Regulating Untaxable Externalities: Are Vehicle Air Pollution Standards Effective and Efficient?*

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Abstract

What is a feasible and efficient policy to regulate air pollution from vehicles? A Pigouvian tax is technologically infeasible. Most countries instead rely on exhaust standards that limit air pollution emissions per mile for new vehicles. We assess the effectiveness and efficiency of these standards, which are the centerpiece of US Clean Air Act regulation of transportation, and counterfactual policies. We show that the air pollution emissions per mile of new US vehicles has fallen spectacularly, by over 99 percent, since standards began in 1967. Several research designs with a half century of data suggest that exhaust standards have caused most of this decline. Yet exhaust standards are not cost-effective in part because they fail to encourage scrap of older vehicles, which account for the majority of emissions. To study counterfactual policies, we develop an analytical and a quantitative model of the vehicle fleet. Analysis of these models suggests that tighter exhaust standards increase social welfare and that increasing registration fees on dirty vehicles yields even larger gains by accelerating scrap, though both reforms have complex effects on inequality.

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1 Introduction

How should governments regulate air pollution from vehicles? This paper studies the effectiveness and efficiency of air pollution exhaust standards and counterfactual policies.

Vehicle transportation is one of the world's largest sources of air pollution. It accounts for 40 percent of total US emissions of two major air pollutants, carbon monoxide and nitrogen oxides, creates $70 billion in annual pollution-related health and other damages, and causes 37,000 annual premature deaths (National Research Council 2010; Fann et al. 2013; U.S. EPA 2014). Globally, air pollution from transportation causes a quarter million deaths each year (World Bank 2014; Chambliss et al. 2014).

Textbooks describe optimal policy to address pollution—a corrective or Pigouvian tax equal to the marginal external cost of emissions, or a comparable quantity mechanism (e.g., cap and trade). But taxing vehicle air pollution emissions is infeasible because direct measurement of pollution from individual vehicles is imperfect and prohibitively expensive (Venigalla 2013). We believe no government has ever directly taxed air pollution from vehicles.[1]

Instead, the US, EU, Japan, China, Russia, India, Brazil, and most other countries rely heavily on new vehicle exhaust standards. Exhaust standards set a maximum emission rate per mile for every vehicle. Some standards also impose fleet-wide average requirements.

Exhaust standards have been controversial for decades due to their large costs and ambiguous effectiveness. In the 1970s, Ford executive Lee Iacoca claimed these standards could stop US vehicle production (Kaiser 2003). Congress has issued three requests to the National Academies of Science to provide advice involving exhaust standards (National Research Council 2001, 2004, 2006). Manufacturers have cheated on these standards, including the Volkswagen scandal that involved $22 billion in payments – the largest auto settlement in US history – leading to questions about standards' effectiveness (Yacobucci 2015).

Little economic research, however, scrutinizes exhaust standards. They are separate from fuel economy standards, which target gasoline consumption and have been the focus of much prior literature, reviewed below.

This paper helps to fill this literature gap by investigating several questions. How have vehicle air pollution emission rates changed over time? To what extent have exhaust standards caused these declines? Are these standards cost-effective? Finally, how might reforms improve policy, either via changes in the stringency of exhaust standards or through the introduction of complementary policies that accelerate vehicle scrap?

[1] Roadside pollution sensing via infrared beams has substantial measurement error for individual vehicles. Scheduled emissions tests ("smog check") when paired with high-stakes incentives can lead to avoidance behaviors, making taxes based on such tests inaccurate (Stedman et al. 1998; Merel et al. 2014; Oliva 2015). Gasoline taxes target greenhouse gas emissions but weakly proxy air pollution (Knittel and Sandler 2018).

We find striking answers to each question. First, the air pollution emissions per mile of the US new vehicle fleet has fallen by more than 99 percent since regulation began in the 1960s. This spectacular decrease may exceed that of any other major sector. Used vehicles follow similar patterns. We conclude that these trends represent genuine, long-term, large declines in exhaust emission rates of US vehicles. We find much smaller declines for carbon dioxide (CO_2) emissions that are the target of fuel economy regulations.

Second, to assess the impact of exhaust standards on emission rates, we exploit variation in exhaust standards between California and federal standards and across classes of vehicles, model years, and pollutants. We find that exhaust standards have caused 50 to 100 percent of the time-series declines in air pollution emission rates. Equivalently, we find an elasticity of vehicle emission rates with respect to exhaust standards of 0.5 to 1.0. Several pieces of evidence support these estimates' internal validity. Event study graphs show that changes in emissions align in time with changes in exhaust standards. We obtain qualitatively similar results when controlling for potential confounding policies—gasoline prices including taxes; and standards for smog check ("inspection and maintenance"), fuel economy, gasoline hydrocarbons, gasoline sulfur content, and ethanol blending. We obtain similar results when separately analyzing each set of standards, generally called Tier 0 (years 1968-1993), Tier 1 (1994-2003), and Tier 2 (2004-2016). While we find that exhaust standards do not change basic vehicle attributes (horsepower, fuel economy, etc.), they do lead manufacturers to install cleaner engines. This statistical evidence echoes informal assertions by engineers and policymakers that exhaust standards, not secular technological innovation or other forces, account for most of the decreases in air pollution emission rates from US vehicles.

Third, while the aforementioned regressions suggest exhaust standards are effective, stylized facts suggest that exhaust standards are not cost-effective. They do not equate the marginal cost of abating pollution across vehicles, a necessary condition for cost-effectiveness, because they only weakly regulate pollution from older vehicles. Emission rates of air pollutants (but not CO_2) increase rapidly with age. A majority of air pollution emissions in a calendar year come from vehicles more than 10-15 years old, which are largely exempt from exhaust standards.[2] Registration fees on the oldest and dirtiest used vehicles could in principle discourage ownership of these vehicles. We build a database containing tax rates we collected from US state and local governments describing their vehicle registration fees, motor vehicle taxes, and vehicle property taxes (which we collectively refer to as "registration fees"). We find that registration fees are higher for newer, cleaner vehicles, and

[2]Smog check programs regulate emissions of old dirty vehicles. Most of our data are from areas with smog check programs, suggesting that older vehicles could account for an even larger share of pollution in the absence of smog check programs.

thus encourage ownership of older, dirtier vehicles, thereby exacerbating inefficiencies in fleet turnover. This echoes the broader idea that a commodity tax system which imposes higher tax rates on cleaner goods can cause substantial environmental damages. For example, most countries' import tariffs, like US vehicle registration fees, are higher on cleaner goods, which increases pollution emissions (Shapiro 2021).

Fourth, we develop an analytical and a quantitative model to evaluate counterfactual policies. The early parts of the paper show regressions analyzing differences in emission rates; the latter parts of the paper combine those data with formal theoretical models to clarify remedies for and implications of the patterns in emission rates. An analytical model with few functional form assumptions provides comparative statics on how counterfactual policies affect social welfare. We analyze the steady state of a continuum of agents who can buy new vehicles from competitive manufacturers or repair new vehicles to drive them as used. Equilibrium used vehicle prices depend on exhaust standards and registration fees, and also determine scrap rates. Our first result shows that tightening new vehicle exhaust standards extends the lifetime of used vehicles, which exacerbates inefficiency from consumers scrapping used vehicles later than is socially optimal. This formalizes the "Gruenspecht Effect," which has been informally noted for many environmental policies. Our second analytical result shows that increasing registration fees on used vehicles can improve social welfare and complement exhaust standards by correcting the low scrap rate for used vehicles.

The quantitative model estimates gains from counterfactual policies. The quantification has a similar basic structure as the analytical model but allows for substitution across over 500 vehicle types differentiated by manufacturer, age, class, and size. The quantitative model also accounts for the engineering cost of meeting exhaust standards and fuel economy standards, Bertrand competition among new vehicle manufacturers, firm expectations, supply-chain (life cycle) emissions from manufacturing vehicles, and transitional dynamics. We study counterfactual changes to exhaust standards or registration fees. For each, we determine the equilibrium that results, then calculate the change in pollution emissions, producer and consumer surplus, environmental damages, and social welfare. The quantification uses data and estimates from earlier parts of the paper.

The quantitative model provides several results. Accelerating the roll-out of tighter (Tier 2) exhaust standards by one year increases social welfare by \$25 to \$30 billion. Policymakers are debating the importance of delays in stringent global climate policy; while we study air pollution rather than climate change, we find large consequences of the timing of an environmental policy. Additionally, we find that the benefits of Tier 2 exhaust standards (which operated in the 2000s and 2010s) are 10 to 15 times its costs, and that Tier 2's measured health benefits are over ten times those of a prominent cap-and-trade market for industrial plants from the same period, the NO_x Budget Program (Deschenes et al. 2018). We find larger gains, around \$300 billion in present value, from reforming annual registration fees to reflect the environmental damage of a vehicle's age×type. Changing registration fees creates these benefits primarily by encouraging scrap of old and dirty vehicles. This counterfactual causes scrap of nearly all vehicles aged 25 years old or more. Echoing the Gruenspecht Effect result from the analytical model, levying such environmental registration fees only on new vehicles actually creates welfare losses because new vehicle fees discourage scrap of old vehicles, extending their lifetimes and emissions.

These counterfactuals have complex effects on inequality. Because households in low-income communities drive older and dirtier vehicles, increasing registration fees for dirtier vehicles may trade off equity and efficiency. Dirty vehicles may also be disproportionately driven in these vulnerable communities, so environmental registration fees may have progressive environmental incidence. This is especially important since transportation is a primary source of pollution in vulnerable communities (Carlson 2018). Additionally, recycling revenues from automobile policy substantially influences its regressivity (Bento et al. 2009). We carefully discuss these channels and their political economy implications.

This paper utilizes the most comprehensive data on vehicle pollution emission rates ever constructed. It includes a half century of comparable pollution data using the same high-quality measurement method. These data cover every new US light-duty vehicle and light-duty truck sold between 1972 and 2020 and many over the period 1957-1971. We believe this is the longest-lasting comparable microdata on pollution emission rates from any country or sector.[3] We supplement these new vehicle records with 65 million used vehicle test records from three types of tests—used vehicle inspections, official regulatory "in-use" tests, and roadside remote sensing. Remote sensing measures are believed to be impervious to manufacturer "defeat devices" used to cheat on emissions tests, though have serious measurement limitations we analyze in detail. Our new vehicle data are national. Our main used vehicle data are from the state with the most high quality and extensive used vehicle tests in the US, Colorado, though we corroborate some patterns with additional data from eleven other states and six other countries. Finally, we use the Leontief Inverse of the US input-output table combined with plant-level industrial emissions data to account for the emissions embodied in the manufacturing of new vehicles and the associated supply chain.

This paper builds on several literatures. We provide the first comprehensive analysis

[3] For example, emissions data from US manufacturing only have firm-level records generally available back to 1990, in many cases come from engineering predictions rather than direct measurement, and can fail data quality tests (Currie et al. 2015). Similarly, pollution monitoring from US power plants began in 1980, is quinquennial through 1995, and in many years covers only the largest electricity generating units.

of exhaust standards, which are the centerpiece of US Clean Air Act regulation of transportation. Landmark and classic environmental economics papers study the Clean Air Act's regulation of industry (e.g., Henderson 1996; Becker and Henderson 2000; Carlson et al. 2000; Greenstone 2002; Walker 2013). Another important literature studies fuel economy standards, which are separate from exhaust standards (Goldberg 1998; West and Williams 2005; Goulder et al. 2012; Jacobsen 2013; Anderson and Sallee 2016; Langer et al. 2017). Analysis of fuel economy standards has developed methods to use the R-squared from a regression to study imperfect targeting of environmental policy (Jacobsen et al. 2020), but the primary challenge we highlight for exhaust standards involves fleet composition and scrap. Existing work largely does not directly analyze exhaust standards' effects.[4]

Additionally, this paper provides the first simple sufficient conditions for stricter environmental policy on new capital to create inefficiency by decreasing scrap, and known as the Gruenspecht Effect (Gruenspecht 1982), has been informally lamented for decades. This phenomenon will be increasingly important as the world deals with climate change. Many prominent environmental regulations differ by capital vintage, such as the US Clean Air Act's New Source Review or energy efficiency construction codes (Gruenspecht and Stavins 2002; Stavins 2006). Existing work uses regressions to analyze effects of vintage-differentiated regulations (Bushnell and Wolfram 2012; Bai et al. 2021), studies vintage-differentiated daily driving restrictions (Barahona et al. 2019), or analyzes new-vehicle purchase fees proportional to CO_2 emissions (Adamou et al. 2013; D'Haultfoeuille et al. 2013). Some papers evaluate programs that encourage retirement of polluting vehicles, including "Cash for Clunkers" (Busse et al. 2012; Sandler 2012; Li et al. 2013; Hoekstra et al. 2017).

This research also provides the first national data on, and economic analysis of, vehicle property taxes. Research has analyzed property taxes for real estate (e.g., Poterba and Sinai 2008; Cabral and Hoxby 2015) but many property taxes also apply to vehicles. We create a dataset of all vehicle property taxes and vehicle registration fees imposed by US states, cities, counties, and special districts.

In addition, this research provides the first equilibrium model of vehicle markets and scrap that accounts for air pollution abatement and emissions. Existing frameworks to analyze

[4] Prior papers describe standards (Bishop and Stedman 2008) or abatement technologies (Bresnahan and Yao 1985); summarize engineering estimates of abatement costs (Fowlie et al. 2012; Cropper et al. 2014); describe model year trends from before versus after standards change using one cross-section of vehicle tests (Kahn 1996a,b), which does not separate effects of age, model year, and standards; undertake simulations of vehicle emissions with a few types of vehicles (Mills and White 1978; Innes 1996; Kohn 1996; Harrington 1997; Walls and Hanson 1999; Fullerton and West 2010; Feng et al. 2013); or compare emissions from electric and gasoline vehicles (Holland et al. 2016). Several papers analyze used vehicle emissions from smog check tests, primarily from California, which measure pollution emission rates from used vehicles and require repairs of the dirtiest vehicles, but those papers do not evaluate exhaust standards (Feng et al. 2013; Merel et al. 2014; Knittel and Sandler 2018; Sanders and Sandler 2020).

fuel economy, economy-wide greenhouse gas emissions, or polluting industrial activity do not apply directly to air pollution from vehicles (Goldberg 1998; Goulder et al. 2012; Busse et al. 2013; Jacobsen and van Benthem 2015).

Finally, this research helps answer the question of why pollution in industrialized countries is declining. We describe a setting where a specific regulation accounts for most of a long-term national decrease in pollution emission rates.[5] While many countries and sectors have had large decreases in pollution over time, and most of this decrease reflects cleaner production within an industry rather than reallocation across industries, studies have struggled to assess which economic forces or policies have caused that decline.

The paper proceeds as follows. Section 2 describes policy and technology. Section 3 discusses the data. Section 4 describes emissions trends. Section 5 estimates effects of exhaust standards. Section 6 establishes stylized facts on cost-effectiveness. Section 7 describes the analytical model, Section 8 describes the quantitative model, and Section 9 concludes.

2 Background on Exhaust Standards

2.1 History of Exhaust Standards

In 1952, chemist A. J. Haagen-Smit discovered that hydrocarbons (HC) and nitrogen oxides (NO_x) emissions from vehicles contribute to smog. By 1959, engineers had developed technology to abate emissions by running exhaust fumes over a catalyst.

Federal regulators have since imposed standards regulating these pollutants, as well as carbon monoxide (CO). We refer to these regulations as "exhaust standards." They are also sometimes called tailpipe or emission standards. These standards limit the emissions per mile of these pollutants. We refer to the grams of pollution emitted per mile driven as a vehicle's emission rate and the total grams of pollution emitted as emissions. We refer to CO, HC, and NO_x as air pollution, though they are sometimes also called local or criteria pollution, to distinguish them from global pollutants like CO_2. Table 1 summarizes the standards. Appendix A discusses details of standards less directly relevant to our paper.

The 1965 Motor Vehicle Air Pollution Control Act created the first national standards, often called "Tier 0." The 1970 Clean Air Act Amendments substantially expanded them.[6]

[5] Following Copeland and Taylor (1994) and Grossman and Krueger (1995), researchers have allocated economy-wide changes in pollution into changes in total output ("scale"); changes in the share of output from different industries ("composition"); and changes in pollution emitted per unit of output within a given industry ("technique"). In many regions, technique accounts for most decreases in pollution from manufacturing (Levinson 2009; Cherniwchan et al. 2017; Shapiro and Walker 2018).

[6] Corporate Average Fuel Economy Standards are enabled by the Energy Policy and Conservation Act of 1975, a separate law from the Clean Air Act.

Standards began for CO and HC in 1968 and for NO_x in 1972.[7] Tier 0 standards periodically tightened through 1993. These "technology-forcing" standards essentially required every vehicle to have a catalytic converter by the mid-1970s, even though catalytic converters were not broadly viable in the late 1960s. Automakers developed and deployed catalytic converters to comply with exhaust standards. We focus on federal exhaust standards but the Clean Air Act lets California set its own, tighter exhaust standards. Other countries' standards have similar structure to US standards.

The 1990 Clean Air Act Amendments required Tier 1 standards, which phased in beginning in 1994 and became binding in 1996.[8] A few light-duty trucks could wait until 1997 to comply. Technically, exhaust standards regulate "light-duty vehicles" and "light-duty trucks"; for simplicity we refer to these categories as cars and trucks. Tier 1 decreased CO and HC standards more for categories of trucks than for cars, though required similar NO_x decreases in emission rates for cars and trucks. Thus, our analysis of Tier 1 does not focus on NO_x since it exploits differences in stringency between vehicle classes. Tier 2 standards phased in over the years 2004-2009 and continued through 2016. Tier 3 is being phased in from 2017 through 2025.

These standards have the same general approach but different details. Tier 0 and Tier 1 define maximum standards. Each standard requires every vehicle in a class (e.g., trucks in a certain weight range) to emit less than the standard. Tier 2 and Tier 3 impose fleet-wide mean standards and tightened the maximum standards. The pollutant used for the fleet-wide average standard differs across regulations.

These standards use the same test to measure a vehicle's emission rate, the Federal Test Procedure. This test specifies the chemical composition of the fuel used in the test, the speed at every second of a 30 minute test, and is run on a dynamometer, a large treadmill-like device; Appendix B discusses details.

Before a vehicle may legally be sold, the EPA must certify that the vehicle meets exhaust standards. In addition to conducting a test, the EPA or manufacturer estimates a "deterioration factor" predicting how emission rates will change during the vehicle's "useful life," which ranges from 50,000 miles and 5 years (whichever comes first) to 150,000 miles or 15 years, depending on the standard. The EPA regulates how manufacturers may determine deterioration factors. Exhaust standards apply to a new vehicle's "certification level," which equals the test result scaled up by the deterioration factor.

Several years after a vehicle is manufactured, the EPA assesses "in-use" compliance.

[7] All years in this section refer to vehicle model years.

[8] Only 40 percent of vehicles had to comply with Tier 1 in the 1994 model year and 80 percent in 1995. Because many vehicles already met Tier 1 standards in 1993, Tier 1 was most binding for the dirtiest vehicles, which could remain at existing emission levels until model year 1996.

Manufacturers conduct emissions tests on samples of vehicles at up to 150,000 miles and the EPA audits some. If these tests find emission rates above the standard, the vehicle is recalled and the emissions control system repaired or replaced. Between 1975 and 2008, 80 million vehicles, or about 16 percent of all vehicles sold, had recalls, though some of these involved minor reclassifications (U.S. EPA 2008; Department of Energy 2016). Accurately predicting a new vehicle's emission rate at 50,000 or 150,000 miles is challenging. In-use tests and the costs of recalls give manufacturers an incentive to over-comply with exhaust standards. Industry engineers and regulators we interviewed describe over-compliance, sometimes called headroom or a safety margin, as typical for this reason.

2.2 Pollution Abatement Technologies

Explaining technologies used to meet these standards helps interpret results; Appendix C provides details. The approach has changed little since the 1970s: expose exhaust to precious metals inside a catalytic converter, which converts pollution into harmless gases. Because these metals are catalysts, pollution can react with them without consuming or changing them. The precious metal palladium primarily abates CO and HC, which have complementary abatement technologies; rhodium primarily abates NO_x; and platinum abates all three. Under ideal conditions, these reactions eliminate 100 percent of CO, HC, and NO_x.

Lead and sulfur render catalytic converters ineffective by coating the catalyst. Our used vehicle data begin after model year 1975, when vehicles required unleaded gasoline (Mondt 2000). Despite the phase-out of lead and sulfur gasoline, catalytic converters decrease in effectiveness over time. Degradation comes from remaining low levels of lead and sulfur in gasoline, wear of precious metals, or breakdown of complementary technologies like oxygen sensors.

Would emission rates decline without regulation, due to secular innovation? Engineers and regulators we interviewed argued that technologies that improve vehicle drivability do not affect pollution, so automakers would only decrease emission rates due to regulation. Crandall et al. (1986, pp. 92-93) summarize this view: "There is little evidence to support the view that emission rates would have fallen significantly without the emissions standards program." Innovation may still decrease the marginal cost of controlling vehicle emission rates over time. Because emissions-related recalls are common and costly, even when policy is constant, decreasing marginal abatement costs over time give auto manufacturers an incentive to decrease emission rates even further (additional "overcontrol"), even without tightening standards, to decrease the rate of unexpected recalls.

One may also wonder whether trends in "green" or "warm glow" preferences for environmentallyfriendly goods could explain changing vehicle emission rates. We believe this is not a major contributor, in part due to limited consumer information. We have not found anecdotal or statistical evidence that consumers value or even know their vehicle's air pollution emissions, though consumers may have information on fuel economy. Unlike fuel economy, information on a vehicle's air pollution is not easy to find and interpret.[9]

2.3 Other Policies Relevant to Emission Rates

Some other environmental policies are relevant to our analysis, and our regressions and quantitative model account for them. Corporate Average Fuel Economy standards regulate the mean fuel economy of new vehicles. Fuel economy standards did not change in the periods we study most closely (Department of Transportation 2014). Federal gasoline excise taxes, state retail gasoline taxes, and gasoline prices could affect miles traveled or driving behavior. Around ten percent of US counties operate smog check programs in which used vehicles must pass regular emissions inspections to be registered. Our data mostly come from areas with smog check, so our findings that vehicle emission rates rise sharply with age, and our estimates of the benefits of scrapping old dirty vehicles, might be even larger without smog check. Some states and cities regulate the chemical content of gasoline in order to decrease emission rates of HC, though not other pollutants (Auffhammer and Kellogg 2011). These regulations are not relevant to our main data from Colorado, since Colorado has not used gasoline with regulated chemical content (U.S. EPA 2019). Ethanol accounts for an increasing share of fuel, in part due to policy incentives. Evidence on how ethanol affects exhaust emission rates is mixed (Hubbard et al. 2014). Finally, many states impose annual vehicle registration fees that vary with vehicle characteristics, especially price and age. We collect and use data on these fees in Sections 6 and 8 below. Our data show that local or state governments in 28 states, listed in Appendix D.8, impose vehicle registration fees that vary with vehicle age or value.

[9] Air pollution emission rates are not shown on most leading consumer automotive websites. The EPA calculates a 1 to 10 "smog rating" for vehicles, which now appears in small font on a vehicle's fuel economy sticker. But this rating is not clearly explained and was absent for most of our sample period.

3 Data

3.1 New Vehicle Pollution Data

We obtain test results for each new vehicle type from the Annual Certification Test Results Report, also called the Federal Register Test Results Report.[10] We obtain electronic records for model years 1979 to 2019 from the EPA and keyed in records for years 1972-1978 from the Federal Register (1978); see Appendix D.2 for details. Although these data determine compliance with the Clean Air Act, we are not aware of any economics research using them.

For model years 1957-1971, we obtain data on used vehicles tested in AES (1973), which applied the Federal Test Procedure to about 1,000 vehicles aged 1 to 14 years old from six cities. The sample statistically represented the national distribution of vehicle characteristics. In model years before exhaust standards, emission rates of these vehicles do not appear to increase with age and are similar to estimates of uncontrolled emission rates. This is sensible because before exhaust standards, vehicles did not have emissions control systems that could break down. Hence, for these pre-regulation years, new and used vehicles likely had similar emission rates. We identify vehicles meeting California standards in AES (1973) as those sold in California and vehicles meeting federal standards as those sold in other states.

3.2 Used Vehicle Pollution Data

Our primary used vehicle emission rates data come from smog check tests in Colorado, which we use for several reasons. While many states have smog check programs, recently only Colorado has used the highest-quality smog check test, called IM240 (the inspection and maintenance test that lasts 240 seconds). This test provides a short version of the Federal Test Procedure and is considered the "gold standard" of smog check tests for its quality and comparability to the Federal Test Procedure (Sierra Research 1997; Joy et al. 2004; U.S. EPA 2006); Appendix D.1 discusses this comparability.[11] Most other states only obtain an internal computer description of the performance of a vehicle's emissions control system (an "on-board diagnostic test") and do not measure exhaust emission rates for most vehicles. Colorado includes about 15 million tests and extensive remote sensing and registration data.[12] Appendix D.3 shows that the Colorado counties have similar driving and emissions patterns

[10] We use "class" to denote cars versus trucks, or weight categories of trucks, and "type" to denote more detailed classification of vehicles such as manufacturer, size, trim, or engine specifications.

[11] The EPA describes the IM240 test as "the most accurate short test available for use in I/M programs" (U.S. EPA 1995). Colorado describes it as "arguably the most accurate emissions test currently in use for replicating the Federal Test Procedure (FTP) that is used to certify new model year vehicles" (AIR 2015).

[12] Most economic research using data on US used vehicle emission rates uses data from California, but its data have lower quality; Appendix B provides details.

to other polluted urban US counties.

The Colorado data cover calendar years 1997 through 2014. In these years, all Colorado gasoline vehicles model year 1982 or later are tested biennially, beginning at age four, so the data cover model year 1982 through 2010. Appendix D.3 describes additional sample restrictions, such as excluding observations missing key variables.

We take a few steps to limit concerns about avoidance and short-term evasion behavior. We restrict the Colorado sample to the first test in a sequence, which is less subject to short-term manipulation concerns. A sequence is a test series for a specific registration, ending in a vehicle passing (and then able to register) or being sold, traded, or driven unregistered. Manipulation is more likely after a vehicle fails the first test. We also include estimates that control for the stringency of the smog check standard for a particular vehicle and test. Additionally, we report sensitivity analyses using remote sensing estimates from a Colorado database with over 50 million remote sensing readings; from smaller samples taken in 11 states; from 4 other countries; and from heavy duty trucks (e.g., 18 wheelers).[13] Appendix D.4 describes details. Remote sensing data come from roadside infrared or ultraviolet beams that measure pollution concentrations in an exhaust plume. Remote sensing data are believed to be impervious to defeat devices.[14]

We use remote sensing data only for sensitivity analyses since they have substantial measurement error, have imperfectly comparable units versus new or used vehicle tests, exclude emissions from idling or deceleration, rarely measure highway driving speeds, and miss the high emission rates from a trip beginning (Borken-Kleefeld 2013). Appendix Table A1 compares remote sensing and smog check readings from the same vehicle in essentially the same week. If remote sensing and smog check data were perfectly comparable, Appendix Table A1 would obtain regression coefficients and elasticities of one. While matched remote sensing and smog check readings are extremely strongly correlated, the magnitude of that regression coefficient in levels ranges from 0.00001 to 470, and the magnitude of the elasticity ranges from 0.01 to 3.14, depending on the pollutant and specification, and none of the 95% confidence regions includes either zero or one. We thus interpret remote sensing as an important check on the sign and precision of changes in emission rates, but interpret magnitudes from remote sensing cautiously due to its differences in units and measurement.

Finally, we report some sensitivity analyses from "in-use" tests in California (see Appendix D.5), which have no direct incentives for vehicle owners so are unlikely to suffer from short-term manipulation. As mentioned earlier, in-use tests apply the Federal Test Proce-

[13] The multi-state remote sensing sample includes data from Arizona, California, Illinois, Maryland, Nebraska, Nevada, Oklahoma, Pennsylvania, Texas, Utah, and Washington.

[14] Defeat devices typically turn on parts of an emissions control system only when they detect that a vehicle is undergoing a laboratory driving test. Remote sensing observes vehicles during typical on-road driving.

dure to a sample of vehicles several years old to assess compliance of the vehicle type with exhaust standards.

3.3 Other Data Notes

Appendix Table A2 summarizes the datasets used in the paper and may help address potential questions about the datasets, samples, and coverage. We use all years to describe emission rate trends and subsets of years to analyze Tiers 0, 1, and 2. In addition, we use vehicles from model year 1993 and calendar year 2000 to describe fleet-wide emissions, and test year 2000-2014 data to calibrate the quantitative model. Appendices D.6 and D.7 discuss details including concordances, use of the US input-output table and plant-level industrial emissions data to measure the emissions from manufacturing vehicles, and the marginal damages of pollution.

Here we briefly summarize the measure of emissions from manufacturing vehicles. We use the Leontief Inverse of the US input-output table, which lets us measure the entire supply chain of all goods used to produce a car. We measure emissions from each industry in the vehicle supply chain by using plant-level air pollution emissions data from the National Emissions Inventory. Aggregated, this calculation suggests that manufacturing a new car or truck creates about $600 in environmental damages due to air pollution in the year 2000, including emissions from the entire supply chain, which is in the ballpark of numbers that engineers have estimated from life cycle analyses. These damages fall over time as manufacturing becomes cleaner.

4 Trends in Emission Rates

We first quantify trends in new and used vehicle emission rates. Figure 1 plots mean emission rates in grams per mile from new US vehicles over the model years 1957-2020. It is rare and potentially unprecedented to have a pollution time series based on source-level microdata with comparable measurement methods for this long of a period. The figure shows the three air pollutants exhaust standards target—CO, HC, and NO_x. It also shows CO_2, which fuel economy standards target. The graphs show the mean certification level for 50,000 miles, i.e., the emission rate of a new vehicle scaled up by an engineering calculation reflecting 50,000 miles of driving. Each y-axis has log scale. The vertical lines show the year before exhaust standards. The lines with blue squares show the unweighted mean across vehicle types. For model years 2000-2015, the lines with hollow red circles show means weighted by fleet size.

Figure 1 shows that the emissions per mile for each air pollutant have fallen by more than 99 percent since regulation began. CO has fallen by 99.5 percent, HC by 99.7 percent, and NO_x by 99.6 percent. For example, the mean CO emission rate of new US vehicles fell from 85 grams per mile in the 1960s to 0.4 grams per mile in 2020. Even between 1990 and 2018, these emission rates fell by 75 to 95 percent. Unweighted trends and trends weighted by fleet size are similar. The long lifetime of vehicles in a setting where emissions are rapidly declining implies that at any given moment, older vehicles are operated alongside newer vehicles that are substantially cleaner. This motivates our consideration of policies targeted to accelerate retirement in Section 7, and the changes in emission rates between model years we document here have an important role in the quantitative model of Section 8.

For context, between 1990 and 2018, ambient pollution levels (which depend on emissions from all sources) of CO, NO_2, and ozone fell by 20 to 75 percent (U.S. EPA 2018), suggesting that new vehicles cleaned up faster than other pollution sources. The decrease in emission rates from new vehicles is more rapid than declines in manufacturing emissions or ambient water pollution over this period (Shapiro and Walker 2018; Keiser and Shapiro 2019).

Comparing emission rates in Figure 1 and exhaust standards in Table 1 shows that emission rates fall most in years when policy tightens. Emission rates are flat before standards begin. Rates then decline rapidly. Figure 1 reflects the large decreases that standards required in 1975. The CO and HC graphs show flatter lines between 1984 and 1993, when standards were largely unchanged. Emission rates and standards were also flatter between 2007 and 2017.

Figure 1 also shows that CO_2 fell less than air pollution. CO_2 only fell by 50 percent between 1957 and 2017 and by 25 percent between 1990 and 2017. The changes in CO_2 rates largely occurred in the late 1970s and 2010s, when fuel economy standards tightened. Between 1982 and 2007, both the CO_2 line and fuel economy standards were flat.

Used vehicle emission rates have similar patterns, though they are available for fewer years and are subject to the challenge of disentangling model year, test year, and age effects. Appendix E.1 explains how we analyze Colorado smog check data here. Appendix Figure A1 shows that mean used vehicle emission rates for each air pollutant fell by roughly 90 percent between 1982 and 2010; new vehicle emission rates from Figure 1 fell by similar amounts. Mean CO_2 emission rates of the used vehicle fleet actually increased between model years 1990 and 2005, partly due to the increasing market share of light-duty trucks.

Many economics papers ask whether economy-wide changes in pollution occur due to changes in the scale of economic activity, the composition of activity across types of goods, or the pollution emission rates (the "technique") for each good. Appendix E.2 describes such a decomposition using these data, and Appendix Figure A2 graphs the result. We find that all the decrease in air pollution is due to technique, which echoes findings from literature on industrial pollution discussed in the introduction. In other words, air pollution emission rates from vehicles are falling not because people are driving less, or driving different types of vehicles, but because the average vehicle of a given type has become cleaner. CO_2 again differs from air pollution in this regard. CO_2 does not have comparable declines, partly due to the growing share of larger vehicles with poor fuel economy.

5 Effects of Exhaust Standards on Emission Rates

This section describes effects of Tier 0, 1, and 2 exhaust standards on emission rates. We use different approaches for each Tier, reflecting relevant regulations and data. One goal is to understand to what extent exhaust standards caused the trends documented in Section 4. We focus on estimates in logs (though also report estimates in levels) because this facilitates comparisons across pollutants and datasets, provides one simple way to address outliers, and has a straightforward interpretation even when manufacturers over-comply with standards.

5.1 Econometrics: Effects of Exhaust Standards on Emission Rates

Tier 0. We analyze how Tier 0 affected emission rates by exploiting the fact that some pollutants became regulated in the 1960s (CO, HC) but others did not (NO_x,CO_2). We use the following equation:

$$lnE_{pry} = \beta_1 lnS_{pry} + \eta_{pr} + \lambda_y + \epsilon_{pry}. \tag{1}$$

We analyze model years with comparable data, 1957-1971. We use grouped data—each observation represents the mean emission rate of vehicles for pollutant p (CO, HC, NO_x, or CO_2), in region r (California or federal), from model year y. The variables E and S represent emission rates and standards. In years before regulation, we define the exhaust standards to equal the unconstrained emission rate, from Table 1. The coefficient β_1 represents the elasticity of emission rates with respect to exhaust standards. Because these are grouped data, we report heteroskedastic-robust standard errors.

Fixed effects control for potential confounding variables. Pollutant×region fixed effects, η_{pr}, address time-invariant differences between vehicles sold in California, which faced California's standards, versus those sold in other states, which faced federal standards, separately for each pollutant. Model year fixed effects, λ_y, address time-varying emission rates common to all vehicles nationally.

Tier 1. For Tier 1, we have measures of both new and used vehicle emission rates; we have vehicle-level data; data do not as clearly distinguish California from federal-certified vehicles; and we exploit that standards change differentially for cars and trucks. We estimate versions of the following equation:

$$lnE_{picy} = \beta_2 lnS_{picy} + X'_{picy}\pi + \mu_{pc} + \nu_{py} + \xi_{pa} + \epsilon_{picy}. \tag{2}$$

We focus on data from model years 1990-2000, surrounding the introduction of Tier 1 standards. We report separate estimates where E represents new or used vehicle emission rates. Each observation represents a reading of pollutant p for vehicle i, belonging to vehicle class $c \in$ (car, truck, or sub-groups by weight) and model year y. For estimates of used (but not new) vehicle emission rates, we include controls X for age fixed effects, odometer, and other policies that could affect emission rates such as fuel economy, fuel content, or smog check standards. The regression also includes fixed effects for pollutant×vehicle class, pollutant×model year, and pollutant×age (μ_{pc}, ν_{py}, and ξ_{pa}). The coefficient β_2 represents the elasticity of emission rates with respect to exhaust standards. We cluster standard errors by model year×vehicle class. As discussed in Section 2.1, we do not analyze NO_x here because Tier 1 had similar NO_x standards changes for cars and trucks. We do not decompose treatment effects by year (Goodman-Bacon 2021) because exhaust standards change for all vehicles in the same model years.

Tier 2. After model year 2000, regulations imposed fleet-wide average standards. This makes it more difficult to use difference-in-differences. Instead, we analyze the extent to which new vehicle emission rates predict used vehicle emission rates of the same vehicle. This is informative because exhaust standards mandate decreases in mean new vehicle rates. Thus, this effectively assesses how standards affect used vehicle emission rates. Specifically, we estimate the following equation:

$$lnE^u_{picy} = \beta_3 lnE^n_{picy} + X'_{picy}\zeta + \nu_{py} + \xi_{pa} + \epsilon_{picy}. \tag{3}$$

We analyze model years 2000-2010 because the concordance file linking new vehicle engine families and used vehicle Vehicle Identification Number prefixes begins in model year 2000, and our Colorado smog check data conclude in model year 2010. Here E^u is the used vehicle test result of vehicle i, E^n is the new vehicle emissions test result corresponding to used vehicle i, and c, y, and X are defined above. The coefficient β_3 represents the elasticity of used vehicle emission rates with respect to new vehicle emission rates.[15] The regression

[15] It might seem useful to estimate an instrumental variables regression, where standards instrument for new vehicle emission rates, i.e., where equation (2) is the first stage and equation (3) is the second stage. This is infeasible because before the new-used vehicle concordance begins in model year 2000 and we do not know the new vehicle emission rate corresponding to a specific used vehicle test. After model year 2000, standards use fleet-wide averages, which makes the cross-class research design from Tier 1 less relevant.

includes age and model year fixed effects (μ_{pa}, ν_{py}), which vary by pollutant.

5.2 Results: Effects of Exhaust Standards on Emission Rates

Before estimating regressions focused on narrow time periods, we start with raw trend data by class. Figure 2 shows the national time series of mean exhaust standards (Panels A-C) and new vehicle emissions (Panels D-F). They cover model years 1982-2010. In each graph, the blue solid line describes cars and the dashed red line describes trucks. The vertical dashed lines show when car standards changed; the vertical solid lines show when car and truck standards changed. Each panel shows a different pollutant (CO, HC, and NO_x). Values are measured in grams of pollution emitted per mile.

These Figure 2 graphs reveal close correspondence between standards and emissions. For example, in 1984, truck standards for CO and HC fall abruptly and emission rates do also. In 1996, when Tier 1 rolled out, standards and emissions again move in tandem. A similar pattern occurs for Tier 2 in the mid-2000s.

The main exception to this correspondence in timing of standards and emissions is the gradual decline in NO_x truck emissions in model years 1982-1987 that Panel F shows. California gradually tightened its standards for light-duty trucks in these years, while the EPA only tightened standards discretely in 1987. The new vehicle emission rate data in the early to mid 1980s do not distinguish California from federal vehicles, so the 1980 trend in NO_x emission rates for trucks likely reflects compliance with California's gradually tightening standards.

These graphs also show over-compliance. New vehicle emissions are typically 40 to 50 percent of exhaust standards. For each pollutant, the y-axis scale in Panels D-F is nearly half the scale in Panels A-C. For example, in 1990, light-duty vehicles and trucks faced CO standards of 10 and 4, but emission rates for these groups were around 4 and 2. As discussed in Section 2.1, manufacturers over-comply with exhaust standards because compliance is ultimately assessed against used vehicles 5 to 10 years later. In addition, violations are costly—emissions-related recalls can decrease stock prices of auto manufacturers by one percent or more and cost thousands of dollars per vehicle (Ferris 2019).

Appendix Figure A3 shows versions of these graphs for used vehicle smog check and remote sensing data. Those used vehicle data suggest similar patterns, though with smoother adjustment potentially in part due to the greater measurement error in used vehicle tests and the complication of separating test year, model year, and age effects.

We now turn to regressions focused on each Tier of exhaust standards separately.

Effects of Tier 0 Exhaust Standards (Model Years 1957-1972)

Figure 3 shows annual emission rates over model years 1957-1972. Panel A shows vehicles facing federal standards and Panel B shows vehicles facing California standards. Each line shows a different pollutant. Federal standards regulated CO and HC in 1968. California standards regulated CO and HC in 1966. Standards only regulated NO_x or CO_2 in 1972 and 1978, respectively. The vertical line in each graph shows the year before regulation began.

Figure 3 suggests that exhaust standards substantially decreased emission rates of regulated pollutants. Before regulation, emission rates of all four pollutants were fairly flat. This is consistent with a limited effect of secular productivity growth on emission rates. When California's exhaust standards began in 1966, CO and HC from California vehicles fell. CO and HC emission rates from federal vehicles only decreased two years later in 1968, when federal regulation began. The other pollutants, CO_2 and NO_x, did not fall when CO and HC standards began, and if anything increased. These other pollutants may have increased because catalytic converters were not commercially viable in the 1960s, so manufacturers at that time responded to CO and HC exhaust standards with technologies, primarily combustion modification, that can increase NO_x and CO_2 (National Research Council 1988, 2006).

Table 2 shows regressions corresponding to equation (1). Panel A pools pollutants. Panels B and C show one pollutant each. Column (1) is a time series estimate comparing across model years and within each pollutant and region. Columns (2) through (7) provide difference-in-differences estimates comparing across regions and model years.

Table 2 shows that Tier 0 exhaust standards substantially decreased emission rates. The time series estimate in column (1) obtains an elasticity of emission rates with respect to exhaust standards of 0.61 (0.07). Our preferred elasticity estimate is 0.80 (0.07), from the difference-in-differences estimate of column (2). The column (3) estimate in levels is moderately larger. Estimates restricted to California only in columns (4) and (5), or federal certified vehicles only in column s(6) and (7), are similar to the overall estimates. The pooled estimates in Panel A are precise, with t-statistics above five, though some pollutant-specific estimates in Panels B and C vary in precision and magnitude.

Effects of Tier 1 Exhaust Standards (Model Years 1990-2000)

Figure 4 shows event study graphs analyzing the roll out of Tier 1 standards between model years 1990 and 2000. Panels A and B show the change in exhaust standards, Panels C and D show the change in new vehicle emission rates, and Panels E and F show the change in used vehicle emission rates. All these graphs plot differences between trucks and cars by model year, with values for 1993 normalized to zero. As discussed earlier, Tier 1 primarily became binding in model year 1996, though the roll out formally began in 1994. Unfortunately, new vehicle emission rate data are unusable for 1994-1995 (see Appendix D.2).

Figure 4 shows that Tier 1 exhaust standards decreased new and used vehicle emission rates. Panels A, B, E and F show that used vehicle emission rates and standards change by roughly similar amounts. Panels C and D show that new vehicle emission rates change less, which is consistent with initial firm over-compliance, as discussed earlier. The new vehicle graphs show some differences between cars and trucks in model years 1990-1992. This 1990-1992 pattern does not appear for used vehicle emission rates, which is important because used vehicle emission rates are likely closer than new vehicle emission rates to what vehicles actually emit on the road. This is one reason we report regressions controlling for model year×vehicle class time trends.

Table 3 reports regressions corresponding to equation (2). The pooled time-series estimate in column (1) compares across model years and within categories of cars and trucks. The difference-in-differences estimate in column (2) adds model year controls, and thus exploits changes within cars and trucks and across model years. Column (3) controls for other policies, each in levels and interacted with a truck indicator—fuel economy standards, smog check standards, each vehicle's gasoline cost per mile (equal to the relevant tax-inclusive retail gasoline price divided by the vehicle's fuel economy), the share of fuel from ethanol, and the sulfur content of fuel. Column (4) adds model year×truck linear trends. Column (5) limits the sample to vehicles aged 4 to 6 years, which is the age that Tier 1 exhaust standards primarily target. Column (6) expands the sample to begin in model year 1982. Column (7) estimates the regression in levels rather than logs. Panels A through C analyze used vehicle (smog check) emission rates, while Panels D through F analyze new vehicle rates. The new vehicle regressions include the subset of the aforementioned controls that are relevant to new vehicle tests. Table 3 uses specifications similar to those of Table 2, with modifications reflecting differences in data and policies between Tier 0 and Tier 1.

Table 3 shows large and precisely estimated effects of exhaust standards on used and new vehicle emission rates. The time series estimate in column (1) shows a large elasticity of used vehicle emission rates with respect to standards. The basic difference-in-differences estimate in column (2) is 0.83 (0.10) for used vehicles and 0.72 (0.14) for new vehicles. Controlling for other environmental policies in column (3) does not change the estimate.[16] Controlling

[16]One interpretation of these estimates is that even if CAFE standards had not been implemented, tightening exhaust standards would have decreased emission rates per mile substantially. But because a vehicle's air pollution emission rates change almost one-for-one with its gasoline consumption, if exhaust standards had not been implemented, tightening CAFE standards would have decreased emissions per mile to some extent. In this sense, each policy alone would have been sufficient to decrease emission rates, though the

for model year×vehicle class trends in column (4) moderately decreases the used vehicle estimates but increases the new vehicle estimates. Most estimates are precise.

Appendix E.3 discusses many sensitivity analyses, which provide qualitatively similar results, and an analysis of mechanisms including vehicle attributes and within- versus between-engine estimates, which shows that two-thirds of the effect of exhaust standards on emission rates comes via improved pollution abatement technology within-engine, and one third comes from replacing dirtier with cleaner engines.

Effects of Tier 2 Exhaust Standards (2000-2010)

Table 4 evaluates the effects of Tier 2 standards on emission rates, using regressions corresponding to equation (3). Columns (1) through (6) repeat the specifications of Table 3. These regressions use the observations which completed all 240 seconds of the smog check test (Appendix D.3 describes details). Columns (7)-(8) add back the abbreviated tests.

Table 4 shows that new vehicle emission rates strongly predict used vehicle emission rates. The pooled elasticities in Panel A are generally around 0.5 to 0.6, though different pollutants and specifications have larger or smaller elasticities. Nearly every estimate rejects elasticities of both zero and one with 99 percent confidence.

Rejecting the null hypothesis of zero implies that new vehicle emissions tests predict a vehicle's actual emission rate. This suggests that even if defeat devices or short-term manipulation occur, enforcement is imperfect, or abatement technologies deteriorate unexpectedly, new vehicle emissions tests strongly predict used vehicle emission rates.

Why are many of these elasticities below one? Panel E of Table 4 for CO_2 suggests that measurement provides an important answer. A vehicle's fuel economy and associated CO_2 emission rate, unlike its air pollution emission rate, does not typically depreciate with age. Hence, the primary reason why the elasticities in Panel E are below one is measurement error both within and between new and used vehicle tests. The CO_2 elasticities in Panel E range from 0.72 to 0.95; all these estimates are significantly less than one, though most are larger than the estimates for air pollution in Panels A through D. Because air pollution emission rates depend on fuel economy, emissions control system performance, and additional variables, measurement error may be more important for air pollution than for CO_2.

Appendix Table A5 obtains qualitatively similar estimates from sensitivity analyses using in-use tests, Colorado remote sensing data, and the multi-state remote sensing sample. As discussed in Section 3.2, the units of the remote sensing tests are less comparable and obtain varying magnitudes, but the signs are in the expected direction and the remote sensing estimates are precise.

decrease due to exhaust standards is larger and would have occurred even without CAFE standards.

Binned scatterplot comparisons of new and used vehicle emission rates in Figure 5 show the tight relationship between new and used emission rates of the same vehicle type. Each graph groups all new vehicles into twenty equal-sized bins, then plots the mean used vehicle emission rate for each bin and the linear trend. For all three air pollutants and for CO_2, the regression line has linear slope, indicating that the elasticity of used to new vehicle emissions is constant.

5.3 Discussion: Effects of Exhaust Standards on Emission Rates

This section has described different data and research designs to assess the effects of Tiers 0, 1, and 2 on new and used vehicle emission rates. These estimates generally imply elasticities between 0.5 and 1.0, suggesting that exhaust standards have caused between half and all of the time series decline measured in Section 4. In this sense, exhaust standards are effective and binding, although we observe over-compliance.

The remainder of the paper uses these results in several ways. The next section uses the data to describe stylized facts on the cost-effectiveness of exhaust standards and registration fees that belie inefficiencies in the current policy regime. The analytical and quantitative models of Sections 7 and 8 take from this section that exhaust standards are effective, assess their efficiency, and suggest counterfactual policies that would increase welfare.

6 Stylized Facts on Cost-Effectiveness and Age

6.1 Emission Rates Increase with Age

We first compare emission rates across ages within a single individual vehicle. Figure 6 shows age fixed effects from a regression that also controls for odometer reading and for a 17-digit vehicle identification number. The figure shows that a vehicle's CO_2 rates and associated fuel economy do not change with age. While some websites and vehicle experts assert that a vehicle's fuel economy does not change with its age (e.g., Consumer Reports 2009), we are unaware of prior statistical evidence for this assertion. By contrast, Figure 6 shows that a vehicle's air pollution exhaust emission rate increases rapidly with vehicle age. For example, a vehicle 25 years old emits 170 percent more NO_x and 750 percent more HC per mile than the same individual vehicle when it was 4 years old. This difference makes sense—as vehicles age, catalytic converters and other pollution abatement technologies break down, increasing emissions. But because end-of-pipe pollution control technologies are not commercially viable for CO_2, vehicles have no CO_2 control systems that would break down with age, and thus a vehicle's CO_2 emission rate does not change with age. Appendix Figure A4 shows similar patterns in other states and countries, and for heavy duty trucks.

To what extent does the age-emissions relationship vary across model years? Figure 7 plots mean emission rates and annual driving by model year and age. Panels A through C show air pollution, Panel D shows CO_2, and Panel E shows annual miles traveled. The y-axes have logarithmic scale. These visually show the extent to which deterioration of emissions control systems has changed across model years.

The upward-sloping lines in Panels A through C of Figure 7 demonstrate that vehicles at older ages of a given model year have higher emission rates. This is unsurprising because emissions control systems deteriorate with age. The upward shift of the lines for earlier model years in Panels A through C implies that earlier model years have higher emission rates. The age-emissions profile is similar for most groups of model years, though NO_x controls may be deteriorating more gradually. The logarithmic scale of the y-axis implies that these effects are proportional to age. Panel D shows that none of these patterns occur for CO_2. The downward slopes in Panel E imply that older vehicles drive fewer annual miles. This may occur because most households have two vehicles and prefer to drive the newer vehicle (Archsmith et al. 2020) or because the households that own older vehicles have lower driving demand. Appendix Table A6 shows regression analogues to these graphs that imply similar conclusions.

6.2 Older Vehicles Account for a Large Share of Emissions

Exhaust standards limit used vehicle emission rates through in-use testing, but in-use tests only apply to vehicles up to 10-15 years old. Exhaust standards are therefore unlikely to equalize abatement costs across vehicles of different ages, which is a necessary condition for cost-effectiveness (the equimarginal principle). Intuitively if older vehicles cause a large share of emissions, exhaust standards will be less cost-effective.

Figure 8 plots the cumulative distribution of emissions versus vehicle age. Panels A through C show a cross-section of vehicles in calendar year 2014. Panel D shows a cohort of model year 1993 vehicles.[17] Panels A and D use smog check data. Panels B and C use remote sensing data. The vertical red lines show ages 10 and 15. Each graph shows separate curves for each pollutant.

Figure 8 shows that a large share of air pollution emissions come from vehicles older than 10 to 15 years. In the 2014 cross-section of Panel A, 70 to 80 percent of air pollution

[17] We show cross-sectional data for 2014 since it is the most recent year when Colorado required smog check test of vehicles aged 4 and older. We show cohort data from 1993 since this is the earliest model year where we observe tests of four-year old vehicles.

emissions come from vehicles older than 10 years. Vehicles older than 15 years account for 30 to 50 percent of air pollution emission but only 10 percent of CO_2 emissions. Less CO_2 comes from older vehicles because fuel economy, unlike air pollution, does not change with vehicle age and because fuel economy standards have changed less than exhaust standards across model years. Although older vehicles are driven fewer miles per year and are more likely to be scrapped, their air pollution emission rates are high enough to offset the lower mileage. Panels B and C show qualitatively similar patterns from Colorado and multi-state remote sensing data.

Figure 8, Panel D, shows cumulative distributions for vehicles manufactured in model year 1993. This captures the effects of age but not model year. Here vehicles older than 10 years account for 25 percent of a vehicle's lifetime emissions. Comparing Panels A through C with Panel D suggests that in a given calendar year, older vehicles emit more pollution mainly because they come from earlier model years; a secondary reason is that they have older age for a given model year.

Secular trends in vehicle longevity in the US fleet amplify these pollution differences. Appendix Figure A5 shows large linear trends in the mean age of US vehicles over the last half century. In 1970, the mean US vehicle was 6 years old; in 2018, mean vehicle age had doubled to 12 years. This aging likely reflects both improved durability technology for automakers and increasing new vehicle prices via the Gruenspecht Effect.

6.3 Annual Registration Fees are Higher on Cleaner Vehicles

Exhaust standards mandate clean new vehicles. They do not give consumers an incentive to scrap dirty old vehicles and do not give manufacturers an incentive to decrease pollution from their vehicles as they get older. Annual ownership fees that increase with the pollution emitted from a vehicle would give drivers and auto manufacturers broader incentives to decrease pollution.

Many states and local governments already impose annual registration fees for vehicles that vary with a vehicle's attributes. How do these existing fees vary with emissions?

Figure 9 plots the mean annual registration fee in dollars for vehicles aged 4 to 18 years, for the 28 states where these fees vary with vehicle value or age. The solid blue line shows the mean annual registration fee, while the dashed red line shows the annual air pollution externality from the calendar year 2000 fleet, all in 2019 dollars.

Figure 9 shows that dirtier vehicles face lower registration fees. In other words, these registration fees resemble a subsidy to encourage emissions, not a tax. Owners of 18-year old vehicles pay \$100 less in annual registration fees than the owners of 4-year old vehicles do. But 18-year old vehicles create about \$700 more in air pollution damages than 4-year old vehicles create. Registration fees are monotone decreasing in age, while annual externalities are monotone increasing in age. Modifying this perverse incentive is one of the key considerations of the next two sections.

7 Analytical Model

The previous sections show that exhaust standards decrease emission rates and that registration fees are higher on cleaner vehicles. We now develop a model with minimal functional form assumptions to clarify how these standards and registration fees affect scrap and welfare. Motivated by the trends, regressions, and stylized facts of Sections 4 through 6, we focus on differences in policy and emissions between vehicles of different ages and model years. The quantitative model in Section 8 has heterogeneity within vehicle ages and transition dynamics; here we focus on the steady state. The goal of these models is to clarify mechanisms by which exhaust standards affect emissions and to address questions that the regressions of the previous sections alone cannot, such as how different types of exhaust standards and registration fees affect social welfare.

7.1 Analytical Model Setup

We consider a single vehicle type that can last up to two time periods t. A vehicle is initially new (n) and becomes used (u) in the next period. Driving new and used vehicles emits pollution. Manufacturing new vehicles also emits pollution. A measure one continuum of risk-neutral consumers demands vehicles. Pollution is a pure externality, so consumers ignore it in making expenditure decisions. Denote the size of the new and used vehicle market as N and U, respectively, where $N + U = 1$ in a period, so that there is no outside good.[18]

Demand reflects consumers' different taste for new versus used vehicles. We normalize the value of a used vehicle to 0 and let w denote willingness to pay for a new vehicle, distributed $G(w)$. All w are weakly positive, i.e., no consumer prefers a used over a new vehicle at the same price. We assume the distribution $G(\cdot)$ is the same for all consumers and time periods and thus abstract from income effects.

New and used vehicle supply have different properties. New vehicle supply comes from competitive, constant returns manufacturing with marginal cost and thus producer price ψ^s. We write the final price to consumers of a new vehicle as $\psi = \psi^s + \tau$, where τ is

[18] Appendix F.2 derives results allowing for an outside good. The key insights of the model derived here carry over to that model, with the exception of one comparative static related to the size of the used vehicle market, which is ambiguous in the case with an outside good.

any tax on new vehicles, explained below. The supply of used vehicles reflects consumer scrap, as follows. A consumer who buys a new vehicle receives a repair cost draw k from the distribution $H(k)$. We assume this distribution is the same for all consumers and time periods. In the next period, this consumer either scraps the vehicle or resells it as used in a competitive, frictionless resale market at price p. We assume the value of scrap is zero.[19]

7.2 Analytical Model Equilibrium

A steady-state equilibrium is a used vehicle price p in all time periods such that consumers choose new versus used vehicle purchases and scrap versus repair to maximize utility, and supply equals demand for both new and used vehicles.

Utility maximization lets us describe used vehicle supply in more detail. A consumer who purchases a new vehicle in one period will repair it in the next period if the used vehicle price exceeds the owner's repair cost draw (i.e., if $p > k$) and will scrap it otherwise. Hence, the share of new vehicles that are repaired and survive as used vehicles equals the cumulative distribution of repair costs, evaluated at the used vehicle price: $H(p)$. Correspondingly, the number of used vehicles supplied equals $U^s = H(p)N$. In equilibrium, $N = 1 - U$, so we can write used vehicle supply as $U^s = H(p)/(1 + H(p))$.

We can also describe used vehicle demand in more detail. The value of a new vehicle to a consumer is its benefit minus its price, $w - \psi$. At the time of vehicle purchase, before a consumer draws a repair cost, the expected value of a used vehicle to a consumer is the normalized value (zero), minus the used vehicle price p, plus the expected resale value. The expected resale value equals $H(p)(p - \bar{k})$, where $\bar{k}$ is the expected cost of repair, conditional on repair being optimal.[20] Thus, a consumer will buy a new vehicle at the start of the period if and only if $w - \psi + H(p)(p - \bar{k}) > -p$. Equivalently, the demand for used vehicles is the probability a consumer does not buy a new vehicle, which is $U^d = G(\psi - p - H(p)(p - \bar{k}))$.

Equating supply and demand for used vehicles provides the key equilibrium condition:

$$\frac{H(p)}{1 + H(p)} = G(\psi - p - H(p)(p - \bar{k})). \tag{4}$$

The left-hand side of equation (4) describes used vehicles supplied as a function of used vehicle prices p; the right-hand side describes used vehicles demanded as a function of p.

[19] A uniform scrap value would be capitalized into used vehicle prices, which would shift up the price of all used vehicles in equilibrium, but this would not impact the sign of our comparative statics. Adding a scrap value would be equivalent to shifting the distribution of w by a constant, as the scrap value is folded into the normalized value of a used vehicle.

[20] The truncated mean $\bar{k}$ of the repair cost distribution is a function of p: $\bar{k} = 1/H(p) \times \int_{-\infty}^{p} k dH(k)$.

7.3 Analytical Model: Pollution and Policy

We assume the following about pollution, which echoes empirical findings from Sections 5 and 6. A new vehicle creates pollution Φ from production and ϕ_t^n from exhaust. A used vehicle creates exhaust emissions ϕ_t^u. The difference in externalities between a new and a used vehicle is $\Delta_t \equiv \Phi + \phi_t^n - \phi_t^u$. Exhaust emissions for a used vehicle exceed exhaust emissions for a new vehicle at a given time ($\phi_t^u > \phi_t^n$), because tightening exhaust standards cleaned up new vehicles over time or because emissions control systems deteriorate (i.e., because $\phi_{t-1}^n > \phi_t^n$ or $\phi_{t+1}^u > \phi_t^n$). If $\Delta_t > 0$, then a new vehicle emits more than a used vehicle, after accounting for production and retirement emissions.

We consider two policies. Exhaust standards ω constrain new vehicle exhaust emissions: $\phi_t^n \leq \omega$. Tighter exhaust standards increase manufacturing costs, so $\psi^{s'}(\omega) \leq 0$.[21] We denote registration fees for new or used vehicles as τ_n and τ_u. Revenues are recycled lump-sum to consumers. With no outside good, only the difference in tax rates between new versus used vehicles $\tau \equiv \tau_n - \tau_u$ is needed for our analysis. We can then write the consumer's price of a new vehicle as $\psi = \psi^s(\omega) + \tau$.

7.4 Analytical Model Results

Proposition 1. *A policy that increases ψ will decrease the scrap rate and increase the market share of used vehicles. Specifically, the derivative of the scrap rate with respect to the new vehicle price is*

$$\frac{d(1-H(p))}{d\psi} = -h(p)\left(\frac{1+H(p)}{\frac{h(p)}{g(w^*)(1+H(p))} + (1+H(p))^2}\right) < 0 \tag{5}$$

where $w^* = \psi - p - H(p)(p - \bar{k})$ is the marginal type indifferent between used and new vehicles in equilibrium.

Appendix F.1 shows proofs. On the left-hand side of equation (5), the numerator of the derivative is the scrap rate and the denominator is the new vehicle price. The right-hand side of equation (5) evaluates this derivative. Proposition 1 shows that tighter exhaust standards extend vehicle lifetimes by decreasing scrap. Tighter exhaust standards – a lower ω – increase production costs ψ. The negative sign of equation (5) shows that higher production costs decrease scrap $1 - H(p)$ and thus extend vehicle lifetimes. The mechanism is intuitive. Increasing new vehicle prices causes higher demand for and thus price p of used vehicles. For

[21] Because we describe a steady-state equilibrium, we focus on exhaust standards that cause a constant shift in vehicle manufacturing costs. If the industry learns over time how to reduce emissions at lower cost, then a steady-state standard is tightening over time such that the marginal cost remains constant.

any given repair cost draw k, higher used vehicle prices make a consumer less likely to scrap vehicles.

A simple example may clarify. Imagine a driver who crashes an old car, has it towed to a repair shop, and must decide whether to repair or scrap it. If exhaust standards are weak, vehicle production costs and used vehicle values will be relatively low. The cost of repairing the crashed vehicle is then more likely to exceed the vehicle's value, so the driver is more likely scrap the vehicle. But if exhaust standards are stringent so that production costs and used vehicle prices are high, the driver is more likely to find that the vehicle's value exceeds the repair cost, and so more likely to repair the vehicle, extending its lifetime.

Proposition 1 also shows that making registration fees higher for new than used vehicles, as Figure 9 shows happens on average in the US, extends vehicle lifetimes. The same holds for adding any new-vehicle tax—higher relative registration fees on new vehicles are equivalent to a higher τ. The negative sign on the right-hand side of equation (5) again shows that this increase in new vehicle purchase prices decreases scrap and extends vehicle lifetimes.

The Gruenspecht Effect posits that policies increasing the prices of new durable goods will extend the life of used durables, which often pollute more. We believe Proposition 1 provides the first formal derivation of it. Gruenspecht (1982) originally considered policy exempting old power plants from pollution standards imposed on new plants, but the Gruenspecht Effect is cited more broadly in discussions of policies affecting power plants, vehicles, home and building construction, and other durables (Keohane et al. 1998; Stavins 2006; Bushnell and Wolfram 2012; Jacobsen and van Benthem 2015; Anderson and Sallee 2016).

Proposition 1 also implies that vehicles survive longer than is socially optimal if and only if $\tau > \Delta_t$. In other words, the market share of used vehicles is larger than is optimal if new vehicles are taxed more than their relative pollution damages. The reason for this implication is that if consumers internalized pollution externalities, they would perceive a price difference between new and used vehicles equal to $(\psi+\Delta_t)-(p-H(p)(p-\bar{k}))$. Because we abstract from outside goods here, this is equivalent to simply treating the new vehicle price as $\psi + \Delta_t$.[22] This leads to the second result.

Proposition 2. *Welfare in period t is maximized when $\tau = \Delta_t$. If $\tau > \Delta_t$, then moving to τ' where $\tau > \tau' \geq \Delta_t$ will increase welfare; if $\tau < \Delta_t$, then moving to τ' where $\tau < \tau' \leq \Delta$ will increase welfare.*

This result is intuitive. In this model, registration fees that differ between new and used

[22] With an outside good, the same results carry over with one exception. Raising the relative price of new vehicles induces a Gruenspecht effect in the same way. The only difference is that, while used vehicles represent a larger share of total vehicle market (i.e., the fleet is older), the total number of used vehicles may rise or fall because the total vehicle market contracts.

vehicles by $\tau = (\Phi + \phi_t^n) - \phi_t^u$ can fully correct the pollution externality.[23] Welfare in a time period is improved if we move the tax rate closer to the fully-corrected benchmark.

Figure 9 shows that existing registration fees are higher for newer and cleaner vehicles. Section 6 shows that used vehicles have higher emission rates than new vehicles. If emissions from manufacturing new vehicles are not too large, then Proposition 2 implies that flattening registration fees or even changing the sign of the correlation between registration fees and age would increase welfare.

Intuitively, exhaust standards and registration fees are complementary. If a counterfactual policy makes exhaust standards tighten more rapidly across model years, the gap Δ_t between emissions of used and new vehicles grows, and the scrap rate deviates further from the optimum. Registration fees correcting the scrap rate then remedy a larger distortion, implying a greater return to taxing the emissions of used versus new vehicles.

8 Quantitative Model

We now impose stronger functional form assumptions to build a quantitative model for estimating the scrap, pollution, composition, and welfare effects of changing exhaust standards and registration fees. The Colorado smog check pollution data described in Section 3 provide key inputs to the model. Propositions 1 and 2 in Section 7 motivate the core questions.

8.1 Quantitative Model Details

The model setup is as follows. A representative agent serves several roles. She demands purchase of new vehicles and rental of used vehicles. She also chooses whether to scrap or repair used vehicles available from the previous time period, and therefore she also serves as a competitive "supplier" of used vehicles.[24] Firms produce new vehicles and engage in Bertrand or perfect competition. Motivated by the differences in exhaust standards and emission rates between vehicle classes and ages found in Sections 5 and 6, we allow vehicles to be differentiated by over 500 combinations of class, size, age, and manufacturer. The model accounts for evolution of the vehicle fleet over time.[25]

[23] In this model, this is the optimal fee policy for a given exhaust standard. In a more detailed setting, miles driven and maintenance could respond to policy, so registration fees would not restore the first-best.

[24] We would obtain analytically equivalent results, at the cost of additional notation, from modeling a representative consumer and used vehicle supplier as separate agents.

[25] For tractability and data availability, we leave spatial modeling across US counties for future research.

Vehicle Demand Decisions

The representative agent chooses vehicles and other goods to maximize nested constant elasticity of substitution (CES) utility in a given time period t (subscript suppressed):

$$\max_{v,x} U(v, x) = (\alpha_v v^{\rho_u} + \alpha_x x^{\rho_u})^{\frac{1}{\rho_u}} - \Omega \quad (6)$$

$$s.t. \quad e_v v + e_x x \leq M. \quad (7)$$

Here U denotes the representative agent's utility, v and x are consumption of the composite vehicle and other goods, α_v and α_x are scale parameters that shift preferences, and ρ_u represents the elasticity of substitution between vehicles and other goods. Pollution damages Ω are a pure externality so consumers do not have "green preferences" leading them to buy cleaner vehicles out of environmental concern. The per-period prices of the composite vehicle and the composite good are e_v and e_x and income is M.

Demand for the composite vehicle v comes from five sequential CES utility nests: vehicles versus other goods, class c, size s, age a, and manufacturer m. Within a nest, demand depends on the per-period cost $e_{c,s,a,m}$ of a differentiated vehicle:

$$e_{c,s,a,m} = r_{c,s,a,m} + \tau_{c,s,a,m} + \sigma_{c,s,a,m}. \quad (8)$$

This cost includes a vehicle rental rate r, which reflects depreciation and repair; vehicle registration fees τ, with revenues rebated lump-sum; and fuel, insurance, and other operating costs σ. In equilibrium, rental rates, taxes and other ownership costs are capitalized in vehicle values.

Appendix G.1 describes how solution of this optimization problem leads to a standard constant elasticity demand system where $q^d_{c,s,a,m}$ denotes demand for each vehicle type conditional on prices. We allow miles driven to vary by vehicle class and age based on data but treat mileage within vehicle type×age as exogenous. Our counterfactual policies change the cost of owning a vehicle but not the per-mile operating cost, so we expect their main impact to be on changes in fleet composition rather than miles traveled.

New Vehicle Manufacturers

We let new vehicle manufacturers engage in either Bertrand or perfect competition and present results for both cases. For each class×size, manufacturer m chooses prices p, emissions ϕ, and fuel economy f to maximize profits in time period t, subject to exhaust and fuel economy standards (subscripts m, $a = 0$ suppressed):

$$\max_{p_{c,s,t},\phi_{c,s,t},f_{c,s,t}} \quad \sum_{c,s=1,2}\left[\left(p_{c,s,t} - C^b_{c,s} - C^{\phi}_{c,s,t}(\phi_{c,s,t}) - C^f_{c,s,t}(f_{c,s,t})\right) * q^d_{c,s,t}(\mathbf{p},\mathbf{f})\right] \tag{9}$$

$$C^{\phi}_{c,s,t}(\phi_{c,s,t}) = \chi^t \zeta_{c,s}\left(\frac{\phi_{c,s,0}}{\phi_{c,s,t}} - 1\right) + \xi_{c,s,t} \tag{10}$$

$$s.t. \quad \phi_{c,s,t} \leq \bar{\phi}_{c,s,t} \tag{11}$$

$$s.t. \quad \frac{\sum_s q^d_{c,s,t}(\mathbf{p},\mathbf{f})}{\sum_s (q^d_{c,s,t}(\mathbf{p},\mathbf{f})/f_{c,s,t})} \geq \overline{f}_{c,t}, c \in 1,2. \tag{12}$$

In the profit equation (9), $C^b_{c,s}$ represents per-vehicle production cost at time period $t = 0$ with emissions and fuel economy levels as observed in the baseline, $C^{\phi}_{c,s,t}$ is the per-vehicle cost of controlling exhaust emissions away from the baseline, and $C^f_{c,s,t}$ is the per-vehicle cost of improving fuel economy relative to the baseline. Demand $q^d_{c,s,t}$ depends on the vector of prices and fuel economies for all vehicles $(\mathbf{p},\mathbf{f})$. Any profits are rebated lump-sum to consumers. We model perfect competition using the limit as $\frac{\partial q^d_{c,s,t}(\mathbf{p},\mathbf{f})}{\partial p_{c,s,t}}$ and $\frac{\partial q^d_{c,s,t}(\mathbf{p},\mathbf{f})}{\partial f_{c,s,t}}$ go to infinity. In this case the first-order conditions of the maximization problem in (9) reduce to zero profit conditions that also satisfy the exhaust emissions and fuel economy constraints in (11) and (12).[26]

Equation (10) describes the cost function for controlling exhaust emissions; it builds on the general convex form in Bovenberg et al. (2008). Motivated by the regressions in Section 5 and the idea that manufacturers primarily or only change exhaust rates due to standards, we assume that exhaust standards bind for all manufacturers. The term $\chi < 1$ describes the rate of innovation in pollution control technology. The term $\zeta_{c,s}$ varies the relative control cost by vehicle class and size. The residual $\xi_{c,s,t}$ comes from the least squares calibration of χ and $\zeta_{c,s}$ to match the EPA's engineering cost estimates for Tier 2 and Tier 3 exhaust standards (Appendix G.4 provides details). This functional form has useful properties—adding no control beyond the baseline has zero cost; a given level of emissions control becomes cheaper over time; marginal pollution control costs rise smoothly; and it adapts engineering data from the EPA's analyses to apply to arbitrary counterfactual exhaust standards. Sensitivity analyses examine alternative control costs.

Exhaust standards $\overline{\phi}$ in equation (11) cap exhaust emissions per vehicle, separately for each vehicle type. We calibrate $\overline{\phi}$ to historical data which already includes any over-compliance, as discussed in Section 2.1. We therefore assume the same degree of over-

[26] Under perfect competition vehicles are priced such that $p_{c,s,t} = C^b_{c,s} + C^{\phi}_{c,s,t}(\phi_{c,s,t}) + C^f_{c,s,t}(f_{c,s,t})$ plus the shadow cost of vehicle c,s with respect to the fuel economy constraint in time t, and such that $\phi_{c,s,t} \leq \bar{\phi}_{c,s,t}$ for each vehicle.

compliance persists in counterfactuals. Fuel economy (CAFE) standards in equation (12) require that the harmonic average of fuel economies within a class $c \in$ (car, truck) must exceed $\overline{f}_{c,t}$, which is the form of CAFE policy relevant over most of the time period this quantitative model analyzes. Because fuel economy standards average within a manufacturer×class, firms will equalize marginal compliance costs across vehicles in each class.

Vehicle Scrap Decisions

We refer to the representative agent's capacity as a competitive supplier of used vehicles as "vehicle rental suppliers." Vehicle rental suppliers begin each period with a stock of used vehicles from the previous period and take as given rental rates $r_{a,t}$ for used vehicles (subscripts c, s and m suppressed). At the period's start, each vehicle receives a repair cost draw $k_{a,t}$ that must be paid to continue in service, otherwise the vehicle is scrapped. To generate a constant-elasticity scrap decision, we assume the cumulative distribution of repair cost shocks is $H(k_{a,t}) = 1 - b_a(k_{a,t})^{\gamma_a}$, where b_a is a scale parameter and γ_a controls the elasticity of the scrap rate with respect to vehicle value. This cumulative density corresponds to a probability density $h(k_{a,t}) = -b_a\gamma_a(k_{a,t})^{\gamma_a - 1}$ defined over the support $k_{a,t} \geq (1/b_a)^{(1/\gamma_a)}$. Vehicle rental suppliers maximize current and expected rental receipts minus the cost of repairs and new vehicle purchases.

Vehicle rental suppliers expect that all rental rates follow $\mathbb{E}[r_{c,s,a,m,t+1}] = r_{c,s,a,m,t}$.[27] With this form for expectations, the overall sequence of used vehicle values is (see Appendix G.2):

$$\begin{aligned} p_{a_{max},t} &= r_{a_{max},t} \\ p_{a,t} &= r_{a,t} + (1 - y_{a+1,t})\left(\frac{p_{a+1,t} - \bar{k}_{a+1,t}}{1+\delta}\right), \qquad a = 1, \ldots, a_{max} - 1. \end{aligned} \tag{13}$$

Here δ is the per-period discount rate, $y_{a,t}$ is the scrap rate, and $\bar{k}_{a,t}$ is expected expenditure on repair per vehicle of a given age, which follows from the repair cost density $h(k_{a,t})$:

$$\begin{aligned} \bar{k}_{a,t} &\equiv \mathbb{E}(k_{a,t} | k_{a,t} < p_{a,t}) \\ &= \frac{b_a^{-1/\gamma_a}\gamma_a - b_a\gamma_a p_{a,t}^{1+\gamma_a}}{(1+\gamma_a)\left(1 - b_a p_{a,t}^{\gamma_a}\right)}. \end{aligned} \tag{14}$$

Applying the used vehicle values from (13), vehicle rental suppliers choose the following set

[27] We do not assume rational expectations about future vehicle rental rates but we do adjust expectations based on upcoming changes in fuel economy and registration fees. This adjustment happens at a slower rate than if suppliers had fully forward looking expectations; see Appendix G.5. "Surprises" are possible along transitions after a policy shock, but once the system reaches a new steady state, this form of naive expectations will (by definition of the steady state) match fully forward looking ones.

of scrap rates and thus used vehicle supply:

$$\begin{aligned} y_{a,t} &= b_a(p_{a,t})^{\gamma_a} \\ q^s_{a,t} &= q_{a-1,t-1} * (1 - y_{a,t}). \end{aligned} \tag{15}$$

We let γ_a vary with class and size and choose b_a to match scrap rates in the baseline data.

Vehicle rental suppliers also choose how many new vehicles to purchase. Vehicle manufacturers sell new vehicles at price $p_{0,t}$ (0 refers to age; t to the time period). Because vehicle rental suppliers earn zero expected and realized profits in steady state, they purchase new vehicles until their profits are zero; $r_{0,t}$ equals depreciation between new and one-period old vehicles adjusted for repair and scrap:[28]

$$r_{0,t} = p_{0,t} - (1 - y_{1,t})\Big(\frac{p_{1,t} - \bar{k}_{1,t}}{1+\delta}\Big). \tag{16}$$

Because $p_{1,t}$ is a function of rental prices and the repair cost density (equation (13) above), new vehicle rental price becomes a function of new vehicle purchase price, used vehicle rental prices, and the repair cost density.

Equilibrium and Welfare

A competitive equilibrium of this model is a series of vectors of new vehicle prices, used vehicle rental rates, new vehicle emission rates, and new vehicle fuel economy levels $(p_{c,s,0,m,t}, r_{c,s,a,m,t}, \phi_{c,s,0,m,t}, f_{c,s,0,m,t})$ such that the representative agent maximizes utility (6) subject to the budget constraint (7); scrap decisions follow equation (15); vehicle manufacturers maximize profits as in (9) subject to exhaust and fuel economy standards in (11) and (12); and supply of each vehicle equals demand ($q^s_{c,s,a,m,t} = q^d_{c,s,a,m,t}$). We solve for equilibrium in each time period in sequence, by iteratively applying the exhaust and fuel economy constraints, and using a globally convergent quasi-Newton algorithm (Broyden's method; Appendix G.3 provides details).

We measure the effect of counterfactual policy on social welfare from the equivalent variation of utility (6). Exhaust standards and registration fees affect social welfare by changing vehicle manufacturing, demand decisions, and environmental externalities.

[28] Along transition paths additional accounting flows need to be tracked. In particular, the supplier can experience rental flows that are greater or less than the depreciation it assigns in any given year along a transition. The timing of changes in accounting profits depends on the depreciation method the supplier uses to value its capital. Appendix G.6 finds that, over the long run, welfare does not depend importantly on this choice; the depreciation method influences only the timing of perceived gains and losses.

8.2 Counterfactual Policies

We evaluate two classes of policy. The first changes exhaust standards. Actual Tier 2 exhaust standards rolled out over the period 2004 through 2006 and then applied through model year 2016. Data and regressions from Section 5 imply that Tier 2 decreased annual damages from new vehicles by about 80 percent. We consider counterfactual policies that delay or accelerate the roll out of Tier 2 standards by four or eight years.[29] We also consider a uniform tightening of exhaust standards by 10 percent.

Mechanically, we implement these counterfactuals by changing the exhaust standards $\overline{\phi}_{c,s,t}$ in equation (11). This affects the per-vehicle cost of controlling exhaust emissions C^{ϕ} in equation (10). It changes surplus and equilibrium patterns in new and used vehicle markets and influences the pollution externality over time.

We choose these specific exhaust standard counterfactuals for several reasons. Tier 2 is the main set of exhaust standards which changed over the years 2000-2020 where we have relatively complete data coverage. Studying acceleration or delay of these standards lets us measure the per-year value of Tier 2. Policymakers also frequently debate the timing of important environmental policies—for example, does it matter if the world implements stringent climate change policy now or in a decade? Our final counterfactual, studying a 10 percent change in exhaust standards, is one way to think about broad changes in exhaust standards unconnected to specific policy details.

The second class of counterfactuals we study covers four possible changes to annual registration fees. The first of these counterfactuals adds fees equal to the annual pollution damages of each age×vehicle type. The second scales fees from the first counterfactual to be revenue-neutral. The third counterfactual imposes fees on new vehicles only, equal to the lifetime environmental damages. The fourth counterfactual makes registration fees flat.

Mechanically, we implement these counterfactuals by changing registration fees τ in equation (8), which changes the vehicle fleet's equilibrium composition over time. These counterfactuals hold the path of exhaust standards fixed at their actual, historical value, and recycle registration fee revenue to the representative agent. Increasing registration fees on used vehicles decreases demand for them and thus decreases their rental prices. In equation (14), this decreases the threshold for scrapping a vehicle and thus increases the scrap rate. This is the key mechanism through which counterfactual registration fees affect emissions. The potential welfare gains mirror those in Proposition 2 in the analytical model.

We study these specific registration fee counterfactuals for several reasons. State and local governments already have registration fees, which makes them potentially plausible to

[29]In the counterfactuals that accelerate Tier 2 by eight years, the first year of the policy change is 2000, making 2008 standards apply in 2000, 2010 standards apply in 2002, etc.

vary. Making fees proportional to the mean damages of a vehicle type×age is a natural policy to evaluate. A revenue-neutral fee may be more politically feasible. Many policies focus on new vehicles, so restricting fees to those vehicles may be more politically feasible.

8.3 Data and Parameters

We allow for two vehicle classes (car and truck), two sizes (small or large), nineteen age categories (ages 0 to 37, grouped in two-year bins to reduce the computational burden) and seven manufacturers (Ford, General Motors, Chrysler, Toyota, Honda, Other Asian, and European). There are thus 28 vehicle types per age and 532 (=28*19) total vehicle types.

We summarize data and parameters for the quantitative model here; Appendix D.8 and Appendix Table A7 provide details. We calibrate the model to leading industry data on vehicle prices and composition for the 2000 U.S. vehicle fleet and follow vehicles through 2020.[30] This period lets us analyze recent years with data and observe the evolution of emission rates over the following 20 years. We use our life cycle measure of the emissions from the supply chain of manufacturing a new vehicle. The model also incorporates age, class, and size specific averages for vehicle miles traveled. We take the elasticity of the scrap rate with respect to vehicle value from Jacobsen and van Benthem (2015). We calculate the value of external damages Ω outside the equilibrium algorithm since it is additively separable.[31] We measure pollution damages from the AP3 model (Tschofen et al. 2019), which accounts for emissions from each US county, atmospheric transport (i.e., wind speed and direction), functions relating ambient pollution concentrations to outcomes like mortality, and the value of a statistical life. Our baseline quantification analyzes perfect competition among new vehicle manufacturers, though a sensitivity analysis accounts for market power.[32] We discuss sensitivity analyses varying many of these parameters.

[30] We begin in the year 2000 because it lets us follow vehicle types as they age, since our data observe them for more years. While this primarily encompasses the roll out of Tier 2 exhaust standards, the finding in Section 5 that different generations of exhaust standards have broadly similar proportional effects on emissions makes this quantification potentially informative for other standards also. This period is also relevant to many other countries which apply U.S.-style standards with a multi-year lag. The main constraint to setting up the model for other time periods is data; pollution and other data for much earlier or later periods would require substantial imputation.

[31] It is $\Omega_t = \sum_{c,s,a,m} \phi_{c,s,a,m,t} vmt_{c,s,a} \theta q_{c,s,a,m,t} + \sum_{c,s,m} \Phi_{c,s,m,t} q_{c,a,0,m,t}$, where $\phi_{c,s,a,m,t}$ indicates per-mile exhaust emissions, $vmt_{c,s,a}$ denotes vehicle miles traveled, θ are damages per ton of emissions, and $\Phi_{c,s,m,t}$ reflects damages from emissions associated with the manufacturing of a new vehicle.

[32] The baseline quantification assumes perfectly competitive manufacturers because then pollution externalities provide the only distortion, letting us focus on the welfare effects of alternative policies that are second-best along a single dimension.

8.4 Results

Table 5 shows how counterfactual policies affect several outcomes. Column (1) describes market surplus, equal to consumer surplus under the assumption of perfect competition that this estimate shows. Column (2) shows the change in pollution damages. Column (3) shows the change in social welfare, and column (4) shows the change in tax revenues, all in cumulative billions of 2019 dollars. Columns (5) through (7) show the percent change in cumulative pollution emissions over the same 20-year horizon, relative to baseline. Each row considers one counterfactual. Panel A examines changes in exhaust standards and Panel B examines changes in registration fees.

Counterfactual Exhaust Standards

Table 5, row 1, shows that delaying implementation of Tier 2 exhaust standards by four years decreases social welfare by \$112 billion, or \$28 billion per year of delay. Delaying these standards trades off a small gain in consumer surplus against a large increase in pollution damages. Over the 20-year period this model analyzes, the four-year delay in Tier 2 increases total pollution emissions by five to ten percent. Exhaust standards generate no tax revenue. Row 2 shows slightly smaller per-year effects for an eight-year delay in rolling out Tier 2 exhaust standards. Columns (5) through (7) show that an eight-year delay produces nearly double the total increase in pollution as a four-year delay. Rows 3-4 show that accelerating Tier 2 by four or eight years increases social welfare by \$117 or \$180 billion in present value. While accelerating Tier 2 decreases surplus in the vehicle market somewhat, it decreases pollution damages by far more. Row 5 of Table 5 describes a more modest 10% improvement in standards relative to the baseline, in every year starting in 2000. This increases welfare by a total of \$25 billion over 20 years.

Several benchmarks suggest these magnitudes are economically important. If the benefits of Tier 2 were measured against a value of a statistical life of \$10 million, they would represent around 2,800 fewer deaths per year. This is an appropriate benchmark because almost all the monetized benefits of decreasing NO_x and VOC emissions are due to avoided premature mortality (Tschofen et al. 2019). Another benchmark is other recent environmental policies. An important cap-and-trade market for industrial NO_x implemented over this period, the NO_x Budget Program (NBP), created an estimated \$2.1 billion in health benefits per year (Deschenes et al. 2018). Tier 2 exhaust standards appear to create over ten times the annual health benefits of the NBP. Comparing columns (1) and (2) suggests Tier 2 has a benefit/cost ratio of ten to fifteen; this ratio is in line with those of other recent federal air quality regulations (Keiser et al. 2019). We do not have all the data needed to apply the quantitative model to policy changes all the way back to the 1960s. If one took the pollution changes documented for Tier 0 and Tier 1 in Section 5 and extrapolated the types of numbers estimated here for Tier 2, however, they would likely imply welfare gains from Tier 0 and Tier 1 exhaust standards in the trillions of dollars.

These counterfactuals also suggest a few more general conclusions. Broadly, each year with Tier 2 exhaust standards creates \$25 to \$30 billion in social welfare gains. Additionally, a one percent decrease in cumulative emissions over 20 years produces a \$15 billion increase in social welfare.

Counterfactual Registration Fees

We also consider counterfactuals that vary registration fees. Table 5, row 6, shows that making registration fees proportional to environmental damages produces a present-value social welfare gain of \$333 billion and produces \$1.2 trillion in additional revenue over 20 years, or about \$60 billion per year. These counterfactual registration fees have double the welfare gains from accelerating counterfactual Tier 2 exhaust standards. The environmental registration fees decrease cumulative vehicle emissions by a third.

This reform heavily taxes the oldest vehicles. Figure 10, Panel A, shows the fee that this counterfactual imposes for vehicles of each age. These graphs average across vehicle types within an age. The fee for 0-year old vehicles reflects both exhaust emissions and environmental damages from vehicle manufacturing. Vehicles more than 20 years old face an annual registration fee of over \$2,000, which exceeds the resale value of these vehicles.

The solid line in Panel B shows that this policy leads households to scrap a third of 15-year old vehicles, half of 20-year old vehicles, and 90 percent of 25 year old vehicles. This is an extraordinary change in the fleet of older vehicles. Put another way, most vehicles aged over 25 and older in these data have environmental damages exceeding their annual ownership cost. The dashed line in Panel B shows the environmental gains due to vehicles of each age, which has a hump shape that peaks at vehicles of age 24. Younger vehicles have lower emissions rates, and vehicles age 25 and older pollute more per mile, but there are few vehicles aged 25+ in the baseline and they are driven few miles per year.

Row 7 of Table 5 shows a revenue-neutral version of the age×vehicle type registration fee, which taxes dirty vehicles and subsidizes clean vehicles (a "feebate"). It increases welfare somewhat less, about \$235 billion, because it encourages composition changes but not a downsizing of the entire fleet, as vehicles remain under priced on average. Rows 6-7 shed light on the role of composition versus scale effects. Roughly, the revenue-neutral fee system creates welfare gains through improved composition. The externality tax improves composition and also reduces the scale of the market in line with the externality.

Table 5, row 8, shows that charging registration fees for new vehicles only, with the fee equal to lifetime external damages from the vehicle, hardly changes social welfare; the model-based estimate actually implies these new vehicle fees *decrease* social welfare by $20 billion in present value. This perverse result reflects the power of the Gruenspecht Effect highlighted in Proposition 1. Although these fees encourage new vehicle buyers to choose cleaner vehicles, they also increase the price of all vehicles, which decreases scrap and keeps dirty used vehicles on the road longer. This phenomenon also underscores why the difference-in-differences regressions of Section 5 imply a mixed review of exhaust standards. While Section 5 shows exhaust standards decrease emission rates, this model quantification implies exhaust standards also extend the lifetime of dirtier used vehicles.

Figure 10 shows this example of the Gruenspecht Effect in action. Panel C shows that the average new vehicle has lifetime pollution damages of about $4,500, though new vehicle registration fees in this counterfactual vary by vehicle type and this graph shows the average across types. Charging that externality only to new vehicles dramatically decreases purchase of new vehicles, by over 25 percent.[33] What replaces the lower new vehicle purchases? Panel D shows that the number of surviving used vehicles increases, especially for vehicles 15-30 years old. In aggregate, the new vehicle fee substantially extends used vehicle lifetimes, for precisely the dirtiest vehicles.

Table 5, row 9, shows the effect of changing current registration fees to be identical for all vehicle ages and types. Figure 10, Panel E, shows that this counterfactual decreases registration fees by up to $50 for vehicles younger than 5 years old and increases them by up to $30 for older vehicles. This reform increases social welfare by $18 billion in present value and decreases pollution emissions by around 2 percent. The smaller impact for this counterfactual versus the externality-based fee in rows 6 and 7 reflects the idea that the inefficiency of current registration fees is less due to an implicit subsidy to pollution (which row 9 remedies) and more due to the failure to price externalities (which rows 5 and 6 address).[34]

Appendix E.4 discusses numerous variations in parameters, data, and assumptions about market power, which produce qualitatively similar results.

[33] This relatively elastic response in the first year of policy diminishes in later years as used vintages become in shorter supply.

[34] A similar pattern occurs with fossil fuel subsidies globally, where the failure to price externalities has much larger social cost than the direct subsidy (IMF 2022).

8.5 Inequality, Environmental Justice, and Political Economy

The quantitative model-based analysis provides a menu describing the consequences of different policies' impacts on pollution, surplus, and social welfare. A full analysis should also consider these policies' effects on different social groups. Incidence is important directly and for assessing political feasibility. Concern about an equal distribution of environmental quality is a top environmental policy priority, and environmental justice concerns have had outsize influence on recent environmental policy debates in California and Washington State.

The counterfactuals we study create distributional consequences through several channels. Lower-income households tend to own older and more polluting vehicles, so increasing registration fees on dirtier used vehicles could have regressive initial incidence. The relationship between income or education and vehicle age, for example, is decreasing. Figure A7 shows that vehicle owners with household income below \$10,000 have a mean vehicle age close to 12 years, while owners with income above \$80,000 have mean vehicle age of 7 years. Similarly, vehicle owners with less than a high school degree have mean vehicle age of 10.5 years, while owners with a graduate degree have mean vehicle age of 7 years. Exhaust standards tend to have the opposite pattern—the initial incidence makes new vehicles more costly, which tends to impose higher costs on higher-income households that disproportionately buy new vehicles.

At the same time, reforming registration fees and exhaust standards affects the resale value of used vehicles. Making registration fees more proportional to pollution will decrease the value of older polluting vehicles that lower-income households disproportionately own. But in the longer run, the lower rental or ownership costs of older and dirtier vehicles will offset some of the effect of changed registration fees.

Registration fees raise revenue, and incidence depends on how the revenues are recycled. This is not relevant for the revenue-neutral registration fees or exhaust standards. But the registration fees proportional to environmental damages generate \$60 billion in annual revenues, which can be redistributed to offset the fees' incidence. Atkinson and Stiglitz (1976) would suggest taxing commodities, including vehicle registration fees, only to reflect their externalities, and using nonlinear income taxation rather than commodity taxation to address distributional concerns. Of course, current taxes are far from optimal, and reforms in the direction of optimal taxation may be politically infeasible.

Additionally, the health impacts of pollution reduction through reforming registration fees and exhaust standards may disproportionately benefit low-income households. Similar patterns occur with other corrective taxes (Allcott et al. 2019). Older and dirtier vehicles are disproportionately owned by households that reside in low-income communities. To the extent that these vehicles are disproportionately driven near those communities, or pollute them, increasing registration fees on dirty used vehicles could create outsize environmental benefits to those communities. Transportation is a leading source of pollution in vulnerable communities, some of which are adjacent to major roads (Stuart et al. 2009; Rowangould 2013; Carlson 2018). The Environmental Justice movement focuses on the distribution of pollution, and cutting pollution from dirty vehicles seems likely to disproportionately benefit low-income communities. Quantifying precisely where vehicles are driven, separately by demographic of owner and vehicle attribute, is a complex task we leave for future research. Thus, changing registration fees to reflect pollution damages is likely to have regressive initial statutory incidence, but may have progressive environmental benefits. The net effect of these two channels is ambiguous and may vary with the specific counterfactual.

One other impact on political feasibility is worth noting. The registration fee policies we analyze increase the cost of owning used vehicles, which can increase new vehicle demand. Hence, auto manufacturers, a powerful interest group, may support such reforms, particularly if revenue-neutral.[35] At the same time, exhaust standards increase new vehicle prices and encourage substitution to used vehicles, so may be expected to receive less support from auto manufacturers.

9 Conclusions

Vehicle air pollution exhaust standards are arguably among the world's most important environmental policies, but have been the subject of little economics research. This contrasts with fuel economy standards, a separate set of regulations that influential economics research has studied carefully. It likewise contrasts with the substantial body of important research on the US Clean Air Act's regulation of industry.

This paper examines US exhaust standards over the last half century. We first document vast declines of over 99 percent in air pollution emissions per mile from new US vehicles since exhaust standards began in the 1960s. Panel data regressions using various time periods, datasets, and research designs find that exhaust standards have caused most of that downward emissions trend. Several stylized facts, however, suggest that these standards are not cost-effective because they do not tightly regulate emissions from older vehicles. Additionally, registration fees and property taxes are lower on older and dirtier used vehicles. An analytical model highlights the "Gruenspecht Effect," which policy debates have informally mentioned for decades but has not been rigorously derived before—environmental standards

[35] Anecdotes cut both ways. Bill Clinton lost his first re-election campaign for governor of Arkansas in 1980 partly because he raised annual vehicle registration fees. Elsewhere, Japan has implemented a national "shaken" registration fee which increases with vehicle age, encouraging scrap of older vehicles.

and other policies raising the price of new, clean capital counterproductively extend the lifetime of used, dirty capital. The analytical model also suggests potential efficiency gains from increasing registration fees on old dirty vehicles. A quantitative model finds present-value net benefits in the hundreds of billions of dollars from setting annual registration fees equal to the pollution damages of a vehicle age×type. Using externality-based registration fees appears to have larger benefits than further tightening standards, though both produce substantial gains. In sum, we conclude that vehicle exhaust standards have been remarkably effective, but they have left room for improvement in cost effectiveness, and feasible policy reforms can thus generate large welfare gains.

Given the enormous decreases in pollution from passenger transportation this paper documents, do additional reforms have economically important magnitudes? Although pollution used to be an even worse problem, the 37,000 annual US deaths mentioned at the beginning highlight that pollution is still costly.

We conclude with four areas we believe are important for future work. First, how important are issues in this paper for ongoing fleet composition trends? Growing market shares of electric vehicles imply that in 20 years, policymakers in regions with a clean electric grid may face a trade-off between clean new electric vehicles and polluting older gasoline vehicles. The question of how policy should deal with legacy pollution at that stage will mirror the questions we analyze here in key ways. Anticipating that transition may inform policy for electric vehicles today. In addition, this paper shows steady downward trends in emission rates even for gasoline vehicles. While we quantify effects of varying past policy reforms, what are potential welfare gains from current or future additional reforms? Such analysis would require projection or imputation of many of the data used in the quantitative model, but are relevant to future policy.

Second, are the environmental benefits of removing the most polluting older vehicles concentrated in low-income communities? While making annual registration fees better reflect pollution damages can create large environmental benefits, it can also create concerns about environmental justice because vulnerable communities may pay a larger share of those fees. At the same time, if vehicle air pollution disproportionately affects vulnerable communities, cleaning it up can improve the equity of overall environmental outcomes.

Third, do the ideas and findings here generalize to other countries? Because most middle- and low-income countries use exhaust standards with stringency set years behind the US, the ideas advanced here are potentially relevant to China, India, Mexico, and many other countries. Testing whether our findings generalize to other countries would be valuable.

Finally, how externally valid are our findings to other types of environmental policy? For example, we find that pollution emission rates have declined precipitously and that environmental policy is the leading cause. Aspects of those findings also appear to apply to electricity generation, industrial air pollution, and municipal water pollution (Shapiro 2022). The Gruenspecht Effect is relevant for drinking water treatment, coal-fired electricity generation, and industrial water pollution regulation (Stavins 2006). Our quantitative model finds that while tightening pollution standards can produce welfare gains, revising tax instruments to reflect environmental damages can produce larger welfare gains; this broad conclusion of the relative efficiency of taxes over standards is a common theme in environmental economics.

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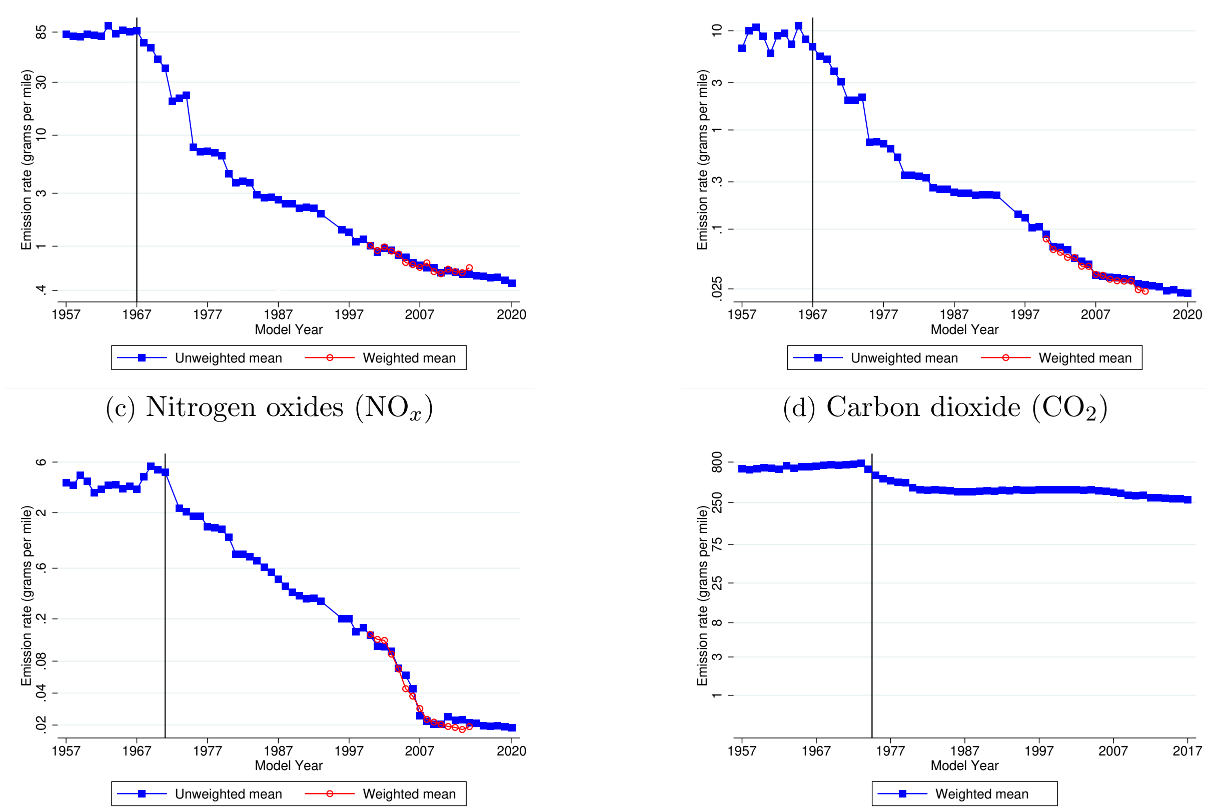
Figures and Tables

Figure 1: Mean Pollution Emission Rates of New US Vehicles, 1957-2020

(a) Carbon monoxide (CO) (b) Hydrocarbons (HC)

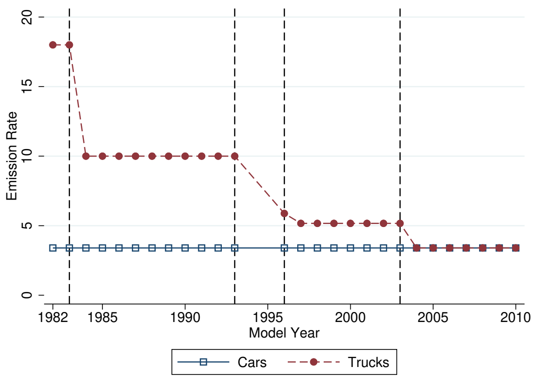
(c) Nitrogen oxides (NO_x) (d) Carbon dioxide (CO_2)



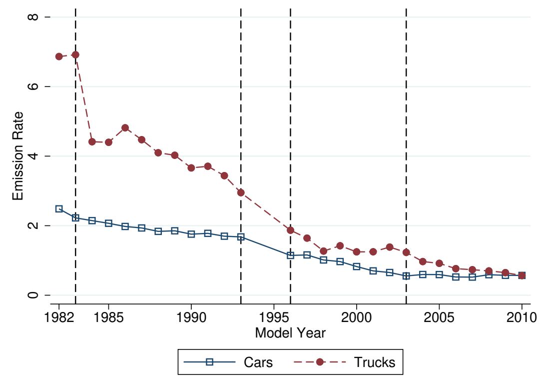
NOTES: Y-axes have logarithmic scale. Graphs use full sample of new vehicle test data and AES (1973). For Panels A-C, model years 1957-1971 are means of a sample of used vehicles given an FTP test (AES 1973). Model years 1972-2020 are from certification test records for 50,000 miles. Model years 1972-4 received an earlier version of the FTP test ("FTP72"). We concord FTP72 to FTP values, separately by pollutant, using ratios for all vehicles in AES (1973). Vertical line depicts year before exhaust standards began. CO_2 data are sales-weighted fleet-wide averages. CO_2 data converted from mile per gallon data, from USEPA (1973) for 1957-1974, USEPA (2009) for 1975-1977, DOT (2014) for 1978-2014, and Oak Ridge (2019) for 2015-2017. We splice each CO_2 series to have the same mean in the year when they overlap (1975, 1978, and 2015). Weights for CO, HC, and NO_x in the red lines with circles are the frequency of each vehicle in Colorado remote sensing data.

Figure 2: Exhaust Standards and Emission Rates, Cars Versus Trucks

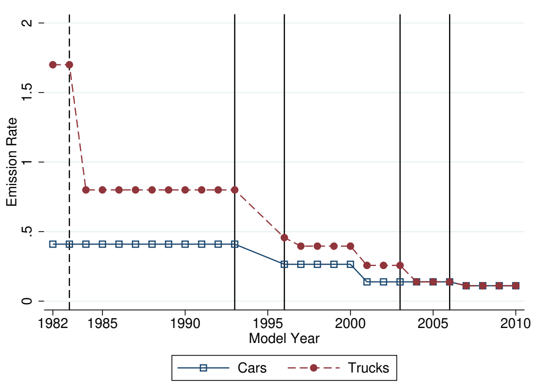
(a) Exhaust standards: CO



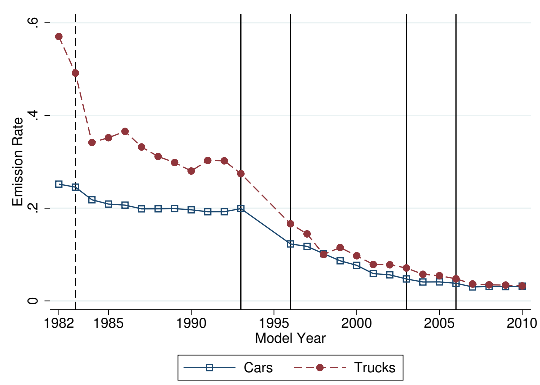
(b) New vehicle rates: CO



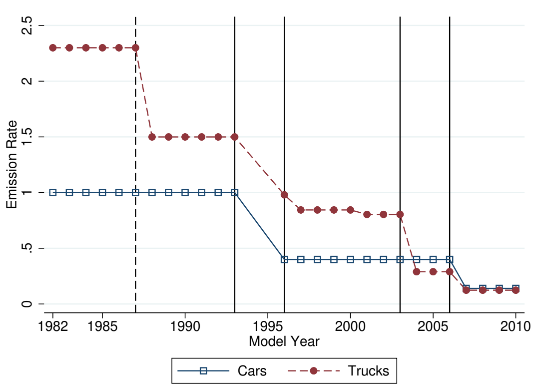
(c) Exhaust standards: HC



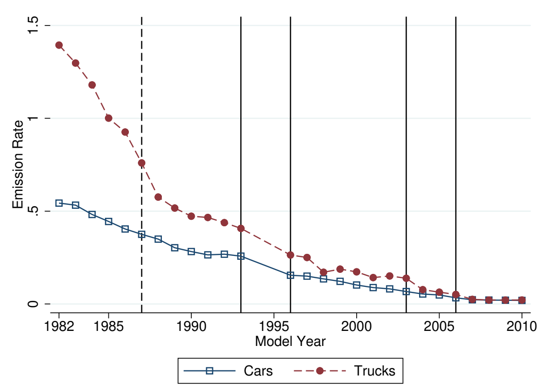
(d) New vehicle rates: HC



(e) Exhaust standards: NO_x



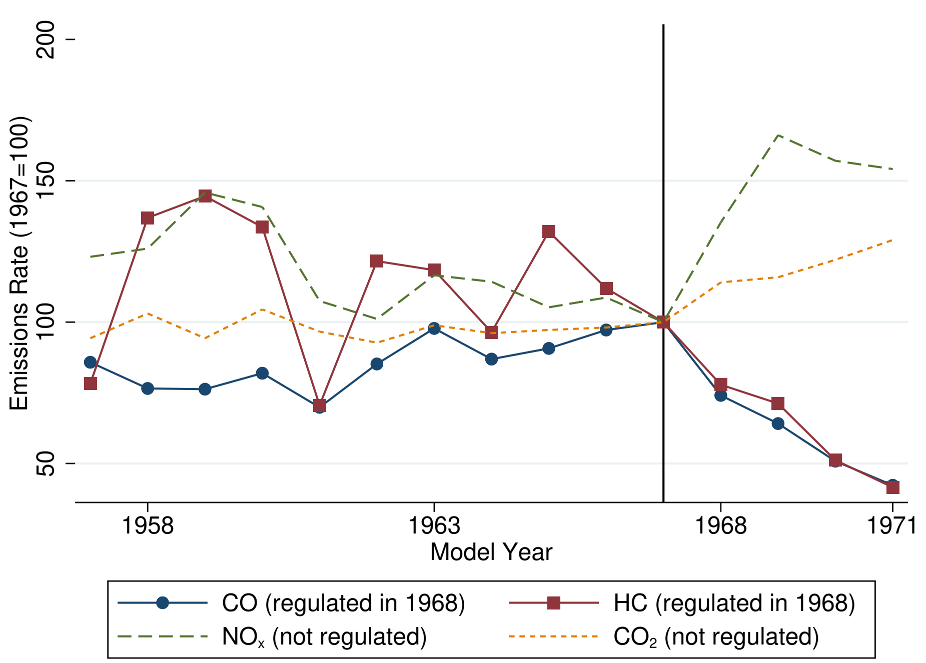
(f) New vehicle rates: NO_x



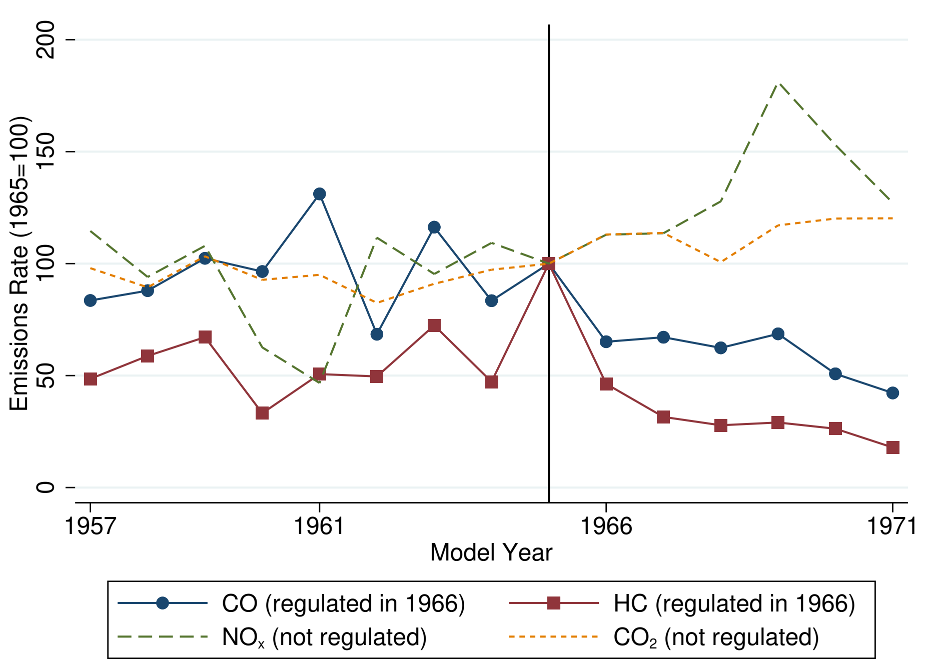
NOTES: Dashed vertical lines show years when standards change for cars only; solid vertical lines show years when standards change for both cars and trucks. Each panel uses full sample, restricted to model years 1982-2010. Panels D through F show certification levels, equal to raw test results scaled up by deterioration factors for 50,000 miles. Appendix A explains details. Beginning in 1988 for NO_x and 1994 for other pollutants, standards distinguish sub-groups of trucks based on weight; graphs show weighted means of standards across these groups, with weights equal to the proportion of each vehicle from model year 1993 in Colorado smog check test data.

Figure 3: Event Study Graphs for Tier 0 Exhaust Standards, 1957-1971

(a) Vehicles outside California, model years 1957-1971



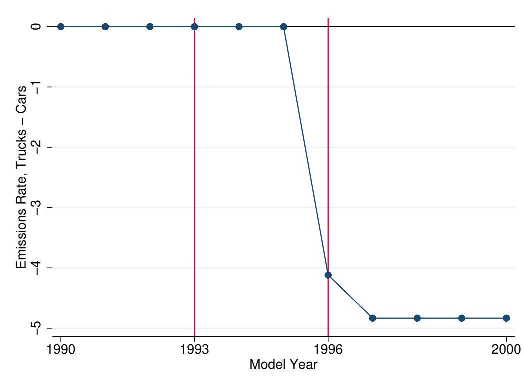
(b) Vehicles in California, model years 1957-1971



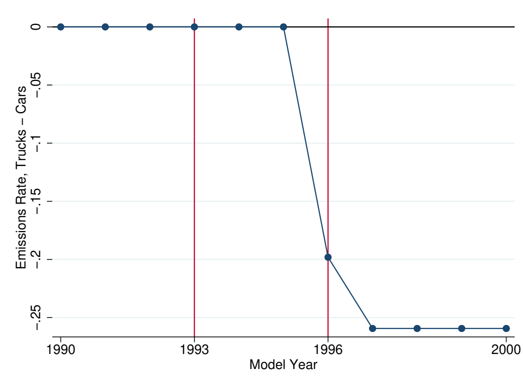
NOTES: Graphs use full sample from AES (1973). All emission rates are in grams per mile, scaled to equal 100 in 1967 (Panel A) or 1965 (Panel B).

Figure 4: Event Study Graphs for Tier 1 Exhaust Standards, 1990-2000

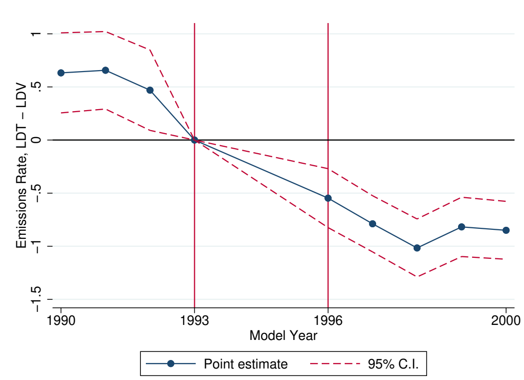
(a) Exhaust standards: CO



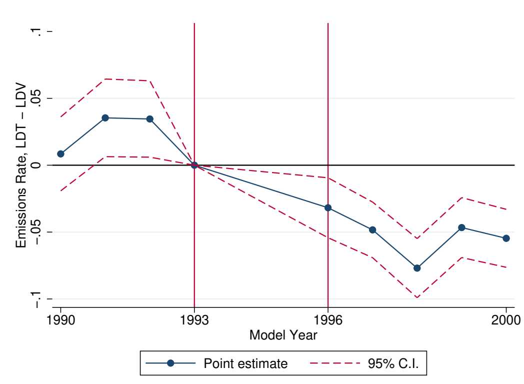
(b) Exhaust standards: HC



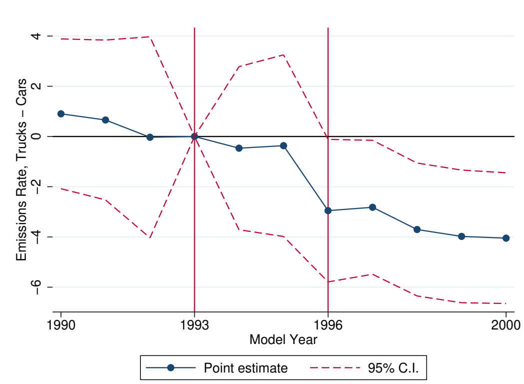
(c) New vehicle emissions: CO



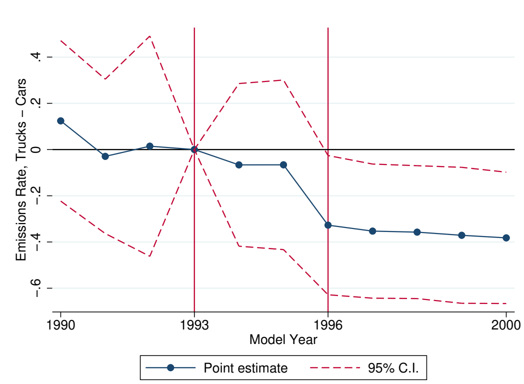
(d) New vehicle emissions: HC



(e) Used vehicle emissions: CO



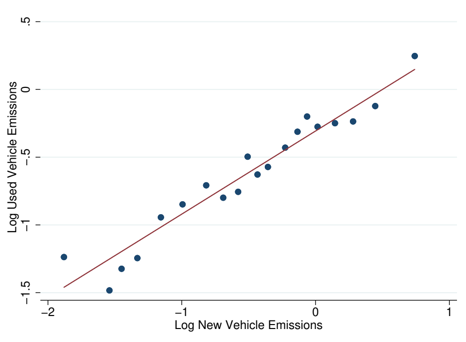
(f) Used vehicle emissions: HC



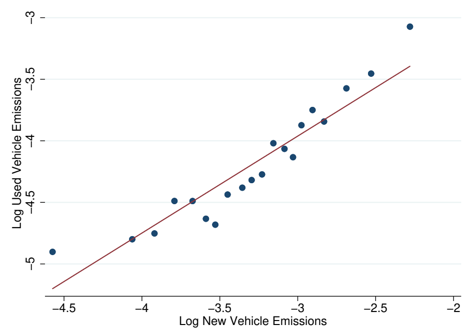
Notes: Graphs use model years 1990-2000 from new vehicle tests (Panels C and D) or Colorado smog check data (Panels E and F). Emissions are measured in grams per mile. Panels weight truck types across weight categories by their shares in the 1993 Colorado smog check test data. Panels C and D show certification levels for 50,000 miles. Standard errors are clustered by model year×truck type.

Figure 5: Used Versus New Emission Rates for Tier 2 Exhaust Standards, 2000-2010

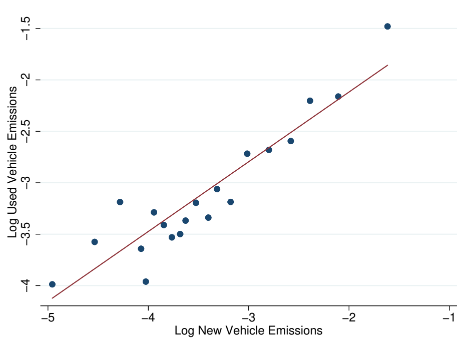
(a) Carbon monoxide (CO)



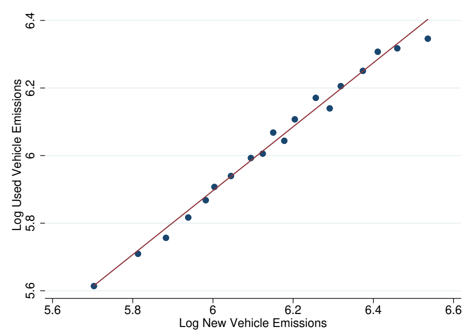
(b) Hydrocarbons (HC)



(c) Nitrogen oxides (NO_x)

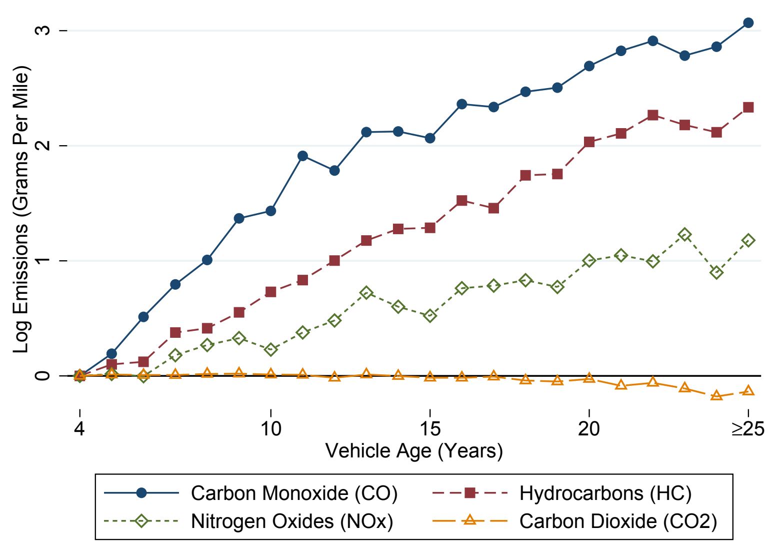


(d) Carbon dioxide (CO_2)



NOTES: Graphs show binned scatterplots. Graphs use new vehicle tests and Colorado smog check data.

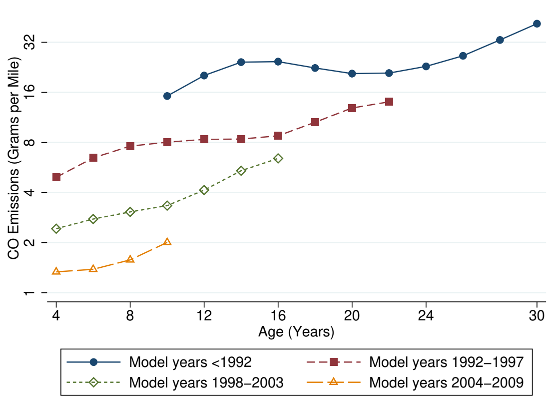
Figure 6: Air Pollution but Not CO_2 Increases with Vehicle Age



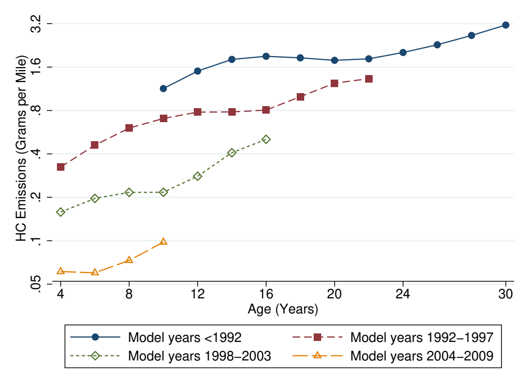
NOTES: Graph shows age fixed effects α_a from a regression including vehicle fixed effects μ_i and odometer controls o: $E^u_{it} = \sum_j \alpha_j 1[age_{it} = j] + \gamma o_{it} + \mu_i + \epsilon_{i,t}$. Regression uses Colorado 240-second sample.

Figure 7: Used Vehicle Emission Rates and Miles Traveled, by Model Year and Age

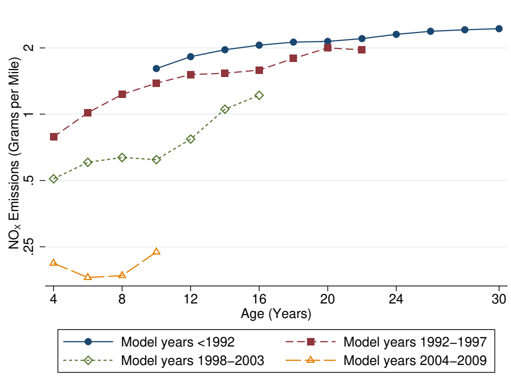
(a) Carbon monoxide (CO)



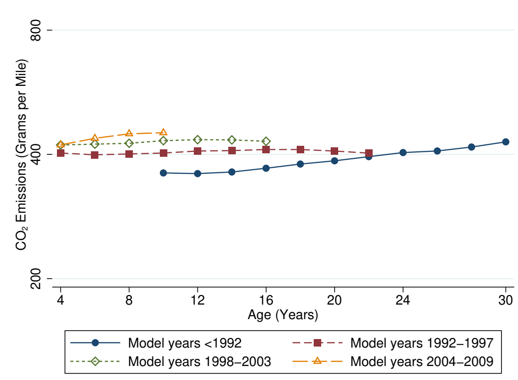
(b) Hydrocarbons (HC)



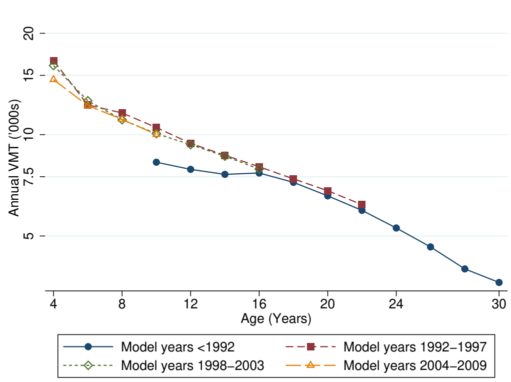
(c) Nitrogen oxides (NO_x)



(d) Carbon dioxide (CO_2)



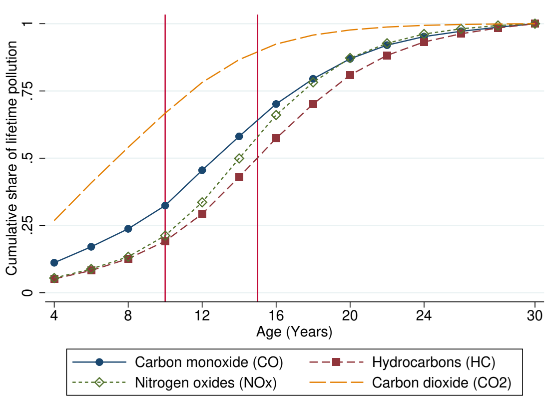
(e) Annual vehicle miles traveled



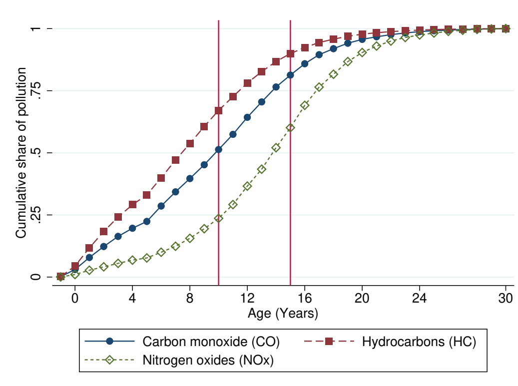
NOTES: Figures use full sample from Colorado smog check data. Points represent mean emission rates in a given model year×age cell, averaged across all vehicles in the data. Y-axes have logarithmic scale.

Figure 8: Cumulative Share of Fleet Emissions from Each Vehicle Age

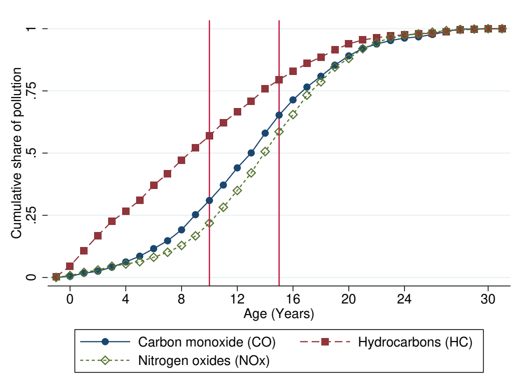
(a) 2014 fleet, Colorado inspections



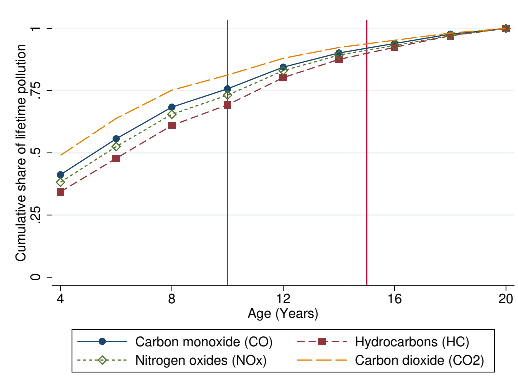
(b) 2014 fleet, Colorado remote sensing



(c) 2014 fleet, multi-state remote sensing

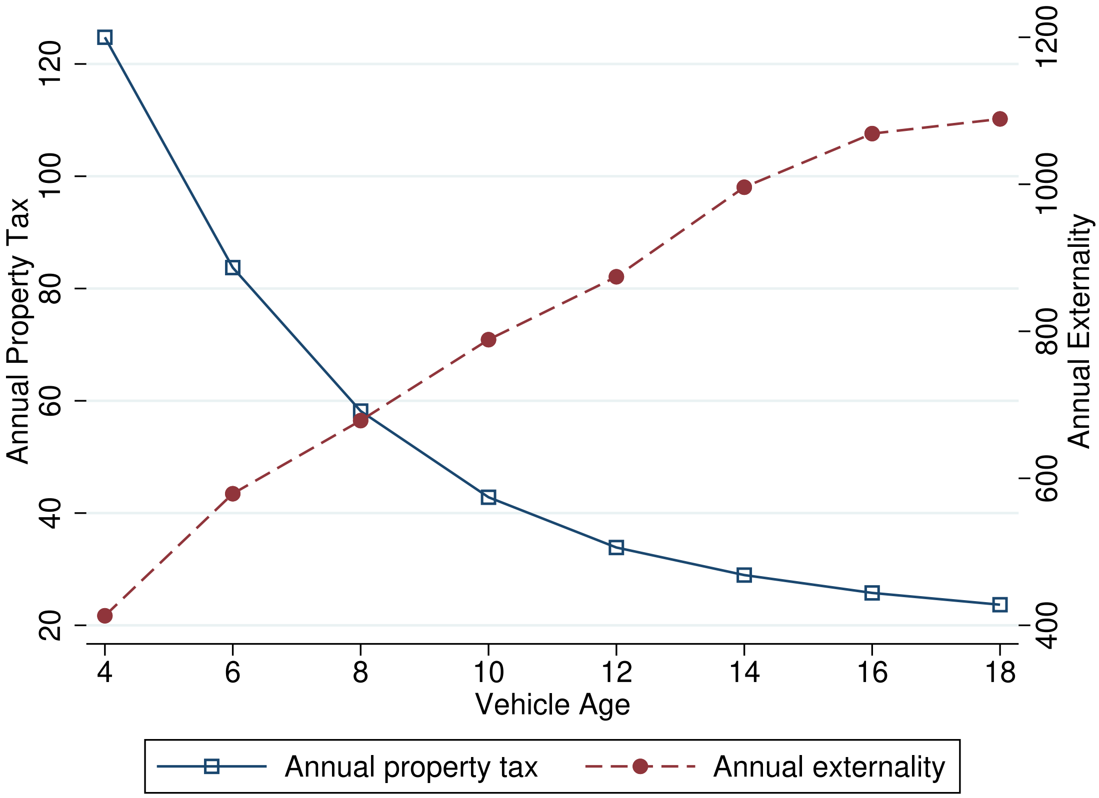


(d) 1993 cohort, Colorado inspections



NOTES: Each line shows the cumulative distribution for total pollution emissions from each age. Each pollutant is a separate line. Vertical lines at ages 10 and 15 show when exhaust standards stop applying. Pollution for an individual vehicle equals the emission rate measured in an individual test times miles driven. Miles driven is calculated as the change in a vehicle's odometer since the last test for that Vehicle Identification Number divided by the number of decimal years since the last test for that Vehicle Identification Number. For a vehicle's first test, this value of years is assumed to equal the vehicle's age. In Panels B and C, we assume that the number of times each vehicle passes a remote sensing detector is proportional to the vehicle's miles driven, so each value equals the share of total emissions detected by remote sensing that come from each age group.

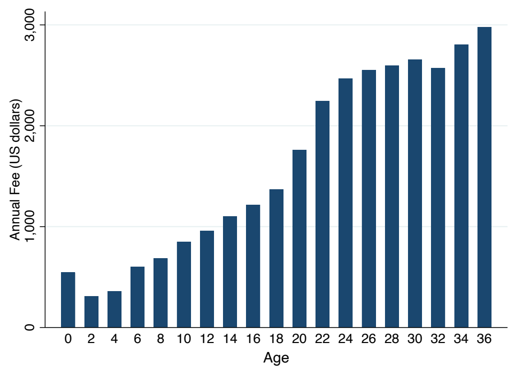
Figure 9: Annual Pollution Externalities, Property Taxes, and Vehicle Age



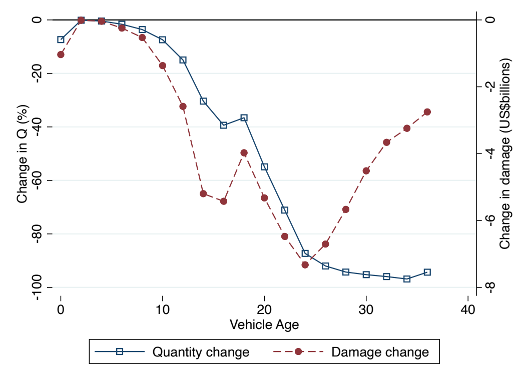
Notes: Graph measures market shares of each VIN prefix using the calendar year 2000 fleet sample from Colorado smog check data to calculate the mean externality and tax by vehicle age. Data describe states and counties with vehicle property taxes. Vehicle miles traveled (VMT) is calculated from Colorado smog check microdata. Vehicle values are calculated from the National Automobile Dealers Association used retail prices. Currency values are in 2019$.

Figure 10: Model-Based Estimates: Levels of Counterfactual Registration Fees and Effects on Fleet Composition and Pollution Damages

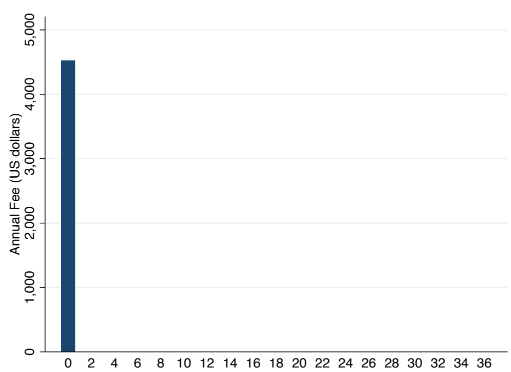
(a) Age×type fee



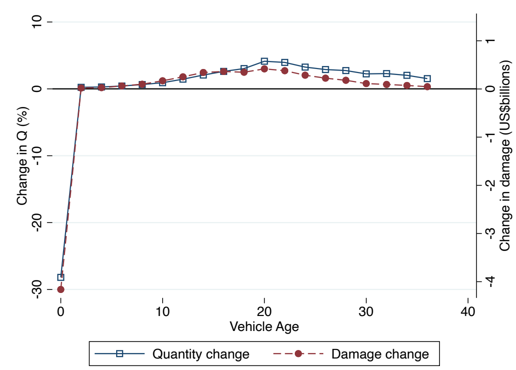
(b) Age×type fee: Effect on fleet



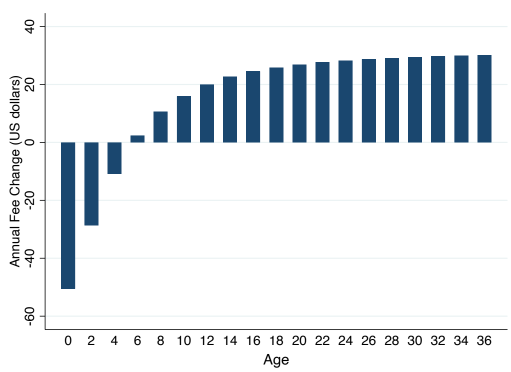
(c) New vehicle fee



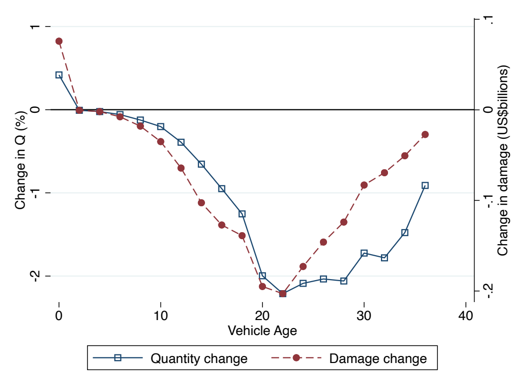
(d) New vehicle fee: Effect on fleet



(e) Change in fees due to flat fee



(f) Flat fee: Effect on fleet



Notes: Panels B, D, and F show the model-based estimates of the impact of counterfactual policies on the calendar year 2000 fleet and environmental damages. Currency values are in 2019$, deflated using the Consumer Price Index for urban consumers.

Table 1: Federal Exhaust Standards

Policy	Model years	Light-duty vehicles CO	HC	NO_x	Light-duty trucks CO	HC	NO_x	Mean Limit	Mean Pollutant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Uncontrolled	-1967	90.0	8.200	3.40	90.0	8.200	3.40	—	—
Tier 0	1968-1971	34.0	4.100	—	34.0	4.100	—	—	—
	1972-1974	28.0	3.000	3.10	28.0	3.000	3.10	—	—
	1975-1976	15.0	1.500	3.10	20.0	2.000	3.10	—	—
	1977-1978	15.0	1.500	2.00	20.0	2.000	3.10	—	—
	1979	15.0	1.500	2.00	18.0	1.700	2.30	—	—
	1980	7.0	0.410	2.00	18.0	1.700	2.30	—	—
	1981-1983	3.4	0.410	1.00	18.0	1.700	2.30	—	—
	1984-1987	3.4	0.410	1.00	10.0	0.800	2.30	—	—
	1988-1993	3.4	0.410	1.00	10.0	0.800	1.50	—	—
Tier 1	1994-1996	3.4	0.250	0.40	10.0	0.250	0.85	—	—
	1997-2000	3.4	0.250	0.40	5.2	0.250	0.85	—	—
NLEV (8 states)	1999-2000	3.4	0.250	0.40	5.2	0.250	0.85	0.075	NMOG
NLEV	2001-2003	3.4	0.139	0.40	5.2	0.250	0.80	0.075	NMOG
Tier 2	2004-2006	3.4	0.125	0.40	3.4	0.139	0.40	0.070	NO_x
	2007-2016	3.4	0.100	0.14	3.4	0.100	0.14	0.070	NO_x
Tier 3	2017-2025	4.2^+	0.16^+		4.2^+	0.16^+		0.030	NMOG+NO_x

NOTES: CO is carbon monoxide, HC is hydrocarbons, NO_x is nitrogen oxides, NMOG is non-methane organic gases. All numbers are for gasoline vehicles, measured in grams per mile by the Federal Test Procedure. See Appendix A for details. Columns (5) through (7) show mean standards across truck types, with weights equal to the proportion of each vehicle from model year 1993 in Colorado smog check data. For policies that impose a fleet-wide mean limit, columns (2) through (7) show the limit for the highest bin. $^+$Tier 3 standards apply at 150,000 miles, whereas earlier policies apply at lower mileage. Tier 3 has a combined NMOG+NO_x standard, which is phased in and reaches 0.03 in the year 2025. Uncontrolled emissions are calculated based on emission rates and estimates from vehicles before emissions controls. Sources: National Commission on Air Quality (1981); Bresnahan and Yao (1985); Davis (1997); U.S. EPA (2016).

Table 2: Effects of Tier 0 Exhaust Standards on Vehicle Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Carbon monoxide and hydrocarbons (CO and HC)						
Exhaust standards	0.61***	0.80***	1.22***	0.62***	0.90***	0.59***	0.83***
	(0.07)	(0.07)	(0.19)	(0.08)	(0.09)	(0.12)	(0.13)
N	120	120	120	60	60	60	60
	Panel B. Carbon monoxide (CO)						
Exhaust standards	0.48***	0.46**	0.76***	0.52***	—	0.52***	—
	(0.07)	(0.18)	(0.18)	(0.07)	—	(0.07)	—
N	30	30	30	15	—	15	—
	Panel C. Hydrocarbons (HC)						
Exhaust standards	0.76***	0.22	0.52*	0.71***	—	0.71***	—
	(0.11)	(0.20)	(0.28)	(0.13)	—	(0.13)	—
N	30	30	30	15	—	15	—
Fixed effects:							
Pollutant*region	X	X	X	X	X	X	X
Model year	—	X	X	—	X	—	X
Levels	—	—	X	—	—	—	—
California only	—	—	—	X	X	—	—
Federal only	—	—	—	—	—	X	X

NOTES: Dependent variable is the emission rate in grams/mile from AES (1973). Regressions are in logs except where otherwise noted. Robust standard errors are in parentheses. Before standards began, "exhaust standards" are defined to equal the unconstrained emission rate from Table 1. Asterisks denote p-value < 0.10 (*), <0.05 (**), or <0.01 (***).

Table 3: Effects of Tier 1 Exhaust Standards on Used and New Vehicle Emission Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Carbon monoxide and hydrocarbons (CO and HC), used vehicles						
Exhaust standard	1.61***	0.83***	0.94***	0.51**	1.08***	0.83***	0.77***
	(0.13)	(0.10)	(0.10)	(0.19)	(0.12)	(0.07)	(0.12)
N	14,253,650	14,253,650	14,253,650	14,253,650	3,402,740	18,469,406	14,253,650
	Panel B. Carbon monoxide (CO), used vehicles						
Exhaust standard	1.60***	0.71***	0.82***	0.51**	0.94***	0.76***	0.77***
	(0.14)	(0.09)	(0.12)	(0.24)	(0.11)	(0.07)	(0.11)
N	7,112,383	7,112,383	7,112,383	7,112,383	1,695,559	9,220,274	7,112,383
	Panel C. Hydrocarbons (HC), used vehicles						
Exhaust standard	1.61***	1.57***	1.80***	1.55**	1.93***	1.08***	1.41***
	(0.13)	(0.24)	(0.27)	(0.66)	(0.25)	(0.17)	(0.23)
N	7,141,267	7,141,267	7,141,267	7,141,267	1,707,181	9,249,132	7,141,267
	Panel D. Carbon monoxide and hydrocarbons (CO and HC), new vehicles						
Exhaust standard	1.49***	0.72***	0.72***	1.01***	—	0.54***	0.38***
	(0.14)	(0.14)	(0.14)	(0.26)	—	(0.09)	(0.06)
N	7,228	7,228	7,228	7,228	—	14,256	7,228
	Panel E. Carbon monoxide (CO), new vehicles						
Exhaust standard	1.64***	0.76***	0.57***	1.07**	—	0.62***	0.38***
	(0.15)	(0.14)	(0.18)	(0.49)	—	(0.08)	(0.06)
N	3,616	3,616	3,616	3,616	—	7,131	3,616
	Panel F. Hydrocarbons (HC), new vehicles						
Exhaust standard	1.45***	0.48**	0.17	1.18	—	0.42***	1.41***
	(0.16)	(0.23)	(0.27)	(0.84)	—	(0.11)	(0.23)
N	3,612	3,612	3,612	3,612	—	7,125	3,612
Fixed effects							
Model yr. × pollutant	X	X	X	X	X	X	X
Truck × pollutant	—	X	X	X	X	X	X
Age × pollutant	X	X	X	X	X	X	X
Odometer	X	X	X	X	X	X	X
CAFE standards	—	—	X	—	—	—	—
Smog check stds.	—	—	X	—	—	—	—
Gasoline cost per mile	—	—	X	—	—	—	—
Ethanol share	—	—	X	—	—	—	—
Sulfur content	—	—	X	—	—	—	—
Model yr. × truck trend	—	—	—	X	—	—	—
Ages 4-6	—	—	—	—	X	—	—
Model yrs. 1982-2000	—	—	—	—	—	X	—
Levels	—	—	—	—	—	—	X

NOTES: Dependent variable is the emission rate in grams/mile. Regressions are in logs except where otherwise noted. Panels A through C use the Tier 1 sample (model years 1990-2000) from Colorado inspection data; Panels D through F use the new vehicle inspection data. Odometer includes linear and squared odometer and odometer terms. New vehicle data in Panels D through F lacks age, odometer, and controls for other policies besides CAFE. Standard errors are clustered by model year×truck type. Asterisks denote p-value <0.10 (*), <0.05 (**), <0.01 (***).

Table 4: Assessment of Tier 2 Exhaust Standards: Do New Predict Used Vehicle Emission Rates?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Carbon monoxide (CO) and hydrocarbons (HC) and nitrogen oxides (NO_x)								
New vehicle emission rate	0.68***	0.53***	0.51***	0.53***	0.49***	0.70***	0.23***	0.45***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.01)	(0.06)
N	429,468	429,468	429,468	429,468	58,080	429,468	10,178,601	10,178,601
Panel B. Carbon monoxide (CO)								
New vehicle emission rate	0.61***	0.64***	0.67***	0.64***	0.63***	0.71***	0.19***	0.57***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.01)	(0.06)
N	143,156	143,156	143,156	143,156	19,360	143,156	3,392,867	3,392,867
Panel C. Hydrocarbons (HC)								
New vehicle emission rate	0.79***	0.62***	0.50***	0.61***	0.40***	0.81***	0.36***	1.38***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.08)	(0.01)	(0.07)
N	143,156	143,156	143,156	143,156	19,360	143,156	3,392,867	3,392,867
Panel D. Nitrogen oxides (NO_x)								
New vehicle emission rate	0.68***	0.37***	0.37***	0.36***	0.35***	1.04***	0.21***	1.42***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.08)	(0.01)	(0.10)
N	143,156	143,156	143,156	143,156	19,360	143,156	3,392,867	3,392,867
Panel E. Carbon dioxide (CO_2)								
New vehicle emission rate	0.95***	0.87***	0.85***	0.87***	0.83***	0.76***	0.78***	0.72***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	143,156	143,156	143,156	143,156	19,360	143,156	3,392,867	3,392,867
Age, model year FE	—	X	X	X	X	X	—	—
Truck indicator	—	X	X	X	X	X	—	—
Odometer	—	X	X	X	X	X	—	—
CAFE standards	—	—	X	—	—	—	—	—
Smog check standards	—	—	X	—	—	—	—	—
Gasoline cost per mile	—	—	X	—	—	—	—	—
Ethanol share	—	—	X	—	—	—	—	—
Sulfur content	—	—	X	—	—	—	—	—
Model year × truck trend	—	—	—	X	—	—	—	—
Ages 4-6	—	—	—	—	X	—	—	—
Levels	—	—	—	—	—	X	—	X
Include abbreviated tests	—	—	—	—	—	—	X	X

Notes: Dependent variable is the used vehicle emission rate in grams/mile. Regressions are in logs except where otherwise noted. Regressions use model years 1990-2000 of new vehicle tests and Colorado smog check data. New vehicle emission rate is certification level for 50,000 miles. Estimates correspond to the specification of Table 3, column (1), except where otherwise noted. Standard errors are clustered by VIN prefix. Asterisks denote p-value <0.10 (*), <0.05 (**), <0.01 (***).

Table 5: Model-Based Estimates: Effects of Counterfactual Exhaust Standards and Registration Fees

	Change in market surplus	Change in pollution damages	Total change in social welfare = (1) - (2)	New tax revenue	Percent change in cumulative emissions		
					CO	HC	NOx
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A. Counterfactual Exhaust Standards				
1. Delay Tier 2 by four years	8.4	120.6	-112.3	0.0	8.0	4.8	10.7
2. Delay Tier 2 by eight years	13.6	207.0	-193.4	0.0	15.6	8.3	18.4
3. Accelerate Tier 2 by four years	-10.5	-127.7	117.2	0.0	-6.3	-4.9	-11.1
4. Accelerate Tier 2 by eight years	-22.4	-202.5	180.1	0.0	-9.7	-7.7	-17.5
5. Tighten standards 10 percent	-2.4	-27.9	25.5	0.0	-1.4	-1.1	-2.4
			Panel B. Counterfactual Registration Fees				
6. Age×type fee	-176.4	-509.7	333.2	1,181.2	-43.4	-43.2	-24.8
7. Age×type fee, revenue neutral	-115.4	-350.8	235.4	0.0	-34.0	-33.6	-15.3
8. New vehicle fee	-19.7	1.4	-21.1	407.1	1.7	1.8	-0.5
9. Flat registration fee	-3.7	-21.9	18.2	0.0	-1.9	-1.9	-1.2

Notes: Policies start in calendar year 2000 and effects are calculated over 20 years. Values in columns (1) through (4) are in billions of \$2019. Values in columns (5) through (7) are percent changes. Social welfare is defined as consumer + producer surplus − pollution damages, which equals welfare for a social welfare function that abstracts from distribution. As we assume perfect competition among vehicle manufacturers, market surplus equals consumer surplus. The main text describes each counterfactual policy.