Do Safety Inspections Improve Safety? Evidence from the Roadside Inspection Program for Commercial Vehicles *

Yuanning Liang

Peking University

Regulatory efforts to mitigate public hazards can be undermined when agents respond strategically to enforcement. This paper evaluates the impact of a nationwide commercial vehicle inspection program on road safety, using comprehensive data on inspections and accidents. The findings reveal a sharp *increase* in a given truck's accident rate immediately following an inspection-driven by reduced caution from recently inspected drivers, such as speeding and neglecting vehicle maintenance, due to the low likelihood of repeated inspections. Comparative policy analysis indicates that less predictable inspection schedules and practices could mitigate these adverse behavioral responses.

Keywords: Enforcement and compliance; regulatory design; road safety; trucking industry

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1 Introduction

The effectiveness of regulation depends critically on how economic agents respond to enforcement designs. According to the expected utility model of Becker (1968), violations decline as the probability of detection rises. While enforcement mechanisms often aim to sustain a high probability of detection in general, in practice this probability varies over time across individuals. A key but underexplored dimension that affects the efficacy of enforcement is how agents respond strategically to temporary reductions in detection risk. For instance, under limited resource to carry out regulations, regulators rarely conduct repeated inspections on recently examined agents, resulting in a sharp drop in detection probability immediately after an inspection. Such fluctuations can undermine regulatory effectiveness if individuals reduce compliance in response. Understanding these behavioral responses is therefore essential for effective enforcement design.

This paper provides new insights into the study of regulatory enforcement and compliance by evaluating a long-standing national road safety regulation: the North American Standard Inspection Program for commercial motor vehicles (CMVs).[1] Using two decades of inspection and accident data, the study quantifies the regulation's effect on road safety for inspected trucks. It analyzes the behavioral mechanisms driving post-inspection accident patterns—specifically, drivers' compensatory responses to inspection design flaws—and offers potential improvements to regulatory design.

The US trucking industry is a multi-billion-dollar sector crucial for transporting freight and providing essential services to passengers across North America. Trucks account for 65% of all goods shipped by value across all transportation modes. However, this sector also represents a significant safety externality (Muehlenbachs, Staubli, and Chu (2021)): over 130,000 people are involved in large truck accidents annually, resulting in approximately 4,000 fatalities.[2] To improve safety, the US Department of Transportation (DOT) implemented a national safety inspection program for all

[1] Section 204 of the Motor Carrier Safety Act of 1984 (MCSA) (Pub. L. 98-554, Title II, 98 Stat. 2832, at 2833) defines a "commercial motor vehicle" as one that has a gross vehicle weight rating (GVWR) of 10,001 pounds or more; is designed to transport more than 15 passengers, including the driver; or transports hazardous materials in quantities requiring the vehicle to be placarded.

[2] National Highway Traffic Safety Administration (NHTSA) data.

CMVs. Inspections are conducted at weigh stations along highways by law enforcement personnel. When weigh stations are open, all trucks must enter; a subset is selected for inspection. Notably, inspectors focus less on recently inspected vehicles to avoid redundant checks. This design feature induces a sharp decline in the probability of reinspection immediately following an inspection.

This paper evaluates the effectiveness of the roadside safety inspection program on trucks inspected, using the most comprehensive data available on trucks, inspections, and accidents assembled from 1996 to 2018. The inspection files were obtained from the US Department of Transportation's national network of highway weigh stations and patrol inspectors. This dataset includes a complete inspection record of over 23 million trucks inspected across all 50 states from 1996 to 2018. Crash files are collected from state police crash reports over the same period, including all accidents involving CMVs. These records offer a key advantage over alternative sources such as those from the Fatality Analysis Reporting System and the National Highway Traffic Safety Administration (NHTSA) State Data System: they record the full vehicle identification number (VIN) for each truck involved. By linking inspection and accident histories through each truck's unique VIN, the data enables the matching of trucks involved in accidents with their inspection records. Consequently, an event study research design can be implemented to tracks a given truck's accident rate shortly before and after an inspection.

The main finding of this paper is a sharp, 45% *increase* in accident rates (2.84 over 6.37 accidents per 100,000 trucks) immediately following an inspection - an effect that lingers for at least 14 days. In the longer term, the increase in accident rates can be detected up to 12 months after inspections; moreover, there is no compensating reduction in accidents after 12 months. The current inspection design is estimated to contribute to approximately 1,803 additional accidents annually, potentially incurring a cost of around $360 million. Effect size heterogeneity is examined across various dimensions: different types of carriers, varying inspection intensity and outcomes, inspection blitz with heightened detection probability, changes across years, accident severity stratified by vehicle weight, and the presence of rest areas.

Several empirical tests are conducted in Section 3.3 to support the identification assumption, address potential confounding factors, and discuss selection issues. To identify the impact of inspections on accidents, the event study framework uses time-series variation in a truck's accident rate around its inspection. The validity of the identification relies on the assumption that, in the absence of an inspection, the trend in the accident rate remains flat.

First, I demonstrate that there is no pre-trend in accidents during the 14 days preceding an inspection, supporting the identification assumption (Figure 1). Second, potential omitted variables-such as changes in weather patterns or traffic conditions-are ruled out as major causes of the change in accidents following inspections (Section 3.3.1).

Third, the analysis addresses sample selection concerns related to inspection endogeneity (Section 3.3.2). Because the dataset only includes inspected trucks, the counterfactual accident rate for uninspected trucks remains unknown. Moreover, since the treatment is defined by inspection events, this introduces a specific selection issue due to survivorship bias. Specifically, trucks involved in accidents are likely to be out of the sample for a certain period, reducing their chances of being inspected. Another potential selection concern is that some trucks may only operate during times when inspections are carried out. Several pieces of evidence address these issues. Trucks typically do not remain idle for extended periods: industry reports indicate that a typical long-haul trucker drives about 500 miles daily for roughly 300 days per year. The robustness of the results is also tested by excluding trucks involved in serious accidents requiring repairs and those removed from the road due to inspection violations. Additionally, non-random inspection selection does not affect identification, as truck-level fixed effects control for differences in truck characteristics that may influence inspection selection. Furthermore, regarding selection concerns, Section 3.3.3 presents three approaches to construct treatment-vs-control comparisons that difference out the baseline accident rate: (1) comparing trucks that received a CVSA decal, which reduces future inspection probability, with those that narrowly missed obtaining the decal due to minor infractions, (2) using trucks inspected slightly later as controls for those inspected today, and (3) creating a counterfactual of uninspected trucks over a short period.

Finally, to mitigate concerns about reverse causality from post-accident inspections, trucks that crashed immediately before inspections are excluded (Section 3.3.4). Collectively, these identification tests and sub-sample analyses confirm that the observed changes in accident rates are attributable to inspections, highlighting enforcement design flaws.

Next, I explore the mechanisms behind the increase in accident rates following inspections. I first document a significant decline in the likelihood of reinspection for at least a quarter after an initial inspection. This pattern reflects a regulatory focus on targeting trucks that have not been inspected recently, effectively lowering the reinspection probability for those already checked. I show that this reduced reinspection probability contributes to higher accident rates. Correspondingly, the increase is more pronounced for single-vehicle accidents—often indicative of driver behavior—than for multi-vehicle accidents. Unlike multi-vehicle accidents, which can arise from various causes, single-vehicle accidents, such as non-collision incidents or collisions with stationary objects, are more directly attributable to driver actions. Additional crash data support this interpretation, revealing an immediate post-inspection rise in accidents linked to reckless driving and poor vehicle maintenance, including incidents involving driving under the influence and unsecured cargo. These findings align with the Becker (1968) model: when drivers perceive a low probability of reinspection, the implicit cost of non-compliance falls, reducing incentives for caution, pre-trip checks, and adherence to driving hour limits—ultimately undermining the safety program's intended effects.

This paper also addresses several policy questions. For instance, in designing inspection regimes for trucks traveling coast-to-coast, how can states enhance deterrence by accounting for drivers' behavioral responses to changes in the risk of detection? Would random inspections-where the probability of detection is independent of past inspection timing-be more effective? To investigate these questions, I compare the effect sizes under different inspection designs across states. First, states with more unpredictable inspection schedules experience a smaller increase, or even a reduction, in post-inspection accident rates. Second, I examine the variation in inspection selection practices across states, particularly the reliance on the time elapsed since the last inspection to determine which trucks are selected for inspection. The results show that the states more likely to reinspect recently inspected trucks experience smaller increase in accident rates. These results suggest that introducing greater randomness in inspection practices may improve national road safety outcomes.

This paper acknowledges limitations in assessing the overall impact of the CMV inspection program. While the analysis reveals an increase in accidents following inspections, the current research design and data constraints do not permit estimation of the counterfactual accident rate without inspections. This rate could be lower than the pre-inspection accident rate, fall between the pre- and post-inspection rates, or even exceed the post-inspection rate. Therefore, the findings should not be interpreted as an argument for discontinuing the inspection program. In fact, inspections remove about 20% of high-risk vehicles and drivers annually, thereby reducing potential hazards. Instead, the results highlight that the current enforcement mechanism may be suboptimal and suggest potential improvements in regulatory design to enhance public safety outcomes.

This paper contributes to four significant areas of economic literature: regulatory enforcement, transportation economics, behavioral economics (with an emphasis on the Peltzman effect), and policy evaluation. These contributions extend beyond the specific context of commercial motor vehicle inspections, offering broader theoretical and practical insights.

The primary contribution of this paper is to the extensive literature on regulatory enforcement through periodic, random, or targeted inspections. While prior research has shown that higher probabilities of detection reduce violations through targeted inspections (Muehlenbachs, Staubli, and Cohen (2016), Duflo et al. (2018), Johnson, Levine, and Toffel (2023), Blundell, Gowrisankaran, and Langer (2020)), it also finds that lower probabilities of detection increase violations due to high predictability in enforcement schedules (Zou (2021)) or corruption in inspections (Oliva (2015)). However, the dynamic effects of detection probability over time remain underexplored. This paper addresses this gap by revealing that strategic responses to temporary reductions in detection probability can significantly undermine regulatory efficacy. By illustrating that randomized inspections can mitigate these strategic behaviors, this study offers new insights into optimizing regulatory designs. These findings have broad implications for regulatory mechanisms across various regulatory contexts (Okat (2016), Banerjee et al. (2019), Gonzalez-Lira and Mobarak (2021)), contributing to a deeper understanding of how to sustain high compliance rates over time.

Second, this paper contributes to the transportation and logistics literature by studying the safety impacts of heavy vehicles, which can lead to severe accidents due to their size and weight. While there has been substantial research on accidents involving heavy vehicles (e.g., White (2004), Li (2012), Anderson and Auffhammer (2014), Graham et al. (2015), Muehlenbachs, Staubli, and Chu (2021)), fewer studies have examined the compliance behavior of carriers and drivers with safety regulations. This paper provides new insights into such behavior, with broader implications for transportation policy and the development for cautionary strategies to strengthen regulatory effectiveness.

Third, this paper contributes to the literature on the Peltzman effect, which suggests that safety regulations may induce riskier behavior among individuals who perceive increased safety (Peltzman (1975), Viscusi (1984), Viscusi (1986)). Amid debates regarding the extent to which drivers' reactions mitigate the effects of regulations (Cohen and Einav (2003), Lv et al. (2015)), this study provides robust evidence within the transportation sector, where the concept originated—thus directly linking this well-known theory to contemporary policy challenges.

On the policy front, this paper is a pioneering effort to assess the impact of the commercial motor vehicle safety inspection program on accidents at the national scale over a long and recent period (1996-2018), overcoming limitations in prior studies related to data availability or empirical methodology (e.g., Loeb and Gilad (1984), GAO (2005)). While some studies examine the consequences of exogenous FMCSA enforcement events—such as the Electronic Logging Device (ELD) mandate (Scott, Balthrop, and Miller (2021)) or CVSA inspection blitzes (Balthrop, Scott, and Miller (2023))—none have explored how individual inspections influence behavior at the truck level. This paper advances the literature by demonstrating how the effectiveness of inspections is diminished by drivers' strategic responses, using detailed truck-level data. The proposed policy recommendations, including more unpredictable inspection schedules, are empirically grounded and could inform broader regulatory reforms.

The paper proceeds as follows. Section 2 reviews the institutional details of the inspection program and describes the data. Section 3 presents the empirical framework, main findings, and identification challenges. Section 4 discusses the mechanisms behind the increase in accidents following inspections and heterogeneity in the effects. Section 5 discusses alternative regulatory designs to improve safety. Section 6 concludes.

2 Institutional Background and Data

2.1 Regulatory Framework

The Trucking Industry The trucking industry is a critical sector in the United States. In 2016, commercial motor vehicles (CMVs)—including trucks and buses—transported goods valued at $700 billion, accounting for 65% of all shipped goods by value across all transportation modes. Of the 269 million registered vehicles, 11 million (4%) were trucks,[3] and 1 million (0.4%) were buses. That year, vehicles traveled a total of 3,174 billion miles, with large trucks accounting for 9.1% (287.9 billion miles) and buses for 0.5% (16.3 billion miles). The industry also employed 6 million truck and bus drivers and had 543,061 active motor carrier companies operating nationwide in 2017.[4]

Commercial Motor Vehicle Safety Every year in the US, over 130,000 people are involved in CMV-related accidents, with more than 60,000 injuries and over 4,000 fatalities.[5] In 2016, large trucks and buses accounted for 7% of all vehicle-related fatalities nationwide. Between 2009 and 2018, fatalities involving large trucks increased by 17%, compared to a 10% increase in total vehicle miles traveled.[6]

Given its implications of truck safety for both truck drivers and other motorists, truck safety is a major consideration for the trucking industry. The Federal Motor Carrier Safety Administration

[3]Trucks include 8.7 million single-unit trucks and 2.8 million combination trucks.
[4]From Federal Motor Carrier Safety Administration (FMCSA) 2018 Pocket Guide to Large Truck and Bus Statistics.
[5]From National Highway Traffic Safety Administration (NHTSA) calculations.
[6]Statistics sources are from NHTSA and the Bureau of Transportation Statistics (BTS). The percentage increase in crashes is calculated by the author.

(FMCSA) is the lead regulatory agency responsible for improving safety and preventing CMV-related accidents. Approximately 7,000 certified roadside inspectors across the US assist the agency by conducting around 3.5 million roadside inspections annually. These inspections are part of the North American Standard Inspection Program.

The safety inspection program Commercial vehicle roadside safety inspections—conducted at weigh stations and mobile sites—aim to ensure the safety of both vehicles and drivers. However, the program's cost-effectiveness is debated. Benefits remain uncertain due to limited evidence on prevented accidents, while the costs to regulators and trucking firms are substantial.[7] Without clear evidence of improves safety outcomes, the inspection program's current design remains difficult to justify.

Weigh Station Inspections All trucks are required to enter weigh stations when they are open.[8] I recorded a video showing that it is indeed the case that all trucks in sight complied. Figure A1 in the appendix illustrates the inspection process: Figure A1(a) shows a line of trucks waiting at the ramp to enter the weigh station. After entering, all trucks drive onto a scale to be weighed (Figure A1(b)). While they are weighed, the inspectors determine whether the truck will receive a closer inspection based on the truck onsite as well as the truck's safety record (Figure A1(c)). Therefore, all trucks must enter the weigh station, but only a subset undergoes inspections; others are allowed to proceed. The inspection data used in this study include only these more detailed inspections.

What Factors Determine If a Truck Will Be Inspected? Inspections are initiated based on two primary criteria. First, trucks undergo checks if inspectors observe any potential issues with the truck or driver on site. Second, trucks may be selected for inspections if they have poor safety his-

[7] Enforcement agencies themselves question the program's efficacy, noting that inspections are "no longer leading to annual increases in the industry-wide level of compliance with safety regulations" (GAO, 2005). Anecdotal evidence from Drivewyze, a company offering a weigh station bypass service, suggests that each inspection stop costs trucks $2.50 per minute.

[8] Two exceptions apply: Carriers with high safety scores qualify for the Weigh Station Bypass system, which notifies trucks if they must stop for inspection. Second, whether passenger carriers must stop at weigh stations depends on different state regulations.

tories or have not been inspected recently. Carriers with poor safety records—derived from previous inspections, crash records, company reviews, and violations from investigations—are specifically targeted. The safety records system algorithm also flags trucks that have not been inspected in the past 12 months. Additionally, to avoid redundant efforts, inspectors focus less on vehicles that have recently passed an inspection.[9] This selection process, which considers recent inspection histories, is crucial to the main findings of this paper.

What Kind of Things Are Checked During Inspections? Depending on the level of scrutiny determined on site, inspections (Figure A1(d)) can include six types of Behavior Analysis and Safety Improvement Category (BASIC) examinations, covering both the driver and the vehicle. Driver inspections check daily log books that record time and distance traveled, trip durations, hours-of-service compliance, controlled substances/alcohol consumption, and driver fitness. Vehicle inspections cover all aspects of maintenance, including brakes, tires, and cargo securement. For hazardous material carriers, inspections also include hazmat compliance. There are six primary levels of inspections, each with different levels of scrutiny or focus: Level I (full inspection) accounts for 41% of inspections, Level II (walk-around driver/vehicle inspection) for 25%, and Level III (driver-only inspection) for 32%. Additionally, there are Level IV (special study), Level V (terminal inspections), and Level VI (radioactive material inspections), which together constitute 2% of the full sample.

What Are The Inspection Outcomes? Multiple violations may be issued during inspections if multiple issues are found.[10] Driver violations typically incur higher fines and can lead to license suspension, serving as a stronger deterrent than vehicle violations. Vehicles with no out-of-service violations can continue operating, but any violations or defects must be corrected within 15 days. If

[9] In recent years, inspection selection has been facilitated by PrePass-equipped weigh-in-motion sensors and in-cab transponders, like Drivewyze. These bypass systems allow certain trucks that are within legal weight limits and have good safety scores, as determined by the FMCSA based on safety and inspection history, to bypass weigh station inspections.

[10] Among all weigh station inspections, 38% find no violation, 41% result in at least one violation without taking the vehicle out of service. Of these, 40% feature driver violations, 75% feature vehicle violations, and 1% feature hazmat carrier violations, with some inspections citing multiple types of violations.

no critical violations are assigned to the vehicle during a thorough vehicle inspection, then the vehicle could be issued a CVSA decal, and those trucks will not be reinspected during the three-month time frame in which the decal is valid.[11] 20% of inspections result in out-of-service violations, indicating that the vehicle or driver presents an imminent hazards to the public. The effect is immediate; the vehicle may not be driven until all repairs and corrections are made.

2.2 Data Description

In this research, I compile a comprehensive database on trucks, safety inspections, and accidents across all U.S. states from 1989 to 2018. The primary data source is the Federal Motor Carrier Safety Administration (FMCSA), which maintains detailed records of inspections and accidents for commercial motor carriers (trucks and buses) and hazardous material shippers. These records are electronically transmitted from the states to the FMCSA via the SAFETYNET reporting system, enabling centralized access to a truck's safety records across different states. I also observe the characteristics of currently active carriers using company census data.[12] In addition to the FMCSA data, I utilize data on fatal accidents from the Fatality Analysis Reporting System (FARS) and accident data from the Texas Department of Transportation (TxDOT). I also incorporate highway traffic volume and daily weather records to construct external condition covariates.[13]

Inspection Files Inspection records are collected by state and federal inspectors. Inspection files contain information on the time, location, inspection facility, and outcome of inspections. Figures A2 and A3 in the appendix show that over the past decade, the number of commercial vehicles

[11] Detailed descriptions of decal issuance are in Section 3.3.3 "CVSA Decal Trucks". While exceptions exist, trucks with a valid decal are expected to have a significantly lower probability of subsequent inspections within three months.

[12] The FMCSA carrier company census file provides a snapshot of all active U.S. carrier companies as of October 2018, including address, registration, cargo type, number of vehicles, and number of drivers.

[13] Supplementary data sets include traffic volume data from the Federal Highway Administration (FHWA) and daily weather records from the Global Historical Climate Network Daily (GHCN-Daily). The traffic data, spanning 2012 to 2018, records hourly traffic volume by vehicle class for participating states, enabling direct observation of truck traffic and control for other vehicle types. The GHCN-Daily data provides weather records, including temperature, precipitation, snowfall, and snow depth, to assess the impact of adverse weather conditions on accident rates post-inspection.

has risen faster than the number of inspections. Consequently, the number of inspections that any given truck could receive has decreased, especially in recent years. Geographically, Figures A4 and A5 in the appendix show that the inspection program covers the entire U.S., although the intensity of inspections varies considerably across states. The inspection data files also contain information on each truck's unique Vehicle Identification Number (VIN), license plate number, and carrier company. This information allows linkage of each truck's inspection record with other records involving the same truck or company.

Crash Files The main crash files I use from FMCSA are collected from state police crash reports. These files contain information on the time, location, number of injuries and fatalities, accident type, VIN, and carrier company for all trucks involved in accidents. Figure A6 in the appendix shows that the annual total number of truck-related accidents increases over time and that the trend is procyclical to the general economy. The vehicle miles traveled by commercial motor vehicles exhibit a much milder increase over the period. The files also record the number of vehicles involved and the circumstances of the accidents, allowing me to infer the contributing factors. This is the key information that enables me to elucidate the mechanism of the findings in the paper.

In addition to the FMCSA files, I explore two other sources of crash records. One is the Fatality Analysis Reporting System (FARS), which includes all fatal crash records maintained by NHTSA from 2000 to 2017. The other source is crash records obtained directly from the Texas Department of Transportation, covering 2010 to 2017.[14]

Both FARS and Texas crash data contain detailed information on the factors contributing to each accident, including driver-related factors such as speeding, reckless lane changing, or driving while intoxicated, and vehicle-related factors such as malfunctioning brakes or lights. Additionally, these data also indicate incidents in which truck drivers were not at fault. Therefore, I use these two datasets to examine the exact causes of accidents, which provides crucial support for the mechanisms underlying my findings.

However, using FARS and Texas crash data has some drawbacks compared to FMCSA data.

[14] The Texas DOT accident data are publicly available only from 2010.

FMCSA crash files include the full 17-digit VIN, essential for linking truck inspection data and comparing crash rates for the same truck before and after inspection. In contrast, FARS contains only the first 12 digits of the VIN due to privacy concerns, omitting the last six digits, which are crucial for precise vehicle identification.[15] Additionally, FMCSA data covers all truck-related accidents, including non-injury and non-fatal ones, which are relevant for a comprehensive safety analysis. Texas DOT data, while covering all crash types, is limited to events within the state of Texas. Thus, I use FMCSA data to estimate the effect of inspection on accidents, and use FARS and Texas data to support the mechanisms and enhance the robustness of my findings with multiple data sources.

Summary Statistics I summarize key variables in Table 1. Panel A presents statistics for the inspection files, which include 69,549,512 inspections conducted from 1996 to 2018, covering 23 million trucks.[16] Nearly half of these inspections occurred at fixed weigh stations, which are the focus of this study. On average, a truck is inspected three times at weigh stations in its lifetime, with 32% of trucks reinspected. Approximately 6 million inspections resulted in at least one Out of Service (OOS) violation, reflecting a notably high probability—around 20%—of receiving an OOS violation. During inspection hours, an average of 856 trucks pass through a county from both directions.[17]

The inspection and crash files are integrated to create a truck-level day-by-day panel that traces all accidents that occurred to the same truck inspected 14 days before and after an inspection. Each truck is identified primarily using its VIN, or, if VIN is missing, using the license plate number.[18]

[15] To identify the 17-digit VIN for FARS data, the primary approach is to first match FMCSA crashes with FARS crashes using 12-digit VINs, crash time, and location. Duplicates are rare (<0.01%) and are excluded from the FARS analysis. After matching, I replace the 12-digit VIN in FARS with the corresponding 17-digit VIN from FMCSA to enable matching with inspection records. Additional matches are found using vehicle licenses.

[16] Data from DOT spans 1989 to 2018, but earlier records suffer from poor quality. VINs are missing before 1996, inspection facility data is sparse before 1994, and records for 1995 are unavailable. Hence, analysis begins in 1996 for consistency.

[17] Truck volume data is obtained from FHWA. The number is aggregated in both travel directions, across all lanes, and all monitoring stations in the county. Some counties have more than 100 stations, which can result in very large numbers due to duplicated counts. Such duplication has little impact because county fixed effects are included in those regressions that include truck volume as additional controls.

[18] Given the computational burden of creating a balanced truck-by-day panel for 11 million inspected trucks of 23 years, which would result in over 50 billion observations, I instead construct a 28-day event window around each

As shown in Panel B of Table 1, there are 635,481,707 observations in the constructed panel. The average daily accident rate is 6.34 per 100,000 trucks.[19] Among these accidents, 58% result in injuries and 4% in fatalities.

To analyze the long-term impact of inspections, I create a monthly event panel with month-level observations spanning from 12 months before to 24 months after inspections. Table 1 panel C presents the summary statistics of this monthly panel, showing an average of 140 crashes per 100,000 trucks per month.

Panel D of Table 1 shows that there were 1,669,661 active companies registered as of October 2018. On average, each carrier company employs five drivers and owns 21 trucks.[20]

Raw Data Patterns: Increased Crash Rates Following Recently Inspected Trucks Before presenting the empirical framework, I first show some raw data patterns. In the top panel of Appendix Figure A7, I plot the relationship between the number of crashes and the crash-inspection time interval. For each truck inspected, I calculate the time interval between the crash and the closest inspection. This raw data, without control variables, shows that more accidents occur shortly after inspections. In the bottom panel of Figure A7, I demonstrate through a state-by-year level analysis that higher crash rates (crashes per million Vehicle Miles Traveled) are correlated with a lower probability of reinspection within a quarter.

The raw plots do not provide conclusive evidence due to selection bias; trucks receiving frequent inspections—thus having shorter time intervals—may be more dangerous. However, they suggest that the current regulatory focus on trucks that haven't been inspected for a while overlooks many involved in accidents. This misalignment motivates the research question in this paper. In the next section, I will empirically identify the causal effect of inspections on accidents and address potential identification concerns.

inspection. This allows for comparing accidents 14 days before and after each inspection. I identify all accidents for the same truck within this window using the VIN or license plate in both files.

[19] The average accident rate is the number of accidents happened for each of the 100,000 trucks inspected in a day. In the data, I only observe trucks that are inspected, not all trucks passing through the weigh station, therefore, the numerator and the denominator of the accident rate both refer to the inspected trucks.

[20] A median-sized carrier company has only one driver and one truck. While half of the carrier companies are very small, there are also a few giant companies in the industry, such as FedEx.

Limitations of the Data In an ideal scenario, each truck would be equipped with a GPS tracker to monitor its location, speed, mileage, and temporal data. This would allow for precise analysis of truck usage before and after inspections or accidents, and facilitate comparisons between inspected and uninspected trucks. Unfortunately, while the available data on truck inspections and accidents are comprehensive, they lack detailed mileage and location information; uninspected trucks are not included in the dataset. I only observe trucks when they crash or receive inspections.

I make several assumptions regarding travel patterns and test their validity in Section 3.3. First, after excluding trucks with recent severe accidents or out-of-service violations, I assume that trucks are driven similar distances before and after inspections, supported by subsample tests (Section 3.3.2). Second, I assume comparable road and traffic conditions before and after inspections (Section 3.3.1). In robustness tests, I account for adverse weather conditions (rain and snow) and county traffic volumes on the hours of inspections and accidents, finding no confounding effects on the estimated impact of inspections. Finally, I construct three control groups for inspected trucks to strengthen the identification strategy (Section 3.3.3).

3 The Impact of Inspection on Truck Accidents

3.1 The Econometric Framework

This section presents the econometric specifications and identification assumptions required to consistently estimate the effect of an inspection on truck accidents. The main specification is an event study that compares accident outcomes for the same truck in the 14 days before and after inspection. This framework allows flexible estimation of dynamic treatment effects and facilitates testing of the parallel trends assumption. I regress the crash indicator for the same truck that received the inspection on a set of inspection indicators from 14 days before to 14 days after the inspection, controlling for individual truck fixed effects, year, month, and day-of-week fixed effects.

The regression equation is specified as:

$$Crash_{it} = \sum_{\tau=-14,\tau\neq-1}^{13} \beta_\tau Insp_{it}^{\tau} + \beta_{-15} Insp_{it}^{-15} + \beta_{14} Insp_{it}^{14} + u_i + \eta_t + \varepsilon_{it}, \quad (1)$$

where $Crash_{it}$ is an indicator variable equal to 1 if truck i experiences a crash on day t.[21] $Insp_{it}^{\tau}$ is an inspection indicator, $Insp_{it}^{\tau} = 1$ if as of time t, truck i experiences an inspection τ days ago. Since inspection happens at event day 0 ($\tau = 0$), the 28-day event window is between event day τ = [-14, 13]. $Insp_{it}^{-15}$ is an indicator for inspections more than 14 days before the current one, starting from the truck's first inspection. $Insp_{it}^{14}$ is an indicator for inspections that occurred between 14 days after the current one and the truck's last recorded inspection. u_i is the individual truck fixed effect. It ensures the identifying variation comes from day-to-day changes in accidents for the same truck.[22] η_t includes year, month and day-of-week fixed effects. Year fixed effects account for technological progress, industry trends, and regulatory changes. Month fixed effects capture seasonality in both demand and supply in freight and passenger transport. Day-of-week fixed effects are included because inspection schedules generally follow a weekday pattern, consistent with heavier weekday truck traffic. Holidays and special inspection events are excluded from the baseline analysis. In robustness tests, I replace year, month, and day-of-week fixed effects with calendar date fixed effects. Location fixed effects, such as county fixed effects, are omitted from the baseline estimation, as robustness tests show they have minimal impact on the results. Trucks that receive out-of-service violations and are subsequently pulled off the road are also excluded from the regressions. Daily inspection indicators are aggregated into two-day bins, such as (-14, -13), (-12, -11), ..., (-2, -1), (0, 1), (2, 3), ..., (12, 13) relative to the day of inspection at day 0, to enhance estimation power.[23] The effect of inspections in the (-2, -1) bin is normalized to 0. Standard errors are clustered at the truck level.[24]

[21] Since most trucks are involved in only one accident per day, defining the outcome variable as an indicator variable helps in interpretation.

[22] Gray and Shimshack (2011) discuss the endogeneity of selected inspections on trucks with poor safety records. Here I resolve the issue by including individual truck fixed effects. I discuss sample selection issues in detail in Section 3.3.2.

[23] Single-day inspection indicators generate similar estimation results.

[24] I perform a placebo test in Appendix A. The t-statistics (Figure A23) from the placebos follow the t-distribution,

To estimate the average effect of an inspection on accidents within the 14 days following an inspection, I regress the crash rate on a post-inspection indicator while controlling for inspections outside the event window, individual truck fixed effects, and year, month, and day-of-week fixed effects. The estimation equation is:

$$Crash_{it} = \gamma post\text{-}insp_{it} + \beta_{-15} Insp_{it}^{-15} + \beta_{14} Insp_{it}^{14} + u_i + \eta_t + \varepsilon_{it}, \tag{2}$$

where $post\text{-}insp_{it}$ is a post-inspection indicator; it equals zero before an inspection happens on truck i, and it equals one on and after the inspection. The other variables are as defined in equation 1.

Both econometric frameworks in the analysis use time-series variation in accident rates to identify the impact of inspections. The validity of this approach depends on the assumption that accident rates would remain flat without an inspection. This assumption is examined in Section 3.3, where I address potential confounders and selection issues. Little treatment effect heterogeneity is found across trucks inspected at different times, shown in Appendix A (De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2020)).

3.2 Main Results

The event study framework described above allows me to flexibly estimate the effect of an inspection on accidents, beginning with the 14th day prior to the inspection and ending with the 14th day after the inspection. The results are summarized in Figure 1. I find that accidents involving inspected trucks *increase* by 45% immediately following an inspection, and this increase persists for at least two weeks after the inspection. The percentage change in accidents is calculated by dividing the coefficients of $Insp_{it}^{\tau}$ from equation 1 by the mean daily crash rate. I illustrate the level shift in the accident rate in Figure 1 by fitting two horizontal lines using the average percentage changes (relative to the normalized (-2, -1) day) before and after the inspection, respectively. Additionally, the figure shows almost no pre-trend during the 14 days before the inspection, suggesting that the

which suggests that the clustering at the truck level is appropriate.

identification assumption is valid.

To gauge the effect of an inspection on accidents more concisely, I estimate equation 2 using one post-inspection indicator instead of 14 lead and lag indicators. Table 2 column 1 shows the regression result, which corroborates the finding from the event study. It shows that the post-inspection increase equates to 2.85 more accidents per 100,000 trucks compared to the pre-inspection level. The increase in accident rate represents a 45% (2.85 relative to a mean of 6.34 accidents per 100,000 trucks) rise relative to the average accident rate. Appendix Table A1 demonstrates that the results remain robust when using truck fixed effects and calendar date fixed effects, as well as when additional controls for weather conditions and inspection durations are included.

Longer-Term Impact on Accidents The economic significance of inspection impacts is assessed by quantifying the long-term cost of accidents. A monthly event study is conducted to estimate the long-term impact of inspections on truck accidents. This exercise uses a similar framework to the daily event study but shifts the time unit from days to months. The event window extends from 12 months before to 24 months after an inspection (or inspections) in month 0 for each truck. The model controls for individual truck fixed effects as well as year and month fixed effects.[25]

The results of the monthly event study are presented in the top panel of Figure 2. There is no significant pre-trend in the 12 months before inspections. A significant increase in accidents is observed in the first two months following an inspection in event month 0. After month 2, the number of accidents gradually declines. The increase in accidents is detectable up to the 12th month post-inspection. The accident rate then reverts to the pre-inspection level and remains stable until the 24th month. There is no compensating reduction in accidents within the 24 months following inspections.

The total effect of one inspection on accidents is calculated by summing the effects observed in the first 12 months post-inspection. Since the crash rate returns to the pre-inspection level after the 12th month, variations in accidents beyond this period are considered noise and are excluded

[25] To ensure robustness, only inspections that occurred at least 12 months after the truck's first inspection and 24 months before its last inspection are included, thus eliminating the influence of trucks entering or exiting the market on the estimation results.

from the calculation. The total effect is 0.00103 additional accidents per inspection. The number of additional accidents is compared to the counterfactual scenario where the accident rate remains unchanged after inspections, rather than to a scenario without any inspection regulation. On average, 1.75 million inspections are conducted at weigh stations annually. Therefore, a back-of-the-envelope calculation suggests that the total number of crashes caused by behavioral responses to the inspection program is roughly 1,803 (=0.00103 * 1.75 million). According to estimates by the National Safety Council, the average cost per large truck crash is approximately $0.2 million.[26] Hence, the total loss due to drivers' compensatory responses to the current inspection design is roughly $360 million per year.

3.3 Tests For Identification

This section addresses potential confounders to the identification strategy and concerns regarding sample selection. As mentioned previously, the econometric framework relies on the assumption that the trend in the accident rate would remain flat in the absence of an inspection. There are three main concerns regarding the identification strategy: First, omitted variables that may be correlated with both inspections and accidents, such as weather conditions and traffic conditions. Second, sample selection issues, including selection of trucks with low pre-trip crash rate, trucks being idle before or after inspections, trucks switching drivers after inspections, and selection of inspection by observable characteristics of the trucks. Third, the possibility of reverse causality, where inspections might be triggered by accidents. To address these concerns, a thorough discussion and tests on the three issues are provided. Additionally, three potential control groups for the inspected trucks are created to enhance the identification strategy. A placebo test is also implemented in Appendix A to demonstrate that there would not be an increase in accidents without the inspections.

[26] The cost of truck accidents varies significantly by injury severity: fatal injury ($13 million), disabling injury ($1 million), evident injury ($0.2 million), possible injury ($0.1 million), and property damage only ($17,500) (National Safety Council, 2022). Taking into account the proportions of different types of accidents, the average cost of all large truck crashes is about $200,000 per crash.

3.3.1 Potential Confounders: Weather and Traffic

Weather and traffic conditions are potential confounders because adverse weather conditions and high traffic volumes contribute to more accidents. If inspections are scheduled during times when the probability of accidents is high, such as during periods of heavy rain or high traffic, the observed increase in accidents following inspections might be due to these conditions rather than the inspections themselves.

To rule out weather conditions as confounders, evidence is provided showing that inspections are not conducted during worse weather conditions (such as rain or snow). On the contrary, inspections tend to occur on days with better weather conditions. Therefore, even if adverse weather conditions lead to higher probabilities of accidents, the observed *increase* in accidents after an inspection cannot be attributed to adverse weather conditions. Further details are included in Appendix A. In addition, I control for the weather condition during inspections in the baseline regression in Appendix Table A1, the results remain robust.[27]

Higher traffic volume can also be ruled out as a confounding factor. Table A2 in the appendix shows that the effect of inspections on accidents remains consistent even after controlling for traffic conditions in the inspection county at the inspection hour in various ways. Additional details of the test are also provided in Appendix A.

3.3.2 Sample Selection Issues

The selection problem arises due to the *endogeneity of inspections to a truck being on the road*. The discussion of potential issues caused by sample selection is broken down into four parts, each addressing specific concerns and discussing solutions or implications for interpreting the estimated effects.

[27] Direct control for daily weather or traffic conditions in the regressions is not feasible due to the lack of data on the exact location of trucks outside of inspection and accident events. As a result, weather and traffic conditions can only be matched to the observed truck locations during these specific events.

Are trucks on the road only during and after the day of inspection, but not before? A typical truck driver covers approximately 500 miles per day for 300 days a year.[28] Even if they are not on the road every single day, it is unlikely that most drivers are idle for many consecutive days, and such idle periods are unlikely to occur exclusively before inspections.

To address this concern, trucks that receive out-of-service violations (20% of all inspections) are excluded from the baseline estimation. These trucks are removed from service after an inspection until all necessary repairs or corrections are made, and they may face different inspection probabilities once back on the road.[29] Additionally, although some trucks attempt to evade weigh-station inspections, the severe consequences of such actions make this behavior relatively rare within the broader truck population.[30]

What if a truck is involved in an accident and needs to be repaired, causing it to drop out of the sample for some time and therefore less likely to be inspected? Conditioning the pre-treatment period on inspected trucks may result in an artificially low pre-inspection accident rate in the estimation sample. To address this concern, a robustness test is performed that focuses solely on no-injury or nonfatal accidents, thereby excluding trucks that stop operating for a long while after a serious accident.[31] Table A3 in the appendix shows that for this subsample of trucks there is still a 45.6% increase in accident rates after inspection. Therefore, the truck selection issue

[28] Long-haul drivers often travel 500 to 700 miles per day, covering over 100,000 miles annually according to the Federal Highway Administration. In contrast, regional less-than-truckload (LTL) drivers might cover between 150 to 400 miles per day due to frequent stops and urban driving conditions. LTL driver jobs usually offer 1 day per week off, plus extra holidays, reported by industry information blogs.

[29] When including out-of-service trucks in the estimation, the effect size remains similar (43.5%) as shown in Figure A24. Dropping OOS trucks from the sample increases the likelihood that the trucks are continuously on the road, reducing endogeneity concerns related to inspections. Regulations require immediate removal of trucks with out-of-service violations from the road. However, data still shows accidents involving these trucks after inspections, suggesting either non-compliance or lax enforcement of these regulations.

[30] For instance, under California Vehicle Code Section 2813, bypassing a weigh station can result in fines up to $500. In New York, the Department of Transportation deducts 2 points from a driver's Commercial Driver's License. Evading a weigh station also leads to increased scrutiny and more frequent inspections, negatively impacting the carrier's and driver's FMCSA Safety Measurement System (SMS) score. Other penalties include license suspension, higher insurance premiums, and out-of-service orders.

[31] In the data, most crashes, even without injuries or fatalities, likely led to vehicle towing. The purpose of this analysis is to stratify the full sample into subsamples based on crash severity. More severe accidents result in longer repair times, reducing the likelihood that the vehicle will be on the road for inspection. Restricting to less severe accidents yields similar effect sizes, suggesting repair-related selection is limited.

described does not bias the main result. Further robustness checks are provided in Section 3.3.3 to mitigate survivorship bias. Specifically, I compare trucks that received the CVSA decal—indicating a reduced probability of re-inspection—with those that narrowly missed receiving the decal due to minor infractions. A dynamic difference-in-differences framework is employed to difference out the pre-treatment crash rate by comparing two groups of trucks with similar safety attributes. The results confirm that inspections lead to higher accident rates, as trucks narrowly missing the decal have a lower crash rate in the 14 days following inspection compared to those that receive the decal.

Does non-random selection of trucks for inspections affect the identification and/or interpretation of the estimated effect size? Trucks that appear problematic or have worse histories (e.g., inspection records, crash records, company reviews) are more likely to receive inspections. Consequently, the sample may over-represent trucks with a higher probability of crashes.[32]

This does not threaten the identification since all estimations in this paper include truck-level fixed effects using each truck's unique VIN, which accounts for differences in baseline accident rates or other unobservable characteristics. Although a strict comparison group of non-inspected trucks cannot be established due to the data collection process only recording inspected trucks, three potential control groups are generated using subsamples, as described in Section 3.3.3.

The non-random truck selection process does affect the interpretation of the estimated effect size. The correct interpretation of the results is how inspections affect accidents for those trucks that are inspected, rather than for any given truck on the highway. However, since all trucks will receive inspections at some point during their lifetime, discussing the regulatory impacts on inspected trucks is still relevant for all trucks on the road.

What if trucks switch drivers after inspections, making truck-level fixed effects insufficient to control for driver behavior? Since driver identities are not recorded in the data, changes in drivers—especially in cases where long-haul trucks might have two drivers—could pose a prob-

[32]The heterogeneity analysis in Section 4.3 stratifies the sample and examines the effects of inspections across different treated groups.

lem for identification. To address this, a subsample of carrier companies with only one truck and one driver (approximately 50% of carrier companies) is examined, as these carriers cannot switch drivers after inspections. The estimated effect of inspections on accidents for this subsample is 44.5%, as shown in Column 3 of Panel A in Appendix Table A7. This finding confirms that driver switches do not affect the estimations. This comparison also addresses related concerns, including the possibility that some companies might use recently inspected trucks more frequently than other trucks within the company.

3.3.3 Potential Control Groups to Address Selection Bias

The analysis in the paper relies on inspection data for treated trucks, leaving the behavior of uninspected trucks—an ideal control group—unobserved. The flat pre-trend observed in the baseline event study (Figure 1) indicates that the crash rate for inspected trucks would likely remain unchanged in the absence of inspections. To strengthen identification, this section presents three approaches to construct control groups within subsamples of inspected trucks: (1) Comparison of CVSA decal trucks, which have lower re-inspection probabilities, with trucks that narrowly missed receiving a decal; (2) Comparison of trucks inspected today vs. those inspected slightly later (Fadlon and Nielsen (2019)); (3) Counterfactual analysis of uninspected trucks in a short period of time.

CVSA Decal Trucks This analysis compares trucks that received the CVSA decal with those that narrowly missed obtaining the decal due to minor infractions, such as a single inoperative running lamp or a disorganized cabin—issues that could be easily rectified. According to FMCSA guidelines, trucks with a valid decal are expected to have a significantly lower probability of subsequent inspections within three months. The decal applies only to the vehicles, while the drivers remain subject to inspections. In the estimation sample, there are 2,797,744 decals issued to trucks after inspection. Among them, 305,381 (20%) receive re-inspection in the 3-month window after decal. By contrast, the re-inspection probability for trucks that narrowly missed the decal is 33% within

3-month. These trucks face higher likelihood of additional inspections both because they did not receive the decal and because inspectors may conduct follow-ups to verify that violations have been corrected. Decal trucks form the treatment group. Since the trucks issued a decal may be slightly safer than the majority of trucks, I construct a control group by restricting the "non-decal" sample to trucks that narrowly missing receiving a decal. This ensures that both groups have similar safety attributes, except for different re-inspection probabilities.

Using a dynamic difference-in-differences approach, I estimate the impact of inspections by comparing decal and just-missed-decal trucks. It is reasonable to assume that their baseline crash rates prior to the inspection are comparable, as both groups are subject to a similar degree of survivorship bias. This framework effectively differences out the baseline crash rate between the two groups, allowing the difference-in-differences estimates to capture the effect of reduced inspection probability on crash rates. Appendix Figure A8 shows that decal trucks, with lower re-inspection probability, experience a significantly greater increase in crash probability following inspections. Column 1 of Appendix Table A4 confirms that decal trucks are 16.9% more likely to be involved in crashes compared to trucks that narrowly missed the decal.

Comparison of Trucks Inspected Today vs. Those Inspected Slightly Later Following the methodology of recent studies (e.g., Fadlon and Nielsen (2019)), I use a difference-in-differences framework to compare the crash probabilities of trucks inspected within the next 30 days (treatment group) versus those inspected 30-60 days later (control group). Trucks inspected in the next 30-60 days serve as an appropriate counterfactual, as they have not yet undergone inspection in the first 30 days. Since these trucks will also be inspected in the near future, this comparison mitigates potential sample selection bias by ensuring that the estimated treatment effect is not driven by pre-existing differences in crash rates between inspected and uninspected trucks. The framework also removes baseline differences by differencing out pre-inspection crash rates between the treatment and control groups.

Appendix Figure A9 displays the dynamic DID event study plot. The estimated difference in effect size is provided in Table A4 Columns 2 to 4. The results indicate that trucks inspected today experience a 62-88% higher crash probability following inspections compared to those inspected later, depending on the time interval (15/30/45 days) chosen, suggesting that the observed increase in crash probability is attributable to the inspections themselves.[33]

Counterfactual Analysis of Uninspected Trucks During a Short Period of Time I use FMCSA Carrier Census data to create a counterfactual of uninspected trucks in 2017 from the same carriers as those inspected in that year.[34] The treatment group includes 1,140,490 inspections for 802,569 trucks inspected in 2017. This year is selected because the census data reflects active truck carriers as of October 2018, and 2017 data is used due to the incomplete 2018 dataset. The control group consists of 807,112 trucks from the same carriers that were not inspected in 2017.[35]

I analyze crash probability from 14 days before to 14 days after an inspection, comparing treatment and control groups. Panel A of Appendix Figure A10 shows a significant increase in crash probability for the treatment group following inspections, while the control group's crash probability remains stable.[36] Column 5 of Table A4 estimates a 31.1% difference in the percentage change in crash probability between the treatment and control groups.

3.3.4 Eliminate Reverse Causality

Inspections induced by accidents should be excluded from the estimation to address concerns of reverse causality. This issue is pertinent because it is not uncommon for a police officer to request an inspection of a truck involved in an accident. In such cases, the accident itself triggers the inspection, leading to reverse causality. To mitigate this concern, all trucks inspected within 18 hours

[33] I examine the sensitivity of the results to different interval choices (0-15 vs. 15-30 days, 0-30 vs. 30-60 days, 0-45 vs. 45-90 days). The findings, presented in Table A4 Columns 2, 3, and 4, show that the estimated difference in effect size remains robust across these intervals.

[34] For all trucks inspected in 2017, I retain their carrier IDs and cross-reference these identifiers with inspection records from 2016 and 2018. This process identifies vehicles registered under the same carriers in those years but excluded from 2017 inspections. The methodology assumes that trucks inspected in 2016 or 2018 were also operational in 2017, allowing each inspected truck in 2017 to be matched with uninspected counterparts from the same carrier. This approach ensures the control group shares similar characteristics with the treated group.

[35] The control group's crash rate is 10.46 per 100,000 trucks, serving as the counterfactual crash rate for inspected trucks. This crash rate indicates that uninspected trucks were indeed active on the road, suggesting that inspected trucks were also likely active before their inspections.

[36] Panel B of Figure A10 shows the dynamic difference-in-differences results confirming the robustness of the estimation.

after an accident are excluded from all analyses. Appendix Figure A11 illustrates the rationale for this interval and shows that the coefficients on other days in the event study remain consistent when varying the length of the time interval—except for the coefficients on days (-2, -1) and (0, 1). This indicates that removing these trucks does not alter the observed increase in accidents in the days following inspections. Further details are provided in Appendix A.

4 Mechanism

This section investigates the primary mechanism underlying the increase in accidents following inspections. The mechanism is consistent with the model proposed by Becker (1968): since inspectors infrequently conduct repeat inspections of trucks that have recently been checked, drivers of these trucks may drive more recklessly and perform fewer safety checks post-inspection, resulting in an increase in accidents. The section first presents evidence supporting this mechanism, followed by direct evidence derived from two supplementary datasets.

4.1 Drivers' Strategic Response to Low Reinspection Probabilities

The Reinspection Probability The first step is to document that trucks are significantly less likely to be reinspected shortly after an inspection. As shown in Figure 3, the probability of reinspection is only 7.1% within the first week after an inspection. This probability increases to 39.3% within the first quarter (13 weeks) and gradually rises to 73.9% over the course of a year (52 weeks).[37] In other words, while trucks that have not been inspected for over six months face a reinspection probability exceeding 60%, the corresponding probability immediately after an inspection is merely 7.1%. This stark decline underscores the low reinspection risk following a recent inspection.

[37]The reinspection probability represents the likelihood of receiving another inspection within N weeks following the most recent inspection. This is calculated by compiling the inspection history for each truck, determining the interval between the current and next inspection. The percentage of reinspections conducted within 1 to 52 weeks is then calculated for each truck and averaged across all trucks. This approach effectively measures the proportion of trucks reinspected within each timeframe. The data do not distinguish between trucks that are retired and those not reinspected for other reasons, so the last inspections are excluded from the sample.

Several institutional features contribute to this pattern. Enforcement through inspections is costly for both regulatory agencies and the trucking industry. To conserve resources and increase coverage, inspectors generally avoid reinspecting trucks that have been recently checked. This approach is embedded in the truck inspection selection process. As discussed in Section 2, when a truck arrives at a weigh station for inspection, inspectors review its inspection and accident history to prioritize trucks with poor records or those that have not been inspected for a while. Trucks with valid CVSA decals are exempt from reinspection for the three-month period during which the decal is valid. Additionally, systems like PrePass enable trucks with strong safety records and up-to-date credentials to bypass weigh stations, further reducing their likelihood of reinspection. These selection algorithms collectively contribute to the low probability of reinspection for trucks with recent inspections and relatively good records.

Drivers' Behavioral Responses The low probability of reinspection may contribute to an increase in accidents following a recent inspection. If drivers anticipate a low likelihood of follow-up inspections after passing one, the implicit cost of subsequent violations decreases. This perceived reduction in cost incentivizes drivers to exercise less caution, thereby elevating the probability of crashes. Long-term data supports this pattern. The lower panel of Figure 2 shows a similar trend in reinspection probability over a two-year period post-inspection. The alignment between the upper and lower panels of Figure 2 further indicates that as the probability of reinspection increases over time, the likelihood of crashes correspondingly decreases.

Next, evidence supporting this mechanism is presented. Using variation in reinspection probabilities across state and time, I show that higher reinspection probability leads to lower crash rates. Figure 3 shows that the average probability of reinspection is approximately 39.3% at 13 weeks (a quarter), representing the average rate across all states. To account for state-specific variations, this probability is computed separately for each state and year. A higher reinspection probability indicates either more frequent reinspection or a focus on trucks recently inspected. To assess how the impact of inspections on accidents varies with reinspection probability, the following model is estimated:

$$
\begin{aligned}
Crash_{it} = & \beta\, post\_insp_{it} + \gamma post\_insp_{it} \times \Pr(reinsp.)_{s,yr} + \theta \Pr(reinsp.)_{s,yr} \\
& + \beta_{-15} Insp_{it}^{-15} + \beta_{14} Insp_{it}^{14} + u_i + \eta_t + \varepsilon_{it}
\end{aligned} \tag{3}
$$

where $\Pr(reinsp.)_{s,yr}$ denotes the average reinspection probability in a quarter for state s in year yr. Equation 3 is a variation of equation 2 that includes an interaction term $post\_insp_{it} \times \Pr(reinsp.)_{s,yr}$ and the main effect of $\Pr(reinsp.)_{s,yr}$. The coefficient of interest, γ, estimates the effect of inspection on accidents across different reinspection probabilities. Results presented in Appendix Table A5 indicate that a 1% increase in reinspection probability leads to a 1.09% reduction in the crash probability following inspections. These results remain robust to the inclusion of additional controls, such as state fixed effects.

Third, the analysis reveals that changes in driver behavior are a key contributor to the increase in accidents. Specifically, the incidence of single-vehicle accidents among recently inspected trucks rises more sharply than that of multi-vehicle accidents. Single-vehicle accidents, which constitute 35% of all accidents, include non-collision incidents, collisions with parked vehicles, fixed objects, and other accidents involving only the truck. In contrast, multi-vehicle accidents, accounting for 64% of all cases, involve collisions with other motor vehicles in transport. Figure 4 illustrates that, following an inspection, single-vehicle accidents increase by 74.9%, while multi-vehicle accidents rise by 28.6%.[38] These effects are immediate, manifesting on the day of inspection and persisting for at least two weeks thereafter, with no observable pre-trend in either case. Regression results presented in Table 2 (columns 2 and 3) further confirm these findings. Figure A12 in the appendix provides a detailed breakdown of single-vehicle accidents[39], showing that most categories exhibit a greater percentage increase compared to multi-vehicle accidents.

[38] To compare the treatment effect sizes, I divided the post-inspection coefficients by the average crash rate for each of the two types of accidents. The average crash rate of single-vehicle accidents is lower than that of multi-vehicle accidents.

[39] Appendix Figure A12 breaks down the single-vehicle accident categories into non-collision ran-off road, non-collision overturn (rollover), non-collision cargo loss or shift, non-collision equipment failure (brake failure, blown tires, etc.), and collision involving fixed objects.

Additionally, the analysis compares the factors contributing to single-vehicle versus multi-vehicle accidents. Factors leading to single-vehicle accidents are primarily associated with the truck driver's behavior, cargo securement, or truck equipment failures, which may result from inadequate maintenance efforts by drivers. These factors can be influenced by the likelihood of inspection. In contrast, factors contributing to multi-vehicle accidents involve not only the truck but also other vehicles involved in the collision. Therefore, a larger percentage increase in single-vehicle accidents following an inspection suggests that the rise is predominantly due to changes in the truck driver's behavior post-inspection. Moreover, the increase in single-vehicle accidents is more pronounced under adverse external conditions (e.g., road, light, and weather).[40] This suggests that the observed increase is attributable to reduced driver attentiveness to driving conditions.

To summarize, three key pieces of evidence support the behavioral mechanism: (i) trucks are significantly less likely to be reinspected for at least a quarter after an inspection; (ii) lower reinspection probabilities are associated with greater increases in crash risk; and (iii) The rise in accidents is concentrated among single-vehicle crashes—a good proxy for driver behavior—relative to multi-vehicle crashes, suggesting a behavioral rather than mechanical or random cause. All evidence indicates that, knowing that the truck will not be reinspected in the near term, drivers may conduct fewer pre-trip checks and drive more recklessly for longer hours. This behavior leads to more accidents and offsets the potential benefits of the safety program. Alternative mechanisms are discussed in Appendix B, including the possibility that drivers may feel safer after passing inspections, leading them to reduce caution, and the incentives for speeding to make up for time lost due to inspections. While these factors may also contribute to the observed treatment effect, they are not identified as the primary factors.

[40]Table A17 compares the impact of inspections on crashes under normal versus adverse conditions. Crashes under normal conditions (dry roads, normal weather, daylight) account for 39.7% of single-vehicle crashes, while crashes under adverse conditions (any deviation from normal) account for 55.7%. Following inspections, crashes under normal conditions increase by 60.9%, while those under adverse conditions increase by 83.7%.

4.2 Direct Evidence Linking Driver Behavior to Increased Accident Rates

Using two supplementary crash datasets, I provide direct evidence that compensatory behaviors by drivers contribute to the post-inspection increase in accidents. Section 4.2.1 discusses the FARS (Fatality Analysis Reporting System) data maintained by the NHTSA, while Section 4.2.2 examines crash data provided by the Texas Department of Transportation (TxDOT). Both datasets offer the advantage of identifying the specific factors contributing to crashes, thereby allowing for a detailed analysis of the causes behind the rise in accidents post-inspection. I find that drivers exhibit more reckless behaviors (such as speeding and driving while intoxicated) and engage in fewer vehicle maintenance checks. These findings support the behavioral mechanisms proposed in the previous section. In addition, the analysis of these independently maintained datasets reveals an increase in the number of crashes following inspections, reinforcing the main findings of this study. The use of FARS data, which focuses on fatal crashes, underscores the importance of these findings.

4.2.1 Evidence from FARS

The Fatality Analysis Reporting System (FARS) data provides detailed information on the factors contributing to fatal accidents, which are not included in the FMCSA crash files. The analysis uses FARS data from 2000 to 2017 to examine the causes of fatal truck crashes following inspections.

First, the top panel of Figure 5 shows that there is a large increase in the raw number of fatal accidents involving trucks following inspections. On average, there are 15 fatal accidents per two-day bin before inspections, which rises to 52 following inspections. The bottom panel of Figure 5 illustrates the event study results estimated using equation 1 with fatal accidents as the outcome variable. Appendix Table A6 Panel A Column 1 presents the estimated increase in the probability of fatal crashes (0.107(s.e.=0.011)), following equation 2.

Second, statistical analysis reveals an increase in fatal accidents attributed to driver- or vehicle-related factors following inspections. The proportion of such accidents rises from an average of 8.6% in the 14 days prior to inspections to 19.3% in the 14 days after. Contributing factors include driver-related issues such as speeding, reckless lane changes, or driving while intoxicated, as well as vehicle-related issues such as loose cargo or malfunctioning brakes and lights. Additionally, there are cases where truck drivers are not at fault, and the other vehicle involved in the accident is responsible. The top panel of Figure 6 shows an increase in accidents due to speeding, driving while intoxicated, and lack of vehicle maintenance. The bottom panel displays the event study results estimated using equation 1 with fatal accidents caused by driver- or vehicle-related factors. Appendix Table A6 Panel A Column 2 presents the estimated increase in fatal crashes caused by driver- or vehicle-related factors (0.036(s.e.=0.005)), following equation 2.

4.2.2 Evidence from Texas Crash Data

In this section, additional supporting evidence is provided using data from the Texas Department of Transportation (Texas DOT) that encompasses all types of accidents. The Texas DOT maintains crash files under the Crash Records Information System (CRIS), which are collected from Texas Peace Officer's crash reports from 2010 to 2018. The advantages of utilizing these files for supplementary analysis are three-fold: first, the CRIS dataset encompasses crashes of varying severity, ranging from property damage only to those involving injuries and fatalities; second, it provides detailed descriptions of the factors contributing to each accident; third, the crash records contain the full Vehicle Identification Number (VIN).

Figure A14 in the appendix illustrates a 39.7% increase in truck crashes following inspections, a result comparable to the effect size estimated using FMCSA data for the entire United States.[41] The effect size is slightly attenuated because the analysis is limited to crashes in Texas involving trucks inspected in Texas, thereby excluding crashes that occurred outside of Texas for trucks inspected in Texas.

The top panel of Figure 7 demonstrates an increase in crashes attributable to driver-related factors, including all moving and parked violations assigned to the truck driver. Among these

[41] The same framework outlined in equation 1 is applied to analyze all inspections and "federal recordable" crashes occurring in Texas. The estimated coefficient on post-inspection is 0.702(s.e.=0.149). The analysis uses 1,204,497 inspections. A "federal recordable" crash, as defined by FMCSA documentation, involves at least one death, one person sustaining bodily injury requiring immediate medical treatment away from the scene, or a vehicle being towed away.

crashes, those involving speeding violations show a significant rise in frequency. The bottom panel displays the event study plot estimated using equation 1, with the outcome variable replaced by all types of driver-related accidents. Appendix Table A6 Panel B presents the estimated increase in driver-related accidents (0.521(s.e.=0.110)), following equation 2. Appendix Figure A15 serves as a falsification test, showing no corresponding increase in crashes unrelated to driver behavior.[42]

Why would inspections change future risky driving behaviors? Inspections can have a deterrent effect on drivers' speeding and drowsy driving behaviors, as inspections typically involve checking drivers' logbooks or electronic logging devices (ELDs) to verify driving time and distance, ensuring compliance with the hour-of-service rule Scott, Balthrop, and Miller (2021). Consequently, when the risk of inspection decreases following an inspection, the likelihood of receiving an hour-of-service violation also diminishes. Additionally, the implicit cost of a traffic violation is reduced because drivers, knowing they have recently been inspected at a weigh station, anticipate a lower likelihood of undergoing an impromptu roadside inspection if stopped by police for speeding or drinking.[43] Moreover, the data indicates an increase in accidents resulting from insufficient vehicle maintenance, such as loose cargo or trailers, which could be attributed to a reduction in the duration and frequency of pre-trip checks. With a lower probability of reinspection, drivers are less likely to adhere to vehicle safety regulations.

4.3 Heterogeneity in Inspection Effects

Effect by Firm Characteristics I perform a heterogeneity analysis focusing on firm size, interstate versus intrastate commerce, vehicle types, and cargo transported. The carrier/shipper census file provides information on cargo type, number of vehicles, and number of drivers for 1.6 million active firms as of October 2018.

Firm size varies considerably in the trucking industry. Panel A of Appendix Table A7 shows

[42] The test for differences in accident rates before and after is 1.63e-06, with a p-value of 0.063.

[43] The percentage of traffic enforcement during any type of inspection is 15.3%, according to the author's calculations from the data.

that large firms—those with more than 48 power units or 47 drivers—experience a slightly higher increase in accidents after inspections compared to smaller firms. Nevertheless, small firms also exhibit a large treatment effect. Panel B confirms similar results when firm size is defined by the number of drivers.[44] These findings indicate that drivers from both large and small firms reduce compliance when reinspection probability is low, though their incentives differ. Drivers from small firms, especially 1-truck/1-driver operators, are motivated to drive longer hours due to their earnings structure (Scott and Nyaga (2019)). In contrast, large firms like FedEx face principal-agent problems, leading to different driving behaviors (Baker and Hubbard (2004)). Thus, the different profit structures and liabilities influence risk preferences.

I further analyze how carriers' responses to inspections vary by their primary operational scope—whether they predominantly operate on interstate or intrastate routes. Panel C in Table A7 shows that the effect for interstate-only firms is larger than for intrastate-only firms. This likely reflects intrastate drivers' familiarity with local routes. Nonetheless, the significant effects for both types of firms suggest that the post-inspection increase in accidents is not primarily driven by the incentive to compensate for lost time.

Passenger carriers are sometimes subject to different inspection routines depending on state regulations.[45] In addition, the hours-of-service regulation for bus drivers is stricter than that for truck drivers. However, Panel D in Table A7 shows that the treatment effects for trucks and buses are similar. Appendix Table A8 further shows that the treatment effect does not vary substantially across carriers with different types of cargo.[46]

In summary, the impact of inspections on accidents shows minimal heterogeneity across firms. Despite different constraints and incentives, the low probability of reinspection results in less cautious driving and a corresponding increase in accidents across all driver types.

[44] Large firms are defined as having more than the median number of power units or drivers among inspected firms, resulting in two equally sized sub-samples.

[45] Whether passenger carriers must stop at weigh stations depends on the regulations of each state. For inspected buses, there is a 43% increase in crash probability after inspections.

[46] I summarize the 30 types of cargo into general freight, chemicals, food and beverage, paper products, building materials, metal sheet, heavy duty commodities, and passengers. Such categorization makes sure that there are enough observations within each category.

Effect by Inspection Outcomes To examine how inspection outcomes affect accident rates, I compare the increase in accidents following inspections across different types of violations. Appendix Table A9, Columns 1 and 2, shows results for subsamples of trucks with no violations (38% in the sample) and those with non-out-of-service violations (41%).[47] Both groups exhibit post-inspection increases in accidents similar to the average effect size for the full sample. Columns 3 and 4 indicate that trucks receiving driver violations experience a slightly larger post-inspection increase in accident rates relative to those with vehicle violations. The little heterogeneity in inspection outcomes may be attributed to the fact that minor violations do not significantly raise the probability of future inspections. The Safety Measurement System (SMS) score algorithm targets the worst-performing 20-30% of trucks—typically those with out-of-service violations—for additional inspections. As a result, trucks with less severe violations are unlikely to face increased inspection probabilities, reducing the deterrent effect.

Effect of Inspection Blitzes The International Roadcheck inspection blitzes, held annually in early June, are well-publicized and pre-announced, creating a three-day period of heightened inspection probability. Anticipating these blitzes, truckers are motivated to fix vehicles and maintain good crash records to avoid violations (Balthrop, Scott, and Miller (2023)). I analyze the weeks leading up to the blitz to assess if this heightened inspection likelihood reduces crash probability.

I compare four periods: four to two weeks before the blitz, the two weeks immediately preceding it, the three days of the blitz, and the two weeks following it. Appendix Figure A16 shows varying impacts on crash probability across these periods. The deterrent effect is significant in the two weeks before the blitz but does not extend further back or persist afterward. Table A10 reveals that the post-inspections increase in crash probability in the two weeks before the blitz is 43% lower compared to other periods.

[47] Trucks with out-of-service violations (20%) are excluded because they must be immediately repaired or parked, preventing any post-inspection accidents.

Heterogeneity in Level of Inspections I examine three primary inspection levels specified by the FMCSA. Level I inspections—being more stringent—check both the vehicle and the driver and typically take longer than Level II and III inspections, which focus on either the driver or the vehicle.[48] Appendix Figure A17 shows that Level I inspections are associated with smaller effect sizes compared to Levels II and III, suggesting that higher inspection intensity may deter reckless driving to some extent.[49]

Change in Effect Size across Years Figure A18 in the appendix shows the impact of inspections on crash probability by year from 1996 to 2018. Effect sizes are represented by dots, with 95% confidence intervals depicted as shaded areas. The horizontal dashed lines represent five-year average effect sizes. The effect size remains stable in the first decade, increases in 2006-2010, and declines over the subsequent eight years. This decline likely reflects improved safety enforcement technologies, such as Prepass and other Bypass systems prevalent after 2010, and the 2017 Electronic Logging Device (ELD) mandate (Scott, Balthrop, and Miller (2021)), likely enhanced regulatory agencies' ability to detect and deter dangerous behaviors, reducing the unintended effects of inspections.

Accident Severity by Vehicle Weight The literature documents that accident severity increases with the weight differences between vehicles involved (e.g., Anderson and Auffhammer (2014)). Table A12 presents the impact of inspections on fatalities (Column 1), injuries (Column 2), and the number of vehicles involved in accidents (Column 3). The results indicate that severe accidents increase following inspections.

[48] In the sample, 41% of inspections are Level I, 25% are Level II, and 32% are Level III. The dataset also includes Level IV (special study) and Level V (terminal inspections), but these constitute only 2% of the full sample, therefore are excluded from the heterogeneity analysis.

[49] Appendix Table A11 Column (1) presents the regression result associated with Appendix Figure A17. Column (2) extends this analysis by incorporating inspection duration. The results indicate that, for a given duration, Level I inspections still have a smaller treatment effect than Levels II or III. The jointly analysis suggests that higher inspection intensity mitigates the post-inspection increase in crash rates, whereas longer inspections slightly amplify this effect. The reduced likelihood of a near-term re-inspection after any inspection—regardless of whether it was brief or lengthy—increases accident risk, but more thorough inspections help improve truck safety.

I further examine the heterogeneous effect of vehicle weight[50] on crash probability and severity.[51] Columns 1 and 2 of Table A13 show that both crash probability and severity increase with vehicle weight, though the effect on severity is imprecise under a linear weight specification. Column 3, which uses four categorical weight groups,[52] finds that heavier vehicles (>80,000 lbs.) are associated with increased crash severity, while lighter ones are not. Table A14 further shows that trucks with weight violations experience larger increases in both crash probability and severity following inspections.

Effects by Rest Area Distribution I find that the availability of highway rest areas can mitigate the increase in accidents following inspections. Safety rest areas, equipped with parking, restrooms, and other facilities, provide truck drivers with opportunities to rest and inspect their vehicles.[53] Column 1 of Appendix Table A15 indicates that each additional rest area in an inspection county is associated with a 7.9% reduction in accident increases post-inspection. Column 3, which includes county-by-year fixed effects, confirms that this effect is not attributable to other unobserved county differences. These findings suggest that, although drivers may engage in compensatory behaviors after inspections, the presence of rest areas provides opportunities to mitigate accident risks.

5 Policy Implications

This section explores two alternative policy options to improve the current inspection program. Although the program is nationwide, each state Department of Transportation (DOT) differs in enforcement strategies—including inspection intensity, truck selection, schedules, and locations—resulting in substantial variation in the treatment effects across regions.

[50] The inspection data records the Gross Combined Vehicle Weight, which includes the total weight of the combination vehicle, any trailers, and cargo at the time of inspection. Weight is recorded for 55% of inspections.

[51] Crash severity is categorized as 0 (no crash), 1 (non-fatal, non-injury crash), 2 (injury crash), and 3 (fatal crash).

[52] Vehicle weight is categorized into four equal quantile groups: (1) <53,000 lbs., (2) 53,000–80,000 lbs., (3) 80,000–117,000 lbs., and (4) >117,000 lbs. This classification accounts for potential nonlinear relationships.

[53] Most rest areas serve different functions from weigh stations, and the two are often not at the same location. I collect location information on all the safety rest areas from Texas Department of Transportation. Appendix Figure A19 shows that many counties have weigh stations but lack rest areas, with an average of two rest areas per county where there is at least one rest area, and about half counties have them.

5.1 Predictability of Inspection Schedules

The first policy alternative examines how the predictability of inspection schedules influences driver behavior. Under highly predictable inspection schedules, drivers can easily anticipate when inspection sites will be open as they travel through a given state. I find that states with unpredictable inspection schedules achieve crash reductions post-inspection, while those with predictable schedules see an increase in accidents.

To measure inspection schedule predictability, I analyze variations in day-of-week inspection schedules across states. Figure 8 illustrates two arbitrary states: State A with a fixed schedule and State B with a random schedule.[54] In State A, inspections occur predictably, making it easier for frequent travelers to anticipate inspections. Conversely, State B's random schedule makes it difficult to predict inspections. Consequently, drivers are likely more cautious in State B due to uncertainty, while in State A, predictable schedules may lead to compensatory behaviors.

I develop a predictability index to measure annual variations in day-of-week inspection schedules for each state, as detailed in Appendix C. Figure 9 shows the yearly average predictability index across states. This index captures the variation left in the schedule after accounting for fixed patterns at the county-by-day-of-week-by-year level, ensuring it is not influenced by inspection frequencies or traffic conditions. Lower indices indicate easier inspection forecast.[55]

I estimate the impact of inspection on accidents depending on differences in inspection schedule predictability by interacting the post-inspection dummy with the predictablity index $std\_pred_{s,yr}$ for state s in year yr.[56] The regression follows equation 3 by replacing $\Pr(reinsp.)$ with $std\_pred_{s,yr}$. The result is shown in Panel A of Table 3. Under highly predictable schedules (low predictability indices), accident rates increase by 52% following inspections; under highly unpredictable sched-

[54] In Figure 8, I compare the number of inspections done in each day of the two weeks in State A and B. The average number of inspections per day is the same (mean = 58) for both states. State A has a fixed day-of-week inspection schedule, meaning that State A is conducting 10 inspections every Sunday, 60 every Monday, 80 every Tuesday, etc.; while State B has a random day-of-week inspection schedule so that the number of inspections done on Sunday this week is different from the next Sunday, this Monday is different from the next Monday, etc.

[55] In the example from Figure 8, State A has a predictability index of 0, while State B has an index of 32.

[56] $std\_pred_{s,yr}$ is the standardized predictability index with mean 0, standard deviation 1.

ules (high predictability indices), accident rates decrease by 6%.[57] A one standard deviation increase in the predictability index (decrease in schedule predictability) reduces the effect size by 9% (=0.59/6.36). Therefore, states with less predictable inspection schedules experienced fewer post-inspection crashes.

5.2 Randomness in Inspection Selection

This section explores a policy variation concerning how inspectors use prior inspection timing to determine which trucks to reinspect. Specifically, the focus is on whether recently inspected trucks are subject to reinspection as frequently as those that have not been inspected, or if selection is more random. This analysis simulates scenarios where resources for selective inspections are limited, evaluating which selection mechanisms are more effective given drivers' compensatory behaviors. A comparison of states with shorter versus longer reinspection intervals reveals that states with shorter intervals experience a smaller increase in accidents following inspections.

I illustrate the policy exercise in Figure 10. In State A, inspectors predominantly select trucks that have not been inspected for a long time, whereas State B employs a more random selection process. State B's shorter reinspection interval reflects a greater degree of randomness in inspection selection.[58] The average reinspection time interval, $Dtime_{s,yr}$, represents the average number of days since the last inspection for trucks in state s in year yr. Figure 11 shows significant variation in this interval, with California averaging 4 months and Michigan over 1 year. Trucks in California face a higher chance of reinspection, even if recently checked, while trucks in Michigan do not. the post-inspection increase in accidents driven by compensatory behaviors is less severe in California than in Michigan.[59]

[57]The change in accident rates are calculated using the lowest and highest 1% in the distribution of $std\_pred_{s,yr}$, which are -0.84 and 5.53, respectively.

[58]In Figure 10, the horizontal axis represents the number of days since the last inspection. Gray bars show all trucks entering weigh stations on a given day, categorized by their time since the previous inspection. Red lines indicate trucks selected for inspection. State A, with a design that resembles many current state practices, selects trucks that have not been inspected for a long time. In contrast, State B employs a random selection method. Both states inspect the same total number of trucks. State A has a longer average reinspection interval compared to State B, indicating that shorter reinspection intervals are associated with more randomness in inspection selection.

[59]In the bottom panel of Appendix Table A19, I control for the total number of inspections a state conducts annually

I estimate the effect of inspection on accidents by different reinspection time intervals using the same framework as in equation 3. Panel B of Table 3 shows that shorter reinspection intervals (under 1 month) are associated with a 25% increase in accident rates post-inspection, while longer intervals (over 1 year) correspond to a 64% increase. A one standard deviation increase in the reinspection interval (5 months) raises the effect size by 9% (0.69/6.36). As a result, states with shorter reinspection intervals face a smaller increase in accident rates following inspections.

6 Conclusion

This paper offers one of the first evaluations of the U.S. commercial vehicle roadside safety inspection program over more than two decades. The primary contribution is demonstrating that regulatory efforts to enhance public safety can be undermined when individuals respond strategically to temporary reductions in detection probability. Using comprehensive data that links each truck's inspection and accident history via its vehicle identification number, the analysis reveals a 44.6% *increase* in accident rates immediately after an inspection, with effects lasting at least 14 days. This elevated risk persists for up to 12 months, resulting in an estimated annual loss of approximately $360 million[60] due to the flaws in the current inspection program design.

The observed increase in accident rates could be attributable to truck drivers' strategic responses to the low probability of reinspection following a recent inspection. Assuming a low likelihood of reinspection, drivers may skip pre-trip safety checks and engage in reckless driving, leading to more accidents from speeding, driving while intoxicated, and equipment failures. These compensatory behaviors undermine the intended benefits of the safety program. Two policy alternatives may help mitigate post-inspection accident rates. First, states could implement less predictable inspection schedules to prevent drivers from anticipating inspections. Second, inspections could be conducted

in the regression. The results show that states with shorter reinspection intervals experience greater reductions in accidents, even when controlling for the total number of inspections. Despite California conducting more inspections than Michigan, this does not confound the effect of reinspection interval length on accident rates.

[60] The details of the calculation are provided in Section 3.2. In summary, drivers' adverse behavioral responses result in an estimated annual increase of approximately 1,803 truck accidents, with each accident costing around $200,000.

without considering recent inspection history, ensuring that recently inspected trucks still face a risk of reinspection.

In response to drivers' strategic behaviors, this paper advocates integrating advanced technologies and enhanced monitoring practices by private companies into the design of safety regulations. Utilizing on-board monitoring systems (Baker and Hubbard, 2004) and newly enforced electronic logging devices could enforce safer driving behaviors before and after inspections. Additionally, a field experiment, inspired by Gosnell, List, and Metcalfe (2020), could assess the effectiveness of various management practices on truck driver performance.

This paper provides compelling evidence that drivers strategically respond to fluctuations in detection probability resulting from regulatory design. Although focused on transportation safety, the findings underscore the broader importance of understanding compliance behavior in designing enforcement mechanisms. The insights from this study extend to other regulatory contexts, such as audit strategies, workplace safety regulations, and criminal deterrence, where agents may alter their behavior between enforcement actions. Effective regulatory regimes should aim to sustain consistently high detection probabilities to minimize violations.

Data Availability

Code replicating the tables and figures in this article can be found in Liang (2025) in the Harvard Dataverse, https://doi.org/10.7910/DVN/EYXQC3. The replication package contains a copy of the programs used to create the final results and a read-me file with further information.

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7 Tables and Figures

Table 1: Summary Statistics

	(1) Observations	(2) Mean	(3) SD	(4) Min.	(5) Med.	(6) Max.
Panel A: Inspection File, 1996 to 2018						
Total inspections	69,549,512	-	-	-	-	-
Weigh stations inspections	30,101,086	-	-	-	-	-
Trucks ever inspected	23,078,901	-	-	-	-	-
OOS violations	6,158,151	1.49	1.02	1	1	56
Driver violations (not OOS)	4,953,818	1.43	0.94	1	1	80
Vehicle violations (not OOS)	9,322,306	2.34	2.05	1	2	85
Truck volume	3,466,803	855.90	1041.49	1	492	9,192
Panel B: Truck-by-Day Event Study Panel: (-14,13) days of inspections						
Crashes	635,481,707	6.34E-05	0.008	0	0	1
Injuries	635,481,707	3.64E-05	0.010	0	0	48
Fatalities	635,481,707	2.43E-06	0.002	0	0	10
Panel C: Monthly Event Study Panel: (-12,24) months of inspections						
Crashes	191,256,774	0.0014	0.037	0	0	1
Injuries	191,256,774	0.0007	0.042	0	0	49
Fatalities	191,256,774	0.00004	0.007	0	0	11
Panel D: Carrier Companies						
No. of trucks	1,669,661	20.91	3420.75	0	1	2,699,990
No. of drivers	1,669,661	5.15	225.72	0	1	110,690

Note: In Panel A, *Total inspections* is the total number of inspections conducted in the whole sample from 1996 to 2018; *Weigh station inspections* are those conducted at the weigh stations, as opposed to at roadside. *Trucks ever inspected* is the number of trucks that ever receive an inspection. *OOS violations* is the number of out-of-service (OOS) violations found in inspections. There could be multiple OOS violations in a single inspection. *Driver violations (not OOS)* is the number of driver violations (but not OOS violations) found in inspections, similarly with *Vehicle violations (not OOS)*. *Truck volume* is the total number of trucks that pass through the inspection county at the inspection hour from both directions.
In Panel B, the number of observations comes from the truck-by-day event study panel from (-14,13) days of inspections, excluding out-of-service inspections. *crashes* is the number of accidents resulting in at least some property damages for a given truck in a day within the event window. *injuries* and *fatalities* represent the number of people injured or killed in the crashes.
In Panel C, *crashes* is the number of crashes for a given truck in a month within the event window.
In Panel D, the carrier company census file shows a snapshot of all active carrier (and shipper) companies as of October 2018. There are 1,669,661 active companies registered at that time. *No. of trucks* is the number of trucks owned by each carrier company recorded in the company census file, similarly with *No. of drivers*.

Table 2: The Impact of An Inspection on Truck Crashes

	(1) Baseline (all crashes)	(2) Single-vehicle crashes	(3) Multi-vehicle crashes
post_insp	2.85***	1.64***	1.17***
	(0.06)	(0.04)	(0.05)
Average crash rate	6.34	2.17	4.07
Effect size	44.95%	75.58%	28.75%
Observations	635,481,707	635,481,707	635,481,707

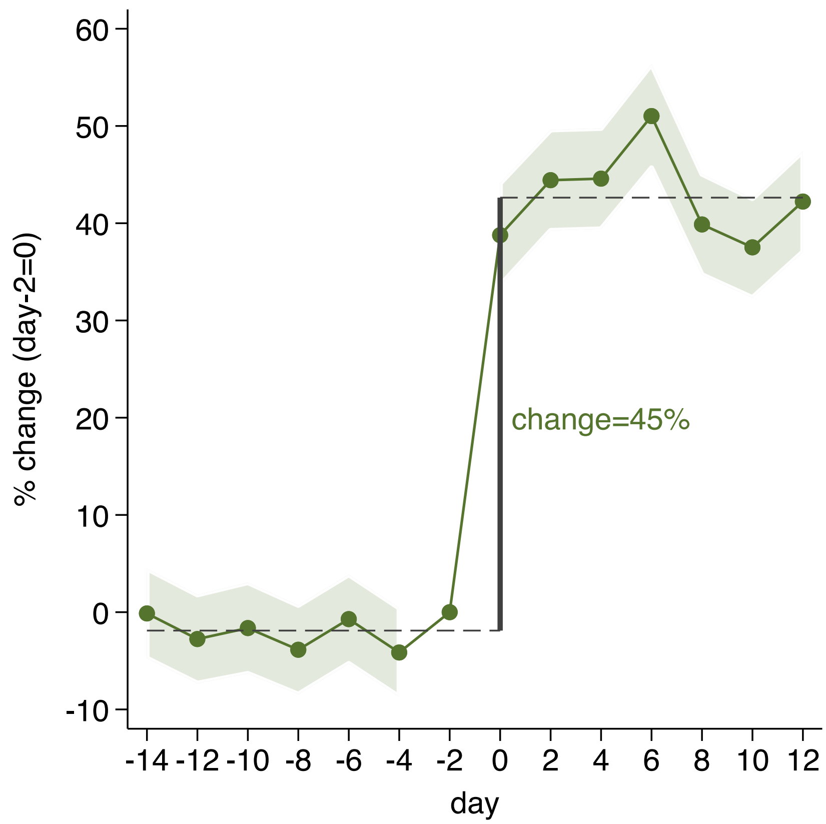
Note: All three columns use the same estimation framework following equation 2, which looks at the impact of an inspection on crashes by comparing 14 days before to 14 days after inspection. *post_insp* is a post-inspection indicator, it equals to 0 before an inspection happen on truck i, and it equals to 1 on and after the inspection. All regressions include dummies for inspection happened outside of the time window of interest, as well as individual truck, year, month, and day-of-week fixed effects. Standard errors are clustered at the truck level. Column 1 looks at the impact of an inspection on all kinds of crashes. Column 2 looks at single-vehicle crashes only. Column 3 looks at multi-vehicle crashes only. All coefficients in the table are presented as level estimates multiplied by 100,000 to enhance readability. The average crash rates are calculated using the number of any kinds of crashes, or only single-, or multi-vehicle crashes per 100,000 trucks. The effect size is calculated by dividing the coefficient of post_insp by the mean daily crash rate of each outcome variable. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Impact of An Inspection on Crashes Under Two Alternative Regulatory Designs

Panel A: Predictability in Schedule	
post_insp	2.83***
	(0.06)
std. $pred_{s,yr}$	-0.07
	(0.07)
post_insp $\times$ std. $pred_{s,yr}$	-0.59***
	(0.05)
Average crash rate	6.36
Panel B: Randomness in Selection	
post_insp	2.83***
	(0.06)
std. $Dtime_{s,yr}$	-0.07**
	(0.09)
post_insp $\times$ std. $Dtime_{s,yr}$	0.69***
	(0.06)
Average crash rate	6.36

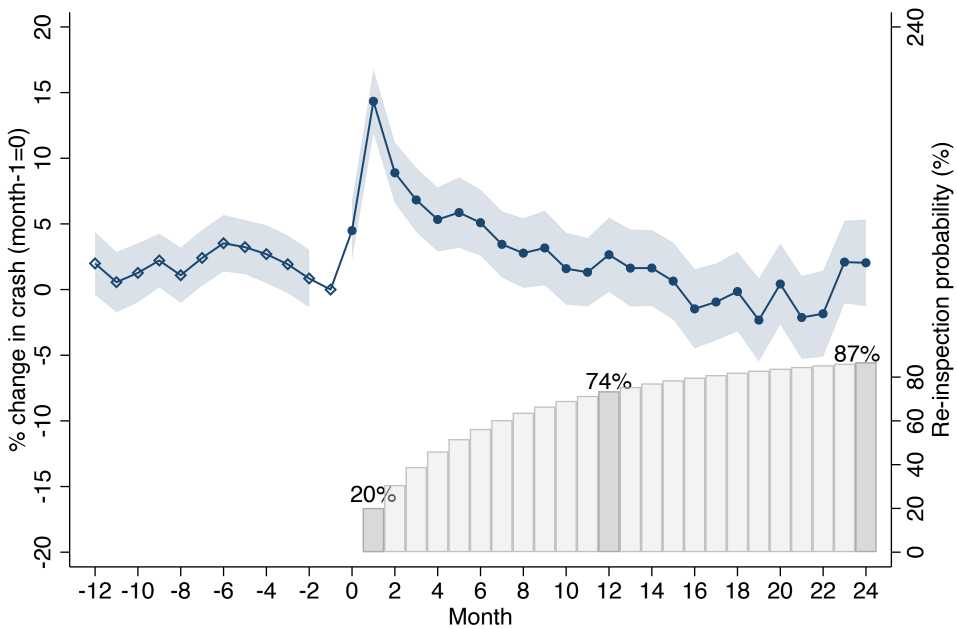
Note: This table shows the treatment effect under two policy options. The regressions add the interaction between post_insp and one of the two indices capturing policy variations in Section 5 on equation 2. $post\_insp$ is a post-inspection indicator, it equals to 0 before an inspection happen on truck i, and it equals to 1 on and after the inspection. $std\_pred_{s,yr}$ is the predictability index of inspection schedule for state s in year yr, standardized to mean 0 and standard deviation 1. $std\_Dtime_{s,yr}$ is the average reinspection time interval calculated for state s in year yr, standardized to mean 0 and standard deviation 1. All regressions include dummies for inspection happened outside of the time window of interest, as well as individual truck, year, month, and day-of-week fixed effects. Standard errors are clustered at the truck level. All coefficients in the table are presented as level estimates multiplied by 100,000 to enhance readability. The average crash rates are calculated using the number of crashes per 100,000 trucks per day. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Event Study: The Impact of Inspection on Truck Accidents



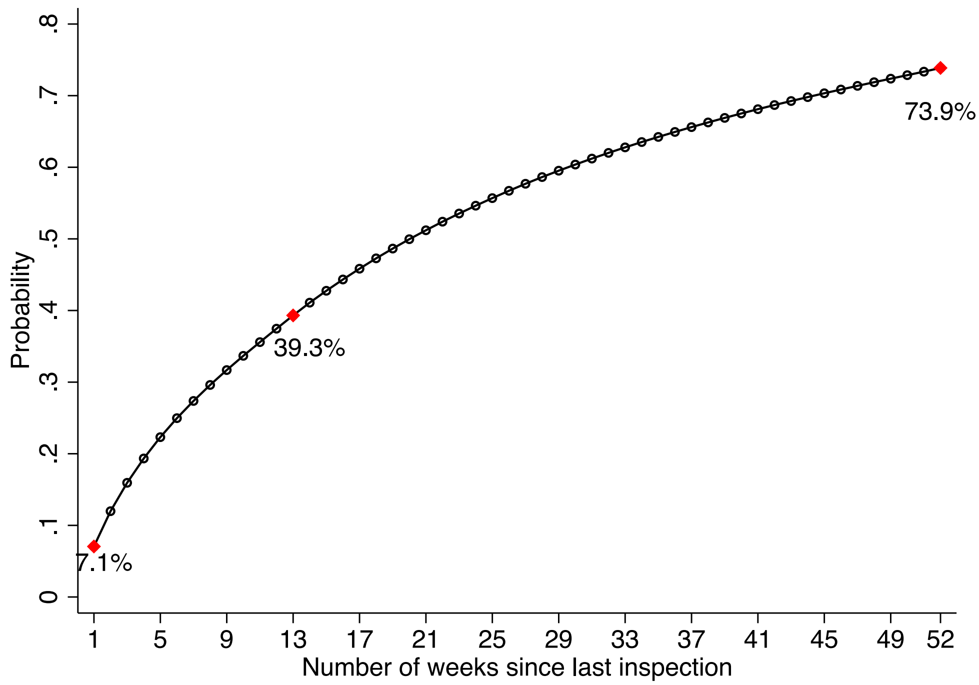
Note: The event study plot is estimated using equation 1 where I regress the number of accidents for the same truck that receives the inspection on a set of inspection indicators from 14 days before an inspection to 14 days after inspection, controlling for individual truck fixed effects, year, month, and day-of-week fixed effects. I illustrate the level shift in accidents before and after the inspection by fitting two horizontal lines using the average of percentage changes respectively. The shaded area is the 95% confidence interval for the estimates. The standard errors are clustered at the truck level. I combine the daily inspection indicators into 2-day bins, such as (-14,-13), (-12,-11), ..., (-2,-1), (0,1), (2,3), ..., (12,13) relative to the day of inspection at day 0. The horizontal axis is labeled by the first day of the 2-day bins. The effect of an inspection on accidents happening in the two-day bin (-2,-1) is normalized to 0. The % change on the y-axis represents the effect size in percentage and is calculated by dividing the coefficient of post_insp from equation (2) by the mean daily crash rate.

Figure 2: In Longer Term: The Impact of An Inspection on Truck Accidents



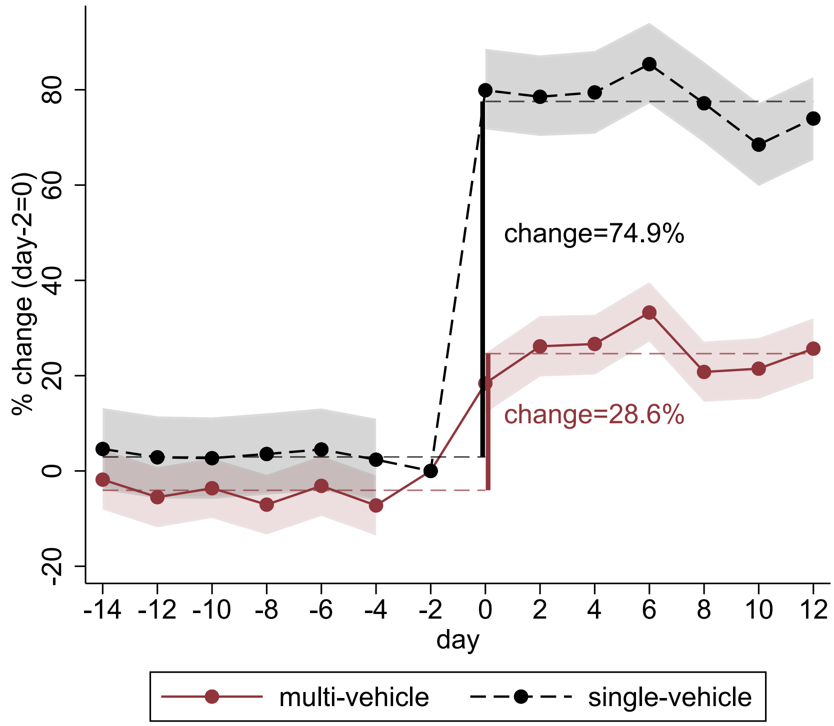
Note: In the upper panel (left y-axis), this plot shows the estimation result of the monthly event study that looks at the impact of inspections on truck accidents in the 12 months before to 24 months after an inspection (or inspections) in month 0 for any given truck. I control for individual truck, year, and month fixed effects. Standard errors are clustered at the truck level. The % change on the y-axis represents the effect size in percentage and is calculated by dividing the coefficient of post_insp by the mean daily crash rate.
In the lower panel (right y-axis), I plot the probability of reinspection for any given truck from month 1 to 24 after the inspection.

Figure 3: Mechanism: Probability of Reinspection



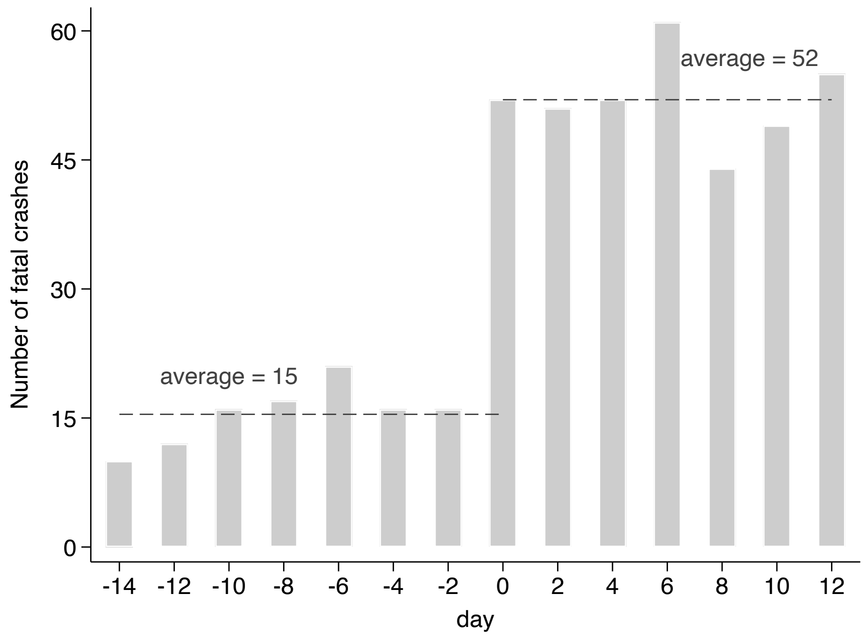
Note: The probability of reinspection plotted in this figure represents the probability of getting another inspection within N weeks after the most recent inspection. This is calculated by compiling the inspection history for each truck, determining the interval between the current and next inspection. The percentage of reinspections conducted within 1 to 52 weeks is then calculated for each truck and averaged across all trucks. This approach effectively measures the proportion of trucks reinspected within each timeframe. The data do not distinguish between trucks that are retired and those not reinspected for other reasons, so the last inspections are excluded from the sample.

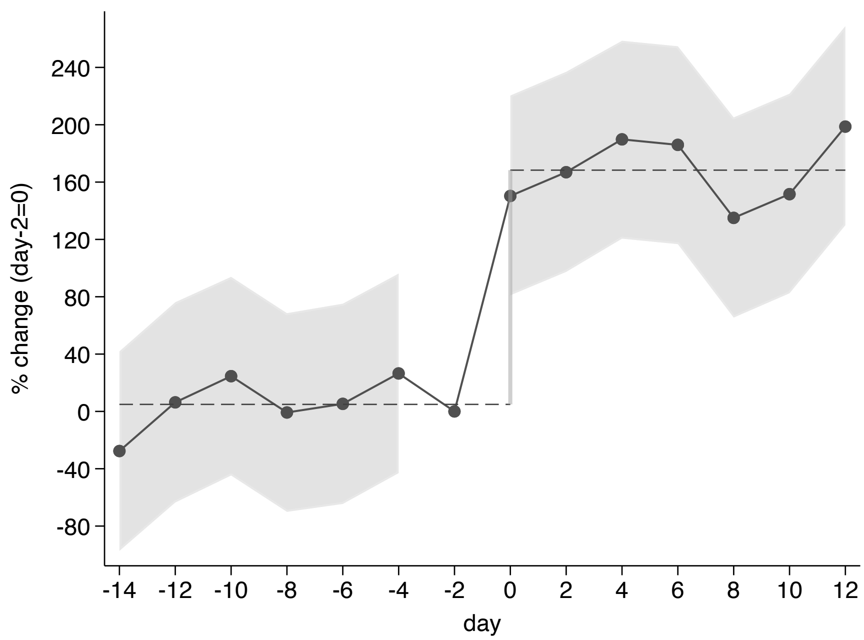
Figure 4: Mechanism: Comparing Effect Sizes in Single- vs Multi-Vehicle Accidents



Note: This figure compares the two event studies estimated using the same framework in equation 1 with different accident categories. I plot the percentage change in each type of accident using the change in number of accidents with respect to the average number of corresponding accidents. Both event studies look at 14 days before to 14 days after an inspection, controlling for individual truck fixed effects, year, month, and day-of-week fixed effects. The standard errors are clustered at the truck level. The shaded areas are the 95% confidence intervals respectively. The % change on the y-axis represents the effect size in percentage and is calculated by dividing the coefficient of post_insp by the mean daily crash rate of the respective outcome variable.

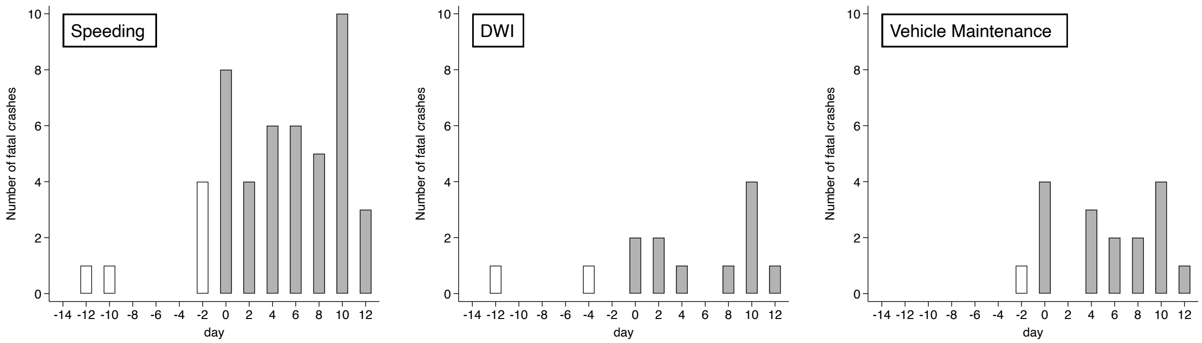
Figure 5: Additional Evidence: Increase in **Fatal** Accidents in FARS

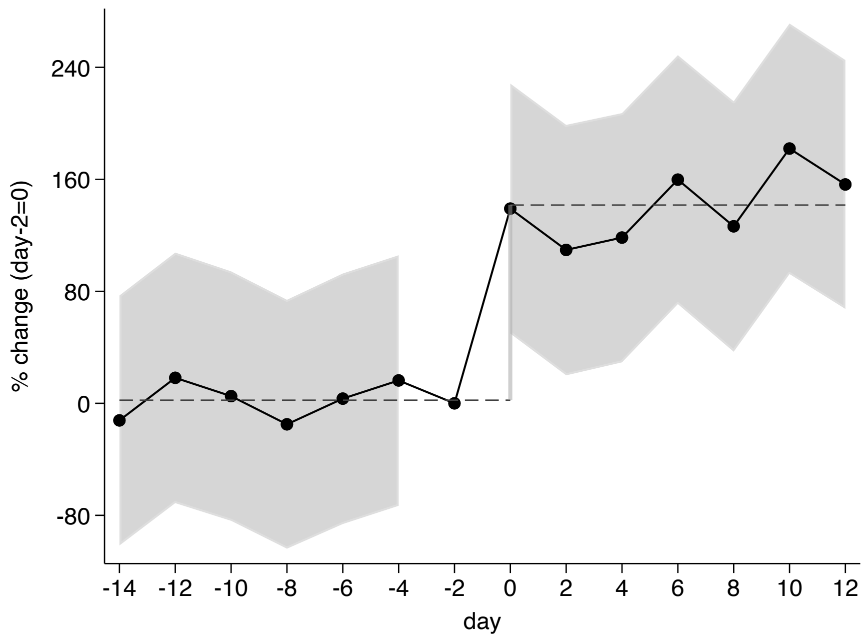




Note: In the top panel, I plot the raw number of fatal crashes involving trucks around inspection days (event time = 0) nationwide in the FARS sample. There are 15 fatal accidents among all trucks in each two-day bin on average before inspections. The number increases to 52 following inspections. The bottom panel shows the event study plot estimated following equation 1 by replacing the outcome variable to fatal accidents.

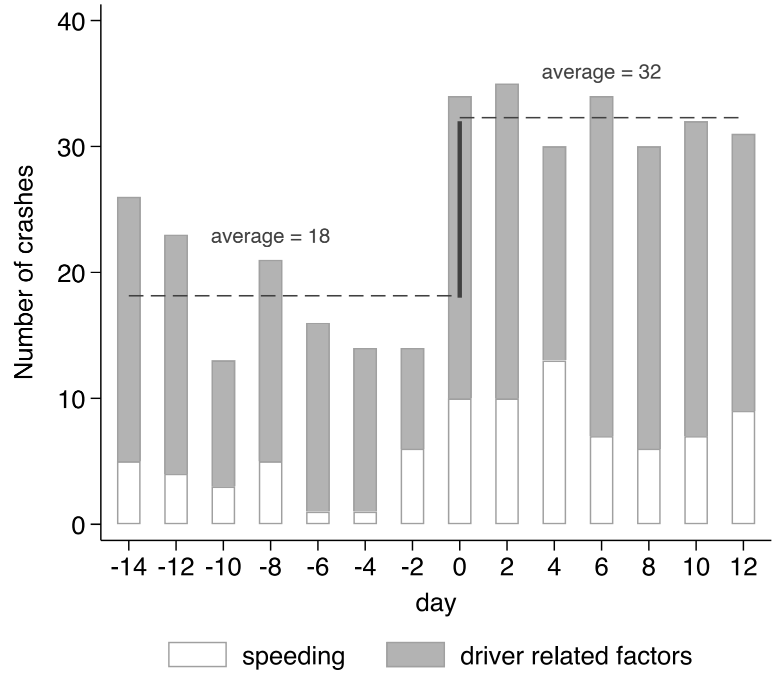
Figure 6: Additional Evidence: Increase in **Fatal** Accidents Due to **Truck** Violations in FARS

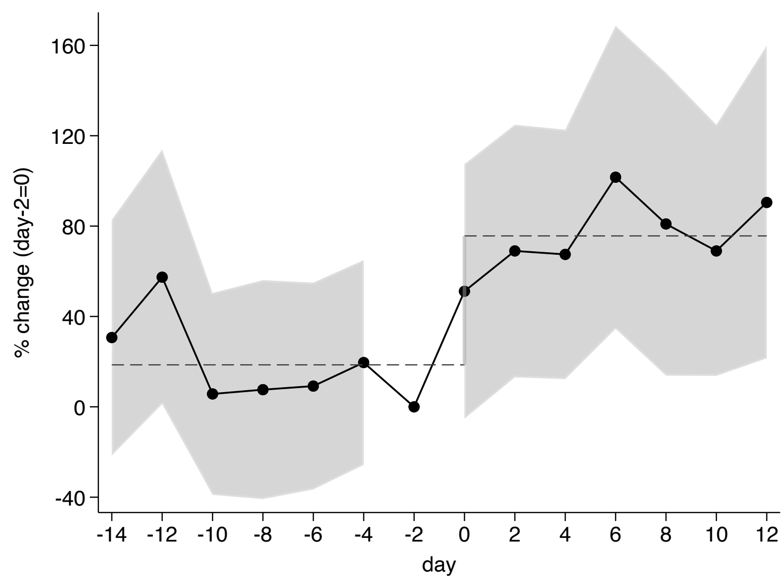




Note: The top panel of Figure 6 looks at the total number of fatal accidents nationwide caused by truck violations before and after inspections. The increases in accidents are due to drivers' reckless driving behaviors, including speeding and driving while intoxicated, and due to a lack of vehicle maintenance, such as loose cargo or trailer, which could be caused by reduced pre-trip checks. The bottom panel shows the event study plot estimated following equation 1 by replacing the outcome variable to fatal accidents caused by any type of truck violations listed in the top panel.

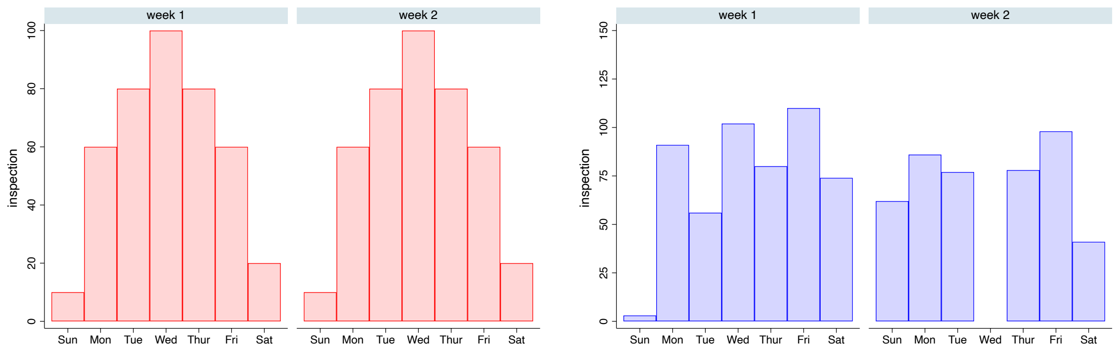
Figure 7: Additional Evidence: Increase in **Driver-Related** Accidents in Texas





Note: The top panel of Figure 7 shows that, before inspections, there are on average 21 crashes due to driver-related factors for each 2-day bin, but the number increases to 37 following inspections. Driver-related factors include all moving and parked violations assigned to truck drivers. Among those crashes, crashes that have a speeding violation exhibit a significant increase. The bottom panel shows the event study plot estimated following equation 1 by replacing the outcome variable to all types of driver-related accidents.

Figure 8: Policy Option 1: Variation in The Day-of-Week Inspection Schedule



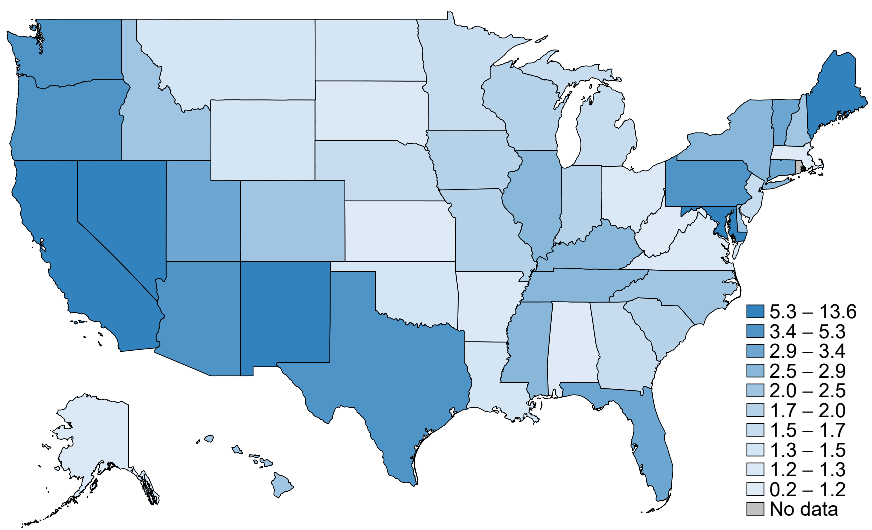
State A

mean = 58, *pred_index* = 0

State B

mean = 58, *pred_index* = 32

Figure 9: Policy Option 1: The Predictability Index



Note: The set of plots in Figure 8 shows an example of two states that have very different day-of-week inspection schedule in terms of the number of inspections done in each day of the two weeks. In order to measure the different predictability of the day-of-week inspection schedule, as in State A and B, I develop a predictability index *pred_index*. The lower *pred_index*, the easier the drivers could forecast an inspection. Here, *pred_index* = 0 for state A, which indicates that the schedule is highly predictable; *pred_index* = 32 for state B, which indicates that the schedule is not quite as predictable.
Figure 9 shows the yearly average of the state$\times$year predictability index (*pred_index*) across all states. In this figure, lighter colors indicate a lower *pred_index* and a higher predictability in inspection schedule, while darker colors indicate a higher *pred_index* and a lower predictability.

Figure 10: Policy Option 2: Differences in Inspection Selection Based On Past Inspection Timing

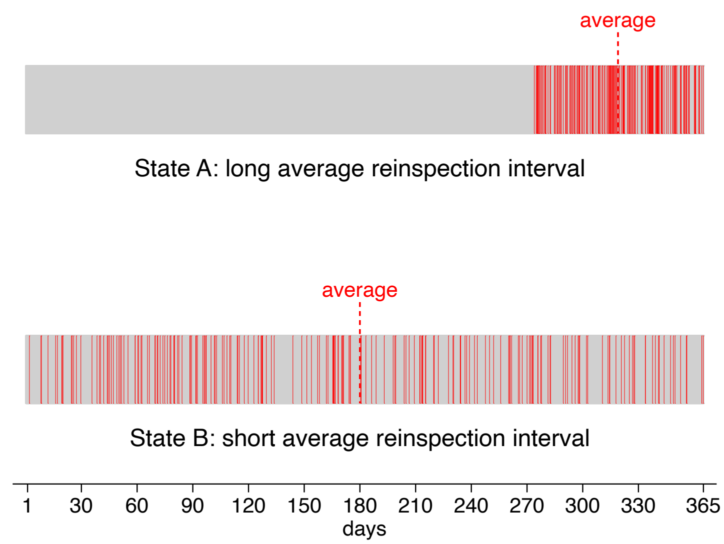
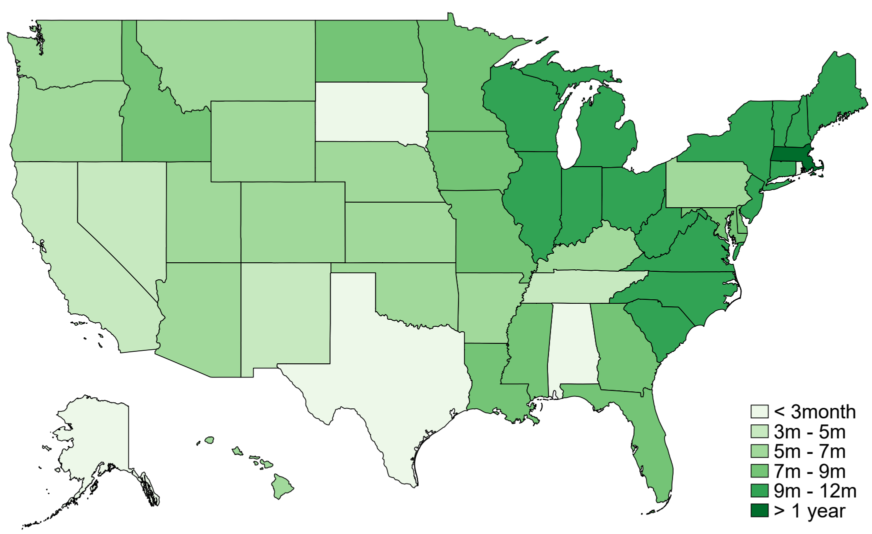


Figure 11: Policy Option 2: Time Interval Between Consecutive Inspections



Note: In Figure 10, the horizontal axis represents the number of days since the last inspection. Gray bars show all trucks entering weigh stations on a given day, categorized by their time since the previous inspection. Red lines indicate trucks selected for inspection. State A, with a design that resembles many current state practices, selects trucks that have not been inspected for a long time. In contrast, State B employs a random selection method. Both states inspect the same total number of trucks. State A has a longer average reinspection interval compared to State B, indicating that shorter reinspection intervals are associated with more randomness in inspection selection. Figure 11 shows the variation of the average reinspection time interval for trucks inspected in a state. Lighter colors in this figure indicate a shorter reinspection interval.