. President Donald Trump (Plungis 2018). Second, in 2020, the number dropped further (from 34 in 2019 to merely 12 in 2020). We

speculate that the COVID-19 pandemic could have been the reason behind the drop. Third, the count had shot to 18 in the first five months of 2021. Unsurprisingly, the trend in the number of investigations closed follows a similar pattern.

**Figure 6. The total number of investigations opened and closed by the NHTSA, by year**

Note: Our data set ended on May 31, 2021, and thus the coverage for 2021 is partial.



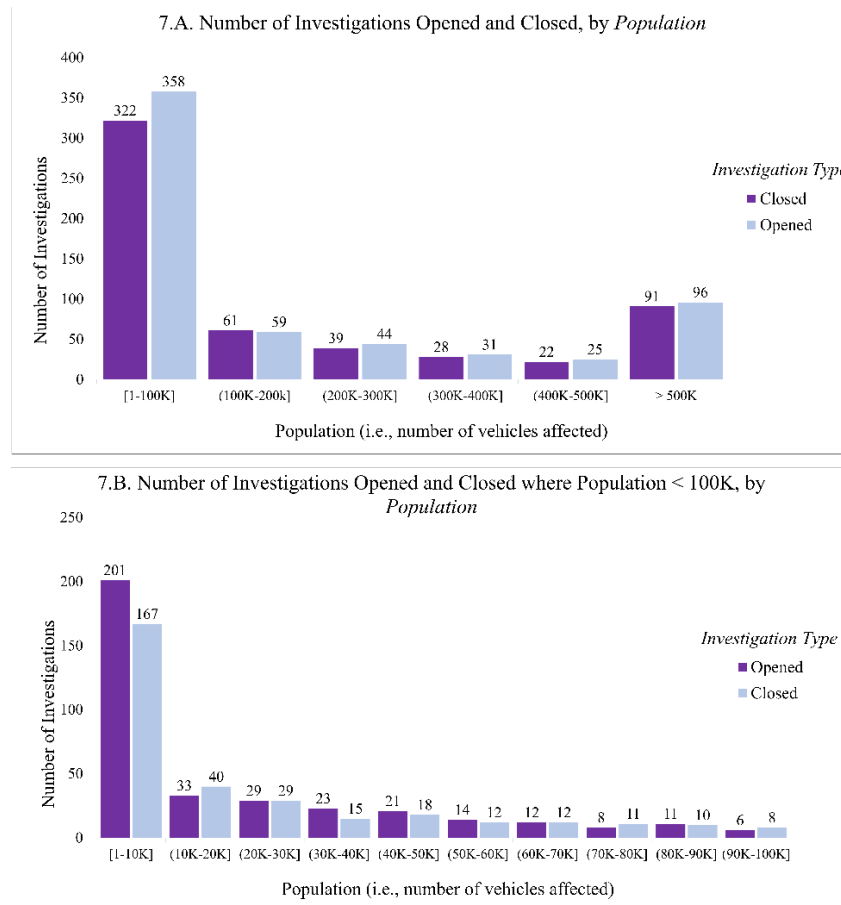
### 5.3. Insights from the number of vehicles involved in the investigations

Next, we examine the distribution of the number of vehicles (i.e., *Population*) involved in the investigations that the NHTSA opened and closed. Figure 7 includes a histogram of the number of vehicles involved in the investigation. Of the 628 investigations opened, 363 (58%) have a population under 100,000. On the other extreme, 96 (15.3%) investigations involve more than 500,000 vehicles each. A reasonable number of investigations belong to each of the bins in between the two extremes, suggesting a variation that users of our data sets can consider examining. Figure 7 also includes an overlay of the same data at the time of the closing of investigations. Unsurprisingly, the percentage of affected vehicles in the bins with higher populations slightly increases between the opening and the closing of an investigation. For instance, the percentage of investigations that involve more than 500,000 vehicles increases from 15.3% at the time of opening to 15.8% at the time of closing.

The insight is that the NHTSA opens and closes many “small” (in terms of the number of affected vehicles) investigations and many “large” investigations. Because the NHTSA is short on resources, we hope NHTSA allocates its personnel disproportionately more to large investigations. More importantly,

when allocating resources, we hope the NHTSA is unbiased by the number of complaints and instead stays focused on the population of affected vehicles.

**Figure 7. Number of investigations opened and closed by the NHTSA, by estimated *Population* (i.e., number of vehicles affected)**



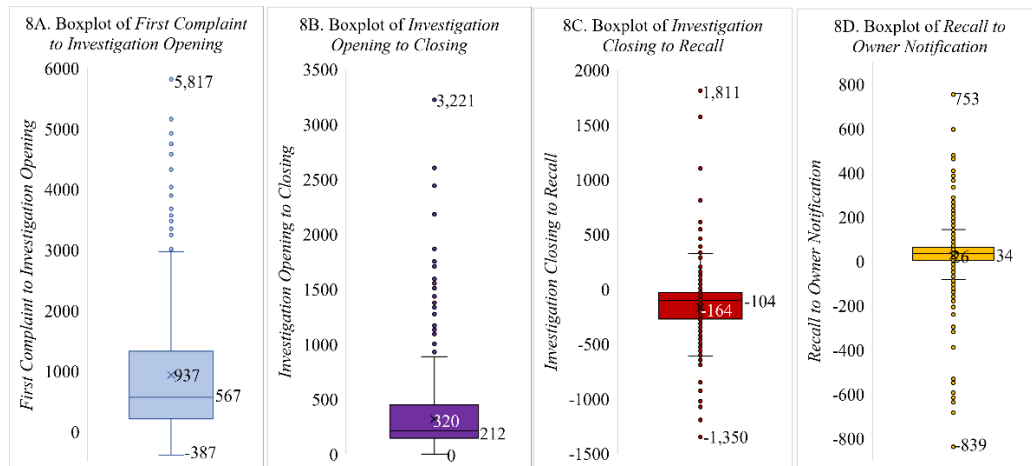
#### 5.4. Insights from the process variables

Last, we turn our attention to the process variables included in our “Outcomes of Inv Data” sheet (see Figure 1 on the process). Figure 8 presents boxplots of the process-time variables.<sup>11</sup> Figure 8A depicts the boxplot of the *First Complaint to Investigation*, which is the number of days between the date the NHTSA received the first harm-incident report and the date the NHTSA opened an investigation into the incident. Similarly, we also present the boxplot of the number of days between NHTSA opening and closing an investigation (i.e., *Investigation Opening to Closing*) (Figure 8B), the number of days between

<sup>11</sup> Figures OS2 through OS5 in the online supplement depict the boxplots of the process variables, separated by *Investigation Type*.

the NHTSA closing an investigation and the manufacturer informing NHTSA of the initiation of a recall (i.e., *Investigation Closing to Recall*) (Figure 8C), and the number of days between the date the manufacturer initiates a recall and the date the manufacturer notifies the owners of the affected vehicles (i.e., *Recall to Owner Notification*) (Figure 8D). We discuss the distribution of the four process variables next one by one (see Figure 1 for the process).

**Figure 8. Boxplots of *First Complaint to Investigation Opening*, *Investigation Opening to Closing*, *Investigation Closing to Recall*, and *Recall to Owner Notification Date***



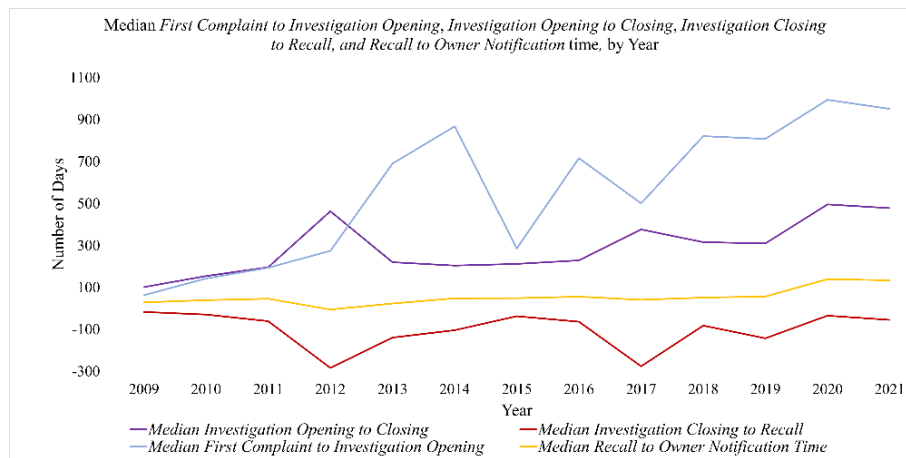
*First Complaint to Investigation Opening* has a minimum of  $-387$ , suggesting that the NHTSA opened an investigation 387 days before it received a complaint. Of the 577 investigations closed in our data set, a total of seven have negative values of this variable. Such relatively rare cases occur when an investigation has no complaint IDs mentioned in the summary field of its opening resume, yet the closing resume mentions associated complaint IDs. This rare event may occur because the NHTSA sometimes opens an investigation after receiving a high volume of EWR data of product damage and warranty claims from the manufacturer. For instance, Investigation PE11026 has a *First Complaint to Investigation Opening* of  $-8$ :

“The Office of Defects Investigation (ODI) has received Early Warning Report (EWR) data from Mazda covering a time period from the first quarter of 2008 (2008Q1) to the third quarter of 2010 (2010Q3) indicating a high number of warranty claims and reports for the ServiceBrake-03 category”.

The maximum value of *First Complaint to Investigation Opening* is 5,817, suggesting that the NHTSA (surprisingly) opened an investigation nearly 16 years after it received the first complaint. The

mean and median values of *First Complaint to Investigation Opening* are 937 days (nearly three years) and 567 days (nearly 1.5 years). The large gap between the two values suggests a positively skewed distribution, and the presence of outliers in the data set. Figure 9 depicts the trend of the median of the four process-time variables from 2009 to 2021, revealing that the median value of *First Complaint to Investigation Opening* has experienced a gradual upward trend over the years.

**Figure 9. Median of *First Complaint to Investigation Opening*, *Investigation Opening to Closing*, *Investigation Closing to Recall*, and *Recall to Owner Notification Date*, by year**



The number of days from *Investigation Opening to Closing* ranges from 0 to 3,221 days. The minimum value of 0 is associated with investigation DP12005, a defect petition that was opened upon a request by The Center for Auto Safety. The NHTSA’s ODI denied the petition and closed the investigation on the same day after reviewing the evidence. The maximum value of 3,221 is associated with investigation AQ09002, an audit query that investigated Navistar’s acquiring of Monaco Coach Corp, and the former’s noncompliance with a prior recall mandate for Monaco’s products.

The mean and median values of *Investigation Opening to Closing* are 320 and 212 days. The insight is that an average NHTSA investigation lasts about 10.5 months, with half of the investigations taking seven months. Figure 9 reveals that the median value of *Investigation Opening to Closing* has experienced an upward trend over the period covered by our data. An upward trend until 2015 can be explained by the fact that the NHTSA was short on personnel (White 2020). However, after the Fixing America’s Surface Transportation (FAST) Act provided the NHTSA with additional funds (U.S.

Department of Transportation 2015a), one would expect the period between opening and closing an investigation to follow a downward trend. Users of our data set may consider examining this trend, potentially measuring whether the FAST Act accelerated or impeded the NHTSA's process.

The number of days from *Investigation Closing to Recall* spans from -1,350 to 1,811 days. The negative minimum suggests that the NHTSA closed an investigation long after the manufacturer has initiated a related recall. The negative values of mean and median (-104 and -164, respectively) suggest that this order of NHTSA's closing of an investigation and the manufacturer's initiation of a recall is common. Indeed, of the 577 closed investigations in our data set, 290 have negative values of *Investigation Closing to Recall*. As indicated in Figure 2 and §3.2, in most cases, the closing resumes of investigations with negative values of *Investigation Closing to Recall* suggest that the NHTSA closes its Preliminary Evaluation when it becomes aware that the manufacturer has already initiated a recall. The extreme negative values of this variable are for audit, equipment, or recall queries issued by the NHTSA's Recall Management Division. For instance, Investigation AQ09001 has an *Investigation Closing to Recall* of -1350. The opening resume of this investigation mentions:

“Based on missing or incomplete documentation, NHTSA identified several hid replacement lighting recall campaigns that appear to have either been not conducted or not conducted properly by the manufacturer. An investigation has been opened to determine the status and adequacy of the involved recall campaigns, and to take whatever action is necessary as to each recall”.

This investigation is a prime example of an Audit Query issued by the NHTSA, following evidence of noncompliance with the Federal Motor Vehicle Safety Standards.

Last, the *Recall to Owner Notification* period spans -839 to 753 days, suggesting that the manufacturer can notify affected owners before notifying the NHTSA. However, the positive values of mean and median (26 and 34 days, respectively) highlights that the negative values are uncommon. Of the 928 recalls resulting from the closed investigations in our data set, 187 have negative values of *Recall to Owner Notification Date*. We examined an outlier investigation that is driving most of the negative values of the *Recall to Owner Notification Date*: investigation EQ10007 led to 111 distinct recall campaigns, and of these 111 recall campaigns, 99 have negative *Recall to Owner Notification Date* values. Examining the

*Recall Date* and *Owner Notification Date* for the recall campaigns resulting from investigation ID EQ10007 made us realize that the NHTSA recorded the same *Owner Notification Date* (October 8, 2010) for most of these recalls. We conjecture that the same values could be driven by (1) the NHTSA's inaccurate reporting of the *Owner Notification Date* for these recalls (i.e., using the correct date for one of these recalls as the value for all), or (2) the manufacturers notifying the owners of affected vehicles on the same date, but taking much longer to submit the defect and noncompliance information report for some of these recalls to the NHTSA.

The first reason—inaccuracy/misreporting in the recall data files—is an unfortunate yet inevitable possibility when working with any data file. Indeed, AutoAp Inc., a vehicle recalls management application provider, reported that the data associated with approximately 30% of the unique NHTSA recall campaigns could include inaccuracies (Cision 2014; MPN 2022). However, we note that the second potential reason for negative values of the *Recall to Owner Notification* variable—a manufacturer notifying owners before the NHTSA—is *not* a case of misreporting. That is, no laws or regulations prohibit a manufacturer from notifying affected vehicle owners before informing the NHTSA.

### **5.5. Further exploring the characteristics of our data with a website**

We create an open-access website (<https://unveiling-regulatory-operations.streamlit.app/>) to allow the users of our data files to further explore the characteristics of our data. The website is powered by Streamlit<sup>12</sup> and has five pages—(1) Main Page, (2) Investigations Variables, (3) Process Variables, (4) Recall Variables, and (5) Data Set Description and Data Dictionary.

When a user clicks on the URL of our website, they land on the *Main page*. This page briefly describes the utility of our data files and explains the functionality of the other four pages. The *Investigations Variables*, *Process Variables*, and *Recall Variables* pages allow the users to choose various variables from our data files and view graphs and tables of these variables. In addition, these pages allow the user to choose the width and height of the graphs and download the graphs. For all categorical

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<sup>12</sup> <https://streamlit.io/>

variables, the website automatically creates a pie chart and a table that summarize the relative frequency of each category (see Figure OS6.A). For numeric variables, the website prints a table of summary statistics, and gives the users the option to choose whether they want to obtain the histogram, boxplot, or time-trend graph of the variable (see Figure OS6.B). Users can rely on histograms and boxplots to assess the variable's distribution, and use the time-trend graphs to investigate the variable's annual trend.

The *Investigations Variables* page provides tables and graphs of the variables in our “Characteristics of Opened Inv” and “Characteristics of Closed Inv”. The *Process Variables* page provides tables and graphs of our process-time variables (e.g., *First Complaint to Investigation Opening*, *Investigation Opening to Closing*), and the *Recall Variables* page provides tables and graphs of the variables explaining the recalls that resulted from the investigations in our data set. Lastly, the *Data Set Construction and Data Dictionary* displays Figure OS1 as an overview of our procedure for data retrieval and data set construction and allows users to preview and download our data dictionary.

## 6. Future Research

The columns in our two data files can be grouped into three categories: (1) the determinants of the NHTSA's decision to open or close an investigation, (2) the process the NHTSA follows between opening an investigation and closing it, and (3) the outcomes of the investigation, observed at the time of closing it. Table 2 lists some research questions (in each category) that our data files help answer. The table also mentions the unit of analysis, the dependent and explanatory variables, and the sources of additional data (if any) required to address the question(s). We briefly discuss each category next.

First, the data can help answer questions on the determinants of a regulator's opening and/or closing of an investigation. For example, on average, how many safety incidents and how much harm occur before the NHTSA opens an investigation? Do these counts vary by whether the recipient of these incidents and harm is the NHTSA or the manufacturer? Do warranty claims and EWR data from the manufacturer influence the NHTSA's decision? Do the number of complaints and how the complaints are textually described affect the NHTSA's time to open an investigation? Our data set lists some complaints by the Congressional office, eliciting the question: Does the presence of complaints by the Congressional

office (vs. consumers) exert a greater influence on the NHTSA? Which features of a complaint boost the prediction accuracy of a machine learning model trained to *predict* the number of days between the NHTSA receiving the complaint and opening an investigation? In regular circumstances, the NHTSA opens a preliminary evaluation and if it has reason to escalate the investigation, it closes the preliminary evaluation and opens an engineering analysis, which consumes far more of the NHTSA's resources. Users of our data set can determine these conditions.

Second, our files can help researchers understand the NHTSA's investigation process. Our data set provides dates on key events in the NHTSA's investigation *process*. Further, we provide a textual description of the NHTSA's knowledge of the defect at the time of opening and closing the investigation. Researchers can assess the similarity of the *Problem Description* in the two files or compare the dominant topic in the *Problem Description* (revealed by our topic modeling) at the time of opening and closing. Differences in the descriptions at the two points in time proxy whether the NHTSA's understanding of the problem has changed from the time of opening to the time of closing the investigation. Similarly, researchers can use the *Summary* column in the two files to identify the steps the NHTSA takes before opening, or between opening and closing an investigation.

Third, stakeholders measure a regulator's performance in terms of the number of investigations it opened and closed in a period (e.g., a quarter) (Felton 2023; Krisher 2023; Plungis 2018; U.S. Department of Transportation 2021, 2023). We provide data on additional measures, such as the time the NHTSA took between receiving the first complaint and opening an investigation, the time it took between opening an investigation and closing it, and whether the investigation resulted in a safety recall and if yes, how many recalls. Our data files allow researchers to measure the variation in the NHTSA's performance on all these dimensions. For example, the longer the NHTSA takes to close an investigation, the more the number of harm incidents and the extent of harm caused by unsafe vehicles. For investigations that yield a recall (confirming a safety defect), one can assess how much additional harm is caused for each additional day the NHTSA takes to close an investigation. Further, Cho et al. (2021) suggested that the announcement of a regulatory investigation hurts the manufacturer's performance, such as profit and sales

revenue. Future research can use our data files to test this suggestion.

In sum, we believe our data files could help academics and nonacademic stakeholders empirically research how a safety regulator (e.g., the NHTSA) manages its operations. This data set thus contributes to research in public policy and industry studies.

**Table 2. Suggested research questions and the variables from our data files required to answer them**

Note: DV = dependent variable; EV = explanatory variable. Names of variables included in our data set are italicized.

Research Question(s)	Unit of Analysis and Variables	Sources of Additional Data
<b>Determinants of the regulator’s decision to open or close an investigation</b>		
On average, (1) how many safety incidents/complaints and (2) how much harm occur before the NHTSA opens an investigation?	Unit of analysis = Each opened investigation DV = <i>First Complaint to Investigation Opening</i> EVs = <i>No. Complaints Reported</i> (or any of the 6 other variables outlining the total count of reports of fires/crashes, injuries, fatalities, and “other” failure)	None
How do the effects of the number of safety incidents/complaints and the extent of harm on the odds of investigation opening differ by whether the incidents are reported to the NHTSA or the manufacturer?	Unit of analysis = Each opened investigation DV = <i>First Complaint to Investigation Opening</i> EVs = <i>No. Complaints Reported to NHTSA</i> (or any of the 6 other variables outlining the total count of reports of fires/crashes, injuries, fatalities, and “other” failure to the NHTSA), <i>No. Complaints Reported to Manufacturer</i> (or any of the 6 other variables outlining the total count of reports of fires/crashes, injuries, fatalities, and “other” failure to the manufacturer)	None
Do warranty claims and news reports influence the NHTSA’s decision to (1) open and (2) close an investigation?	The number of warranty claims (can be extracted from <i>No. Other Types of Failures Reported</i> when <i>Description of Other</i> mentions warranty claims) Number of news reports related to the product defect	RavenPack Analytics, RepRisk, Nexis Uni, or Factiva
What determines the NHTSA’s choice of the type of investigation (e.g., an engineering analysis in place of a preliminary evaluation)?	Unit of analysis = Investigation DV = <i>Investigation Type</i> EVs = Other characteristics of investigation or complaints and failures reported at the time of opening (e.g., <i>Population, No. Complaints Reported, Complainer Type</i> )	None
What characteristics of a consumer complaint raise the odds that it will lead to the opening of an investigation?	Unit of analysis = A safety incident report DV = Whether the report featured in the opening of at least one investigation DV2: The number of opened investigations that mentioned the report EVs: <i>Complainer Type, Complaint Description</i>	None
How do the manufacturer’s (1) reputation for product reliability, (2) headquarters’ location, (3) supply-chain characteristics, and (4) outcomes of prior investigations impact the investigation outcomes?	Unit of analysis = Each opened investigation DV = <i>Investigation Opening to Closing</i> EVs = Manufacturer’s reputation and number of investigations in the prior period (e.g., one year) which led to recalls	YouGov BrandIndex, Fortune’s Most Admired Companies, Brand Finance, or Kantar Media BrandZ
<b>The process the regulator follows between opening and investigation and closing it</b>		
Does the time the NHTSA takes between opening and closing an investigation enrich its understanding of the defect?	DV = <i>Problem Description, Problem Description Dominant Topic, Problem Description Dominant Topic Percentage</i> EV = <i>Investigation Opening to Closing</i>	None
What steps did the NHTSA take before opening the investigation to expedite the investigation?	DV: <i>Investigation Opening to Closing</i> EVs = <i>Summary, Summary Dominant Topic, Summary Dominant Topic Percentage</i>	None

<b>The outcome of an investigation, observed at the time of its closing</b>		
How much additional harm is caused for each additional day the NHTSA takes to open or close an investigation?	Unit of analysis = Investigation DV = <i>First Complaint to Investigation Opening, Investigation Opening to Closing</i> , and the difference between the two variables EVs = <i>No. Complaints Reported</i> (or any of the 6 other variables outlining the total count of reports of fires/crashes, injuries, fatalities, and “other” failure)	None
Do the NHTSA’s opening and closing of investigations against a manufacturer’s products impact the manufacturer’s performance (Cho et al. 2021)?	Units of analyses = Investigation, product-month, manufacturer-quarter, manufacturer-year DV = Cumulative abnormal stock return (using short-term event study and long-term event study, such as calendar-time portfolio or buy-and-hold stock return analysis) DV2 = Sales volume of the product (i.e., year-make-model) DV3 = Reliability and perceived quality rating of the product EVs = <i>Date Investigation Opened, Date Investigation Closed</i> , Number of investigations the NHTSA opened/closed in a period	(1) CRSP for stock return data, (2) Ward’s Automotive Intelligence for sales volume data, (3) Consumer Reports’ “overall problem rate” for product reliability, (4) NHTSA’s complaints data for perceived quality
Does the NHTSA’s number of investigations lower the extent of harm?	Unit of analysis = month/quarter/year DV = Number of injuries, crashes/fires, and deaths EV = Number of investigations opened and/or closed in the period	None

## 7. Conclusion

Academics in OM and other business and nonbusiness disciplines have extensively researched a product manufacturer’s investigation of product safety defects (see Tables OS1-OS6). Consequently, much empirical evidence under the rubric of product recall has accumulated, advising managerial practice on product recall. However, academics have missed the opportunity to also research a product safety regulator’s investigation of safety defects. We reason that this missed opportunity prevents academics from testing organizational theories that should apply to not only for-profit organizations, but also their nonprofit counterparts, such as regulators. In addition, such research would allow academics to understand regulatory operations and offer practical contributions to regulators and public policy.

Our data files seek to seize this missed opportunity. We describe a hand-collected and novel data set of product defect investigations undertaken by the NHTSA. We provide two Microsoft Excel data files, one for the data on investigations that the NHTSA opened from 2009 to 2021, and the other for investigations that the NHTSA closed in the same period. The data files include novel numeric, categorical, and textual variables and are thus amenable to econometric modeling and machine learning. Plus, the variables cover the process that the NHTSA traverses, from receiving a safety incident report to

opening an investigation and eventually closing it. The closing may lead to the initiation of zero or more recalls. Throughout this process, the NHTSA and the manufacturer receive reports of safety incidents, each of which might include different levels of harm to the public and property.

Game theorists have viewed the strategic interaction between the NHTSA and a manufacturer as a discrete game (Singh and Grewal 2023). Both parties use their asymmetric objectives in a tradeoff between their private information and common information (Colak and Bray 2016). The NHTSA must balance its shortage of personnel (White 2020) with its watchdog responsibilities (Plungis 2018). The manufacturer must signal responsiveness (Hora et al. 2011) and responsibility (Chen et al. 2009; Eilert et al. 2017). Simultaneously, the manufacturer must avoid a rushed investigation that could trigger an underprepared recall, creating anxiety among consumers and delaying the repair of the unsafe units (Ni and Huang 2018). Because our data set includes variables on the incident reports and the harm visible to the NHTSA and the manufacturer, game theorists can test a theoretical model on the strategic interaction between the two parties. Table 2 lists some research questions that our data files help answer.

Empiricists in OM and other business and nonbusiness (e.g., mechanical and industrial engineering) disciplines would also find our data useful. For example, public policy academics may focus on the NHTSA's efficiency in closing an investigation. Marketing academics may pay greater attention to consumer harm (Pagiavlas et al. 2022), whereas OM researchers may examine the NHTSA's decision-making process. Management academics have long been interested in nonmarket strategy, including decisions of the regulatory agencies. Last, we foresee our data files to be useful to nonacademic stakeholders, such as governments, journalists, liability lawyers, the NHTSA, and safety advocates.

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## Unveiling Regulatory Operations: A Data Set of the Determinants, Process, and Outcomes of Product Defect Investigations by the U.S. Automotive Safety Regulator

### Online Supplement

#### A tabular review of the multidisciplinary literature on the determinants, process, and outcomes of safety defects

This section provides a tabular review of the multidisciplinary empirical research on product safety defects. By “empirical,” we mean research that uses secondary/observational data (rather than surveys or experiments). We organized the research into two three-table sets, focusing on the determinants, the process, or the outcomes of product safety defects, in the automotive and non-automotive contexts. This organization helps researchers uncover common themes, highlight the comparative academic effort, and pinpoint the gaps that require further research. In all tables, DV stands for Dependent variable, EV stands for Explanatory variable, CAR stands for Cumulative abnormal stock return, and OEM stands for Original Equipment Manufacturer.

**Table OS1. Empirical research on the determinants of automotive safety defects**

Note: The table below summarizes articles published where the DV is a characteristic of a product recall or a safety defect.

Study and Theoretical perspective(s)	Sample	Key variables	Key finding(s)
<b>Bray et al. (2019)</b> <b>Geographical proximity</b>	NHTSA complaints data, 685 car models, and 47 types of components	<i>DV</i> : Failure rate (complaints divided by vehicle-year registrations) <i>EV</i> : Distance between the OEM’s and supplier’s factory/plants <i>Moderators</i> : Whether the model is luxury, model development stage, model sales, number of subcomponents	The distance between OEM’s assembly plant and the factory/plant of the component supplier increases OEM’s failure rate.
<b>Cockrell et al. (2024)</b> <b>Radicalness of an innovation, breadth of product line</b>	NHTSA recalls data, 184 vehicle make-years, from 18 OEMs, 11 years	<i>DV</i> : Number of recalls (at vehicle make-level) <i>EVs</i> : Innovation radicalness of the make’s models, number of models the make manufactures in a year <i>Moderator</i> : Recall size	The innovation radicalness of a make’s models in a year, and the make’s model-line breadth (# of models the make produces in a year) increase the number of recalls in the following year. Recall size moderates the effect of innovation radicalness on the number of recalls.
<b>Geiger et al. (2022)</b> <b>Trading concentration by mutual funds, consumer complaints as information advantage</b>	NHTSA consumer complaints and recalls data, complaints for 19 makes and 526 recalls, 1996-2012	<i>DV</i> : Recall incidence, CAR, stock return, abnormal value of shares sold by the firm’s top five executives, and by mutual fund investors <i>EV</i> : Recall announcement, number of complaints in the previous four quarters	Complaints in the prior four quarters increase recall incidence. Complaints positively affect the value of the sold shares by the top five executives in [-90, -1] and the value of mutual fund investors’ sold shares in the pre-recall period. Complaints negatively affect CAR [2,63] to a recall and return in the following year.
<b>Haunschild and Rhee (2004)</b> <b>Internal versus external mandate/pressure,</b>	NHTSA recall reports, 2,287 recalls by 47 OEMs, 1966-1999	<i>DVs</i> : Number of severe recalls, number of involuntary and voluntary recalls <i>EVs</i> : Cumulative production, cumulative voluntary/involuntary recalls in the past three years, the cumulative ratio of voluntary to	Cumulative production decreases the number of severe recalls.

<b>volition/autonomy, and organizational learning</b>		involuntary recalls, generalism (versus specialism)	Prior voluntary recalls decrease subsequent involuntary recalls, but prior involuntary recalls do not affect subsequent involuntary recalls. Voluntary recalls lead to deeper learning.
<b>Kalaiganam et al. (2013) Organizational learning</b>	NHTSA recalls data, recalls by 27 automotive makes, 1995-2011	<i>DVs</i> : Recall incidence, harm incidence, and future product reliability <i>EVs</i> : Recall size <i>Moderator</i> : Shared product assets, perceived brand quality	Recall size decreases future recall incidence and harm incidence. Future product reliability mediates these effects. Shared product assets and prior perceived brand quality moderate the above effect.
<b>Kalaiganam et al. (2017) Structure of buyer-supplier network, and product architecture</b>	NHTSA recalls data, recalls by 13 auto makes, 2012	<i>DVs</i> : Number of recalls, and future perceived reliability of the product <i>EVs</i> : Network density and structural holes <i>Moderator</i> : Strength of design interface	The density of the OEM's network of tier-1 suppliers decreases the number of recalled vehicles, but structural holes increase the number of vehicles recalled. Perceived product reliability mediates the above effects, and the strength of the design interface moderates them.
<b>Kini et al. (2017) Financial leverage, financial distress</b>	NHTSA recalls data, 687 recalls, 2006-2010	<i>DVs</i> : Recall incidence, number of recalls, and severity of recalls <i>EVs</i> : Financial leverage, debt due in three years, residual leverage, the extent of unionization in the industry, number of suppliers, size	Leverage, distress likelihood, and cash flow shocks (Altman $z$ ) raise the likelihood of a recall. The extent of unionization in the industry, the number of suppliers, and firm size increase the number of recalls. Vertical integration and R&D investment decrease the number of recalls.
<b>Kini et al. (2022) Labor unions, product quality failures</b>	NHTSA recalls data, 1982 recalls, 2003-2013	<i>DVs</i> : Number of recalls in years t+1, t+2, t+3, CAR, J D Power's quality ratings, IT spending, employee satisfaction/morale, COGS, operating leverage, discretionary investment <i>EVs</i> : Whether a firm is unionized, the proportion of unionized employees, whether an establishment is unionized <i>Moderator</i> : headquarter state, non-proactive recalls	Unionization in year t increases the number of recalls by a firm (establishment) in years t+1,2, and 3. The effect is weaker for firms headquartered in a Right to Work state and exists for non-proactive recalls. A union win raises the intensity of COGS and operating leverage, and suppresses discretionary investment, discretionary investment in nonfinancial stakeholders, employee satisfaction and culture/morale, and IT spending.
<b>Shah et al. (2017) Product/plant variety, capacity utilization</b>	NHTSA recalls data and defect reports, 67 recalls, 2000-2006	<i>DV</i> : Number of recalls <i>EVs</i> : Product variety, plant variety, plant utilization	Product variety and plant utilization increase the number of recalls in the same year. Plant variety does not matter.

**Table OS2. Empirical research on the process of automotive safety defects**

The table below summarizes articles where the DV is a characteristic of the process of initiating a product recall.

<b>Study and Theoretical perspective(s)</b>	<b>Sample</b>	<b>Key variables</b>	<b>Key finding(s)</b>
<b>Çolak and Bray (2016) Discrete choice, structural game</b>	NHTSA consumer complaints data, 17 firms and 49 brands	<i>DVs</i> : Number of voluntary and involuntary recalls, cost of recalls <i>EVs</i> : Number of consumer complaints, and number of complaints with each of the 48 signals (complaint narratives are text-mined to generate 48 defect signals)	OEMs initiate recalls to avoid receiving defect reports, not to preempt anticipated involuntary recalls, and the cost of recalls does not depend on whether the recall is voluntary or involuntary (i.e., government- vs. OEM-initiated) All 48 text-mined defect signals predict the number of voluntary and involuntary recalls.
<b>Eilert et al. (2017) Behavioral theory of the firm, ability and motivation</b>	NHTSA recalls and investigations data, 381 defect investigations, 1999-2012	<i>DV</i> : Investigation opening to recall (Date OEM notifies NHTSA of a recall – date investigation opened), CAR <i>EV</i> : Recall harm severity <i>Moderators</i> : reliability, past recall intensity, brand diversification	Recall harm severity increases investigation opening to recall time. Brand reliability and past recall intensity weaken the above effect, and brand diversification strengthens it. CAR to investigation opening to recall time is negative and significant.

<b>Majid and Bapuji (2018)</b> <b>Country of headquarters, component sourcing, organizational responsiveness</b>	NHTSA recalls data, recalls by 12 auto makes, 2002-2010	<i>DV</i> : Manufacturing to recall (Date OEM notifies NHTSA of a recall – manufacturing date) <i>EVs</i> : Firm’s region of headquarters and region of sourcing parts	OEMs headquartered outside the U.S. take longer than U.S. manufacturers to initiate a recall. Sourcing parts from the U.S. or Canada shortens manufacturing to recall time for OEMs headquartered outside the U.S., and sourcing parts from outside the U.S. and Canada lengthens manufacturing to recall time for OEMs in the United States.
<b>Ni and Huang (2018)</b> <b>Problem-solving, quality failure, recall timing decisions</b>	NHTSA recalls data and defect reports, 1,251 recalls, 2000–2012	<i>DV</i> : Discovery to recall (Date OEM notifies NHTSA of a recall – the date the OEM discovers a defect) <i>EVs</i> : past recalls, defects reported by an external stakeholder, supplier-attributable, design defect, models	The number of past recalls decreases discovery to recall. External stakeholder reports, supplier-attributable recalls, design recalls, and recalls involving more models increase discovery-to-recall.
<b>Pagiavlas et al. (2022)</b> <b>Digital marketing campaign, consumer compliance</b>	NHTSA recalls and recall completion data, 296 recalls before and after the “Save Cars Save Lives” campaign, 2016	<i>DV</i> : Consumer recall compliance <i>EV</i> : Time since the start of the NHTSA’s digital marketing campaign <i>Moderators</i> : Media coverage, the average age of recalled models, the time needed to repair the defective component	NHTSA’s direct marketing campaign increased the number of vehicles repaired per recall by 20,712. The campaign was more effective for recalls with high media coverage and older models and less effective for recalls requiring longer repair time.
<b>Pupovac et al. (2022)</b> <b>Slicing versus chunking strategy</b>	NHTSA recalls data, 378 large recalls, 2006-2017	<i>DV</i> : Whether a recall is sliced (i.e., slicing the set of affected vehicles into different recalls, versus chunked), CAR <i>EVs</i> : Firm slack, firm size, firm reputation, recall size, whether the firm sliced the affected vehicles	CAR to a sliced (versus chunked) recall is stronger. Firm size lowers the likelihood of recall slicing, while firm R&D, reputation, and the number of affected vehicles increase the likelihood of slicing.
<b>Singh and Grewal (2023)</b> <b>Legitimacy-based institutional theory, efficiency</b>	NHTSA recalls data, 678 recalls by 16 OEMs, 2008-2016	<i>DVs</i> : Number of voluntary and involuntary recalls <i>EV</i> : Lobbying spending directed at the regulator <i>Moderator</i> : Defect severity, media coverage	The firm’s lobbying spending directed at the regulator decreases its number of voluntary recalls and its number of involuntary recalls. Defect severity and number of media reports attenuate the above effects.

**Table OS3. Empirical research on outcomes of automotive safety defects**

The table below summarizes articles where the EV is a characteristic of a product recall or safety defect. *WSJ* = *Wall Street Journal*

<b>Study and Theoretical perspective(s)</b>	<b>Sample</b>	<b>Key variables</b>	<b>Key finding(s)</b>
<b>Astvanish and Eshghi (2023)</b> <b>Shareholder reaction, regulatory investigation, recall costs, attribution</b>	NHTSA recalls data, recalls by 14 OEMs, 2009-2019	<i>DV</i> : CAR <i>EVs</i> : Recall announcement, duration of regulatory investigation (Investigation opening date – recall date), supplier (vs. OEM) defect, and market age of the recalled product-lines	CAR to a recall announcement is negative and significant. The duration of the regulatory investigation aggravates, and the market age of the recalled product-lines attenuates the above effect. Whether the defective component was manufactured by the recalling OEM does not impact the effect.
<b>Borah and Tellis (2016)</b> <b>User-generated content, negative spillover</b>	NHTSA recalls data, 2009-2010	<i>DV</i> : CAR, sales volume <i>EV</i> : User-generated content about recalls <i>Moderators</i> : Country of origin, brand dominance, and ad content (apology, promotion, leasing)	Negative UGC about a car model’s recalls decreases sales and CAR for same-brand models across segments, and models from rival brands. The spillover is the strongest for brands from the same country and from more dominant to less dominant brands, and apologetic ads strengthen the spillover.
<b>Bromiley and Marcus (1989)</b> <b>Dubious corporate behavior, market reaction as a deterrent and social control</b>	<i>WSJ</i> ’s recall announcements in the U.S., 1967-1983	<i>DV</i> : CAR <i>EV</i> : Recall announcement	The CAR to a recall announcement is negative but insignificant on day –1 through day 4. It becomes positive but insignificant on day 5 and positive and significant on day 6.

<b>Davidson and Worrell (1992)</b> <b>Managerial discretion, deterrent</b>	<i>WSJ</i> 's recall announcements in the U.S., 1968-1987	<i>DV</i> : CAR <i>EV</i> : Recall announcement <i>Moderators</i> : Recall type (replace/memory back or repair/check), recall origin (government-ordered or voluntary), product taken off the market or recalled	CAR to a recall announcement is negative and significant. The CAR is more negative when the product is replaced or the purchase price returned than when the product is checked and repaired or taken off the market or recalled. Government-ordered recalls do not have more negative returns.
<b>Gao et al. (2015)</b> <b>Signaling effect, expectation effect, advertising strategy</b>	NHTSA recalls data, 2005-2012	<i>DV</i> : CAR <i>EV</i> : Recall announcement <i>Moderators</i> : Ad spending before recall, recall publicity, voluntary	CAR to a recall announcement is negative and significant on days 0 and 1. Decreasing ad spending before initiating a recall, recall publicity, and voluntary recalls strengthen the negative effect on stock return.
<b>Germann et al. (2014)</b> <b>Brand commitment</b>	<i>WSJ</i> 's recall announcements, U.S. recalls, 2005-2012	<i>DV</i> : CAR <i>EV</i> : Recall announcement (high severity vs. low severity) <i>Moderators</i> : Brand commitment	CAR to high severity and low severity recall announcements is negative and significant. High brand commitment weakens the negative return to a low-severity recall but strengthens the negative return to a high-severity recall.
<b>Giannetti and Srinivasan (2021)</b> <b>Spillover, country of origin effect</b>	NHTSA recalls data, large recalls (price lower than \$150k, and affecting more than 15k vehicles), 2006-2015	<i>DV</i> : Sales <i>EVs</i> : Number of recalls by (1) parent manufacturer, (2) other models from the parent make, and (3) other manufacturers with the same country of origin <i>Moderators</i> : Advertising and price	Recalls by the parent manufacturer do not affect sales of the focal model. Recalls by other models by the parent company decrease the sales of the focal model. The focal model's advertising and price weaken this negative effect. The number of recalls by other manufacturers from the same country increases the sales of the focal model. The focal model's advertising and price weaken the positive effect.
<b>Gokhale et al. (2014)</b> <b>Government investigation, reputation, exoneration, value-destroying events</b>	Toyota's defective floor mats and accelerator pedal, 2007	<i>DV</i> : CAR <i>EVs</i> : Four events related to Toyota's vehicles (recall announcement, news about crash of a Lexus, second major recall announcement, NHTSA's closing of the investigation)	CAR is not significantly different from 0 in events 1 and 2. For event 3, AR is negative on days 3, 6, 7, and 8. For event 4, the AR is positive on each day, ranging from day 0 to day 10.
<b>Hoffer et al. (1994)</b> <b>Owner response</b>	<i>WSJ</i> 's recall announcements and NHTSA recall completion, 108 recalls, 1984-1986	<i>DV</i> : Consumer recall compliance <i>EVs</i> : Product age, recall's harm severity, recall size, <i>WSJ</i> publicity, firm's region of headquarters	Vehicles two or more model-year old and vehicles from Japanese/European manufacturers are less likely to be returned for repair, and vehicles with high-severity defects are more likely to be returned.
<b>Huang and Radighieri (2021)</b>	NHTSA recalls data, 93 recalls, 2011-2015	<i>DV</i> : OEM's sales, sales volume of the recalled model <i>EVs</i> : Recall incidence, firm's change in total ad spending, spending on the recalled model, and spending on the nonrecalled model from the same make <i>Moderator</i> : Recall severity	An increase in the ad spending of the nonrecalled model increases the sales volume of the recalled model. Recall severity weakens the above effect. None of the EVs affect the firm's total sales.
<b>Javadinia et al. (2023)</b> <b>Recall environment intensity</b>	NHTSA recalls data, 497 large recalls by six OEMs, 2007-2019	<i>DV</i> : CAR <i>EV</i> : Recall announcement <i>Moderators</i> : Recall environment intensity, recalled product's age (year of recall minus year of the recalled model), reputation for reliability	CAR to a recall announcement is negative and significant. Recall environment intensity weakens the above effect. Recall environment intensity's moderating effect is stronger for firms with higher reputation for reliability, and weaker for older products.
<b>Liu and Shankar (2015)</b> <b>Brand preference, advertising effectiveness</b>	NHTSA recalls data, 1997-2002	<i>DV</i> : Sales, ad spending for the focal model and its parent brand <i>EV</i> : Recall size (per month) <i>Moderators</i> : Harm severity, publicity, perceived reliability	The effect of recall size on sales is more negative when the recall receives more media attention, has more severe consequences, and the recalled product has higher perceived reliability.

<b>Liu et al. (2017)</b> <b>Crisis management, firm value</b>	NHTSA recalls data, 2005-2015	<i>DV:</i> CAR <i>EV:</i> Recall announcements <i>Moderators:</i> Recall size (normalized by sales), ad spending (branding vs. promotional), voluntary initiation, rate of post-recall remedy	Recall size decreases the recalled brand's advertising spending. The effect is stronger for the recalled brand than for the parent brand. Short-term and long-term CAR to recall announcements are negative and significant. Recall size strengthens both effects. The recalling firm's ad spending on branding strengthens the effect on short-term returns but weakens the effect on long-term returns. Ad spending on promotion weakens the short-term effect but strengthens the long-term effect. Voluntary initiation and rate of post-recall remedy weaken the long-term effect.
<b>Liu and Varki (2021)</b> <b>Negative spillover</b>	NHTSA recalls data, 2011-2016	<i>DV:</i> Rival's CAR <i>EV:</i> Recalling firm's corporate product reliability <i>Moderator:</i> Rival's product reliability	Recalls by a manufacturer with high corporate product reliability negatively affect the CAR for the rival firm. The rival's corporate product reliability weakens the negative effect.
<b>Mukherjee et al. (2022)</b> <b>Geographic clustering</b>	NHTSA recalls data & defect and noncompliance reports, 1966-2013	<i>DV:</i> CAR <i>EV:</i> Recall announcement <i>Moderator:</i> Days elapsed between the last day of the previous cluster and the date of announcement of the focal recall	Recalls in an industry are initiated in clusters. That is, a recall by a firm leads to other recalls initiated by other firms in close temporal proximity to the initial recall. A cluster forms after a 16-day gap in which no recalls are announced. The CAR to a recall announcement becomes less negative each day passing the leading recall in the focal cluster.
<b>Topaloglu and Gokalp (2018)</b> <b>Brand concept</b>	NHTSA recalls data, recalls by 18 OEMs, 2003-2014	<i>DV:</i> Year-on-year monthly sales volume growth <i>EV:</i> Number of severe recalls <i>Moderator:</i> functional or luxury model, reliability rating	The number of severe recalls in the preceding quarter decreases year-on-year monthly sales. The above negative effect is stronger for functional (vs. luxury) models, and further strengthened by the functional model's reliability rating.
<b>Wei et al. (2019)</b> <b>Public/user engagement</b>	AQSIQ recalls data, 432 recalls in China, 2010-2014	<i>DV:</i> Number of likes, number of comments, and number of shares for recall announcement on Sina Weibo's <i>EVs:</i> Recall size, recall counter, remedy, age of recalled product, average price, and country of origin	Recall size, recall counter, replacement remedy, model price, and China-headquartered manufacturer increase social media users' engagement with the recall announcement. The age of the recalled model does not matter.
<b>Zhao et al. (2013)</b> <b>Brand equity, firm reputation</b>	China Security Journal, Shanghai Securities News, Securities Daily and Secutimes, 20 recalls, 2002- 2011	<i>DV:</i> CAR <i>EVs:</i> Recall strategy (proactive vs. passive), industry (automotive, food, and electronics)	AR[1] to a recall by a China-located firm is -2.21% and 78.57% of the sampled recalls have a negative CAR. Automotive (vs. food) recalls are more likely initiated following a proactive strategy, and AR is more negative for passive (vs. proactive) recalls and for food recalls compared to automotive recalls.
<b>Zhou et al. (2019)</b> <b>Competitive reaction, promotion</b>	NHTSA safety ratings, Toyota's acceleration recall, 2009-2010	<i>DV:</i> Sales volume <i>EVs:</i> Toyota's recall announcement, price discounting	Following Toyota's recall, 50% of Toyota's premium rival brands and 36% of its nonpremium rivals discounted their price by \$850 on average. Among premium brands, 86% benefitted in terms of higher sales, whereas nonpremium brands either did not benefit or lost sales.

**Table OS4. Empirical research on the determinants of non-automotive safety defects**

Note: The table below summarizes articles published where the DV is a characteristic of a product recall or a safety defect.

Study and Theoretical perspective(s)	Sample	Key variables	Key finding(s)
<b>Ball et al. (2018)</b> <b>Product competition, managerial discretion</b>	U.S. drug recalls by 64 firms, 2002-2014	<i>DV:</i> Number of recalls <i>EV:</i> Product competition	Product competition increases the number of high-severity, low-discretion recalls but decreases the number of low-severity, high-discretion recalls.

<i>Moderator: Managerial discretion</i>			
<b>Ball et al. (2017)</b> <b>Regulatory inspections of manufacturing plants, regulator experience</b>	U.S. medical device recalls, 2,244 plants, 2000-2006	<i>DV:</i> Recall hazard <i>EVs:</i> Inspection frequency, inspection outcome, inspector's experience	Each additional visit to a plant by an inspector increases recall hazard. A favorable inspection outcome decreases recall hazard, contingent on inspector experience.
<b>Bendig et al. (2018)</b> <b>Investor pressure, marketing investment, managerial myopia</b>	U.S. general consumer goods recalls, 804 firm-years, 2008-2013	<i>DV:</i> Recall incidence <i>EV:</i> Myopic marketing spending and share repurchase	A firm's myopic marketing spending and share repurchase increase its recall incidence in the $t + 2$ (but not in $t + 1$ or $t + 3$ ).
<b>Bruccoleri et al. (2019)</b> <b>Offshore outsourcing, captive offshoring</b>	U.S. drug recalls, 1,411 recalls, 2012-2016	<i>DV:</i> Recall size <i>EVs:</i> Offshore outsourcing, captive outsourcing	Offshore (captive) outsourcing decreases (increases) recall size.
<b>Byun and Al-Shammari (2021)</b> <b>Upper echelon, CEO characteristics</b>	U.S. general consumer goods recalls by 84 firms, 2006-2013	<i>DV:</i> Recall incidence <i>EVs:</i> CEO narcissism, CEO structural power, CEO ownership power, and CEO age	CEO narcissism, structural power, and age decrease the odds of recall incidence, whereas CEO ownership power increases it. CEO ownership power and age moderate the effect of CEO narcissism on recall incidence.
<b>Chakravarty et al. (2022)</b> <b>Marketing capability, operations capability</b>	U.S. consumer goods recalls, 276 recalls, 2000-2014	<i>DV:</i> Number of recalls, marketing operations, and capabilities <i>EV:</i> CAR to prior recall	CAR to a recall decreases the number of recalls in the following year, by improving the firm's marketing operations and capabilities.
<b>Giannetti and Srinivasan (2022)</b> <b>Lobbying, emphasis on product safety</b>	U.S. medical device, by 86 public firms, 2005-2018	<i>DV:</i> Number of recalls <i>EV:</i> Lobbying spending <i>Moderators:</i> Innovation radicalness, CEO's background in marketing/R&D	Lobbying spending increases the firm's number of recalls. Innovation radicalness, and CEO's background in marketing and R&D moderate the above effect.
<b>Hall and Johnson-Hall (2017)</b> <b>Organizational learning, uncertainty</b>	U.S. food recalls, 518 recalls by 125 public firms, 2004-2013	<i>DV:</i> Number of recalls <i>EVs:</i> Direct and indirect (supplier) recall experience, industry recalls	Direct and indirect recall experience decreases the number of future recalls. The number of industry recalls do not affect the number of future recalls.
<b>Kashmiri and Brower (2016)</b> <b>Agency theory, crisis management</b>	Product safety defects by 116 S&P firms, 2006-2011	<i>DV:</i> Safety defect incidence <i>EV:</i> CMO presence, family ownership, and director/executive stock ownership	CMO presence, family ownership, and director/executive stock ownership decrease the likelihood of safety defects.
<b>Kashmiri et al. (2017)</b> <b>CEO narcissism, competitive aggressiveness</b>	Product safety defects by 395 public U.S. firms, 2006-2010	<i>DV:</i> Safety defect incidence <i>EV:</i> CEO narcissism <i>Moderators:</i> Power of the marketing department in the top management team	CEO narcissism increases the likelihood of safety defects. Marketing department's power in the top-management team moderates the above effect.
<b>Mayo et al. (2022)</b> <b>CEO tenure, recall risk management, managerial discretion</b>	U.S. consumer goods recalls, 584 recalls by 125 publicly traded firms, 1992-2016	<i>DV:</i> Recall hazard (Recall date – the first recorded date for the firm) <i>EV:</i> CEO tenure <i>Moderators:</i> Prior CEO's forced exit, discretionary recall	Recall hazard is higher in the early tenure of the CEO. Prior CEO's forced exit moderates this hazard. Recall hazard is lower in the late tenure of the CEO. Discretionary recalls moderate this hazard.
<b>Steven and Britto (2016)</b> <b>Emerging markets</b>	U.S. consumer goods recalls, recalls by 327 firms, 2011	<i>DV:</i> Number of recalls <i>EVs:</i> Outsourcing to emerging markets, sales penetration in emerging markets	Outsourcing to emerging markets increases the number of recalls, whereas sales penetration in emerging markets decreases it.
<b>Steven et al. (2014)</b> <b>Offshore outsourcing, offshoring</b>	U.S. consumer goods recalls, recalls by 165 firms, 2012	<i>DV:</i> Number of recalls <i>EVs:</i> Offshore (vs. domestic) outsourcing	Offshore (vs. domestic) outsourcing increases the number of recalls.
<b>Thirumalai and Sinha (2011)</b> <b>Market penalties</b>	U.S. medical device recalls, 276 recalls 2002-2005	<i>DVs:</i> Number of recalls, CAR <i>EVs:</i> Recall class, recall product scope, recall experience	CAR to the recall announcement is insignificant. Recall experience and proportion of class II recalls decrease future recalls but recall scope increases it.

<b>Wowak et al. (2015)</b> <b>CEO pay options, risk-taking</b>	U.S. drug and food recalls, 386 CEOs, 2004-2011	<i>DVs:</i> Recall incidence, number of recalls <i>EV:</i> CEO stock-based compensation <i>Moderators:</i> founder-CEO, CEO tenure	CEO stock compensation increases recall incidence and the number of recalls by a firm. The presence of a founder-CEO and CEO tenure weakens these effects.
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**Table OS5. Empirical research on the process of non-automotive safety defects**

The table below summarizes articles where the DV is a characteristic of the process of initiating a product recall.

Study and Theoretical perspective(s)	Sample	Key variables	Key finding(s)
<b>Hora et al. (2011)</b> <b>Recall strategy, supply-chain player</b>	Toy recalls in the U.S., 528 recalls by 216 firms, 1993-2008	<i>DVs:</i> First sale to recall (Recall date – product’s first sales date) <i>EVs:</i> Preventive (vs. reactive) recall initiation, design (vs. manufacturing) defect, supply chain distance	Preventive (vs. reactive) recalls, products with design (vs. manufacturing) defects, and the firm-end customer supply chain distance are associated with a longer first-sale-to-recall time.
<b>Liu et al. (2023)</b> <b>Recall strategy, CMO impact</b>	Consumer goods recalls in the U.S., 380 recalls, 2001-2014	<i>DVs:</i> Number of proactive and passive recalls, number of harm incidents reported before recall initiation, CAR <i>EV:</i> CMO presence	A firm with a CMO has more proactive recalls, and fewer product-harm incident reports. The negative CAR to a recall announcement is stronger for a firm with a CMO.
<b>Mukherjee and Sinha (2018)</b> <b>Adverse event report, user feedback, managerial bias</b>	Medical device recalls, recalls by 108 firms, 2002-2012	<i>DV:</i> Recall under/over-reaction bias <i>EVs:</i> Distribution and severity of adverse events, firm size, product portfolio entropy	Distribution of adverse events, firm size, and product portfolio entropy increase (decrease) under-reaction (over-reaction) bias. The severity of adverse events decreases (increases) under-reaction (over-reaction) bias.
<b>Muralidharan et al. (2022)</b> <b>Recall experience</b>	Toy recalls in the U.S., 833 recalls initiated by 445 firms, 1988-2018	<i>DV:</i> First sale to recall (Recall date – product’s first sales date) <i>EVs:</i> Defect severity, recall experience, design (vs. manufacturing) defect, price	Recall experience shortens the product’s first-sale-to-recall time for low-severity defects. Design defects and higher price increase first sale to recall for high-severity defects.
<b>Raithel et al. (2023)</b> <b>Recall effectiveness, firm reputation</b>	U.S. consumer goods recalls, 338 recalls, 2001-2013	<i>DV:</i> Recall effectiveness <i>EVs:</i> Full (vs. partial) remedy, reputation	Full (vs. partial) remedy increases recall effectiveness, whereas firm reputation lowers it.
<b>Mafael et al. (2022)</b> <b>Customer satisfaction, brand equity</b>	Consumer goods recalls, 159 recalls, 2008-2020	<i>DV:</i> Full (vs. partial) remedy <i>EVs:</i> Defect severity, brand equity	Defect severity increases the odds of full (vs. partial) remedy, whereas brand equity has an inverted U-effect effect contingent on severity.
<b>Wowak et al. (2021)</b> <b>Female representation, managerial discretion</b>	U.S. medical device recalls, recalls by public firms, 2002-2013	<i>DVs:</i> Discovery to recall (Recall initiation date – defect discovery date), number of recalls <i>EV:</i> Female board representation <i>Moderator:</i> Recall severity	Female board representation decreases the firm’s discovery-to-recall time for high-severity defects. Female board representation increases the number of future low-severity recalls, but does not affect the firm’s future high-severity recalls.

**Table OS6. Empirical research on outcomes of non-automotive safety defects**

The table below summarizes articles where the EV is a characteristic of a product recall or safety defect. *WSJ* = *Wall Street Journal*

Study and Theoretical perspective(s)	Sample	Key variables	Key finding(s)
<b>Ball et al. (2022)</b> <b>Competitors’ failures, new-product submission</b>	U.S. medical device recalls, 2003-2015	<i>DVs:</i> Recalling brand’s incremental and radical innovation, rival brand’s incremental and radical innovation <i>EV:</i> Number of recalls	The number of recalls decreases the rate of a recalling firm’s incremental innovation but not its radical innovation, and increases the rate of the rival firm’s incremental and radical innovation.
<b>Byun et al. (2020)</b> <b>Customer loyalty, promotion strategies</b>	U.S. consumer goods recalls, 31 product recalls in 31 categories, 2011-2013	<i>DVs:</i> Repurchase, time to repurchase <i>EV:</i> Recall incidence <i>Moderators:</i> Loyalty with the recalled product, strength of shopping habit, promotion sensitivity	Customer’s loyalty to the product raises the odds of repurchasing but increases the time to repurchase. Customer’s shopping habit strength and promotion sensitivity lower the odds of repurchasing and decrease the time to repurchase.
<b>Cheah et al. (2007)</b> <b>CSR</b>	Drug recalls in the U.S. and the U.K., 1998-2004	<i>DV:</i> CAR <i>EV:</i> Recall announcement	CAR to a recall announcement is negative.

		<i>Moderators:</i> Recall severity, country, whether the firm is a member of either FTSE4Good or DJSI index	Defect severity moderates the above effect for a U.S. public firm, but not a U.K. public firm. FTSE4Good or DJSI membership strengthens the effect for all public firms, and not being a member weakens the effect for the U.K. public firm.
<b>Chen et al. (2009)</b> <b>Recall strategy, firm reputation, crisis management</b>	U.S. consumer goods recalls, 1996-2007	<i>DV:</i> CAR <i>EV:</i> Recall strategy (proactive vs. passive) <i>Moderators:</i> Reputation, recall hazard, age of recalled products	The CAR to a proactive recall is negative and statistically significant, whereas the CAR to a passive recall is positive and nonsignificant. Recall hazard moderates the CAR to recall. Reputation, recall volume, recalled products' age lower the odds of a proactive recall strategy.
<b>Cleeren et al. (2008)</b> <b>Advertising strategy</b>	Kraft and Eta peanut butter recalls in Australia, 1996	<i>DV:</i> Time to repurchase <i>EVs:</i> Loyalty, category usage, ad spending by the recalling brand, ad spending by the rival brand	The customer's loyalty to the recalled product and category usage reduce time to repurchase. Ad spending by premium recalling brand (Kraft) reduces time-to-repurchase, while rival brand's ad spending increases time-to-repurchase.
<b>Cleeren et al. (2013)</b> <b>Advertising and pricing strategy, household category purchases</b>	Consumer goods recalls in the U.K. and Netherlands, 60 recalls, 2000-2007	<i>DVs:</i> Market share, category sales <i>EVs:</i> Recalling brand's ad spending, category ad spending, price <i>Moderators:</i> negative publicity, blame acceptance	Increased ad spending after a recall increases market share, and increased category ad spending increases category sales. Negative publicity and blame acceptance moderate these effects. Increased category prices decrease category sales, and negative publicity moderates this effect.
<b>Hsu and Lawrence (2016)</b> <b>Brand equity, social media impact</b>	U.S. drugs and consumer goods recalls, 2010-2012	<i>DV:</i> CAR <i>EV:</i> Recall announcement <i>Moderators:</i> Recall-specific UGC, firm's participation in recall-specific UGC	The CAR to a recall announcement is negative and significant. The volume, valence, growth rate, breadth of recall-specific UGC, and the firm's participation in recall-specific UGC moderate the above effect.
<b>Johnson-Hall (2017)</b> <b>Corrective action, organizational learning, locus of failure, regulatory agency discovery</b>	U.S. food recalls, 322 recalls, 2009-2012	<i>DV:</i> Post-recall corrective action <i>EVs:</i> supplier-attributable, involuntary initiation, recall volume, firm size, contamination type (pathogen vs. not)	Nonmajor supplier-attributable recalls, involuntary recalls, and recalls with higher volume have a higher probability of corrective action. Major supplier-attributable recalls, larger firms, and recalls resulting from pathogen contaminations are less likely to result in corrective action.
<b>Mackalski and Belisle (2015)</b> <b>Negative spillover, competitor brands</b>	Land O'Lakes recall of its salted stick butter, 2003	<i>DV:</i> Sales <i>EVs:</i> Recall incidence	A firm's recall of one brand's product has a negative spillover effect on the sales of other brands/products from the same firm, and the sale of same product from other firms.
<b>Mafael et al. (2022)</b> <b>Customer satisfaction, remedy, brand equity</b>	U.S. consumer goods recalls, 159 recalls, 2008-2020	<i>DV:</i> Customer satisfaction <i>EVs:</i> Full (vs. partial) recall remedy <i>Moderators:</i> Brand equity, failure severity	A full (vs. partial) remedy increases customer satisfaction. Brand equity and failure severity moderate the above effect.
<b>Marcus and Goodman (1991)</b> <b>Crisis, agency theory, signaling theory</b>	<i>WSJ's</i> recall announcements in various product categories in the U.S., 1978-1982	<i>DV:</i> CAR <i>EV:</i> Recall announcement <i>Moderator:</i> Signaling a defensive (vs. accommodative) policy	CAR to a recall announcement is insignificant. Signaling a defensive (vs. accommodative) policy does not affect the above (null) effect.
<b>Noack et al. (2019)</b> <b>CSR</b>	Recalls by U.S. public firms, 197 recalls by 168 firms, 1999-2009	<i>DV:</i> BHAR <i>EVs:</i> Number of news articles about the recall, CAR, CSR intensity, CSR timing, CSR frequency	The number of news articles about the recall and CAR are negatively associated with BHAR. CSR intensity, timing, and frequency weaken the negative effect of CAR on BHAR.
<b>Ni et al. (2016)</b>	U.S. toy recalls, 145 recalls, 2000-2014	<i>DV:</i> Abnormal returns (AR) <i>EV:</i> Recall announcement <i>Moderator:</i> Proactive (vs. reactive) recall	AR to recall is negative and significant. Proactive (vs. reactive) initiation moderates the above effect.
<b>Raithel and Hock (2020)</b>	U.S. consumer goods recalls, 443	<i>DVs:</i> CAR, perceived reputation, competence, and likability	CAR to a recall is negative and significant.

<b>Strategy conformance, firm reputation</b>	recalls by 112 public firms, 1996-2014	<i>EV</i> : Recall incidence <i>Moderators</i> : Full (vs. partial) remedy, proactive (vs. reactive) recall, responsibility acceptance, crisis internal (vs. external) attribution	Providing a full remedy for a reactive recall or a partial remedy for a proactive recall weakens the above effect. A match between the firm's responsibility acceptance and the crisis' attribution increases perceived reputation, competence, and likability.
<b>Van Heerde et al. (2007) Advertising and pricing strategy</b>	Kraft and Eta peanut butter recalls in Australia, 1996	<i>DV</i> : Ad effectiveness, price effectiveness <i>EV</i> : Recall incidence <i>Moderator</i> : Value (vs. premium) brand	Recall incidence reduces ad effectiveness for value and premium brands. Recall incidence reduces price effectiveness for premium brands but not for value brands.
<b>Wood et al. (2017) Outsourcing, growth potential</b>	U.S. toy recalls, 135 recalls by 27 firms, 1979–2016	<i>DV</i> : CAR <i>EV</i> : Recall announcement <i>Moderators</i> : Business and geographic diversification, inventory, capacity, and financial slack, first sale to recall	CAR to a recall is negative and significant. Business diversification, inventory slack, capacity slack, and first sale to recall moderate the above effect.
<b>Zavyalova et al. (2012)</b>	U.S. consumer good recalls, recalls by 21 firms, 1998-2007	<i>DV</i> : Valence of media coverage <i>EV</i> : Recall incidence <i>Moderator</i> : number of technical (vs. ceremonial) action announcements	Recalls negatively affect media coverage valence. The number of technical (ceremonial) action announcements moderates the above effect.
<b>Zhao et al. (2011) Spillover, expectancy violation, safety-in-numbers</b>	Kraft and Eta peanut butter recalls in Australia, 1996	<i>DV</i> : Ad effectiveness, price effectiveness, quality consciousness <i>EV</i> : Recall incidence <i>Moderator</i> : Brand's perceived quality	Recall incidence reduces advertising and price effectiveness and reduces (increases) quality consciousness for a brand with high (low) perceived quality.

### Related Data Used or Provided in the Literature

Our data are related but distinct from data provided by Astvansh et al. (2022) and used by Eilert et al. (2017), and Shen (2021). Next, we elaborate on the relatedness and distinctness.

Astvansh et al. (2022) read the chronology section of the defect and noncompliance information report and identified the *Defect Awareness Date*. They subtracted the recall date from the *Defect Awareness Date* to calculate THE *Time to Recall*, the key variable in their data set. In addition, their data set includes the text of the chronology of the defect reports. We highlight that our data files complement—rather than substitute or duplicate—Astvansh et al.’s (2022) data. Astvansh et al.’s (2022) data set enables academics to research the *manufacturer’s* investigation process revealed at the time of recall. Our data enables academics to study the *regulator’s* investigation process, which *sometimes* closes with a recall. We emphasize “sometimes” because several NHTSA investigations close without the initiation of any recalls. Reciprocally, not all recalls are preceded by an investigation. Specifically, the NHTSA’s recall data file (flat\_rcl.txt) contains a field named *Influenced\_by*, which takes one of three values: MFR, ODI, and OVSC. If a recall’s *Influenced\_by* is equal to “ODI” or “OVSC,” the recall was preceded by an investigation by the NHTSA’s Office of Defect Investigations (ODI) or Office of Vehicle Safety Compliance (OVSC). The NHTSA’s label of influenced recall parallels academics’ label of involuntary recall. In contrast, if a recall’s *Influenced\_by* equals “MFR,” the recall is uninfluenced or voluntary. We downloaded NHTSA’s flat\_rcl.txt file on August 7, 2024. The file contained 28,231 distinct recalls identified by unique *NHTSA Campaign Numbers* (field name: *Campno*). Of these 28,231 recalls, 23,327 (82.63%) are uninfluenced or voluntary. The remaining 4,904 recalls (17.38%) are influenced or involuntary. 3,312 of the 4,904 influenced recalls were initiated before January 1, 2009, making them unlikely to be influenced by the investigations in the period covered by our data set. Of the 1,592 influenced recalls initiated after January 1, 2009, 914 (57%) are associated with the investigations covered in our data set, and thus included in our “Outcomes of Inv” data file. As our data files cover all investigations closed by the NHTSA between January 1, 2009, and May 31, 2021, the remaining 578 influenced recall campaigns are likely associated with investigations that were closed either before

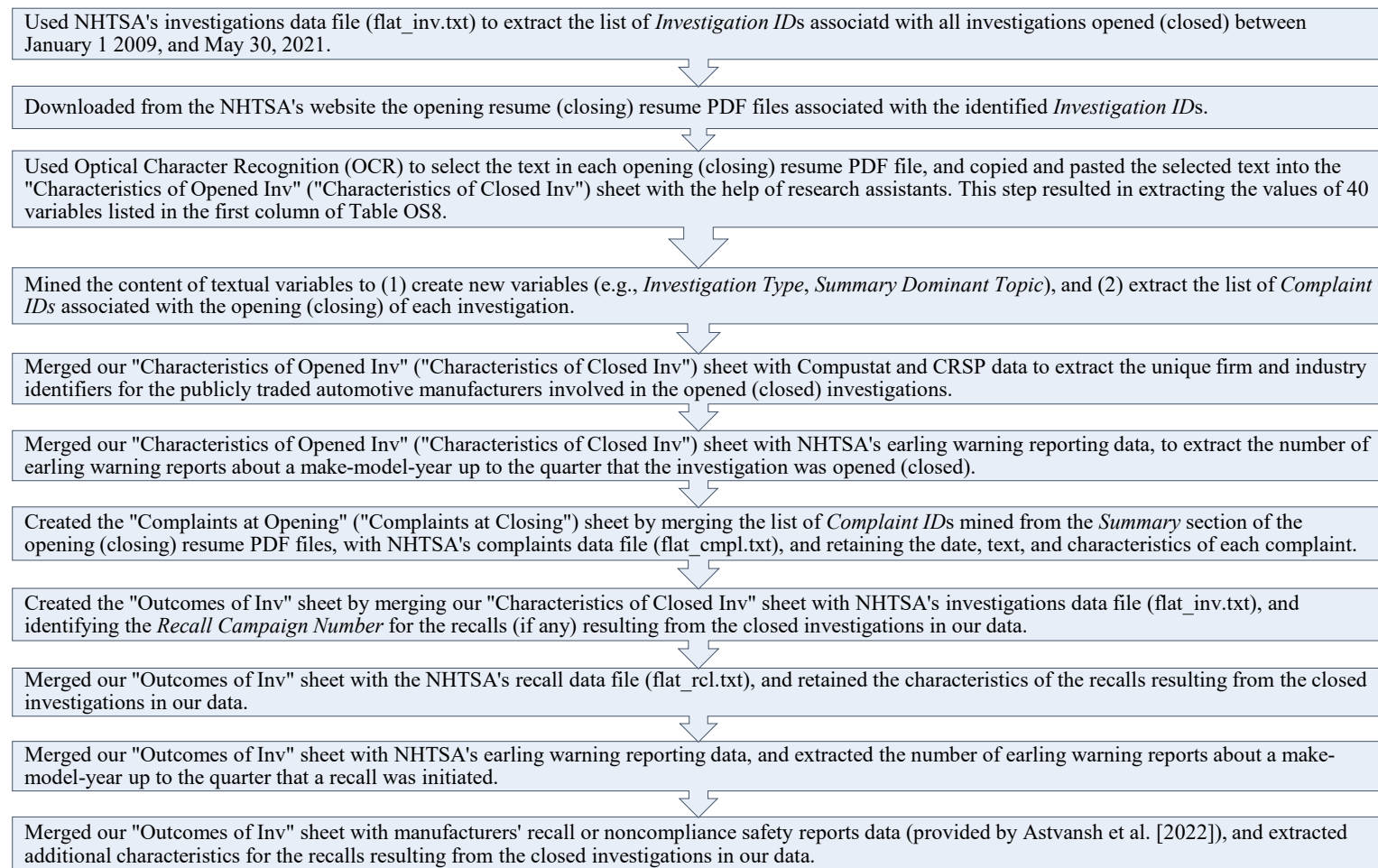
January 1, 2009, or after May 31, 2021. Further, we merged our data with Astvansh et al.'s (2022). The authors' data file reports 2,120 distinct recalls initiated between January 1, 2009, and May 31, 2018. Of these recalls, only 262 are influenced. 140 (53%) of these recalls are included in our "Outcomes of Inv" data, confirming that the two data sets overlap only marginally. The remaining 122 influenced recalls are likely associated with investigations closed before January 2009 or after May 2021.

Our data files overlap with data used by Eilert et al. (2017) in their empirical article and Shen (2021) in their doctoral dissertation. Specifically, Eilert et al. (2017) sampled NHTSA investigations that led to the opening of one or more recalls. The authors identified their sample using *NHTSA ACTION NUMBER* and *CAMPNO* in *flat\_inv.txt*. They focused on time-to-recall and thus sampled investigations that yielded at least one recall. We assume they measured time-to-recall using *RDATE* in *flat\_rcl.txt* and *ODATE* in *flat\_inv.txt*. Next, they likely used the following fields to measure their hypothesized determinants and control variables: (1) problem severity (*Odino* in *flat\_cmpl.txt*, and the presence of "crash," "fire," or deaths" in the values of *Consequence\_defect* (sic) field of *flat\_rcl.txt*), (2) past recall intensity (*Potaff* in *flat\_rcl.txt*), (3) recall size (*Potaff* in *flat\_rcl.txt*), and (4) investigation type (*NHTSA Action Number* in *flat\_inv.txt*). Although our data set includes all the variables that Eilert et al. (2017) used, we do not claim contribution in any of these variables because they are available in NHTSA's ready-to-analyze files. We contribute by providing the data embedded in the NHTSA's opening and closing resume PDF files, which Eilert et al. (2017) did not seem to have used.

Shen's (2021) dissertation essay 1 measures *Time to Recall* similar to Astvansh et al. (2022), as the number of days between the manufacturer's *Defect Awareness Date* and *Recall Date* (*Rcdate*, see Table 1.1 on p. 15). Shen's (2022) essay 2 used the chronology of investigation steps that the manufacturer mentions in its defect and noncompliance information report (again, like Astvansh et al.'s [2022]). Thus, like Eilert et al. (2017) and Astvansh et al. (2022), Shen (2021) examined the manufacturer's investigation, whereas we (and our data files) focused on the regulatory investigation.

## Dataset Description

**Figure OS1. Our procedure for data retrieval and data set construction**



**Table OS7. Data dictionary - Variable definition and computation**

Variable Label	Data Type	Description	Source	Variable Present in Which Sheet(s)?
<b>Investigation ID</b>	String	Unique 7-character field NHTSA-assigned alphanumeric ID that NHTSA uses to identify an investigation. Users can concatenate the <i>Investigation ID</i> to <a href="https://www.nhtsa.gov/recalls?nhtsaId=&lt; Investigation ID &gt;">https://www.nhtsa.gov/recalls?nhtsaId=&lt; Investigation ID &gt;</a> for the raw PDF files.	NHTSA's investigations data & opening/closing resume	Characteristics of Opened/Closed Inv Complaints at Opening/Closing Outcomes of Inv
<b>Date Investigation Opened</b>	Date	The date when the NHTSA opened the investigation.	Opening/closing resume	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>Date Investigation Closed</b>	Date	The date when (and if) the NHTSA closed the investigation. The variable has no value for open investigations as of December 17, 2021.	Closing resume	Characteristics of Closed Inv Outcomes of Inv
<b>Principal Investigator</b>	String	Name of the ODI's principal investigator for the focal investigation. 76 and 63 distinct full names in the opening data set and the closing data set, respectively.	Opening/closing resume	Characteristics of Opened/Closed Inv

<b>Subject</b>	String	Textual subject (or headline) of the investigation.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Manufacturer</b>	String	Cleaned name of one or more manufacturers whose products have the alleged defect. 180 and 169 distinct values in the opening data set and the closing data set, respectively	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Products</b>	String	The set of distinct model-year, make, and models of the vehicles with the alleged defect.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Population Raw</b>	String	The raw value of the number of vehicles potentially affected by the defect, extracted from the population field in the opening/closing resume PDF files. For any investigation, this number can be different in the opening and closing data sets.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Prompted By</b>	String	What or who prompted the opening of the investigation? Examples of values are complaints, petition, a prior investigation, and recall. If a prior investigation led to the focal investigation, <i>Prompted By</i> reports the ID of the previous investigation.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Reviewer</b>	String	Name of the ODI's reviewer for the focal investigation. 18 and 16 distinct names in the opening and closing data set, respectively.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Approver</b>	String	Name of the ODI's approver for the focal investigation. 15 and 14 distinct full names in the opening and closing data set, respectively	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Problem Description</b>	Long string	A one- or two-sentence description of the alleged defect/problem.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Complaints Reported to NHTSA</b>	Integer	The number of complaints about the focal defect reported to the NHTSA as of the investigation was opened (or closed for the variables in the Data on Investigations Closed file). A difference between the opening and the closing values proxies the increased harm or the harm incidents while the NHTSA investigated the defect.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Crashes and Fires Reported to NHTSA</b>	Integer	The number of reports of crashes and fires attributed to the focal defect and reported to the NHTSA as of the date the investigation was opened or closed (depending on whether the variable is in the Data on Investigations Opened or Closed file).	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Injury Incidents Reported to NHTSA</b>	Short integer	The number of reports of injury incidents attributed to the focal defect and reported to the NHTSA as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Injuries Reported to NHTSA</b>	Short integer	The number of injuries attributed to the focal defect and reported to the NHTSA as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No Fatality Incidents Reported to NHTSA</b>	Short integer	The number of reports of fatality incidents attributed to the focal defect and reported to the NHTSA as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Fatalities Reported to NHTSA</b>	Short integer	The number of fatalities attributed to the focal defect and reported to the NHTSA as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Other Types of Failures Reported to NHTSA</b>	Integer	The number of other types of reports (e.g., warranty claims, news) attributed to the focal defect and reported to the NHTSA as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Complaints Reported to Manufacturer</b>	Integer	The number of complaints about the focal defect reported to the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Crashes and Fires Reported to Manufacturer</b>	Integer	The number of reports of crashes and fires attributed to the focal defect and reported to the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>No. Injury Incidents Reported to Manufacturer</b>	Short integer	The number of reports of injury incidents attributed to the focal defect and reported to the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv

<b><i>No. Injuries Reported to Manufacturer</i></b>	Short integer	The number of injuries attributed to the focal defect and reported to the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Fatality Incidents Reported to Manufacturer</i></b>	Short integer	The number of reports of fatality incidents attributed to the focal defect and reported to the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Fatalities Reported to Manufacturer</i></b>	Short integer	The number of fatalities reported to the manufacturer regarding the focal defect as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Other Types of Failures Reported to Manufacturer</i></b>	Long integer	The number of other types of reports reported to the manufacturer regarding the focal defect as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Complaints Reported</i></b>	Integer	The number of distinct complaints about the focal defect reported to the NHTSA or the manufacturer as of the date the investigation was opened or closed (not double counting)	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Crashes and Fires Reported</i></b>	Integer	The number of reports of crashes and fires attributed to the focal defect and reported to the NHTSA or the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Injury Incidents Reported</i></b>	Short integer	The number of distinct reports of injury incidents attributed to the focal defect and reported to the NHTSA or the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Injuries Reported</i></b>	Short integer	The number of distinct injuries attributed to the focal defect and reported to the NHTSA or the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Fatalities Incidents Reported</i></b>	Short integer	The number of reports of fatality incidents attributed to the focal defect and reported to the NHTSA or the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No. Fatalities Reported</i></b>	Short integer	The number of distinct fatalities attributed to the focal defect and reported to the NHTSA or the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>No Other Failures Reported</i></b>	Long integer	The number of distinct other types of reports attributed to the focal defect and reported to the NHTSA or the manufacturer as of the date the investigation was opened or closed.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>Description of Other</i></b>	String	A short description of the “other” types of failure reports attributed to the focal defect and reported to the NHTSA or the manufacturer. “Other” includes warranty claims and manufacturer’s technical service bulletins sent to dealers.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>Action</i></b>	String	A one- or two-sentence description of the action performed by the NHTSA.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>Engineer</i></b>	String	The ODI engineer assigned to the focal investigation. 23 and 19 distinct full names in the opening and closing data set, respectively.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>Divisional Chief</i></b>	String	The chief of the Recall Management Division when the investigation was opened/closed. The opening data set and the closing data set have seven and six distinct full names, respectively.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>Office Director</i></b>	String	The director of the Office of Defect Investigations when the focal investigation was opened/closed. The opening data set and closing data set each have one distinct value.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>Summary</i></b>	Long string	In an opening resume, a summary of what led to the investigation and in a closing resume, a summary of what steps the NHTSA took as part of the investigation, and what will happen after the NHTSA closes the investigation.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b><i>File Name</i></b>	String	The name of the PDF file from which we copied the values.	Opening/closing resume	Characteristics of Opened/Closed Inv

<b>Population</b>	Long integer	The cleaned integer value of the <i>Population Raw</i> field.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Investigation Type</b>	String	The type of investigation the NHTSA opened. Extracted from the first two characters of <i>Investigation ID</i> .	Opening/closing resume	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>Problem Description Dominant Topic ID</b>	Short integer	The topic number for the dominant topic in <i>Problem Description</i> , taking a value between 1 and 17 for opened investigations, and 1 and 4 for closed investigations. We use the LdaMulticore module of the gensim Python package to build our topic model.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Problem Description Dominant Topic Percentage</b>	Float	The percentage of words in <i>Problem Description</i> that belong to the list of keywords associated with <i>Problem Description Dominant Topic</i> .	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Problem Description Dominant Topic Keywords</b>	String	The keywords associated with the <i>Problem Description Dominant Topic ID</i> .	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Problem Description Sentiment</b>	Float	This is the compound sentiment score of the Problem Description field. The sentiment scores are computed using the VADER dictionary and are standardized scores taking values between -1 and 1. -1 indicates an all-negative report, 1 indicates an all-positive report, and 0 indicates a neutral report. We use the nltk Python package's SentimentIntensityAnalyzer module.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Summary Dominant Topic ID</b>	Short integer	The topic number for the dominant topic in <i>Summary</i> , taking a value between 1 and 4.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Summary Dominant Topic Percentage</b>	Float	The percentage of words in <i>Summary</i> that belong to the list of keywords associated with <i>Summary Dominant Topic</i> .	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Summary Dominant Topic Keywords</b>	String	The keywords associated with the <i>Summary Dominant Topic</i> .	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>Summary Sentiment</b>	Float	Is the average of the compound sentiment score of the <i>Summary</i> field.	Opening/closing resume	Characteristics of Opened/Closed Inv
<b>GVKEY</b>	String	The manufacturer's Global company key, available for the publicly traded firms found in Compustat data.	Opening/closing resume and Compustat	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>TIC</b>	String	The manufacturer's ticker symbol, available for the publicly traded firms found in Compustat data.	Opening/closing resume and Compustat	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>CUSIP</b>	String	The manufacturer's CUSIP number, available for the publicly traded firms found in Compustat data. CUSIP stands for the Committee on Uniform Securities Identification Procedures. A CUSIP number is a unique nine-digit identification number assigned to equity, debt, and other securities registered bonds in the United States and Canada.	Opening/closing resume and Compustat	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>PERMNO</b>	Integer	The manufacturer's historical CRSP PERMNO link to Compustat data, available for the publicly traded firms found in Compustat & CRSP data.	Opening/closing resume and CRSP	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>PERMCO</b>	Integer	The manufacturer's historical CRSP PERMCO link to Compustat data, available for the publicly traded firms found in Compustat & CRSP data.	Opening/closing resume and CRSP	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>SIC</b>	String	The manufacturer's 4-digit standard industry classification code, available for the publicly traded firms found in Compustat data. SIC categorizes the industries that companies belong to, based on their primary business activities.	Opening/closing resume and Compustat	Characteristics of Opened/Closed Inv Outcomes of Inv
<b>NAICS</b>	String	The manufacturer's NAICS code, available for the publicly traded firms found in Compustat data. NAICS is North American Industry Classification System.	Opening/closing resume and Compustat	Characteristics of Opened/Closed Inv Outcomes of Inv

<b>No. Injury and Death Reports Up to Quarter</b>	Integer	The total number of injury or death reports for the make-model-year, based on the manufacturers' early warning reports, up to the quarter of the year that the investigation was opened or closed.	NHTSA's recalls and early warnings data	Characteristics of Opened/Closed Inv
<b>No. Injury Incidents Up to Quarter</b>	Integer	The total number of injuries reported for the make-model-year, based on the manufacturers' early warning reports, up to the quarter of the year that the investigation was opened or closed.	NHTSA's recalls and early warnings data	Characteristics of Opened/Closed Inv
<b>No. Death Incidents Up to Quarter</b>	Integer	The total number of injuries reported for the make-model-year, based on the manufacturers' early warning reports, up to the quarter of the year that the investigation was opened or closed.	NHTSA's recalls and early warnings data	Characteristics of Opened/Closed Inv
<b>No. Product Damage Reports Up to Quarter</b>	Integer	The total number of product damage reports for the make-model-year based on the manufacturers' early warning reports, up to the quarter of the year that the investigation was opened or closed.	NHTSA's recalls and early warnings data	Characteristics of Opened/Closed Inv
<b>Investigation Opening to Closing</b>	Integer	<i>DateClosed</i> minus <i>DateOpened</i> . Missing for investigations that are still open.	Closing resume	Characteristics of Opened/Closed Inv
<b>Complaint ID</b>	Long integer	The NHTSA-specified identification number of the complaint leading to the investigation. These IDs are extracted from the <i>Summary</i> section of the opening resume PDF files.	Opening/closing resume	Complaints at Opening/Closing
<b>No. Complaint IDs</b>	Integer	Number of distinct complaint IDs mentioned in the summary section of the investigation's opening/closing resume.	Opening/closing resume	Complaints at Opening/Closing
<b>Complaint Date</b>	Date	The date when the NHTSA received the distinct consumer complaint.	NHTSA's complaints data	Complaints at Opening/Closing
<b>Complainer Type</b>	String	Takes the values of consumer, or U.S. Congressional office.	NHTSA's complaints data	Complaints at Opening/Closing
<b>Complaints Components</b>	String	Is the set of the names of the components reported in the complaint.	NHTSA's complaints data	Complaints at Opening/Closing
<b>Complaints Products</b>	String	The set of distinct make, model, and make-year combinations reported in the complaints.	NHTSA's complaints data	Complaints at Opening/Closing
<b>Complaint Description</b>	Long string	The text of the complaint received by the NHTSA.	NHTSA's complaints data	Complaints at Opening/Closing
<b>First Complaint Date</b>	Date	Date when the NHTSA received the first complaint associated with the investigation.	NHTSA's complaints data & opening resume	Complaints at Opening/Closing
<b>First Complaint to Investigation Opening</b>	Integer	Days elapsed between the date the NHTSA received the first complaint associated with the investigation and the date it opened the investigation.	NHTSA's complaints data & opening resume	Complaints at Opening/Closing
<b>First Complaint to Investigation Closing</b>	Integer	Days elapsed between the date the NHTSA received the first complaint associated with the investigation and the date it closed the investigation.	NHTSA's complaints data & opening resume	Complaints at Closing
<b>NHTSA Campaign Number</b>	String	If the focal investigation led to a recall, this field stores the NHTSA's unique identifier for each recall attributed to the focal investigation. The variable (and all following recall-related variables) does not have a value if the focal investigation did not result in a recall.	NHTSA's investigations and recall data	Outcomes of Inv
<b>No. NHTSA Campaign Numbers</b>	Integer	Number of distinct NHTSA recall campaigns resulting from the closed investigation. Takes values between 0 and 100.	NHTSA's investigations and recalls data	Outcomes of Inv
<b>Recall Date</b>	Date	The date when the NHTSA received the manufacturer's recall notice. No value if the investigation did not result in a recall.	NHTSA's recalls data	Outcomes of Inv
<b>Investigation Closing to Recall</b>	Integer	Subtracting <i>the Date Investigation Closed from the Recall Date</i> measures the number of days it took between the NHTSA closing the investigation and the manufacturer legally initiating the recall. The variable has negative values for cases where the manufacturer initiated a recall before the NHTSA closed an investigation.	Closing resume and NHTSA's recalls data	Outcomes of Inv

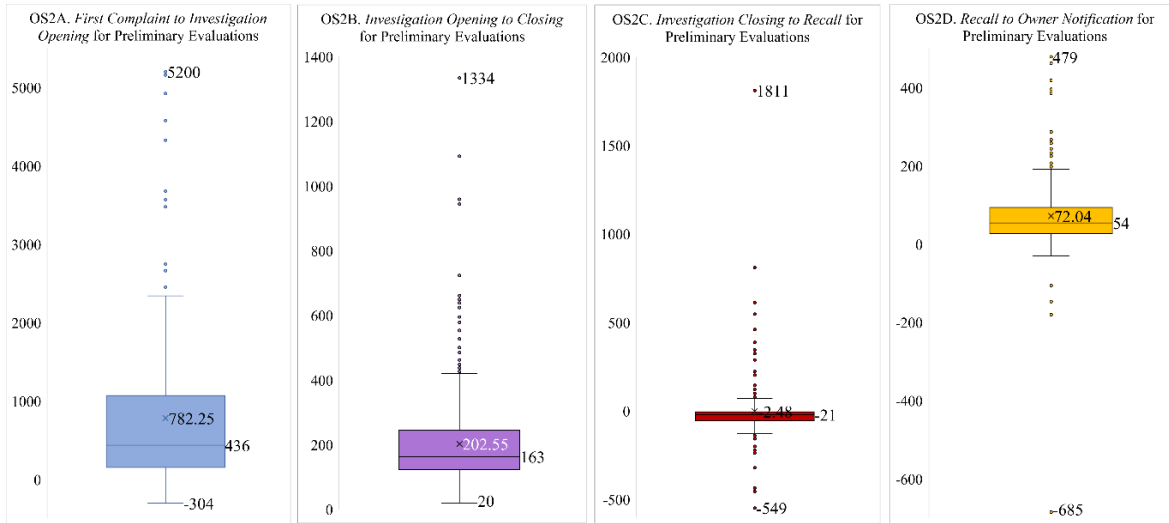
<b>Owner Notification Date</b>	Date	The date when the manufacturer notified the affected vehicle owners.	NHTSA's recalls data	Outcomes of Inv
<b>Recall to Owner Notification</b>	Integer	Subtracting the <i>Recall Date</i> from the <i>Owner Notification Date</i> measures the number of days it took for the manufacturer to legally initiate the recall and notify the owners of the affected vehicles. The variable has negative values for cases where the manufacturer notified the owners before legally initiating the recall.	Closing resume and NHTSA's recalls data	Outcomes of Inv
<b>Recall Size</b>	Long integer	The number of vehicles recalled.	NHTSA's recalls data	Outcomes of Inv
<b>Recall Scope</b>	Long integer	The number of make-year, make, and model combinations affected by the recall.	NHTSA's recalls data	Outcomes of Inv
<b>Recall Products</b>	Long string	The set of distinct make, model, and make-year combinations affected by the recall.	NHTSA's recalls data	Outcomes of Inv
<b>Recall Components</b>	String	Is the set of the names of the components involved in the recall.	NHTSA's recalls data	Outcomes of Inv
<b>Manufacturer</b>	String	The name of the manufacturer that filed the defect or noncompliance report.	NHTSA's recalls data	Outcomes of Inv
<b>No. Distinct Manufacturers of Recalled Products</b>	Integer	The number of distinct manufacturers that initiated recalls under the unique <i>NHTSA Campaign Number</i> .	NHTSA's recalls data	Outcomes of Inv
<b>Manufacturers of Recalled Products</b>	String	Name of all the distinct manufacturers of the components or products recalled as part of the unique recall campaign ID.	NHTSA's recalls data	Outcomes of Inv
<b>Recall Type</b>	String	Recall type, taking values of V for vehicle, E for equipment, T for tire report, and C for component.	NHTSA's recalls data	Outcomes of Inv
<b>Influenced By</b>	String	The recall initiator, taking values of MFR for manufacturer, OVSC for the Office of Vehicle Safety Compliance, and ODI for the Office of Defect Investigations.	NHTSA's recalls data	Outcomes of Inv
<b>Defect Description</b>	String	Defect or noncompliance summary.	NHTSA's recalls data	Outcomes of Inv
<b>Defect Consequence</b>	String	Summary of the consequence of product defect or noncompliance.	NHTSA's recalls data	Outcomes of Inv
<b>Corrective Action</b>	String	Summary of the corrective action taken by the manufacturer.	NHTSA's recalls data	Outcomes of Inv
<b>No. Product Damage Reports Up to Quarter of Recall</b>	Integer	The total number of injury or death reports for the make-model-year, based on the manufacturers' early warning reports, up to the quarter of the year that the recall was initiated.	NHTSA's recalls and early warnings data	Outcomes of Inv
<b>No. Deaths Reports Up to Quarter of Recall</b>	Integer	The total number of injuries reported for the make-model-year, based on the manufacturers' early warning reports, up to the quarter of the year that the recall was initiated.	NHTSA's recalls and early warnings data	Outcomes of Inv
<b>No. Injuries Reports Up to Quarter of Recall</b>	Integer	The total number of injuries reported for the make-model-year, based on the manufacturers' early warning reports, up to the quarter of the year that the recall was initiated.	NHTSA's recalls and early warnings data	Outcomes of Inv
<b>No. Injury and Death Reports Up to Quarter of Recall</b>	Integer	The total number of product damage reports for the make-model-year based on the manufacturers' early warning reports, up to the quarter of the year that the recall was initiated.	NHTSA's recalls and early warnings data	Outcomes of Inv
<b>Manufacturer Awareness Date</b>	Date	The date when the manufacturer first became aware of the defect or noncompliance.	Astvansh et al. (2022)	Outcomes of Inv
<b>Manufacturer Awareness to Recall</b>	Integer	The number of days between the <i>Manufacturer Awareness Date</i> and <i>Recall Date</i> .	Astvansh et al. (2022)	Outcomes of Inv
<b>Supplier Mentioned</b>	String	Does the chronology mention a supplier? Yes or no.	Astvansh et al. (2022)	Outcomes of Inv

Table OS8: Variables included in our data files, categorized by their source

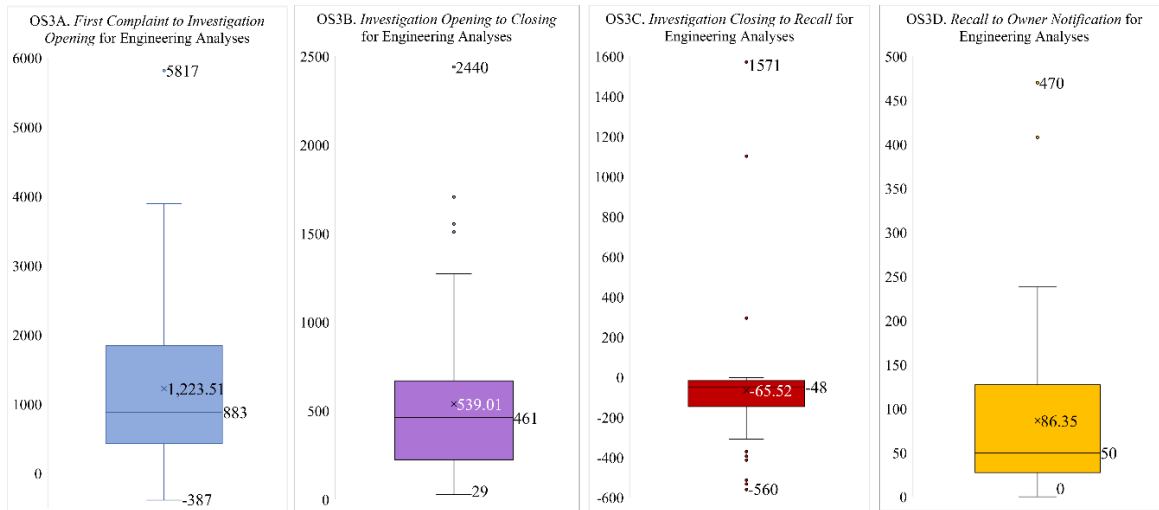
40 variables directly extracted from the NHTSA's opening and closing resume PDF files	35 variables directly extracted from merging our data with external data files ( <i>source</i> )	22 variables created from mining/combining the variables listed in the other two columns
- Investigation ID	- GVKEY ( <i>Compustat</i> )	- Population
- Date Investigation Opened	- TIC ( <i>Compustat</i> )	- Investigation Type
- Date Investigation Closed	- CUSIP ( <i>Compustat</i> )	- Problem Description Dominant Topic

- <b>Principal investigator</b>	- PERMNO ( <i>CRSP</i> )	- Problem Description Dominant Topic Percentage
- <b>Subject</b>	- PERMCO ( <i>CRSP</i> )	- Problem Description Dominant Topic Keywords
- <b>Manufacturer</b>	- SIC ( <i>Compustat</i> )	- Problem Description Sentiment
- <b>Products</b>	- NAICS ( <i>Compustat</i> )	- Summary Dominant Topic
- <b>Population Raw</b>	- No. Injury and Death Reports Up to Quarter of Investigation Opening/Closing ( <i>EWR</i> )	- Summary Dominant Topic Percentage
- <b>Prompted By</b>	- No. Injury Incidents Up to Quarter of Investigation Opening/Closing ( <i>EWR</i> )	- Summary Topic Keywords
- <b>Reviewer</b>	- No. Death Incidents Up to Quarter of Investigation Opening/Closing ( <i>EWR</i> )	- Summary Sentiment
- <b>Approver</b>	- No. Product Damage Reports Up to Quarter of Investigation Opening/Closing ( <i>EWR</i> )	- Investigation Opening to Closing
- <b>Problem Description</b>	- No. Complaint Date ( <i>NHTSA flat_cmpl.txt</i> )	- First Complaint Date
- <b>No. Complaints Reported to the NHTSA</b>	- Complainer Type ( <i>flat_cmpl.txt</i> )	- First Complaint to Investigation Opening
- <b>No. Crashes and Fires Reported to the NHTSA</b>	- Complaints Components ( <i>flat_cmpl.txt</i> )	- First Complaint to Investigation Closing
- <b>No. Injury Incidents Reported to the NHTSA</b>	- Complaint Products ( <i>flat_cmpl.txt</i> )	- Complaint ID
- <b>No. Injuries Reported to the NHTSA</b>	- Complaint Description ( <i>flat_cmpl.txt</i> )	- No. Complaint IDs
- <b>No. Fatality Incidents Reported to the NHTSA</b>	- NHTSA Campaign Number ( <i>flat_rcl.txt</i> )	- No. NHTSA Campaign Numbers
- <b>No. Fatalities Reported to the NHTSA</b>	- Recall date ( <i>flat_rcl.txt</i> )	- Investigation Closing to Recall
- <b>No. Other Types of Failures Reported to the NHTSA</b>	- Owner Notification Date ( <i>flat_rcl.txt</i> )	- Recall to Owner Notification
- <b>No. Complaints Reported to the Manufacturer</b>	- Recall Size ( <i>flat_rcl.txt</i> )	- Recall Products
- <b>No. Crashes and Fires Reported to the Manufacturer</b>	- Recall Scope ( <i>flat_rcl.txt</i> )	- No. Distinct Manufacturers of Recalled Products
- <b>No. Injury Incidents Reported to the Manufacturer</b>	- Recall Components ( <i>flat_rcl.txt</i> )	- Manufacturers of Recalled Products
- <b>No. Injuries Reported to the Manufacturer</b>	- Manufacturer ( <i>flat_rcl.txt</i> )	
- <b>No. Fatality Incidents Reported to the Manufacturer</b>	- Recall Type ( <i>flat_rcl.txt</i> )	
- <b>No. Fatalities Reported to the Manufacturer</b>	- Influenced By ( <i>flat_rcl.txt</i> )	
- <b>No. Other Types of Failures Reported to the Manufacturer</b>	- Defect Description ( <i>flat_rcl.txt</i> )	
- <b>No. Complaints Reported</b>	- Defect Consequence ( <i>flat_rcl.txt</i> )	
- <b>No. Crashes and Fires Reported</b>	- Corrective Action ( <i>flat_rcl.txt</i> )	
- <b>No. Injury Incidents Reported</b>	- No. Injury and Death Reports Up to Quarter of Recall ( <i>EWR</i> and <i>flat_rcl.txt</i> )	
- <b>No. Injuries Reported</b>	- No. Injury Incidents Up to Quarter of Recall ( <i>EWR</i> and <i>flat_rcl.txt</i> )	
- <b>No. Fatality Incidents Reported</b>	- No. Death Incidents Up to Quarter of Recall ( <i>EWR</i> and <i>flat_rcl.txt</i> )	
- <b>No. Fatalities Reported</b>	- No. Product Damage Reports Up to Quarter of Recall ( <i>EWR</i> and <i>flat_rcl.txt</i> )	
- <b>No. Other Types of Failures Reported</b>	- Manufacturer Awareness Date (Astvansh et al. 2022)	
- <b>Description of Other</b>	- Manufacturer Awareness to Recall (Astvansh et al. 2022)	
- <b>Action</b>	- Supplier Mentioned (Astvansh et al. 2022)	
- <b>Engineer</b>		
- <b>Divisional Chief</b>		
- <b>Office Director</b>		
- <b>Summary</b>		
- <b>File name</b>		

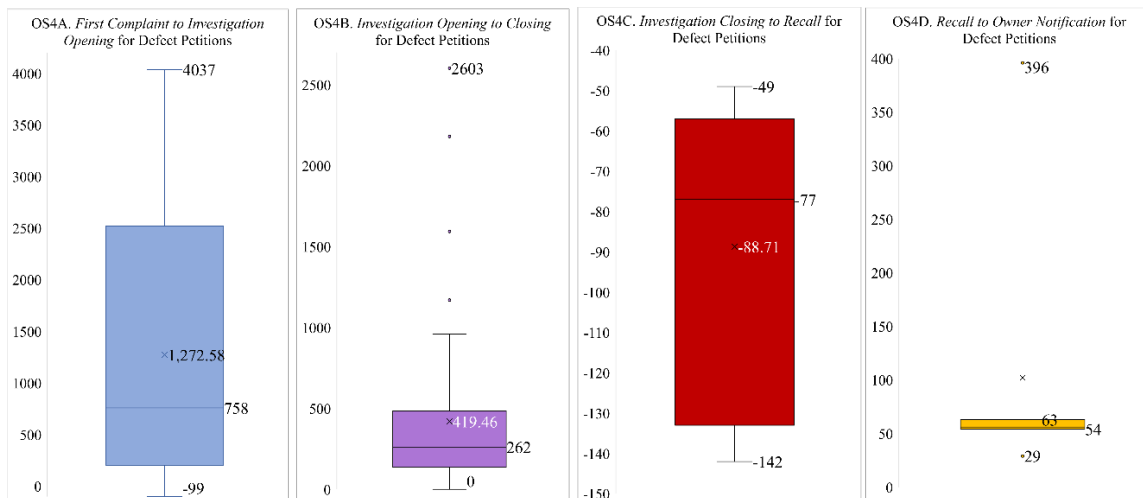
**Figure OS2. Boxplots of the Process Variables for Preliminary Evaluations**



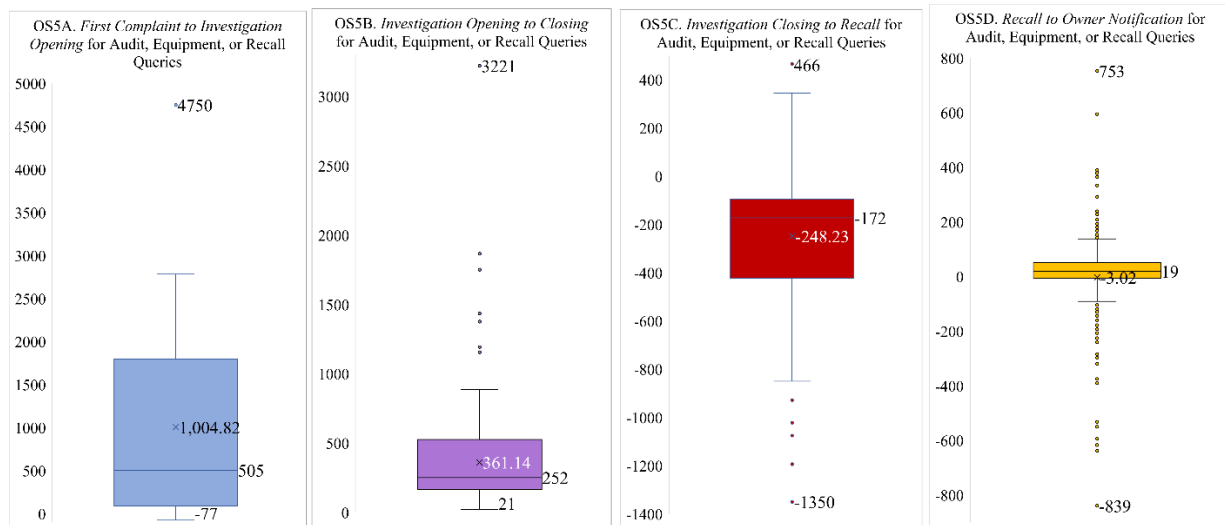
**Figure OS3. Boxplots of the Process Variables for Engineering Analyses**



**Figure OS4. Boxplots of the Process Variables for Defect Petitions**



**Figure OS5. Boxplots of the Process Variables for Audit, Equipment, and Recall Queries**



**Figure OS6: The Output of the Website**

OS6.A. Output for Categorical Variables



OS6.B. Output for Numeric Variables

