The impact of periodic passenger vehicle safety inspection programs on roadway fatalities: Evidence from U.S. states using panel data.*

Prithvi S. Acharya†[a], Laila AitBihiOuali[b], H. Scott Matthews[a], and Daniel J. Graham[b]

[a]Carnegie Mellon University
[b]Imperial College London

Abstract

Presently, 15 U.S. states require passenger vehicles to undergo periodic safety inspections. Past studies estimating the effectiveness of these safety inspection and maintenance programs (I/M programs) in their stated aim of mitigating road accidents and fatalities have tended to rely on outdated data-sets, or to focus on specific geographic regions. Since inspection program effectiveness continues to be deliberated in legislative bodies across the country, this paper aims to present a replicable and data-driven quantification of the effects of I/M programs on road fatalities, applying the largest available data-set, covering all 50 U.S. states over a 44-year period. This paper presents strong evidence that jurisdictions experience lower roadway fatality rates due to the presence of an active safety I/M program for passenger vehicles. Panel data regressions showed a negative correlation between the presence of state I/M programs, and the fleet-size-adjusted roadway fatality rate. Fixed effects (FE) estimates suggest that states with I/M programs had 2.8% fewer roadway fatalities per 100,000 registered passenger vehicles (90% CI: 0% to 5.6%) nationwide, based on data from 1975–2018. A two-stage least-squares (2SLS) specification is also presented, which not only supports this finding, but also implies a causal relationship between the presence of I/M programs, and lower road fatality rates.

1 Introduction

About 6.5 million roadway accidents occur in the United States each year, costing upwards of $240 billion, and causing over 30,000 fatalities: the Centers for Disease Control and Prevention (CDC) list motor accidents as a leading cause of adult mortality in the United States (**nassgess**; Blincoe et al., 2015; CDC, 2020; NHTSA, 2018). To mitigate roadway fatalities, government agencies have established a slew of regulations such as seat-belt laws, improved roadway design and speed-limit reductions. Over the last fifty years, these regulations have had measurable success in reducing roadway fatalities (Brüde, 1995; Evans, 2014).

Additionally, the National Traffic and Motor Vehicle Safety Act of 1966 requires the National Highway Traffic Safety Administration (NHTSA) to implement and update Federal Motor

*This document is a condensed version of a study that appears in the lead author's doctoral thesis acharya$_{p}hd$.

†Corresponding author. acharyap@cmu.edu. 5000 Forbes Ave., BPH129, Pittsburgh, PA 15213, USA

Vehicle Safety Standards (FMVSS), enforceable on vehicle manufacturers (49 C.F.R. §571, 2004). Mandatory standards for new light-duty passenger vehicles (LDV's)—which include, *e.g.,* the installation of airbags and child-restraint anchors on all LDV's, and requirements for crash-worthiness testing—have been shown to significantly lower the rate of roadway fatalities (Bento et al., 2017; Kahane, 2015). However, while federal standards have made new vehicles increasingly safe, government agencies have long recognized that LDV's must continue to meet these standards over their lifetime. While recent FMVSS regulations have required the incorporation of modern technologies (*e.g.,* anti-lock brakes and back-up cameras) into LDV's, these standards are not intended to regulate the proper use and maintenance of even the most basic safety features (*e.g.,* sufficient tire tread depth or brake-pad thickness) after an LDV has left the assembly line. The performance of individual vehicles' components and safety features over time varies widely and regardless of the standards to which they were built. It is influenced by several factors including but not limited to where and how they are used, and how well they are maintained by vehicle-owners.

1.1 Vehicle safety inspection and maintenance programs

To ensure that vehicles continue to meet safety standards over their lifetimes, jurisdictions may establish vehicle safety inspection and maintenance programs (I/M programs). The aim of these programs is to mitigate motor accidents or roadway fatalities which can be attributed to vehicles operating unsafely due to wear-and-tear or insufficient and improper maintenance. I/M programs exist across the world, and are typically administered by national or (as in the case of the U.S.), state-level departments of transportation (DOT's). Typically, these programs require that vehicles be periodically brought to an inspection station, where a road-worthiness certificate is issued only to LDV's meeting all standards and requirements. For example in Pennsylvania, annual "safety inspections for passenger cars and light-duty trucks require that the following items be checked: suspension components, steering, braking systems, tires and wheels, lighting and electrical systems, glazing (glass), mirrors, windshield washer, defroster, wipers, fuel systems, the speedometer, the odometer, the exhaust systems, horns and warning devices, the body, and the chassis" (PennDOT, 2017). Vehicles are only certified upon the completion of any requisite maintenance.

I/M programs were among the earliest strategies implemented to regulate vehicle safety in the United States. The first programs were voluntary (*i.e.,* states recommended periodic in-

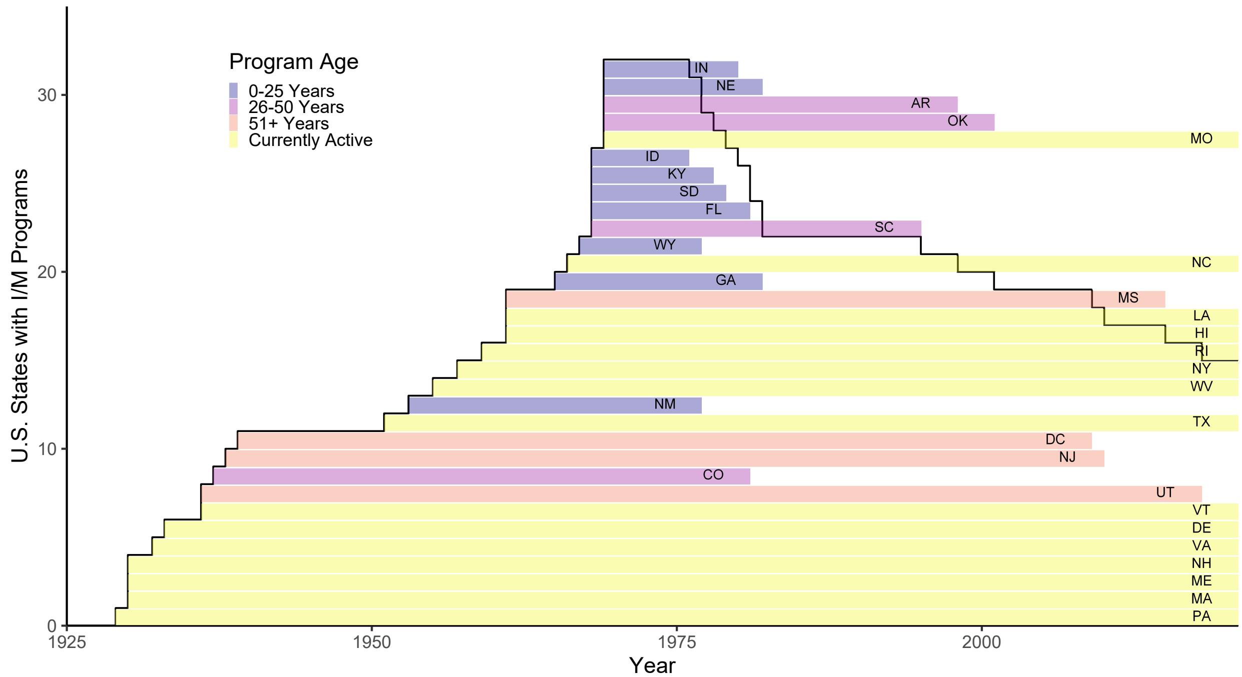

Figure 1: Timeline of establishment and repeal of U.S. I/M programs

spections, but did not mandate them). Massachusetts' voluntary program, founded in 1926, was followed in quick succession by similar offerings at states across the eastern seaboard. The first mandatory safety I/M program was established in 1929 in Pennsylvania; this program continues to be active and is the nation's longest running safety I/M program. After a 1968 hearing in the U.S. Senate found that vehicle-owners were incurring high costs for unsatisfactory vehicle repairs, the Motor Vehicle Information and Cost Savings Act was passed, giving the U.S. Department of Transportation (through state agencies, if needed) the power to establish inspection stations and conduct vehicle safety inspections (Schroer & Peyton, 1979). As a result, in 1973, NHTSA issued vehicle in-use (VIU) standards, with the intention of requiring every U.S. state to institute a safety I/M program. This rule received almost immediate push-back from the states, compelling NHTSA to weaken the VIU standards in 1976, no longer requiring mandatory inspections (Thompson, 1985). As a result, while over a dozen U.S. states established programs in the 1960's and '70's, several of them were repealed soon after. While not mandating I/M programs, NHTSA continues to promote safety inspections in recommendations and guidance such as routinely-published 'Proactive Safety Principles'. Yet, of the 32 active I/M programs in 1976, 18 have since been repealed, and no new programs have been established (GAO, 2015). As shown in Figure 1, only 14 U.S. states continue to have mandatory periodic vehicle safety inspection programs in 2020.

The decline in legislative and popular support for these programs since the mid-1970s which has led to this string of repeals, was primarily motivated by "waning public concern with highway safety" and the perception "that mechanical defects cause a small portion of" accidents (Thompson, 1985, pp. 696). While there may be a perception that I/M programs are ineffective since newer vehicles rarely fail safety inspections, Peck et al. (2015) note that this perception hinges on a significant under-estimation of the number of LDV's failing safety inspections. Additionally, they argue that since inspection failure rates do not tend to zero, they are still an important means of identifying the need for, and enforcing, critical vehicle maintenance. Stakeholders across the United States continue to advocate for the elimination of I/M programs, arguing that they are expensive to consumers, and cause no significant change in the rate of road accidents or fatalities. A large strand of literature contain studies that have attempted to quantify this change. However, most of these earlier studies (discussed below) have been narrowly defined—either focusing only on one region, or limiting their analyses to a short time-frame. Several others also use data which may now be considered outdated. The 1970's and 1980's saw the implementation of FMVSS as well as laws lowering speed limits and mandating seat-belt use, making vehicles and roads safer and incomparable with data or analyses from earlier decades. We believe that using outdated studies, based on small subsets of data from many years ago, is not sufficient to support current considerations of the effectiveness of these I/M programs.

1.2 Review of literature

A large number of studies in the literature examine the effect between safety inspection programs and road accident or fatality rates, but this question has rarely been explored with a panel-data approach Early studies were typically limited to data from as far back as the 1930's, and typically limited to only a single state or region (Garbacz, 1990; Garbacz & Kelly, 1987; Loeb & Gilad, 1984; Loeb, 1990; Peltzman, 1975; Schroer & Peyton, 1979; Zlatoper, 1989). More recent studies limited to specific regions (states, urban areas, or foreign countries) have also been conducted (Blows et al., 2003; Christensen & Elvik, 2007; Fosser, 1992; Hoagland & Woolley, 2018; Murphy et al., 2018; White, 1986).

Numerous studies with a national scope also exist in the literature, typically based on data the federal *Highway Statistics* database (Merrell et al., 1999; Poitras & Sutter, 2002; Sutter & Poitras, 2002). However, the *Highway Statistics* data applied in the aforementioned are based on representative samples, and are designed only to be nationally representative (FHWA, 2018). That data-set is not designed to be accurate at higher resolutions, and the application of these data for state-level analyses as conducted by Merrell et al. (1999) may suffer from errors due to sampling biases.

1.3 Motivation

Jurisdictions continue to debate the need for, and effectiveness of, I/M programs while relying on outdated or narrowly-focused evidence in the literature. To better inform future legislation and policy development, this study aims to develop a reproducible and data-driven analysis that applies nationally representative data over the longest possible period, to quantify the mitigating effect—if any—of safety I/M programs on motor accidents and roadway fatalities. Applying a panel of fatal accident data representing all 50 states (and the District of Columbia) over a 44-year period, we develop a fixed effects regression to control for the potential state and time effects in order to improve the robustness of our estimates. Our specification regresses the presence of state I/M programs against adjusted roadway fatality rates, while controlling for several related factors. The results obtained from the fixed effects regression are supported by several supplementary regressions, including an instrument variable regression that relaxes the assumption that the implementation of the I/M program (*i.e.*, the treatment) is random across states.

1.4 Contributions of this study

Passenger vehicle safety inspections in the U.S. are based on a patchwork of state-level regulations, while accident and fatality rates continue to also depend on nationwide trends and federal laws. The results presented below have been developed from U.S. accident and demographic data of uniform resolution (rather than sampled surveys) in all fifty states and the District of Columbia, allowing stakeholders to access relevant, national-level results, instead of interpolating from regional or international studies. Rather than assessing only one state or region, the results presented below indicate an average treatment effect (ATE) of I/M programs on roadway fatalities across the United States. Furthermore, as discussed in Section 2, the data used in this study is the largest publicly available road fatality database in the United States, recording nearly every fatal accident having occurred anywhere in the country, over a period of more than four decades.

2 Data

Consistent data that are of similar quality and resolution in each jurisdiction and over time are critical to assessing the effects of establishing or repealing a state-level passenger vehicle inspection program. However, since accident data collection is typically managed by state-level DOT's, first-responders, and law-enforcement agencies are managed at the city- or county-level, there exists neither a framework nor an incentive for the uniform collection and nationwide dissemination of data from every fatal motor accident. While the NHTSA National Automotive Sampling System–General Estimates System (NASS-GES) may provide valuable insights at the national level, it is based on sampled data, and, as such, is not designed to have meaning at the state-level (NHTSA, 2020b; Peck, 2015). Databases maintained by state DOT's (for example, in Texas, as described by Murphy et al. (2018)) may account for all accidents in that state, but these data are likely to vary widely in resolution and format between states. As such, a database of all motor accidents in the U.S. which is uniformly resolved at the state-level, is not publicly available. For this reason, the models presented in this study have been restricted to evaluating I/M programs' impact on fatal accidents—for which such a database is free and publicly accessible.

2.1 The Fatality Analysis Reporting System

Every year, states share data with NHTSA on all police-reported fatal motor accidents in their jurisdiction through the Fatality Analysis Reporting System (FARS), which was created by an act of Congress (NHTSA, 2020a). "The FARS crash data files contain more than 100 coded data elements characterizing the crash, vehicles, and people involved." (NHTSA, 2010). This feature-rich data-set is maintained primarily to inform regulation in Congress and at the USDOT. While reporting data to FARS is entirely voluntary and governed by cooperative agreements, most states have regulations mandating the collection and submission of data on fatal accidents. This reporting—since 1975—has led to the development of a nationwide census of fatal accidents over the last four decades. The FARS database provides a uniform and systematic format for states to record and share fatal accident data, which is why it was selected for this study. We decide to focus on road fatality rates as our primary outcome of interest, since the likelihood of reduction in fatalities are a strong element in decisions surrounding the implementation, withdrawal or maintenance of I/M programs. Another advantage of the FARS database is that, unlike the limitations of other data sources used in previous studies, the FARS database provides feature-rich, uniform and systematically recorded data on fatal accidents in every state, and over several decades. Due to this consistency, the models presented below—in line with numerous past studies—use the FARS database to assess I/M programs' effect on fatality rates. While the task of collecting, collating, and submitting data to the FARS database falls on first responders and on staff at state DOT's, the process is heavily controlled by NHTSA.

Vehicle contributing factors The FARS database includes records of 'vehicle contributing factors', *i.e.,* factors related to involved vehicles' safety features that first responders perceive to have led to the accident. The FARS data format allows for the recording of over a dozen 'contributing factors'. These factors—such as low tire-tread depth, or worn brakes—involve components which would typically be inspected and remedied during a periodic inspection. In theory, these data would be the most reliable indicator of the impact of I/M programs on preventing fatal accidents, since a vast majority of these 'factors' would likely have been identified and remedied during a safety inspection. There is evidence in the literature that these data may be under-reported: while they did not examine vehicle contributing factors specifically, Rolison et al. (2018, pp 22) found that other contributing factors (such as driver distraction and impairment, cell-phone use, etc.,) are under-reported, since the priority of responding officers at the scene of an accident is to ensure the safety of road users, rather than to collect these data. This evidence is also supported by anecdotal accounts of numerous I/M program administrators. Given our belief that these data are under-reported, the specifications developed in this study apply a dependent variable based on all fatal accidents, regardless of whether such a 'contributing factor' was recorded. However, the proportion of accidents with a recorded 'contributing factor' was included as a control to evaluate its correlation respectively with other exogenous variables, and with the rate of fatalities.

Furthermore, we choose not to focus our analyses on these contributing factors, since, unlike the control studies conducted by Fosser (1992) and Christensen and Elvik (2007), data on defects or 'contributing factors' are not publicly available in the United States for vehicles which were not involved in accidents.

2.2 Complementary data

In addition to FARS, this analysis uses numerous other data sources, and all of which are free and publicly available (FHWA, 2018; NCEI, 2020; NCSL, 2020; U. S. Census Bureau, 2016, 2020). Further discussion of these supplementary data sources, and the regressors developed from them are presented in Section 3.4.

3 Methodology

3.1 Time-series regression models

The availability of longitudinal data on accidents occurring at the state level enable us to gather information and responses to a total of 51 jurisdictions over 44 years (1975-2018). Given the large temporal span and geographical coverage of the data, we build our econometric specifications based on panel data models as they allow us to control for broader time trends and state effects across observed units (Chamberlain, 1984; Hsiao, 2003) that should clear our estimates from external biases unrelated to the implementation of I/M programs (*e.g.*, improved standards, seat-belt laws, etc.) that can still impact the road fatality rates. Therefore, the specifications in our analysis use both time and state fixed effects. The decision to use panel data models is in line with the recent strands of the literature, as several recent studies discussing model and regressor specifications for the prediction of accident and fatality rates concur on the use of panel data models to assess weighted fatality rates (Chen et al., 2018; Fountas et al., 2018; Hauer, 2010; Liu et al., 2018; Siegrist, 2010; Stipdonk et al., 2010).

We note here that by modeling average or mean values, rather than looking at each vehicle's inspection status during an accident, that our analyses may be subject to an ecological fallacy. However, we believe that by limiting our analyses to in-state passenger vehicles, we are able to reasonably assume the inspection status of each individual vehicle and of the group as a whole, based on the inspection requirements in each state at the time of analysis. Furthermore, mean accident data are calculated based on individual-vehicle level records, and resultant errors are explicitly stated in our analyses.

3.2 Accounting for I/M program jurisdiction

The FARS database includes fatal road accidents of all types, including those involving commercial vehicles (buses, trucks, other commercial equipment, etc.), which are governed by safety standards and I/M programs unrelated to the LDV I/M programs which are the focus of this study. Therefore, we exclude accidents involving only other types of vehicles and accidents involving passenger vehicles as well as other types from the present analysis. This allows for models to be developed around only those vehicles which are likely covered by the I/M programs in question.

Passenger vehicle I/M programs are administered at the state-level, usually by transportation agencies, which implies that the jurisdiction of each I/M program is assumed to be limited to vehicles registered in said states. However, a considerable proportion of vehicle miles are traveled out-of-state, and as a result, vehicles may be involved in accidents outside their home state. One previous study addresses that issue by ignoring the location of the accident and develop panels based solely on the vehicles' state of registration (Hoagland & Woolley, 2018), but this strategy is limited by the fact that it does not control for state-based differences across states in first-responder procedures which can lead to biases since as the data collection and reporting norms can differ significantly from one state to another. The present study contributes to the literature by clearing up this potential threat to estimates' quality: we restrict the analysis to accidents in which all vehicles involved were registered in the state where the accident occurred. This approach (of restricting analyses to vehicles under the jurisdiction of specific I/M programs) does not appear in recent literature, and its application to quantifying the effectiveness of I/M programs is a unique contribution of this paper. These restrictions do not impair the size of our final sample: the present analysis was built on over 80% of accidents recorded in FARS data for each year over the period 1975–2018 (for Panel I, as described below) and totals over 1.33 million fatal accidents.

3.3 Dependent variable

The dependent variable selected for these models was an LDV fleet-size adjusted statewide annual road fatality rate. This allows us to uncover any links between trends in these fatality rates and the regression variables. The rate was expressed in fatalities per 100,000 registered passenger vehicles, as shown in Equation 1. The choice to develop these models based on a fleet-size adjusted variable was made to control for the variability in per capita vehicle ownership (*i.e.*, population may not be an accurate measure of the number of passenger vehicles on a state's roadways), and to simplify the interpretation of results.

$$Adjusted\ Fatality\ Rate_{year=A,state=B} = \frac{100,000 \times \text{Fatalities in year A, from accidents in state B}^*}{\text{Number of registered passenger vehicles in state B in year A}} \tag{1}$$

*where all vehicles involved in the accident were passenger vehicles, registered in State B

3.4 Exogenous variables

Two data panels (referred to henceforth as Panels I and II) were developed for this analysis. Each was indexed by state and by year, and contained the dependent variable and the treatment variable, in addition to a list of exogenous variables.

Panel I For use in the first model, a balanced panel indexed by state (50 states and the District of Columbia) and by year (1975–2018) was developed from the FARS database. These variables are listed in Table 1. The *treatment variable*, 'Program' is a Boolean variable indicating whether or not an LDV safety inspection program was active in that state during that year. The specification also includes other variables influencing the likelihood of an accident to occur (*e.g.*, precipitation).

Table 1: List of exogenous variables included in Panel I.

Variable Name	Description
Program	Does this state have a program in this year? (Y = 1, N = 0)
Program_Repeal	Was this program repealed in this year? (Y = 1, N = 0)
Program_Ever	Did this jurisdiction ever have a program? (Y = 1, N = 0)
Population	Statewide population (x100,000)
VMT	Statewide total passenger vehicle miles traveled (VMT) (billions)
Prop_Rural_VMT	Fraction of VMT estimated to be on rural roads
Registered_Vehicles	Number of registered passenger vehicles in the state (x100,000)
Fatal_Accidents	Total number of fatal accidents
Driver_Age	Mean age of all drivers involved in fatal accidents
Median_Income	Median statewide income
Fatalities	Total number of road fatalities
Vehicle_Age	Mean age of vehicles in fatal accidents
Vehicles_Per_Accident	Mean number of vehicles in each fatal accident
Lanes	Mean number of lanes at all accident sites
Speed_Limit	Mean speed limit at all accident sites (MPH)
Prop_DUI	Fraction of accidents with at least one recorded DUI
Prop_Speeding	Fraction of accidents where at least one vehicle was speeding
Prop_VehCF	Fraction of accidents with at least one 'vehicle contributing factor'
Prop_Weather	Fraction of accidents in inclement weather
Prop_Surface	Fraction of accidents with inclement surface conditions
VMT_Per_Vehicle	Statewide mean annual VMT per vehicle (x1,000 miles)
Veh_Per_Capita	Statewide mean number of registered passenger vehicles per capita

Panel II Additional variables were collected and used in the development of a second panel (in addition to all variables included in Panel I, as listed in Section 3.4). These variables include economic indicators. Regressions applying the within estimator work under the assumption that the application of treatment (*i.e.,* which states have or do not have I/M programs) is random. However, the establishment and repeal of state I/M programs are likely not random. The presence of a program in a state is reliant on support from legislators and state government officials. We include a binary variable indicating which political party was in power in the state legislature, since the estimated treatment effect could be subject to an omitted variable bias if these political factors were not controlled for in the specification. Additionally, this 'party in power' variable also allows us to test Leigh (1994)'s hypothesis that I/M program 'strength' may be politically endogenous. Further, as noted in several examples in the literature, the political party of the state government also impacts key economic indicators, including "pollution, spending, policies, and labor market outcomes" (Beland, 2016, pp. 2).

Panel II is an unbalanced panel, since these data are only available for every other year between 1980 and 2006 (inclusive), and for every year 2008–2017. This second set of specifications includes more variables and serves to complement Panel I. To trade-off between the availability of more regressors, and this reduced frequency, we present two complementary fixed effects regressions.

Table 2: List of additional exogenous variables included in Panel II.

Variable Name	Description
Area	State Area (mi^2)
Road.length	Total length of road (mi)
Road.density	State Road Density (mi/mi^2)
GDP	Statewide average GDP per capita ($2017)
Pop.density	Statewide population density ($/mi^2$)
Disposable.income	Median statewide disposable income ($2017)
Highway_expend_perCap	State Highway Expenditure ($2017) per capita
Driver_per_capita	Number of licensed drivers per capita
Precipitation	Statewide Average Annual Precipitation (in)
Dem	Legislative Party in Power (Dem = 1, Rep = 0)

3.5 Variable transformation

An inverse hyperbolic sine transformation of both the dependent and independent variables was used to improve regression performance and to facilitate easier interpretation of results (Bellemare & Wichman, 2020; Burbidge et al., 1988).

3.6 Fixed effects regressions

We present two FE regressions: Model I was developed based on the Panel I (a balanced panel for 51 jurisdictions, and each year 1975–2018), and Model II was developed on Panel II (which contains data for all 51 jurisdictions, but only a subset between 1975–2017). Panels I and II are further described in Section 3.4 and 3.4 respectively. To address any possible correlation between exogenous variables, FE models I and II use only a subset of variables from the corresponding panels. We selected variables for each regression on the basis of variance inflation factors (VIF's), calculated for ordinary least squares (OLS) regressions for each panel, containing all exogenous variables from that panel. Both models regress the treatment variable (*i.e.,* the presence or absence of a state I/M program) against the dependent variable (described in Section 3.3). FE models were chosen based on the result of (i) a robust Hausman Specification Test and (ii) an F-test. Since the literature indicates effects both across time and states (*i.e.*, 'individual'-effect), FE Models I and II are two-way models and controls for both state and time fixed effects.

3.7 Two-stage least squares regression

A core assumption of fixed effects specifications is that treatment (*i.e.*, the presence or absence of the I/M program) are considered randomly distributed. In reality, the establishment or repeal of I/M programs are driven by a multitude of factors including the affiliation and strength of state legislatures and election cycles (Graham & Garber, 1984; Leigh, 1994). Therefore, we complement the FE analysis with a two-stage least squares (2SLS) regression to account for reverse causality and omitted variables, which may bias the FE regressions, preventing any meaningful causal inferences from being drawn. By controlling for time-dependent omitted variable bias, the 2SLS could uncover any causal relationship between the treatment and dependent variables (James & Singh, 1978). The 2SLS model presented in this study applied the same panel and set of regressors as FE Model I. Two instrument variables were selected for this regression: the third lags of the 'Prop_Speeding' (*i.e.*, fraction of fatal accidents involving at least one speeding vehicle) and 'Prop_DUI' (i.e., fraction of fatal accidents involving at least one instance of DUI) variables. The authors assert these variables to fit both conditions for unbiased instruments. These variables were also found to reject the null hypotheses of a Sargan test (for over-identification) as well as a Durbin-Wu-Hausman test (for estimator consistency).

4 Results

4.1 Fixed effects regressions

Table 3 presents estimates from Models I and II. The coefficient for the treatment variable is found to be negative and statistically significant in both models (respectively at the 90% and 95% levels), indicating that states with I/M programs have a lower fatality rate than those without. Model II showed a reduction in fatality rates of 5.5% (95% CI: 0.4% to 10.6%), and Model I—with fewer variables, but over a longer period—found a complementary result: jurisdictions with I/M programs had 2.8% (90% CI: 0% to 5.6%) fewer fatalities per 100,000 registered vehicles than those which did not.

Table 3: Fixed-effects regression results.

	Dependent Variable: Fatals_Per_100k_Veh†	
	Model I	Model II
Program	-0.028 $(0.017)^{*}$	-0.055 $(0.026)^{**}$
Program_Repeal	-0.035 (0.035)	-0.054 (0.053)
Population†	-0.418 $(0.034)^{***}$	
Driver_Age†	-0.284 $(0.080)^{***}$	0.055 (0.101)
Median_Income†	0.038 (0.078)	0.105 (0.104)
Vehicle_Age†	0.145 $(0.048)^{***}$	0.344 $(0.070)^{***}$
Vehicles_Per_Accident†	0.523 $(0.116)^{***}$	0.175 (0.144)
Lanes†	0.032 (0.047)	-0.125 $(0.059)^{**}$
Speed_Limit†	0.119 (0.095)	0.290 $(0.131)^{**}$
Prop_DUI†	0.213 $(0.051)^{***}$	0.326 $(0.076)^{***}$
Prop_Speeding†	-0.147 $(0.043)^{***}$	-0.020 (0.055)
Prop_VehCF†	-0.115 (0.156)	-0.293 (0.242)
Prop_Weather†	0.121 $(0.061)^{**}$	0.076 (0.067)
Prop_Surface†	-0.066 (0.097)	0.084 (0.122)
Veh_Per_Capita†	-2.552 $(0.084)^{***}$	-2.515 $(0.106)^{***}$
Prop_Rural_VMT†		0.460 $(0.144)^{***}$
GDP†		0.470 $(0.073)^{***}$
Highway_expend_perCap†		-0.027 (0.020)
Precipitation†		0.021 (0.025)
Dem		-0.063 $(0.011)^{***}$
R^2	0.584	0.609
F Statistic	70.291	38.469
Observations	2244	1224

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

† Inverse hyperbolic sine transformation applied to this variable.

Both models also indicate that fatality rates are negatively correlated with mean vehicle age, which corroborates findings in the literature that crashes involving older vehicles are more likely to result in fatalities. The models also indicate a negative correlation between the accident rate and the number of passenger vehicles registered per capita. Model II also found two of the additional demographic variables to be statistically significant—the statewide GDP, and the political party in power at the state level. Further, the results are robust to the inclusion of the 'party in power' controls which indicates that our conclusions are not impaired by non-randomness or omitted variable bias. Neither Models I nor II found the proportion of accidents with a recorded 'vehicle contributing factor' to be significant.

4.2 Two-stage least squares regression

Table 4 show results from the 2SLS regressions. Estimates corroborate the previous findings from the fixed effects models as they indicate that there exists a statistically significant negative relationship between the presence of an I/M program, and the road fatality rate.

Table 4: 2SLS regression results.

	Dependent Variable: Fatals_Per_100k_Veh†
Program	-0.41 $(0.11)^{***}$
Program_Repeal	-0.19 $(0.06)^{***}$
Population†	-0.44 $(0.04)^{***}$
Driver_Age†	-0.07 (0.12)
Median_Income†	-0.04 (0.09)
Vehicle_Age†	0.17 $(0.05)^{***}$
Vehicles_Per_Accident†	0.58 $(0.13)^{***}$
Lanes†	0.02 (0.05)
Speed_Limit†	0.25 $(0.11)^{**}$
Prop_VehCF†	-0.30 (0.18)
Prop_Weather†	0.28 $(0.08)^{***}$
Prop_Surface†	-0.22 $(0.11)^{**}$
Veh_Per_Capita†	-2.62 $(0.10)^{***}$
R^2	0.88
Num. obs.	2244
Diagnostic test statistics:	
Weak instruments	26.447^{***}
Durbin-Wu-Hausman	9.379^{**}
Sargan	10.695^{**}

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

†Inverse hyperbolic sine transformation applied to this variable.

5 Discussion and Conclusions

Panel data model results provide strong evidence that jurisdictions experience lower road fatality rates due to the presence of an active safety I/M program for passenger vehicles. FE Models I and II showed a negative correlation between the presence of state I/M programs and the fleet-adjusted fatality rate: Model II had the more statistically robust result, likely as a result of the additional control variables. This specification showed the average treatment effect—*i.e.,* the average reduction in fatality rates between 1980 and 2017, for states with I/M programs in comparison to those without—of 5.5% (95% CI: 0.4% to 10.6%). Model I, which has fewer control variables, but applies the specification across all years from 1975–2018 shows a complementary result that supports the findings of Model II. As per Model I, states with I/M programs were found to have 2.8% fewer fatalities (90% CI: 0% to 5.6%) over the period of analysis.

The existence of a statistically significant, negative, average treatment effect is further supported by the value of the 2SLS regression estimates. The treatment variable coefficient is -0.41 (95% CI: -0.52 to -0.30) which is of a significantly larger magnitude than the corresponding coefficients in FE Models I and II. This indicates that omitted variable bias in the FE models' error terms causes those models to underestimate the reduction in the fatality rate in jurisdictions with active I/M programs.

Further, the application of statistically robust instruments (as verified by the Sargan and Durbin-Wu-Hausman tests) indicate that the 2SLS models controls for both omitted variable bias and any effect of reverse causality on the FE model errors. The authors argue that a statistically significant coefficient for the treatment variable in the 2SLS specification, is thus an indicator of causality—a negative coefficient (with 95% confidence) implies that the presence of state safety inspection programs likely causes a measurable and significant reduction in the number of roadway fatalities per 100,000 registered passenger vehicles in the state.

5.1 Influence of vehicle, infrastructure and traffic characteristics

Several other regression variables were found to have a statistically significant correlation with the fatality rate. Models I & II found the mean age of vehicles involved in accidents to be positively correlated to the fatality rate. This finding is supported by literature showing that given an accident occurs, occupants of older vehicles are more likely to be fatally injured (Martin

& Lenguerrand, 2008; O'Donnell & Connor, 1996). Both FE regressions also found the proportion of fatal accidents involving DUI to have a significant positive correlation with the dependent variable. This may be attributable to that drunk drivers tend to drive more aggressively: Zador et al. (2000) finds that "the relative risk of involvement in a fatal vehicle crash increased steadily" as driver blood-alcohol content increased. The FE regressions also indicated that states with more registered passenger vehicles per capita had a lower fatality rate. This relationship has been explored extensively in the literature. Smeed (1949) first showed how increased traffic density would tend to decrease the number of roadway fatalities per vehicle (Oppe, 1991; Ross, 1985).

Model I also indicates an inverse relation between fatality rates and median driver age—supporting several similar findings in the literature (McCartt et al., 2009). Model I assigned negative coefficients for the variable corresponding to the proportion of fatal accidents where speeding was recorded. With respect to additional demographic variables, Model II found there to be more road fatalities in states where a greater fraction of road miles were travelled on rural roads—in keeping with most similar studies in the literature (Merrell et al., 1999; Peltzman, 1975; Zlatoper, 1989)—and in states with a lower GDP (supporting the 'Peltzman effect' hypothesis). The positively correlated GDP (and the positively correlated median household income) align with findings in the literature that higher-income drivers are less likely to drive defensively and therefore more likely to be involved in accidents (Males, 2009; Shinar et al., 2001). The positive coefficients may also be caused by a positive correlation between GDP and recreational travel (McMullen & Eckstein, 2012). Increased travel–especially long-distance travel and driving on rural roads—would increase the number of fatal accidents. Model II also found a statistically significant relationship between the party in power in a state legislature, and the adjusted roadway fatality rate, which aligns with the political endogeneity argument made by Leigh (1994).

5.2 Policy implications

Our results affirm—based on data from 50 states and D.C. over a 44 year period—that I/M programs have a negative and causal relationship with roadway fatalities, and that these programs are effective in their stated aim of mitigating roadway fatalities. In this paper, we choose not to comment on the financial cost of I/M program administration, or on the potential public cost savings from mitigated accidents and fatalities. While acknowledging these to be important factors, we argue that legislative bodies must consider the reduction in fatalities as a statistically significant benefit resulting from inspections, when debating the establishment or repeal of state safety I/M programs.

The findings of this study are limited to fatal accidents, which comprise about 0.5% of all road accidents occurring in the U.S. each year (NHTSA, 2020b). Based solely on the analyses presented here, no inferences may be made about the impact of I/M programs on less severe motor accidents, however Blows et al. (2003) has shown that changes in the rate of all motor accidents are of the same order as changes in the rate of fatal accidents. We posit that safety inspections will only become more important as Advanced Driver Assistance Systems (ADAS) and autonomous vehicle (AV) technology become more prevalent: while several international jurisdictions have already adapted safety inspections to include testing and calibrating ADAS systems, this has yet to be applied in the United States (Bellon, 2020).

Data availability statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgements

This project is funded in part by Carnegie Mellon University's Mobility21 National University Transportation Center, which is sponsored by the US Department of Transportation. The Center also receives sponsorship through grants and donations from several sources, including the International Motor Vehicle Inspection Committee (CITA). Dana E. Peck, Paul S. Fischbeck, and Brent R. Heard provided input on earlier iterations of this analysis.

ascexmpl-new

A List of abbreviations

Table 5 lists the abbreviations used in this paper.

Table 5: Abbreviations and terms referenced in this study.

Abbreviation	Definition
2SLS	Two-stage Least Squares (Regression)
ADAS	Advanced driver-assistance systems
ATE	Average treatment effect
AV	Autonomous vehicle
BTS	(U.S.) Bureau of Transportation Statistics
CDC	United States Centers for Disease Control
DOT	(state) Department of Transportation
DUI	Driving Under the Influence (of alcohol, drugs, etc.,)
EPA	(U.S.) Environmental Protection Agency
FARS	Fatality Analysis Reporting System
FE	Fixed Effects
FHWA	(U.S.) Federal Highway Administration
FMVSS	Federal Motor Vehicle Safety Standards
GAO	(U.S.) Government Accountability Office
I/M Program	(Vehicle) inspection & maintenance program
NASS-GES	National Automotive Sampling System–General Estimation System
NCEI	National Centers for Environmental Information
NHTSA	National Highway Traffic Safety Administration
NOAA	National Oceanic and Atmospheric Administration
PennDOT	Pennsylvania Department of Transportation
USDOT	United States Department of Transportation
VIF	Variance Inflation Factor
VIU	Vehicle-in-use (standard)
VMT	Vehicle miles traveled (usually, annual)

B Dependent variable normalization

As discussed in Section 3.3, our regression specifications measure the dependent variable (*i.e.,* the fatality rate) in the number of fatalities each year per 100,000 registered passenger vehicles in each state. We chose to use a fatality rate (by the number of vehicles, in this case) rather than directly applying the absolute number of fatalities, since the former provides a more meaningful basis for comparing the number and frequency of fatal accidents between states (given the large variance in area, population, VMT and road density across states). Comparable analyses in the literature have applied several different methods of normalizing the number of fatalities. To ensure that our regressions are robust to the various means of normalization, we also present variants of Model I, with the dependent variable replaced by population- and annual statewide VMT-adjusted fatality rates (*i.e.*, roadway fatalities per 100,000 state residents, and per billion passenger miles traveled in the state). Not only would these serve as a robustness check, but these models' results—if significant—help the interpretation of coefficients, and in comparing the results presented here, to findings from other studies in the literature.

It must be noted that these models were developed from Model I, and hence restricted to accidents involving only passenger vehicles occurring in the state where all vehicles were registered—precluding direct comparison with earlier models in the literature, most of which tend to include all accident records. Results from these two models are presented in Table 6, and show similar coefficients for the treatment variable (albeit, with differing levels of confidence), regardless of how the dependent variable was normalized. This consistency in the sign and magnitude of the treatment variable coefficient indicates that the negative correlation between fatality rates and the presence of I/M programs is independent of the denominator applied to the number of fatalities. As such we find that Model I's specifications are robust to changes in the normalization of the dependent variable. Specifically, the coefficient for the treatment variable was negative regardless of whether the dependent variable (*i.e.,* the fatality rate) was defined as a function of vehicle registrations, vehicle miles traveled, or total state population.

Table 6: Variations of FE Model I with different dependent variables.

	Dependent Variable: Roadway Fatalities per		
	100k Vehicles†	Billion VMT†	100k Population†
Program	-0.028 (0.017)*	-0.035 (0.016)**	-0.025 (0.016)
Program_Repeal	-0.035 (0.035)	-0.052 (0.033)	-0.039 (0.034)
Population†	-0.418 (0.034)***	-0.174 (0.032)***	-0.417 (0.033)***
Driver_Age†	-0.284 (0.080)***	-0.237 (0.074)***	-0.310 (0.077)***
Median_Income†	0.038 (0.078)	-0.024 (0.072)	0.090 (0.076)
Vehicle_Age†	0.145 (0.048)***	0.086 (0.045)*	0.148 (0.047)***
Vehicles_Per_Accident†	0.523 (0.116)***	0.315 (0.107)***	0.458 (0.112)***
Lanes†	0.032 (0.047)	-0.031 (0.044)	0.027 (0.045)
Speed_Limit†	0.119 (0.095)	0.069 (0.088)	0.082 (0.092)
Prop_DUI†	0.213 (0.051)***	0.069 (0.047)	0.182 (0.049)***
Prop_Speeding†	-0.147 (0.043)***	-0.027 (0.040)	-0.134 (0.042)***
Prop_VehCF†	-0.115 (0.156)	-0.275 (0.145)*	-0.139 (0.151)
Prop_Weather†	0.121 (0.061)**	0.071 (0.057)	0.086 (0.060)
Prop_Surface†	-0.066 (0.097)	-0.113 (0.090)	-0.052 (0.094)
Veh_Per_Capita†	-2.552 (0.084)***	-0.046 (0.078)	0.043 (0.081)
R^2	0.584	0.896	0.901
Observations	2244	2244	2244

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

†Inverse hyperbolic sine transformation applied to this variable.