Do Smog Checks Affect Smog? Emissions Inspections, Station Quality and Local Air Pollution

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Abstract

Personal automobile emissions are a major source of urban air pollution. Many U.S. states control emissions through mandated vehicle inspections and repairs. But there is little empirical evidence directly linking mandated inspections, maintenance, and local air pollution levels. Using individual-level data from 1998–2012 from California's inspection program, we estimate the contemporaneous effect of inspections on local air quality by exploiting day-to-day, within-county variation in the number of vehicles nominally repaired and recertified after failing an initial inspection. Additional re-inspections of pre-1985 model year vehicles reduce local carbon monoxide, nitrogen oxide, and particulate matter levels, while re-inspections of newer vehicles with more modern engine technology have no economically significant effect on air pollution. This suggests emissions inspections become less effective at reducing local air pollution as more high-polluting vehicles from the 1970s and 1980s leave the road. We also estimate the importance of station quality, using a metric devised for California's new STAR certification program. We show re-inspections of older vehicles conducted by low quality inspection stations do not change air pollution, while inspections at high quality stations have a moderate effect on pollution concentrations. We find little effect on ambient ozone levels, regardless of station quality or vehicle age.

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1 Introduction

Automobile pollution has substantial impacts on health, and regulating ambient air pollution from automobile traffic is a public concern both in the United States and abroad.[1] Despite regulatory advancements and improvements in engine technology, motor vehicles remain responsible for 75% of carbon monoxide (CO) emissions in the United States, and over 50% of nitrogen oxide (NO_x) emissions.[2] Governments in both developed and developing countries have tried a number of policies to reduce pollution from personal automobiles. Improving fuel standards can decrease emissions per mile driven, but such programs disproportionally impact low-income households and decrease average road safety (Jacobsen, 2013a,b). Driving restriction programs have varied success rates when it comes to actually reducing local pollution (Davis, 2008; Wolff, 2014). Scrappage programs, often referred to as "Cash for Clunkers," can directly remove the dirtiest vehicles from the road, but recent work shows that such programs have substantial problems with adverse selection and may only slightly shift forward the timing of vehicle replacement (Sandler, 2012; Mian and Sufi, 2012; Li et al., 2013; Hoekstra et al., 2014). Inspection and maintenance programs (I/M), the focus of this paper, attempt to limit tailpipe emissions through regular inspections and repairs, without changing driving behavior or fleet composition. Such programs are costly both to governments and individuals (Ando et al., 2000), are subject to potential fraud (Oliva, 2015), and although mandated repairs of high-emitting vehicles often show reduced tailpipe emissions in a testing environment, there exists no large-scale analysis of how I/M programs affect local air pollution. Understanding the effectiveness of I/M in practice is especially important in light of the recent allegations of cheating on emissions tests involving Volkswagen diesel vehicles in U.S. and Europe, where vehicles recorded as passing EPA tests actually produced emissions far above allowable levels on the road.[3]

We provide the first causal analysis of vehicle inspections and local air pollution, using extensive Smog Check data from the state of California.[4] We find an additional inspection-driven repair of a faulty vehicle reduces contemporaneous local air pollution. However, we only find economically meaningful results from inspections of older (1985 and prior) model-year vehicles, suggesting the benefits of I/M programs decline as engine

[1]See Currie and Walker (2011) and Knittel et al. (2015).

[2]Emissions data from `http://www.epa.gov/airquality/peg_caa/carstrucks.html` (accessed online June 1, 2015). For discussion on automobile NO_x regulation, see Fowlie et al. (2012).

[3]See `http://www.nytimes.com/2015/09/23/business/international/volkswagen-diesel-car-scandal.html?_r=0` (Accessed September 23, 2015).

[4](Harrington et al., 2000) calculate cost-effectiveness of a similar inspection program in Arizona, but do not link inspections to ambient air pollution levels.

technology improves. Further, we examine a recent reform to California's I/M program that incorporates measures of inspection station quality. We find increasing station quality may help further reduce some pollutants, but again only through inspections and repairs of faulty older cars that are becoming scarce on the road.

To identify the effectiveness of the California inspection program, we leverage the fact that although the implementation of the overall inspection program is endogenous to air pollution, the timing of individual vehicle repairs—the mechanism through which inspections should affect pollution—is essentially random and exogenous. We use counts of final re-inspections following a failed inspection to capture the intensity of I/M-related vehicle repairs. Controlling for local weather effects and a battery of time and region fixed effects, we find repairing cars that failed initial inspections reduces local CO and NO_x levels in a statistically and economically significant fashion in the period following the repairs. Repairing and re-inspecting 1,000 vehicles of 1985 model year or older decreases ambient CO by 26 parts per billion and ambient NO_x by 1.9 parts per billion, about 7% of a standard deviation for each pollutant. For scale, the average California county re-inspects 1,000 failing vehicles of all ages every 12 days. Re-inspections of vehicles manufactured after 1985 have much smaller effects on air pollution.

California recently passed substantial reforms of inspection station requirements, hoping to improve inspection reliability (Bureau of Automotive Repair, 2014). Under the new "STAR" system, inspection and repair providers must pass certain quality criteria before the state certifies them to inspect the most high-polluting vehicles.[5] Testing the effectiveness of such a program is subject to a number of confounding factors including strategic customer and station responses to the rating system. To avoid such problems, we use historic data to construct the STAR program measures of station quality before the announcement of the policy, and test the relationship between ambient air pollution and re-inspections at high scoring stations. We find re-inspections of older vehicles at high quality stations reduce airborne levels of CO and NO_x while re-inspections at low quality stations yield no change in local air pollution levels—consistent with the theory that low quality stations allow vehicles to pass re-inspection without appropriate repairs. Much like our findings on the general effectiveness of I/M programs, we find re-inspections of newer cars have little impact on air pollution, regardless of station quality. We use this information to simulate the eventual effectiveness of the STAR program, and show that benefits of the more strict inspection system are likely to fade in the future.

[5] The STAR program also requires that newer vehicles with onboard monitoring computers be tested by computer, rather than by direct tailpipe measurements. In addition, new regulations provide for heavier penalties for stations that are found cheating, as well as for consumers who try to falsify an inspection.

Section 2 outlines the California Smog Check Program and the new STAR system. Section 3 describes the Smog Check and pollution data. Section 4 describes our identification technique and construction of *ex ante* STAR quality measures. Section 5 presents our estimates of how the Smog Check program changed local pollution levels, and section 6 uses these results to simulate the impact of the STAR program. Section 7 concludes.

2 Background on California's Emissions Testing Program

California provides an excellent backdrop for the study of tailpipe emissions programs. Of the approximately 110 million registered automobiles in the United States in 2012, almost 13 million were in California, more than any other single state.[6] California has a history of extensive automobile pollution regulation, and other states often adopt or build off California regulations (Engel, 2015). Prompted by the federal 1977 Clean Air Act Amendments, California began mandating biennial emissions inspections in 1984. Current California law allows the Bureau of Automotive Repair (BAR) to mandate regular measures of tailpipe emissions through "Smog Checks." Most vehicles in California must obtain a Smog Check every two years before renewing their annual vehicle registration. If a vehicle displays emissions levels above the threshold for any regulated pollutant, the owner must repair the vehicle and demonstrate passing levels in a later "re-inspection" before registering it, thereby removing high-polluting vehicles from the fleet by inducing repairs or forcing irreparable vehicles off the road.

The California Smog Check program is a decentralized system. Privately-owned repair shops conduct vehicle inspections and, should the vehicle fail initial inspection, these shops make the necessary repairs to bring cars to passing status. Early research found the first incarnation of the Smog Check program was rife with problems that decreased or eliminated ambient air pollution benefits (Glazer et al., 1995; Hubbard, 1998), and identified fraud by private station technicians as a major source of problems.

California passed the first major overhaul of the Smog Check program in 1994 in response to the 1990 Clean Air Act Amendments. The state implemented an "Electronic Transmission System" (ETS) to automatically send test results to the BAR, and created an "enhanced" inspection regime for the most polluted areas of the state. In addition to

[6] Bureau of Transportation Statistics, 2014 State Transportation Statistics data, Table 5-1. Available online at `http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/state_transportation_statistics/state_transportation_statistics_2014/index.html/chapter5/table5-1`.

requiring improved testing equipment, the program began directing vehicles in enhanced regions to specially certified stations authorized only to conduct tests but not make repairs. A vehicle is directed for inspections in a testing cycle if a BAR statistical model flags it as meeting a "high emitter profile," and is directed for all follow-up inspections if it fails the initial inspection with emissions greater than or equal to double the legal limits. The BAR also directs a 2% random sample of all vehicles registered in enhanced areas. The BAR directs 30-40% of Smog Checks each year, and directed inspections are a major source of revenue for eligible stations (Eisinger, 2010). The policy of directing vehicles was intended to make California's privately run system more like government-run systems in other states, which were thought to be less prone to fraud. However, test-only stations were still privately run, and lacked the incentive of a test-and-repair station to profit from performing necessary repairs. In 2005, the program allowed a special class of "Gold Shield" test-and-repair stations to inspect directed vehicles as well.

In 2008, the BAR conducted random roadside emissions inspections and compared the roadside results to the same cars' most recent official Smog Check. Many cars listed as passing their last Smog Check failed the equivalent roadside inspection; 19% of older cars passing inspection less than a year prior failed the roadside test. Of the cars that failed roadside testing, approximately half had failed their *initial* official inspection, but then (supposedly) obtained the necessary repairs and passed their final re-inspection at a Smog Check station.[7] A potential implication of the discrepancy is that these cars did not truly pass the re-inspections: someone had instead manipulated the testing outcome.[8]

In response to the roadside inspection study, the California State Legislature further overhauled the Smog Check program. California Assembly Bill AB2289, passed in 2010, directed the BAR to design a new system for certifying stations to inspect directed vehicles, using metrics based on testing results. The system the BAR proposed and eventually implemented was dubbed STAR. Under the new regulations, owners of directed vehicles must obtain checks at STAR-certified locations. STAR stations could be either Test-and-Repair stations or Test-Only, and had to meet specific thresholds on three metrics based on the Smog Check inspection data reported to the BAR. We discuss the three thresholds in detail below.

The BAR finalized regulations for the STAR Program in November 2011, and published STAR scores for all stations in the spring of 2012. The program officially began

[7] "Evaluation of the California Smog Check Program Using Random Roadside Data", 2010 Addendum, California Air Resources Board, February 2010. Available online at `http://www.bar.ca.gov/80_BARResources/02_SmogCheck/addendum_with_report.pdf`.

[8] An alternative explanation is that the effects of most emissions repairs are short-lived, lasting long enough to pass the follow-up inspection, but degrading to the pre-repair state within a few months.

the next year—all directed vehicles must be inspected at STAR stations as of January 1, 2013.

3 Data

To measure the volume of re-inspections and generate our versions of the STAR quality metrics, we employ inspection-level data from the California Smog Check program. Stations conduct all Smog Check inspections using equipment attached to the ETS that automatically sends results of the test to the California BAR.[9] Our data consist of the population of vehicle inspections conducted in California between 1996 and 2012 and transmitted through ETS.[10]

Each observation in the Smog Check data represents a single inspection, and includes the Vehicle Identification Number (VIN) of the vehicle tested, the date and time of the inspection, the odometer reading, an indicator for the outcome of the test, and emissions readings for hydrocarbons (HCs), NO_x, and CO. Each Smog Check inspection record further contains a 6-digit station identifier, which we join to a crosswalk giving the zipcode of each station.[11]

We determine model year and vehicle type from the included VIN.[12] We also utilize the provided odometer reading in calculating our hypothetical STAR scores.[13]

We use pollution data from the CARB Air Quality Database, a collection of air monitors taking hourly pollution readings. We use data from 1998 to 2009, and focus on CO, NO_x, ozone (O3), and particulate matter (PM). We aggregate hourly readings for CO, NO_x and O3 to the county-day level by averaging individual monitor readings in a given county, and aggregate daily PM readings to the weekly level (most PM monitors take measurements once every six days). We do not weight monitors by any distance

[9] We obtained access to the Smog Check data via a Public Records Act request, the California equivalent of the Freedom of Information Act.

[10] Data from 1996 and 1997 are incomplete, as the BAR was phasing in the ETS during these years. When available, we use these data to construct any lagged measures for inspections in later years, but our contemporary analysis does not begin until 1998 when the data are more reliable.

[11] We are grateful to Emily Wimberger for providing this crosswalk.

[12] Although the Smog Check data contain some direct information on vehicle types, it is messy and at times unreliable when compared to known VIN information. All vehicles manufactured after 1980 have a standardized 17-digit VIN: the first 8 digits plus the 10th and 11th precisely indicate the vehicle type, at the level of make/model/engine/body type/transmission/year/plant. For earlier vehicles, different manufacturers used their own formats. We determine make, model year and an approximation of the vehicle-identifying prefix for most of the vehicles manufactured 1975-1980.

[13] We employ an algorithm to "clean" the odometer variable, correcting for rollovers, typos and other glitches that produce unbelievable values for miles traveled between inspections. Specifics of our algorithm are available upon request.

metric, and use an unbalanced panel of monitors to maximize available data. To improve readability of our results, we scale pollution readings for CO, NO_x and O3 to parts per billion (PPB).

O3, a major component of the atmospheric condition commonly known as smog, is a secondary pollutant, generated by atmospheric mixing of volatile organic compounds (VOCs) and NO_x. Depending on the current state of local VOC and NO_x levels, additional NO_x can either increase or decrease O3, which makes O3 a difficult pollutant to analyze on a large scale. Regardless, a primary interest of the program was to reduce smog, so we test for general impacts of O3. The link between PM and automobile use is also largely secondary. The largest sources of PM from automobile traffic are combustion of diesel fuel and wear from road and engine friction. We expect little change in these sources from Smog Check—California does not require Smog Checks for diesel vehicle from model years prior to 1997, and Smog Checks should do nothing to change road wear. However, through atmospheric reactions NO_x can form fine particles, providing a vector for an impact, and given the literature on the negative health effects of PM, we include this pollutant as well.[14] Our PM data gives the concentration of particles less than 10 micrometers (PM_{10}) in units of micrograms per cubic meter (μ/m^3). Local weather influences both general air pollution and the types of emissions automobiles generate (Knittel et al., 2015). Ambient temperature can also influence inspection results, as emissions control systems function better when warm. We control for daily high and low temperatures and daily precipitation at the county level. We generate weather data following the methodology of Schlenker and Roberts (2006): taking spatially detailed monthly weather data generated by Oregon State University's PRISM model, aggregating the resulting grid of weather data by county using GIS, and using historical daily averages to interpolate a daily weather.[15] We note weather fluctuations should be exogenous to inspection timing, and their inclusion should do little to change our primary estimates.

4 Empirical Methodology

We estimate the impact of the Smog Check program, and the projected impact the new STAR program in particular, by leveraging random variation in the timing and location of repairs of failing vehicles. Unfortunately, we cannot observe actual repairs. Instead, we focus on the timing of final re-inspections following a failed inspection. A passing

[14] See `http://www3.epa.gov/airtrends/aqtrnd95/pm10.html`, (accessed October 30th, 2015). See also Dominici et al. (2014) for a review of recent literature on particulates.

[15] We are grateful to Wolfram Schlenker for providing code to create the interpolated daily weather series.

re-inspection theoretically indicates a repair took place to reduce a vehicle's emissions below the legal thresholds. Thus, we use final re-inspections in an inspection cycle as a proxy for repairs.

The effectiveness of I/M depends on inspections accurately assessing vehicle-level emissions, and both inspectors and vehicle owners can influence test results through dishonest behavior (Oliva, 2015). Evaluating the environmental benefits of the STAR program using a simple pre/post examination of air pollution levels is problematic due to the possibility of stations attempting to game the rating system. Drivers of marginal cars have an incentive to seek test providers that are more lax in testing or willing to falsify tests, which in turn provides an incentive for test providers to engage in such duplicitous behavior to draw business. To avoid such problems, we examine the role of "better" stations, as measured by the STAR metrics, *before* the development of the program. We generate retrospective STAR scores for the period 1998–2009 based on the metrics the BAR eventually used. This allows us to establish the link between station quality and local air pollution using what *would be* "better" stations by STAR standards before the state even proposed the program, such that no gaming behavior is possible. This section describes our methodology in detail, including construction of our retrospective station quality metric and our identification of the effects of Smog Check and STAR.

4.1 STAR-based Station Quality Metrics

The STAR program certifies stations based on past inspection results. To qualify for the program and receive business from "directed" vehicles as defined in section 2, stations must have a passing grade on three metrics, based on the results of their inspections in the Smog Check database. These include a short-term measure called the Similar Vehicle Failure Rate (SVFR) using inspections taking place in the most recent calendar quarter, and a longer-term measure called the Follow-up Pass Rate (FPR), based on *current* inspection results of vehicles that a station inspected and passed on the *previous* inspection. The other measure involves deviations from standard Smog Check test procedure.[16]

All STAR metrics compare test outcomes at the station in question to average rates for similar vehicles statewide. The BAR defines "similar" vehicles as having the same make, model, year, engine displacement, transmission type, and body style. Both the long-term FPR and the key short-term measure, the SVFR, construct expected total failure rates

[16] If a station deviates from procedure more than the average for similar vehicles, the station can be ineligible for STAR. The STAR program separates out one of these deviations, selecting the incorrect gear during the test, from seven other deviations. Stations can fail on up to one of the set of seven deviations and still be eligible for STAR, but cannot fail the incorrect gear selection metric.

based on similar vehicles. The BAR compares these measures to the actual failure rate for vehicles inspected at a given station. Although the BAR did not start calculating these measures until after our sample period, we have all available information the STAR program uses and can construct our own measures of both the FPR and SVFR using observed historical inspection results.

Vehicles registered in basic and enhanced Smog Check areas must be inspected every two years. We use the term "cycle" to refer to each time the vehicle is up for inspection before registration. Each cycle may involve multiple inspections if the initial inspection is failed, culminating with a final re-inspection where the vehicle eventually passes. Let s index inspection station, n index vehicle, m vehicle type, c inspection cycle, and q calendar quarter. We index inspections within cycles with $i \in \{1...I\}$. If a vehicle passes the first inspection of a cycle, $I = 1$. Let $\eta_s(c,i)$ denote the set of vehicles that receive their ith inspection at station s during cycle c . We define the general expected failure rate for station s as:

$$\Theta(\eta_s(c,i), c', i') = \frac{1}{|\eta_s(c,i)|} \sum_{n \in \eta_s(c,i)} P(fail_{nc'i'} = 1 | m_n, q, X_{nmc'}),$$

where $fail_{nc'i'}$ is an indicator equal to one if vehicle n fails the i' inspection of cycle c', and $X_{nmqc'}$ is a vector of time-varying vehicle characteristics (e.g., mileage). We calculate $P(fail_{nc'i'} = 1 | m_n, q, X_{nmc'})$ as:

$$P(fail_{nc'i'} = 1 | m_n, q, X_{nmc'}) = F(m,q) + (X_{nmc'} - \bar{X}_{mc'})\beta,$$

where $F(m,q)$ is the proportion of type m vehicles that fail during quarter q, $\bar{X}_{mc'}$ denotes the type-specific mean of $X_{nmc'}$ during cycle c' and β is derived from the following linear probability model using only initial inspections ($i = 1$):

$$P(fail_{nc1} = 1) = \alpha_m + \gamma_q + X_{nmc}\beta + \varepsilon_m,$$

where α_m and γ_q are vehicle type and quarter fixed effects, respectively. Following the BAR procedure, X includes odometer reading at the time of the inspection and days since last inspection. In words, the expected failure rate is the mean of the predicted failure probability for vehicles inspected during the relevant cycle at the station in question.

Using the notation above, we define the SVFR for station s in quarter q as:

$$SVFR_{sq} = \frac{\frac{1}{|\eta_s(c,1)|} \sum_{n \in \eta_s(c,1)} fail_{nc1}}{\Theta(\eta_s(c,1), c, 1)}.$$

The SVFR is the ratio of the actual failure rate for initial inspections at the station during the current period to the expected failure rate for those inspections.

The BAR calculates the FPR score used by the STAR program as the p-value of the following hypothesis test:

$$h_0 : \frac{1}{|\eta_s(c-1,I)|} \sum_{n \in \eta_s(c-1,I)} fail_{nc1} \leq \Theta(\eta_s(c-1,I), c, 1) \tag{1}$$

$$h_A : \frac{1}{|\eta_s(c-1,I)|} \sum_{n \in \eta_s(c-1,I)} fail_{nc1} > \Theta(\eta_s(c-1,I), c, 1) \tag{2}$$

The FPR tests whether vehicles given final inspections by station s on the previous cycle fail more than expected during the current cycle. Note the vehicles in $\eta_s(c-1,I)$ need not be inspected at station s during cycle c.[17]

We use the Smog Check inspection data to test how well these measures reflect the ability of stations to reduce measured vehicle emissions. We calculate our STAR metrics for the period before the program was in place, and thus not subject to gaming or any other responses to implementation of STAR. We regress emissions at a vehicle's initial current inspection on the SVFR or FPR of the station that conducted the final, *passing* inspection of the previous inspection cycle. If STAR metrics capture station quality, vehicles passed by higher scoring stations should be less likely to fail, and thus have lower emissions, on their next inspection. To flexibly estimate the relationship between quality scores and later emissions, we use indicators for 10 bins of equal width to measure the STAR scores, and interact the indicator for each bin with an indicator for whether each vehicle failed the initial inspection of the previous cycle—i.e., whether it should have been repaired before eventually passing. We control for the SVFR of the station conducting the *current* initial inspection, to hold constant the probability of failing independent of underlying emissions, and include controls for the type of inspection and vehicle type, vehicle age, year, and county fixed effects

Figure 1 plots the coefficients on the STAR score indicators for CO emissions—results for NO_x emissions are similar, and versions of figure 1 are available in the appendix as figure A1. Panel (A) shows results for bins of SVFR, and panel (B) shows results for bins of FPR. For both measures, vehicles that fail the initial inspection on the previous cycle are more likely to fail (have higher emissions) on the initial test of the next inspection

[17] The STAR program actually calculates FPR at the technician level, and assigns stations the lowest score of all their registered technicians. Because we calculate our version of the FPR at the station level, we abstract from this distinction for clarity of notation.

cycle. While we do see lower emissions for vehicles passed by stations with higher SVFR scores, the effect flattens out at higher levels, reflecting an undesirable feature of the SVFR as a quality metric: a very high SVFR does not necessarily mean a station is high quality. Low failure rates may indicate fraud against the Smog Check program, but unusually high failure rates may indicate fraud against consumers rather than rigorous inspections (Schneider, 2012). For the FPR, the relationship is the opposite of that intended. For vehicles that failed the initial inspection on the previous cycle, the relationship between emissions and FPR is essentially flat. For vehicles that pass the initial inspection, higher FPR correlates with *higher* CO emissions at the next initial inspection. This counter-intuitive result suggests vehicles inspected and passed at nominally higher quality stations, as measured by the FPR, have greater emissions in the future.

What explains this odd result? The theoretical appeal of the FPR for measuring station quality is that it captures whether or not failing vehicles inspected at a station are correctly repaired before eventually being certified. As we discuss in the next section, this assumption is critical for any I/M program to reduce pollution levels—inspections only reduce pollution if they lead to repairs that reduce emissions. The downside of the FPR score used by the STAR program is that it is necessarily retrospective, capturing a station's performance generally two years in the past. This lagged performance metric may not correlate with current performance, which presents a potential problem for implementation and effectiveness of the current STAR program. We discuss this issue in detail in section 5.

As we use retrospective data, and have the entire history of each station's inspections up through 2012, we can calculate an alternate version of the FPR capturing *contemporaneous* final inspections, including re-inspections. We refer to this contemporaneous FPR as the C-FPR. This score is the p-value from the following hypothesis test:

$$h_0 : \frac{1}{|\eta_s(c,I)|} \sum_{n \in \eta_s(c,I)} fail_{n(c+1)1} \leq \Theta(s, \eta(c+1, I), c, 1) \tag{3}$$

$$h_A : \frac{1}{|\eta_s(c,I)|} \sum_{n \in \eta_s(c,I)} fail_{n(c+1)1} > \Theta(s, \eta(c+1, I), c, 1) \tag{4}$$

Our C-FPR tests whether vehicles given their final inspections by station s in the current cycle fail more than average on their initial inspections in the next cycle (which may be conducted at other stations). Panel (C) of figure 1 shows the relationship between the C-FPR score and future emissions rates. Not only are higher C-FPR scores associated with lower CO emissions on the next inspection, the relationship is nearly linear. We focus on measuring station quality using the C-FPR for our air pollution results in the section 5.

4.2 The Effect of Smog Checks on Local Air Pollution

Counties and air quality management districts must implement the basic or enhanced Smog Check program when pollution levels cross thresholds set by the federal Clean Air Act. As a result, not only will the pre-trend of increasing emissions lead to bias in estimating the effect of the Smog Check program, exceeding the federal air pollution standards may trigger additional policy responses. For instance, policymakers may respond to high pollution levels by increasing mass transit options, or subsidizing engine modifications on commercial trucks. Further, any kind of before/after comparison risks confounding effects of Smog Check with effects of state- and nation-wide policy changes, particularly emissions standards on new vehicles.

To avoid such issues, we estimate the effect of Smog Check and the new STAR program by exploiting a key realization about the nature of vehicle inspection programs. Initial inspections, passed or failed, correct or not, cannot directly impact air pollution. That is, to a first approximation, *inspections do not affect local air pollution levels*; detection of faulty engines and subsequent repairs do. The only way inspections affect air pollution is through inducing repairs. If a vehicle is actually in a failing status but is incorrectly passed on an initial inspection, this should not change air pollution levels—emissions will be high both before and after the inspection. However, local air pollution levels would improve if stations conduct repairs as a result of a failed initial inspection, and correctly verify the effectiveness of the repair by re-inspecting the failing vehicle. Station quality is thus important, as a sham initial inspection, or an omitted repair followed by a sham re-inspection, should have no more effect on air pollution than no inspection program at all.

Conveniently, the timing of inspections is exogenous to both levels and (non-Smog Check) policy-driven changes in local air pollution. An annual vehicle registration notice from the California DMV prompts vehicle owners to obtain a Smog Check every two years. Vehicle registrations are due on the anniversary of the date the vehicle was initially registered in California, and the registration notice comes in the mail around 60 days before the vehicle's registration expires. In California, the expiration date for a vehicle's registration stays constant even if the vehicle is sold. Thus, if a vehicle ever changes owners, the timing of the biennial Smog Check is unrelated to any choice on the part of the current vehicle owner. This provides variation in registration dates, variation in when the vehicle owner obtains the initial inspection, variation in whether a vehicle fails the initial inspection, and variation in how quickly the owner repairs the vehicle and schedules the re-inspection in the event of an inspection failure. None of these sources of variation should correlate with levels of air pollution, except possibly through seasonality, which we control for using fixed effects.

We create a daily panel of re-inspection counts aggregated by county of the station conducting each inspection. Choosing an overly fine geography risks attributing inspections to the wrong location and ignoring spillover effects from pollutants blown to neighboring areas. At the same time, broad geographic definitions reduce our sample size and may obscure important variation. We aggregate at the county level as a compromise between these constraints. Counties in California are large relative to other parts of the country, and a county is a reasonable approximation of the area in which a vehicle owner does most of their commute driving.[18] Data on county-to-county migration flows from the 2000 Census show that 82% California workers live and work in the same county.[19] Further, the EPA determines Clean Air Act attainment status at the county level, making it a policy-relevant level of aggregation.

Although daily variation in re-inspections is useful for identification, there is a lag between the repair of a failed vehicle and when we expect to see a change in air pollution levels. Pollutants like NO_x and CO persist in the air and may take time to drift to a sensor, and there may be a period of days between a repair and the date the station records the re-inspection. Thus, associating air pollution levels on a specific day with re-inspections on the same day is overly restrictive. To address this issue, we use a 90-day rolling total of re-inspections as our measure of the intensity of re-inspections.[20]

Because older vehicles are more polluting on average and thus more likely to be targeted by California's policy of directing vehicles, we split results by vehicle age to estimate separate effects for re-inspections of older vs. newer vehicles. This requires we formally define "older" in our context. Beginning in 1980 three major improvements in engine technology led to significant reductions in vehicle emissions: the three-way catalytic converter, introduced in 1980; fuel-injection systems, introduced in 1985; and second-generation onboard monitoring computers (called OBDII), introduced in 1996. Each of these technologies were adopted rapidly, and affected emissions both under normal operating conditions and potentially under "failing" conditions as measured by Smog Checks.

To help determine a reasonable cutpoint for old versus new vehicles, we plot average

[18] We obtain qualitatively similar results when we aggregate at the air basin level instead.

[19] See `http://www.census.gov/population/www/cen2000/commuting/index.html`, accessed August 1, 2015.

[20] We obtain qualitatively similar results using a 30-, 60- or 120-day window.

CO and NO_x emissions measured at passed and failed Smog Checks by model year.[21] Figure 2 shows that, for both pollutants, emissions at passing inspections are decreasing across model years in a largely continuous fashion as general automobile technology improves. For failed inspections, average Smog Check test results exhibit a strong decline in CO levels beginning with the 1985 model year, and a strong decline in NO_x levels beginning with the 1994 model year. To be more conservative in what we call "older" cars, we opt for 1985 as the cut-off year between old and new vehicles.[22]

We estimate the effect of re-inspections on levels of a pollutant $p \in \{NO_x, CO, O3, PM_{10}\}$ as:

$$p_{tg} = \left(\sum_{i=0}^{90} R^{old}_{g(t-i)}\right)\beta_1 + \left(\sum_{i=0}^{90} R^{new}_{g(t-i)}\right)\beta_2 + \gamma X_{gt} + \varepsilon_{gt}, \tag{5}$$

where R^{old}_{ct} and R^{new}_{ct} denote the number of re-inspections of older and newer vehicles, respectively, occurring in county g on date t, X_{gt} is a vector of covariates, and ε_{gt} is an error term. We specify re-inspections in levels. Holding weather, county geography and related factors constant via fixed effects, to a first approximation repairing one failing vehicle should remove the same quantity of emissions, and by extension reduce air pollution levels by the same amount, regardless of whether this represents a 1% change or a 0.001% change in the level of re-inspections. This will cause the model to predict much larger effects for densely populated areas such as Los Angeles County, a desirable feature of our specification. Los Angeles County is heavily polluted in part because it has a very large number of cars on the road, and we expect it to experience large reductions in pollution relative to the counterfactual if the Smog Check program causes large numbers of high-polluting vehicles to receive repairs.[23] β_1 and β_2 give the causal effect of additional re-inspections on air pollution levels. In our preferred specification, X_{gt} includes controls for weather, county fixed effects, calendar-week fixed effects to control for statewide trends, and county-specific cubic time trends.

Identification of the effect of station quality follows from the same logic as the effect of re-inspections. The number of re-inspections at higher- and lower-quality stations will fluctuate over time with the variation in the timing of the initial Smog Checks of vehicles eventually taken to those stations. As our quality metric was unobservable during the

[21] O3 and PM_{10} are not tailpipe pollutants and as such are not measured directly by Smog Check inspections.

[22] If we separate out effects into three groups, one for each "era" of pollution control technology, we obtain essentially identical effects from re-inspections of the 1985–1995 and 1995+ vehicles, with no change in the effect of 1975–1985 vehicles, indicating that the split at 1985 is appropriate. See appendix table A1.

[23] Our results are robust to excluding Los Angeles County.

period covered by our air pollution data, and the study of roadside inspections leading to the development of the STAR program was not even released until 2010, the distribution of vehicles across high- and low-quality stations is exogenous.[24] Given our argument that only accurate re-inspections reduce local air pollution, we expect to see smaller or zero effects from re-inspections at low-quality stations, and larger effects from re-inspections at high-quality stations.

Conducting analysis at the county rather than station level requires we construct a county-level measure of station quality. We estimate the interaction of station quality and re-inspections using two different approaches. First, we calculate a 90-day rolling average of the C-FPR score at the county level, weighting our individual station C-FPR scores by the number of re-inspections at each station. We interact this county-level average with the count of re-inspections:

$$p_{tg} = \left(\sum_{i=0}^{90} R^{old}_{g(t-i)}\right)\beta_1 + \left(\frac{1}{91}\sum_{i=0}^{90} CFPR^{old}_{g(t-i)} \cdot \sum_{i=0}^{90} R^{old}_{g(t-i)}\right)\delta_1 + \left(\sum_{i=0}^{90} R^{new}_{g(t-i)}\right)\beta_2 \quad (6)$$
$$+ \left(\frac{1}{91}\sum_{i=0}^{90} CFPR^{new}_{g(t-i)} \cdot \sum_{i=0}^{90} R^{new}_{g(t-i)}\right)\delta_2 + \gamma X_{gt} + \varepsilon_g,$$

where $CFPR^{old}_{gt}$ and $CFPR^{new}_{gt}$ denote the county average C-FPR of stations conducting re-inspections of older and newer cars, respectively.

We next take a more flexible semi-parametric approach, equivalent to interacting re-inspections with bins of average county-level C-FPR scores. Because our air pollution analysis uses aggregated data, this takes the form of counting re-inspections of older and newer cars at stations falling into each of 20 equal-size C-FPR bins:

$$p_{tg} = \sum_{b=1}^{20} \beta^b_1 \left(\sum_{i=0}^{90} R^{old}_{bg(t-i)}\right) + \sum_{b=1}^{20} \beta^b_2 \left(\sum_{i=0}^{90} R^{new}_{bg(t-i)}\right)\beta_2 + \gamma X_{gt} + \varepsilon_g, \quad (7)$$

where $R^{old}_{bg(t-i)}$ counts total re-inspections of older vehicles conducted at stations with C-FPR scores falling in bin b within a county, and $R^{new}_{bg(t-i)}$ is the corresponding count for newer vehicles.

[24]This further assumes consumers had no other way to identify low-quality stations willing to pass a failing vehicle before STAR. One way to test this assumption is to compare the average C-FPR of stations inspecting older vehicles to the average for stations inspecting newer vehicles. Pre-1985 model year vehicles are more likely to fail and likely more expensive to fix. If consumers had any systematic way of identifying "bad" stations willing to give a sham inspection, we would expect to see older vehicles disproportionately inspected at lower quality stations. We observe the mean C-FPR for older and newer vehicles is essentially the same.

5 Results

Panel A of table 1 summarizes our variables of interest. For consistency with our regression results, we show NO_x, O3 and CO in parts per billion (ppb).[25] Average levels of both NO_x and CO fell across our sample period, dropping almost 350 ppb (0.35 ppm) for CO and 10 ppb for NO_x. O3 was largely unchanged, remaining within 0.5 ppb of initial 1998 levels. We note the number of personal automobiles on the road in California increased by almost 1.5 million vehicles across this period, so no change in O3 levels does not necessarily mean that the Smog Check program had no impact on O3. PM_{10} levels fluctuate from year to year with no obvious pattern.

California is a large and geographically diverse state, with very different climate, topology and population density in the northern and southern regions. For southern California, panel B shows averages for Los Angeles County, the county with the most annual inspections. Improvements in CO were more drastic in Los Angeles County than the state as a whole, decreasing by over 800 ppb (0.8 ppm). NOx decreased around 40 ppb, just over 50% of 1998 levels, while O3 levels increased. For northern California, panel C shows averages for the 9 counties that make up the San Francisco Bay Area.[26] The San Francisco Bay Area follows the general pattern of California, with similar improvements in both CO and NO_x and little change in O3 and PM_{10}.

Turning to the data on Smog Check, two general trends appear. First, increases in inspections (and re-inspections) correlate with decreases in both CO and NO_x but with little change in O3. Second, neither total inspections nor re-inspections increase monotonically with time. Total inspections peak in 2004 and then drop, likely due to a 2005 Smog Check policy change that exempted pre-1975 vehicles from inspections.[27] In most of the state, re-inspections decline around 2002, corresponding to a decrease in the overall failure rate (and thus the need for re-inspection/repair). As a caveat, we note the San Francisco Bay Area seems to be missing a large number of inspections from 2002 through mid-2003—we exclude these years for these counties from our empirical analysis. We are not aware as to why these counties are "missing" inspections for this period, though we note the timing corresponds to a shift in the Smog Check regime in these

[25]Researchers often show CO in parts per million (ppm), so at first glance our CO numbers appear larger than prior studies looking at CO in California. For example, Currie and Neidell (2005) show that in 2000, the average California 8-hour high CO level was 1.3 ppm (1,300 ppb), compared to a full day average of 649 ppb for the same period in our data.

[26]The counties in the San Francisco Bay Area are: Alameda County, Contra Costa County, Marin County, Napa County, San Francisco County, San Mateo County, Santa Clara County, Solano County and Sonoma County.

[27]Note we control flexibly for such state-level changes across time in our regressions.

counties, during which stations in the region were upgrading the machines used for Smog Checks. Results are robust to inclusion of this period for these counties.

5.1 Effect of Re-inspections

To establish a causal link between re-inspections (our proxy for repairs) and local air pollution, we estimate a series of regression models based on equation (5), where the coefficient of interest is the effect of re-inspections of failing cars on local air pollution. Specifically, in table 2 we estimate the link between the number of county-level re-inspections and county-level measures of the direct pollutants CO and NO_x. We scale our results to show the effect per 1,000 re-inspections in the past 90 days. Using values from table 1, the average California county sees 1,000 re-inspections of all vehicle ages every 12 days, while Los Angeles County has an average of just over 1,000 re-inspections every day. The nine counties making up the San Francisco Bay Area conduct about 1,000 re-inspections every two days.

Column 1, the most basic model, includes no controls. Both CO and NO_x show a positive correlation between county pollution levels and the number of re-inspections for older cars: an additional 1,000 re-inspections correlates with a 41.7 ppb increase in CO (0.09 of a standard deviation) and a 1.9 ppb increase in NO_x. When we focus on newer cars, the sign flips for CO to a 2.2 ppb decrease per additional 1,000 re-inspections. The sign on NO_x remains positive, but is smaller at 0.2 ppb per 1,000 cars. All results are statistically significant at either the 5% or 1% level.

Adding county fixed effects (Column 2) increases the negative effect of newer car re-inspections on CO to 10.5 ppb per 1,000 re-inspections, but the impact from older cars remains similar. The sign on NO_x is now negative for newer cars, with an additional 1,000 re-inspections lowering ambient levels by 0.5 ppb. Adding controls for weather (Column 3) does little to change the size or sign of our results—while weather can influence the relationship between emissions and ambient pollution levels, we expect it to be exogenous to the number of re-inspections. Thus, controlling for weather serves largely to increase precision of our estimates. Column 4 adds calendar week effects to flexibly control for state-wide trends and within-year seasonality.[28] Controlling for state-wide time effects pushes coefficients toward zero for both vehicle age groups and both pollutants, but the coefficients on re-inspections of older cars remain positive.

Finally, Column 5 controls for local trends using a third-order polynomial time trend

[28] While weather is exogenous to the number of inspections, time of year is not: inspection timing corresponds with time of initial purchase, and the number of new cars sold varies systematically across time of year.

for each county, in addition to county fixed effects, weather controls, and calendar week fixed effects. After controlling for differential trends across counties, increasing re-inspections (repairs) of both older and newer cars *reduces* ambient CO and NO_x. This suggests counties with increasing air quality saw decreases in the number of re-inspections of older cars over time. Older cars are more polluting than newer cars, but also more likely to be scrapped or sold out of state, especially if these vehicles cannot pass a Smog Check without significant repairs. Counties with many older cars early in our sample period would see fewer re-inspections of older cars over time due to increased scrappage and thus declining air pollution that is not directly related to Smog Check inspections and repairs. Failing to account for such trends biases the estimated impact of repairing older cars. In our preferred specification, re-inspecting an additional 1,000 older cars *decreases* ambient CO by 26.6 ppb and ambient NO_x by 1.9 ppb (0.07 of a standard deviation of both pollutants). An additional 1,000 newer car re-inspections decreases ambient CO by 4.8 ppb and NOx by 0.8 ppb (0.01 and 0.03 of a standard deviation, respectively).

As a whole, we find the Smog Check program's requirements to repair and re-inspect high-polluting vehicles moderately improved local CO and NO_x levels, particularly when repairing older model-year cars. We next consider how station quality controls, as proposed in the new STAR program, affect the benefits of I/M.

5.2 Station Quality

To test for the role of station quality, we examine how our C-FPR score correlates with the effect of re-inspections. We first calculate the C-FPR score for all stations in the county, then aggregate up to the county level, weighting by the number of re-inspections conducted over the previous 90 days (see section 4).

Table 3 shows our results. All columns use the controls from Column 5 of table 2: weather controls, county fixed effects, county cubic trends, and calendar week fixed effects. Column 1 repeats the model of table 2 Column 5 for comparison. Column 2 includes an additional interaction between the number of re-inspected vehicles in the last 90 days with the continuous C-FPR measure. Higher C-FPR corresponds to the county having a greater share of re-inspections at stations the STAR program would consider to be of better quality, had STAR existed at the time.

Column 2 shows station quality clearly matters in the case of older vehicles. As an extreme example, re-inspections in a county with an average C-FPR of zero would have essentially zero effect on either pollutant, but the effect of re-inspections increases with average station quality. For ease of interpretation, we present the estimated effect for each vehicle age calculated at the average county-level C-FPR in our sample. For older cars, this suggests an additional 1,000 re-inspections in a county of average C-FPR would decrease ambient CO levels by 55.44 ppb and average NO_xlevels by 4.55 ppb.[29] Both average effects are statistically significant at 1%.

The case for station quality when testing newer vehicles is less clear. The signs of both the baseline effect and the interaction effect are reversed from that of older vehicles: a greater share of re-tests at higher quality stations reduces the effect of re-inspections on ambient pollution for both CO and NO_x. Importantly, these results are precisely estimated but economically insignificant, which is clear when considering the marginal effect at the mean. At the average county C-FPR of around 0.59, an additional 1,000 re-inspected newer cars would decrease pollution levels by around 0.004 standard deviations for CO and 0.016 standard deviations for NO_x. The result is not statistically significant for CO, and the average effects on both pollutants are about half the size of the already small overall effects for newer cars from table 2.

Figure 3 clearly illustrates the effect of station quality for newer cars is effectively zero. Following equation (7), we generate 20 bins of C-FPR scores, in units of 0.05, from 0 to 1. We include sets of 20 variables each for older and newer cars, giving the counts of re-inspections at stations in the appropriate C-FPR bin. Figure 3 plots each coefficient on the bin-specific count variables, and provides a LOWESS fit with bandwidth $N * 0.8$ to illustrate the general patterns across the C-FPR distribution.

Panel A shows results for CO, and panel B shows results for NO_x. For newer cars, the effect of a re-inspection is approximately constant at zero across our estimated measure of station quality. Visual analysis shows the puzzling positive results from table 3 are a result of effects for counties with average FPRs very close to 1, which represent a small share of re-inspections overall. For example, only 24% of total newer vehicle re-inspections across our entire sample occurred at stations with C-FPR levels greater than 0.9. Panel B shows that with older cars, there is a clear differential between a re-inspection at a lower-quality vs. a higher-quality station. Increasing re-inspections in areas with C-FPR scores below approximately 0.3 has no effect on local air pollution, with increasing benefits of re-inspections for higher-quality stations.

Table 3 and figure 3 jointly suggest increasing re-inspections of older cars in areas with higher estimated station quality reduces air pollution in an economically and statistically significant manner. However, there is no effect for areas with lower station quality, and economically insignificant effects regardless of quality when considering newer model-year cars.

[29]We calculate the effect at the average level using the *margins* command in Stata.

The small effect of re-inspections of newer cars on air pollution is to be expected, to some extent. As we showed in figure 2, the average differential in tailpipe emissions between a passing and a failing vehicle decreases with model year. Bringing an average failing 1984 model year vehicle up to passing standard reduces the CO concentration in its tailpipe emissions by around 14,000 parts per million, while fixing an average 2001 model year vehicle reduces CO emissions by about 1,300 parts per million, more than 10 times less. With a smaller effect on emissions per vehicle of conducting repairs, it should not be surprising that the effect of repairing 1,000 vehicles on ambient pollution is smaller. The small effect of re-inspections and the zero effect of station quality may also have to do with the OBDII computers installed in vehicles manufactured after 1996. These computers trigger the familiar "check engine" light when they detect an emissions failure, possibly leading to repairs outside the Smog Check inspection cycle. Station quality at the biennial inspection would then have little effect, as most serious emissions failures would have already been fixed. More troublingly, OBDII systems may make it easier to consistently defeat detection of emissions failures, as was the case in the recent scandal involving Volkswagen diesel vehicles. The STAR quality metrics, including our C-FPR variant, are designed to catch cheating stations by comparing their results to others statewide. However, if a vehicle passes incorrectly at every inspection, this will lead to scores that are uncorrelated with actual inspection results, especially if the cheating behavior is on the part of the vehicle owner or manufacturer rather than the inspection station. A related issue with inspection programs, identified by Mérel et al. (2014), is that vehicle repairs may not last for the full period between inspections. Depending on the rate of repair decay, the benefits of passed re-inspections could be highly transient.

Regardless of the reason, the small effect of re-inspections of newer cars and the negligible effect of station quality for those vehicles is problematic for the efficacy of the Smog Check program in general, and STAR in particular going forward. Newer vehicles make up the majority of inspections, and the majority of the costs of both inspections and repairs come from these vehicles. If the Smog Check program, even enhanced by STAR, is not delivering air pollution benefits from newer vehicles, the value of the program is diminished.

5.3 Effects of Re-inspections on Secondary Pollutants

We focus on the effect of Smog Checks on CO and NO_x because these pollutants are directly emitted by motor vehicles and thus we most expect to see an effect on levels of these pollutants. However, the main social harms from NO_x and the policy interest in controlling it stem from its role in forming secondary pollutants, principally O3 and particulate matter. O3 in particular has a complicated formation process, and it is possible that the moderate reductions in NO_x caused by Smog Check might not translate into reductions in O3. In table 4 we estimate our empirical model using ambient O3 as the outcome. Columns 1 and 2 replicate the analysis of tables 2 and 3 using ozone levels in parts per billion as the outcome variable. The point estimates have the wrong sign, indicating re-inspections increase ozone levels, but although some estimates are statistically significant, they are economically zero. For the average county, re-testing an additional 1,000 cars increases ambient ozone by 0.0007 of a standard deviation for older cars and increases ambient ozone by 0.014 of a standard deviation for newer cars.

O3 levels are negatively correlated with CO and NO_x levels in our sample, and so the small effect and "wrong sign" for our ozone results could simply reflect that correlation. The process by which NO_x and VOCs form ozone resembles a Leontieff production function, such that when NO_x levels are high, reducing NO_x emissions may have limited effect on ozone levels.[30] To test this, in columns 3 and 4 we control for the level of NO_x and NO_x squared. Our coefficients acquire the "right" sign, with re-inspections of older cars reducing O3 levels, but the magnitudes are still very small. In appendix table A3 we allow the coefficients on re-inspections to vary depending on whether the NO_x level is high or low on a given day. We get similar results as those in table 4. It does not appear our zero findings for ozone are a result of the availability of NO_x. Finally, figure 6 plots results by C-FPR bins, and we see no visual effect.

We next test for the effect of re-inspections on levels of PM_{10}. Because PM_{10} sensors only take readings every 6 days, we collapse to the county-week level. For counties with more than one sensor and thus more than one observation per week, we take the average PM_{10} reading for each week and use the weather controls and the rolling total of re-inspections for the day of the last reading. Table 5 repeats the analysis of table 3 with PM_{10} as the dependent variable. Without controlling for station quality, our estimates are imprecise, but the point estimates indicate re-inspections of older vehicles have a small negative effect on PM_{10} levels, while re-inspections of newer cars have a near-zero effect. Adding an interaction with county-average C-FPR, we find that re-inspections of older vehicles have no effect on PM_{10} levels when conducted at poor quality stations, while re-inspections at high quality stations moderately reduce PM_{10} levels, a result that is statistically significant at 5%. At the average C-FPR, 1,000 re-inspections of older vehicles leads to a 1.9 μ/m^3 reduction in PM_{10} levels, about 0.08 of a standard deviation.

[30] There is an additional process by which certain forms of NO_x can actually reduce ozone when NO_x is sufficiently abundant. See Muller et al. (2009).

As with CO and NO_x, re-inspections of newer cars have the wrong relationship with station quality, although the effect at the mean C-FPR is economically insignificant. Figure 4 plots results for PM_{10} by C-FPR bins, and shows that the effect of re-inspections of older cars increases with the C-FPR score of the stations doing the inspections, while the effect re-inspections of newer cars is effectively zero at all station quality levels.

6 Predicting the Impact of STAR

We have thus far considered average effects of the Smog Check program across the entire period from 1998 to 2009. We next use our results to simulate the effect of the specific requirements of the STAR program at the beginning and end of our sample. Knowing the theoretical impact of STAR in 1998 is interesting, but tells us little about what to expect as the policy goes forward. Thus, we focus on the *future* impact of more stringent I/M requirements.

To project future impacts of STAR, we ask how increasing mean station quality would change the impact of the existing level of re-inspections. The minimum acceptable FPR for STAR certification is 0.4. Thus, we estimate changes in air pollution if every re-inspection of an older vehicle were conducted at a station with our C-FPR score of 0.4 or higher. We take every station with a C-FPR below 0.4, and re-assign re-inspections of older vehicles from those stations to stations in the same county with C-FPR greater than or equal to 0.4. Re-inspections are redistributed to "good" stations in proportion to each station's share of re-inspections in same county and the current quarter. Then, given the simulated distribution of re-inspections over inspection stations, we recalculate the 90-day county-level moving average C-FPR, and predict counterfactual air pollution levels using the model and results from column 2 of table 3. One can think of this exercise as simulating the effect of an idealized certification program targeting true station quality, as distinct from observable quality. Recall our C-FPR measure is not feasible for use in certifying stations. The actual STAR program uses the FPR, which uses contemporaneous inspections to evaluate lagged station performance, and as we showed in section 4 the FPR metric poorly predicts future vehicle emissions.

Figure 5 maps our predicted results by county for the years 1998 (top) and 2009 (bottom), with results for CO and NO_x on the left and right, respectively. The counties making up the San Francisco Bay Area see relatively small changes in 1998, in part because these counties historically had what would be high C-FPR score stations to begin with: our theoretical exercise of removing "bad" station re-inspections thus has little bite. But improving station quality in 1998 would have substantially reduced CO and NO_x levels in a number of California's urban areas, with Los Angeles County and nearby portions of southern California receiving the greatest benefit. Although relatively few counties see a large change in pollution levels, in 1998 more than 15 million people lived in counties with counterfactual decreases of 20% or more, so welfare effects would have been large. We discuss such welfare effects further below.

The case for improving inspection station quality in 2009 is less clear. As a result of older vehicles aging out of circulation, the effect of moving older vehicles to higher quality stations is limited. Many counties, including the most populous in the state, see reductions of less than 1% from already lower baseline pollution levels.

These estimates likely overstate the potential impact of STAR, as our measure of station quality, while based on the STAR program methodology, uses future inspection results to rate current stations. This improves accuracy in measuring low- vs. high-quality stations, but is impossible to use in practice. To predict the effect of the STAR program using the standard STAR measures, we conduct another simulation, this time reassigning re-inspections of pre-1985 vehicles from stations with STAR metrics below the cut-offs (FPR below 0.4 and SVFR below 0.75) to stations with STAR scores above those cut-offs.

Table 6 shows the results of simulating implementation of the STAR program in 2009. Assigning all older vehicles to stations with our C-FPR of 0.4 or higher would raise the average C-FPR of stations inspecting older vehicles from 0.6 to 0.77. This would cause the average 2009 CO level to decrease by just under 10 ppb, the NO_x level by 0.8 ppb, and the PM_{10} level by 0.3 μ/m^3. The statewide effect of implementing the STAR program is much smaller, with a 3.1 ppb reduction in CO, a 0.26 ppb reduction in NO_x, and a 0.1 μ/m^3 reduction in PM_{10}. The statewide effect hides substantial variation across the state's most polluted areas. The average C-FPR in Los Angeles County was 0.39 in 2009. Moving re-inspections at low quality stations to stations with C-FPR of 0.4 or higher would raise the average C-FPR to 0.65, lowering CO levels by 68 ppb, lowering NO_x levels by 6.4 ppb, and lowering PM_{10} by 3 μ/m^3. Implementing the actual STAR program in Los Angeles County in 2009 would raise the C-FPR to just 0.46, with an effect on all three pollutants roughly one fourth as large as the idealized program. The San Francisco Bay Area had higher than average C-FPR in 2009, and either of our simulations has only a small effect on both average station quality and air pollution. In contrast, San Diego County had an average C-FPR score of 0.33 in 2009, and as in Los Angeles County, implementing the actual STAR program would have about one fourth the effect of using the C-FPR to certify stations.

The effect of increasing station quality is quite small in either simulation for 2009. Even this overestimates the *future* effect of STAR, as the number of older model year vehicles on the road falls with time.

6.1 Welfare Effects of STAR

Our simulations suggest the current incarnation of the STAR program will do little to further improve local air pollution in California. Because the gains from inspections mostly derive from older vehicles that are becoming scarce on the road, even an inspection program using our contemporaneous quality measure would have a small impact by 2013. Further, the STAR quality metrics available in practice appear to do a poor job of measuring current station quality. As a result, moving vehicle inspections to STAR-approved stations is unlikely to meaningfully reduce air pollution.

While STAR is unlikely to have a substantial impact on air pollution levels, it is a relatively inexpensive policy, and may have net positive effects on welfare. The benefits of pollution reduction predominantly arise from reduced infant and elder mortality—although pollution impacts other health outcomes, the value of a statistical life (VSL) is generally high enough that it dwarfs morbidity effects, which are also more difficult to measure. Effects on infant mortality tend to be the best measured, and we use this as our measure of the benefits of pollution reduction. CO has documented effects on infant mortality, while the harms of NO_x derive from its role in forming ozone and particulate matter. As we find no economically significant effect of the Smog Check program on O3, we focus on benefits from reducing CO and PM_{10}.

Currie and Neidell (2005) find a 1 part per million (1,000 ppb) reduction in CO lowers the infant mortality rate by 18.125 deaths per 100,000 live births, and Currie et al. (2009) find a similar effect, 17.6 deaths per 100,000 live births; we use the latter of these.[31] Estimates of the effects of PM_{10} vary widely. Instrumental variables estimates from Knittel et al. (2015), Chay and Greenstone (2003) and Arceo et al. (2015) find effects of around 10 infant deaths prevented per 100,000 births for each unit of PM_{10} reduced, while OLS fixed effect model results in Currie and Neidell (2005) and Currie et al. (2009) find essentially zero effect of PM_{10} on infant mortality.

Using 2009 county-level birth rates, our predicted effect of STAR on CO would have prevented an expected 0.64 infant deaths over the year statewide. Using the U.S. EPA's preferred estimate of the VSL, \$7.6 million, this translates to annual benefits of about \$4.9 million. If PM_{10} affects infant mortality, STAR would have prevented an additional 16.5 infant deaths in California, with welfare benefits of about \$125 million. Note that

[31] Knittel et al. (2015) find a larger effect of CO, but with a wide confidence interval including zero. Arceo et al. (2015) find much higher effects of CO in the context of the much higher levels of CO found in Mexico City, and document nonlinearities in the effects of CO.

these results assume a *lasting* decrease in pollution levels following faulty car repairs. If the benefits of repairs degrade with time, the health gains will be more short lived and thus the social benefits lower.

While the benefits of STAR for CO in particular are modest, STAR is a fairly inexpensive program. The California State Legislature estimated administrative costs of $350,000-$450,000 per year.[32] The more significant source of costs is in time—directing vehicles to STAR stations instead of the more abundant test-only stations might lead to increased driving times. In 2009, there were about 3.6 million directed inspections in the state of California. At the 2009 average hourly wage for California, $23.82,[33] if STAR caused owners of directed vehicles to drive an extra 10 minutes round trip to their Smog Checks, the time costs would total more than $14.5 million that year.

7 Conclusion

Motor vehicles generate a number of pollutants, many of which have an established negative impact on human health. To reduce the public damages of automobile use, governments may use inspection and maintenance (I/M) programs, where stations routinely test engines for compliance with emissions standards, and require repairs and further tests in the event of failure. These inspections and repairs are costly to consumers, and while follow-up tests can show repairs improve emissions at the tailpipe, there is little causal evidence of how such programs change local air quality. We test two important questions related to such programs. First, do I/M programs improve local air pollution in an observable manner on a large scale, beyond laboratory conditions? Using over a decade of data from the state of California, we show an increase in emissions-related repairs, as proxied by passing post-repair inspections, corresponds to local improvement in CO, NO_x and PM_{10} levels, but with little change in local O3. This relationship persists after controlling for a wide variety of location and time fixed effects and ambient weather controls, and shows California's Smog Check program has successfully improved local air pollution. However, *additional* gains from the Smog Check program are decreasing with time, as almost all benefits of repairs and re-inspections come from fixing failing older model cars (1985 and prior) with inferior emissions control technology. As older technology cars disappear from the road, the differential between failing and repaired emissions decreases.

[32] See `http://www.leginfo.ca.gov/pub/09-10/bill/asm/ab_2251-2300/ab_2289_cfa_20100617_172946_sen_comm.html` (Accessed September 23, 2015).

[33] See `http://www.bls.gov/oes/2009/may/oes_ca.htm`, (accessed November 9, 2015)

Second, we consider whether using a certifying high quality stations using inspection results can further reduce air pollution. Given fears of false or low-quality repairs of failing vehicles followed by potentially fraudulent re-inspections, the new California STAR program uses a calculated "Follow-up Pass Rate" (FPR) to determine which stations the state allows to provide repairs and re-inspections. A number of factors, including potential system fraud, complicate measuring the role of the FPR after the implementation of the program, making estimation of program effects difficult. We use the California Smog Check data from 1998-2009 to construct a modified station-level FPR that conveys information similar to that of the STAR program, but without concerns of secondary program effects. We show how local air pollution changes with an increase in average quality of local stations allowed to administer inspections and repairs. When a greater share I/M stations are of high quality, an additional repair corresponds to a greater marginal improvement in contemporaneous air pollution. However, the gains of estimated station quality are again limited to repairs and re-inspections of older model. For newer cars with modern emissions control technology, there is no economically meaningful benefit to restricting repairs to high-quality stations. Between a decline in effectiveness of the overall Smog Check program as older vehicles age out of the fleet and poor predictive power of the actual STAR quality metrics, it is unlikely the new STAR program as designed will further improve the effectiveness of Smog Check for reducing air pollution.

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Table 1: Average Daily Air Quality and Smog Check Inspections in California Counties, 1998-2009

			Panel A: All California			
	CO (PPB)	NO_x (PPB)	Ozone (PPB)	PM_{10} (μ/m^3)	# Inspections	# Re-Inspections
1998	703.0	28.89	28.04	25.50	587.5	63.07
1999	716.2	32.40	28.32	31.00	678.5	74.12
2000	649.6	30.19	26.65	27.16	706.2	85.29
2001	612.1	27.68	27.60	27.79	755.2	93.99
2002	600.8	28.18	29.04	30.10	719.6	96.61
2003	562.6	26.36	28.69	26.78	825.0	107.2
2004	499.6	24.20	27.66	26.38	795.7	101.7
2005	458.4	24.23	26.60	24.05	669.7	84.99
2006	466.8	23.41	28.19	26.14	678.3	78.04
2007	431.7	22.05	27.61	25.90	667.6	73.65
2008	422.3	20.38	28.93	26.75	671.6	72.64
2009	363.5	18.03	27.66	22.18	688.5	73.90
Average	551.9	25.57	27.89	26.61	701.5	83.19
			Panel B: Los Angeles County			
	CO (PPB)	NO_x (PPB)	Ozone (PPB)	PM_10 (μ/m^3)	# Inspections	# Re-Inspections
1998	1254.5	71.45	21.73		7064.1	814.8
1999	1203.6	79.36	20.78		8324.6	1023.0
2000	1029.1	70.98	20.73		8489.6	1121.0
2001	936.9	64.25	21.58		9015.2	1253.4
2002	869.9	60.89	24.30	37.60	9255.0	1318.1
2003	814.0	58.35	25.27	32.40	9328.7	1316.7
2004	663.9	51.49	26.49	32.41	9418.5	1271.9
2005	580.2	47.09	24.48	30.45	7838.1	1042.3
2006	548.8	47.35	25.48	29.98	7880.1	962.3
2007	506.6	43.86	25.05	33.32	7644.7	900.2
2008	470.3	40.49	25.93	30.66	7600.5	871.8
2009	417.4	35.99	26.59	29.86	7781.6	895.2
Average	774.6	55.96	24.04	32.06	8303.5	1065.9
			Panel C: San Francisco Bay Area			
	CO (PPB)	NO_x (PPB)	Ozone (PPB)	PM_{10} (μ/m^3)	# Inspections	# Re-Inspections
1998	756.8	33.81	19.76	18.00	5078.1	422.3
1999	769.7	37.48	19.84	21.40	5571.8	403.6
2000	699.7	35.02	18.41	18.45	5941.3	514.9
2001	636.5	31.51	19.86	20.16	6223.4	567.5
2002	599.5	31.08	20.61	21.67	865.1	69.89
2003	569.4	27.56	20.41	16.55	3849.2	379.1
2004	502.9	25.80	20.43	17.32	6820.2	831.2
2005	486.7	25.51	20.21	16.31	5731.4	693.5
2006	466.9	24.93	21.90	18.34	5867.2	608.5
2007	418.2	23.18	21.68	16.47	5795.3	561.4
2008	387.5	21.82	22.80	17.44	5820.1	545.0
2009	350.4	21.08	21.24	14.21	5960.5	553.0
Average	553.7	28.23	20.60	18.07	5294.2	512.6

Note: Excludes counties and years where biennial inspections are not required

Table 2: Re-Inspections and County-Level Daily Air Quality

	A: Outcome is Carbon Monoxide (PPB)				
	(1)	(2)	(3)	(4)	(5)
000s of Re-Inspections Last 90 Days					
1975-1985 Vehicles	41.68***	35.41***	36.96***	16.25***	-26.61***
	(9.780)	(8.601)	(9.284)	(2.219)	(5.856)
1985+ Vehicles	-2.229**	-13.98**	-10.54**	-4.480***	-4.849**
	(1.089)	(5.198)	(4.142)	(1.301)	(2.228)
County FE	No	Yes	Yes	Yes	Yes
Weather Controls	No	No	Yes	Yes	Yes
Calendar Week FE	No	No	No	Yes	Yes
County Time Trends	No	No	No	No	Yes
	B: Outcome is NO_x (PPB)				
	(1)	(2)	(3)	(4)	(5)
000s of Re-Inspections Last 90 Days					
1975-1985 Vehicles	1.925***	1.392***	1.497***	0.843***	-1.913***
	(0.287)	(0.221)	(0.275)	(0.0921)	(0.514)
1985+ Vehicles	0.161***	-0.749***	-0.517***	-0.269***	-0.829***
	(0.0404)	(0.249)	(0.174)	(0.0569)	(0.164)
County FE	No	Yes	Yes	Yes	Yes
Weather Controls	No	No	Yes	Yes	Yes
Calendar Week FE	No	No	No	Yes	Yes
County Time Trends	No	No	No	No	Yes
Observations	143440	143440	143440	143440	143440

* $p < .1$, ** $p < .05$, *** $p < .01$

Note: Observations are county-days. Standard errors clustered by county reported in parentheses.

Table 3: Station Quality and County-Level Air Pollution

	A: Outcome is CO (PPB) (1)	(2)
000s of Re-Inspections Last 90 Days		
1975-1985 Vehicles	-26.61***	-6.231
	(5.856)	(4.872)
1975-1985 Vehicles · C-FPR		-87.79***
		(19.55)
Effect at Mean C-FPR		*-55.44****
		(10.64)
1985+ Vehicles	-4.849**	-13.01***
	(2.228)	(3.791)
1985+ Vehicles · C-FPR		22.13***
		(7.891)
Effect at Mean C-FPR		*-0.369*
		(2.584)
	B: Outcome is NO_x (PPB) (1)	(2)
000s of Re-Inspections Last 90 Days		
1975-1985 Vehicles	-1.913***	0.0724
	(0.514)	(0.444)
1975-1985 Vehicles · C-FPR		-8.347***
		(1.067)
Effect at Mean C-FPR		*-4.548****
		(0.820)
1985+ Vehicles	-0.829***	-1.661***
	(0.164)	(0.278)
1985+ Vehicles · C-FPR		2.240***
		(0.462)
Effect at Mean C-FPR		*-0.404****
		(0.172)

* $p < .1$, ** $p < .05$, *** $p < .01$

Note: Observations are county-days. All regressions control for daily weather, county fixed effects, calendar week fixed effects, and county-specific cubic time trends. Standard errors clusted by county reported in parentheses.

Table 4: Station Quality and County-Level Ozone Pollution

	Base		NO_x Controls	
	(1)	(2)	(3)	(4)
000s of Re-Inspections Last 90 Days				
1975-1985 Vehicles	0.00951	-0.230*	-0.203*	-0.181
	(0.138)	(0.122)	(0.114)	(0.115)
1975-1985 Vehicles · C-FPR		0.632*		-0.533
		(0.373)		(0.383)
Effect at Mean C-FPR		*0.137*		*-0.476***
		(0.204)		*(0.192)*
1985+ Vehicles	0.171***	0.440**	0.0828*	0.227
	(0.0461)	(0.185)	(0.0412)	(0.153)
1985+ Vehicles · C-FPR		-0.579*		-0.270
		(0.289)		(0.245)
Effect at Mean C-FPR		*0.0984***		*0.0752*
		(0.0487)		*(0.0468)*

* $p < .1$, ** $p < .05$, *** $p < .01$

Note: Observations are county-days. All regressions control for daily weather, county fixed effects, calendar week fixed effects, and county-specific cubic time trends. Columns (3) and (4) control for a quadratic in the level of NO_x. Standard errors clusted by county reported in parentheses.

Table 5: Station Quality and County-Level PM10 Pollution

	Outcome is PM_{10} (μ/m^3)	
	(1)	(2)
000s of Re-Inspections Last 90 Days		
1975-1985 Vehicles	-0.929	0.443
	(0.623)	(0.800)
1975-1985 Vehicles · C-FPR		-3.921**
		(1.700)
Effect at Mean C-FPR		*-1.865******
		(0.801)
1985+ Vehicles	0.132	-0.0855
	(0.160)	(0.395)
1985+ Vehicles · C-FPR		0.589
		(0.505)
Effect at Mean C-FPR		*0.265******
		(0.154)

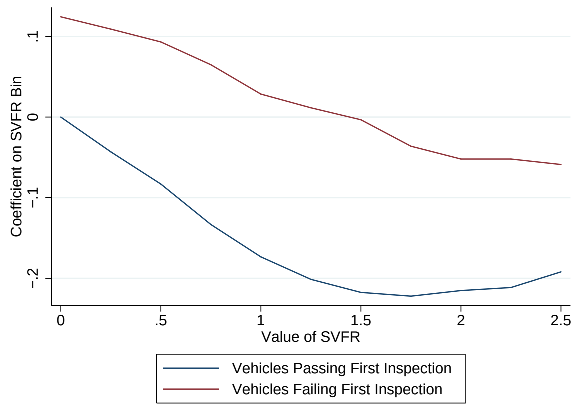
* $p < .1$, ** $p < .05$, *** $p < .01$

Note: Observations are county-weeks. All regressions control for daily weather, county fixed effects, calendar week fixed effects, and county-specific cubic time trends. Standard errors clusted by county reported in parentheses.

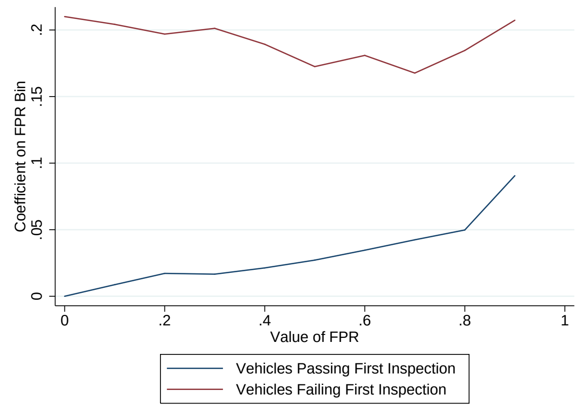
Table 6: Predicted 2009 Station Quality and Pollution, Simulating an Ideal and Real STAR Program

	All CA	LA County	Bay Area	San Diego
C-FPR Score				
Baseline	0.596	0.393	0.631	0.327
Re-assign using C-FPR	0.772	0.653	0.786	0.697
Reassign using SVFR & FPR	0.663	0.458	0.696	0.413
CO Level (PPB)				
Baseline	363.9	457.3	340.3	612.7
Re-assign using C-FPR	354.0	389.3	336.9	582.1
Reassign using SVFR & FPR	360.8	440.1	339.2	605.7
NO_x Level (PPB)				
Baseline	17.54	38.87	20.84	23.98
Re-assign using C-FPR	16.78	32.41	20.52	21.07
Reassign using SVFR & FPR	17.28	37.24	20.74	23.31
PM_10 Level (mu/m^3)				
Baseline	20.92	28.62	16.75	28.74
Re-assign using C-FPR	20.62	25.58	16.60	27.38
Reassign using SVFR & FPR	20.82	27.84	16.69	28.43

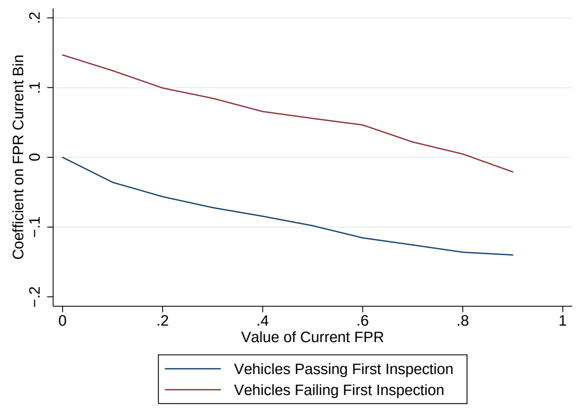
Notes: Baseline scenario shows actual average C-FPR and predicted CO and NO_x from the model in column 2 of table 3. "Reassign using C-FPR" redistributes inspections at stations with C-FPR below 0.4 to stations which pass these measures, recalculates the county average C-FPR accordingly, and predicts CO and NO_x. "Reassign to STAR Stations" redistributes inspections at stations failing the SVFR and FPR threshholds to stations which pass these measures.



(A) STAR SVFR Score



(B) STAR FPR Score



(C) Contemporaneous FPR (C-FPR)

Figure 1: STAR Metrics of Re-inspection Station and Log CO Emissions at Next Inspection

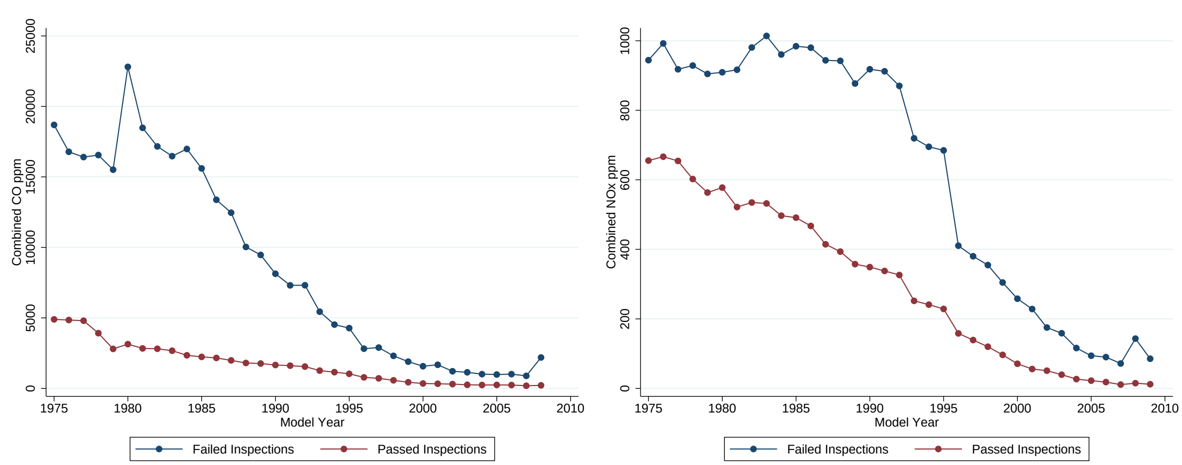


Figure 2: Average Smog Check Measured Emissions by Model Year

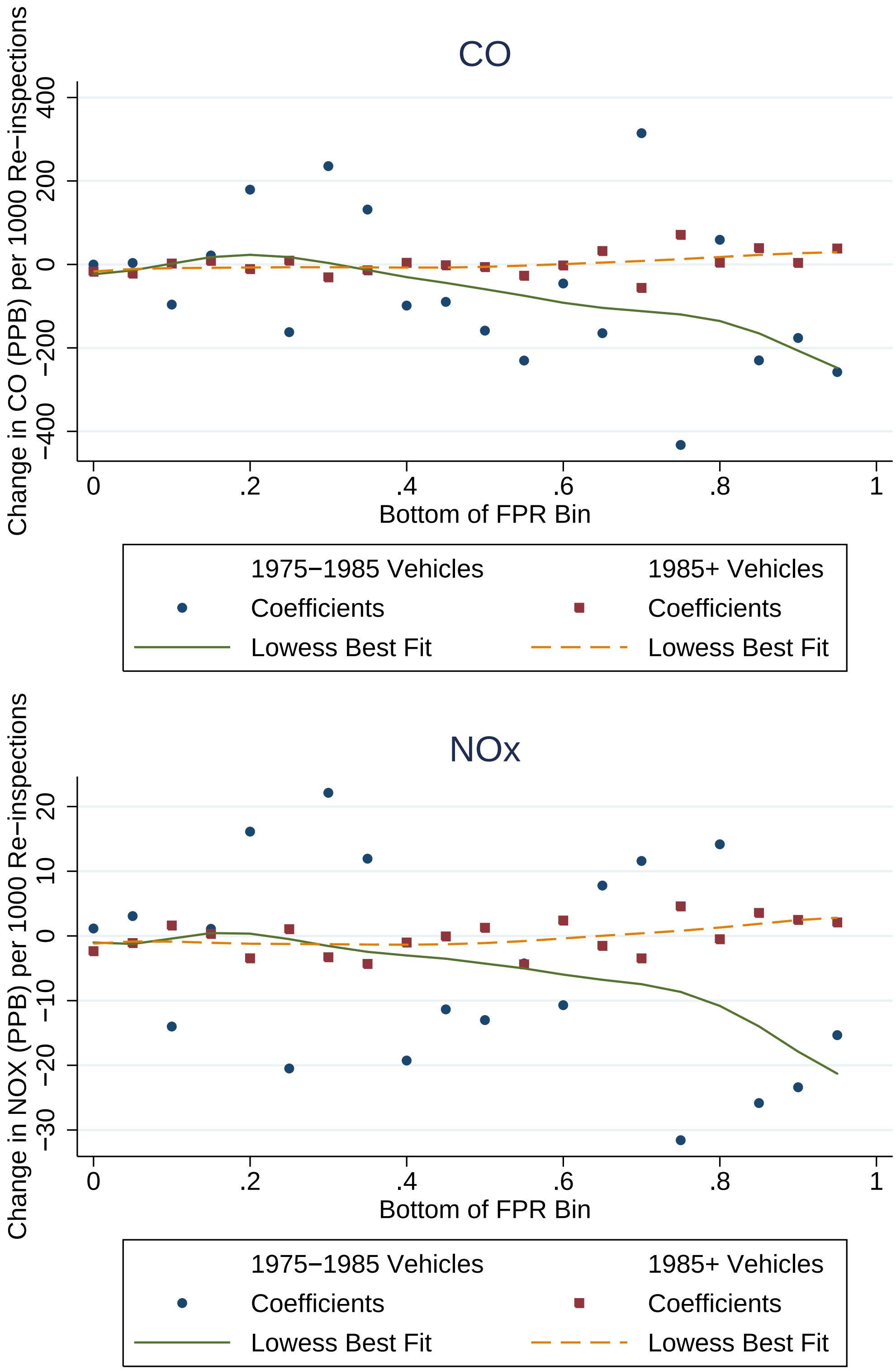


Figure 3: Effect of Reinspections on Daily Air pollution, by FPR Score of Test Stations

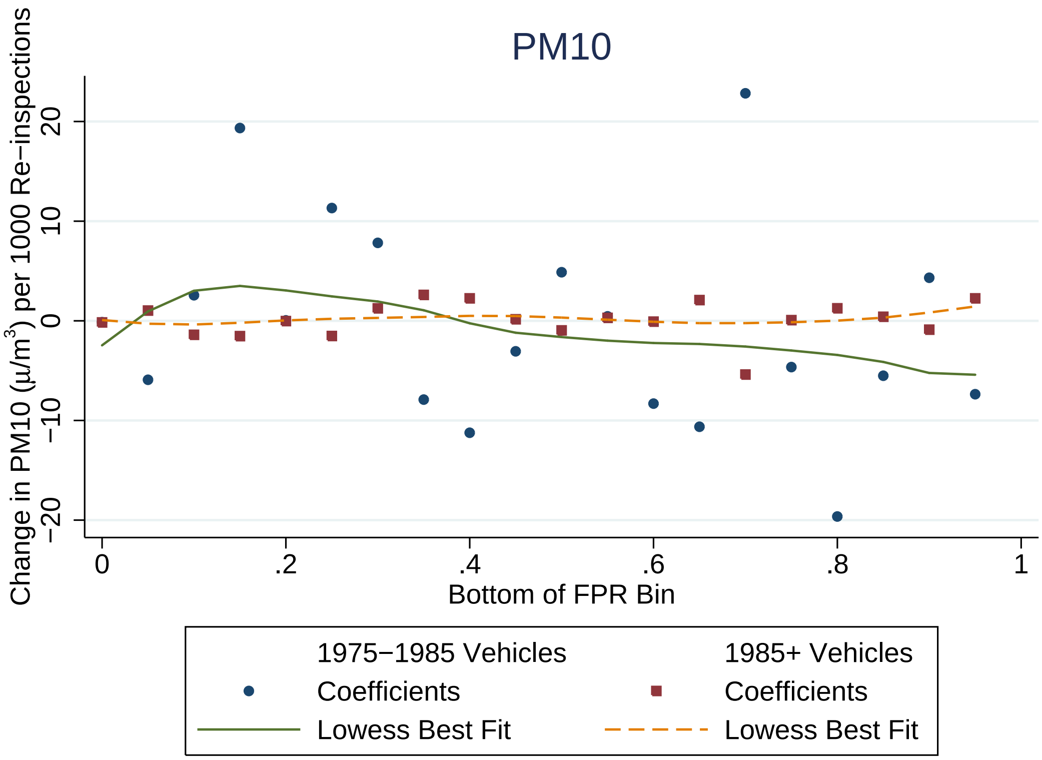


Figure 4: Effect of Reinspections on Weekly PM10 Levels, by FPR Score of Test Stations

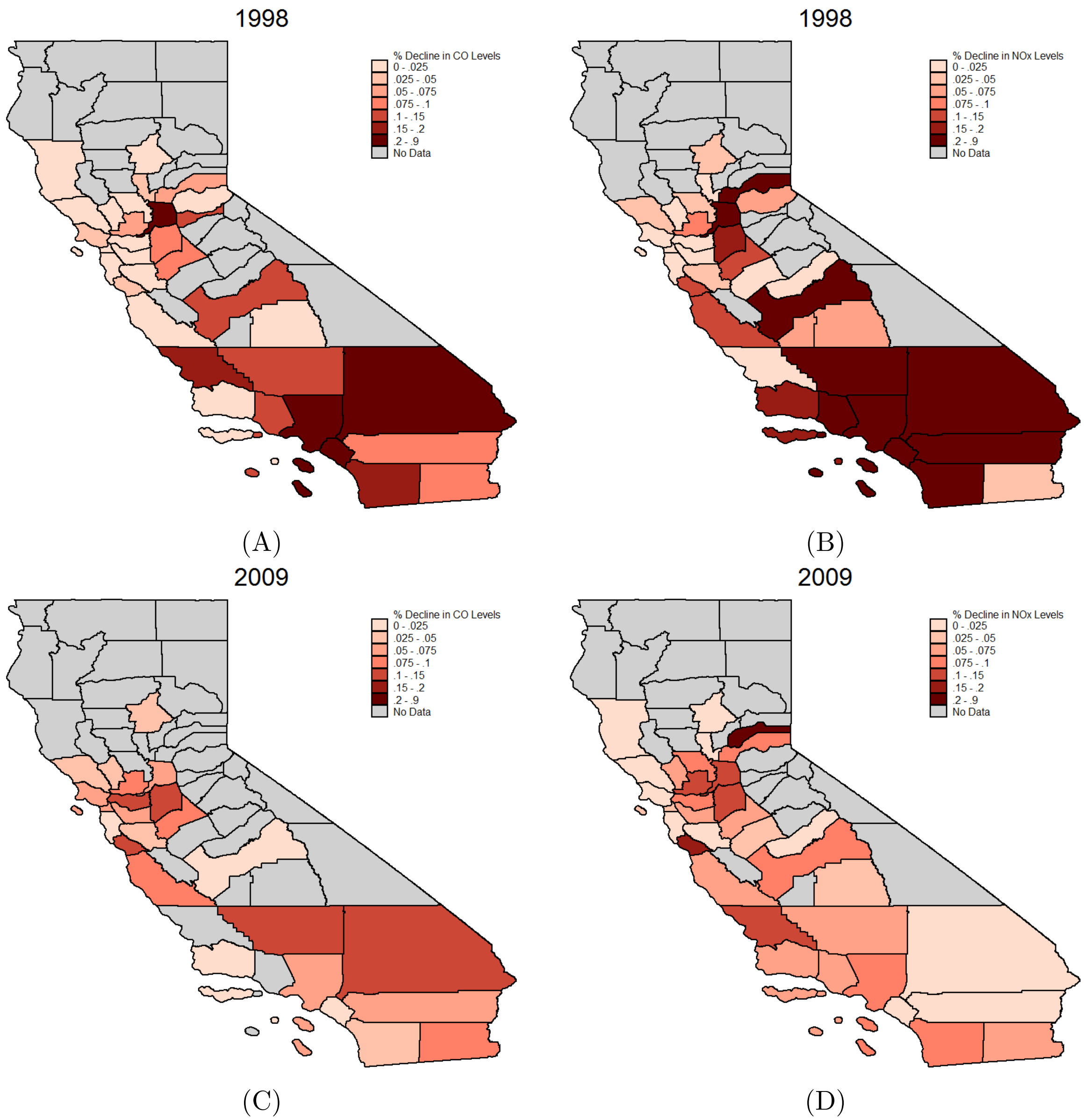


Figure 5: Predicted Percent Change in Pollution Levels From Re-inspection All 1975–1985 vehicles at STAR stations

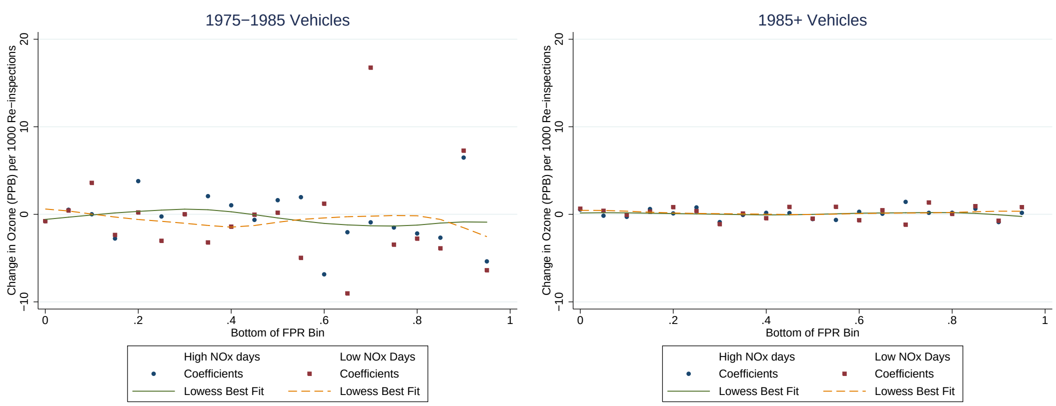


Figure 6: Effect of Reinspections on Daily Ozone Levels, by FPR Score of Test Stations

A Appendix

Table A1: Re-Inspections and County-Level Daily Air Quality: Robustness Checks

	CO	NO_x
000s of Re-Inspections Last 90 Days		
1975–1985 Vehicles	-26.81***	-1.915***
	(5.800)	(0.494)
1985-1995 Vehicles	-4.517*	-0.826***
	(2.300)	(0.231)
1995+ Vehicles	-5.520	-0.837***
	(3.356)	(0.179)
County FE	Yes	Yes
Weather Controls	Yes	Yes
Calendar Week FE	Yes	Yes
County Time Trends	Yes	Yes
Observations	129260	143440

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table A2: Re-Inspections and County-Level Daily Air Quality: Robustness Checks

	A: Outcome is Carbon Monoxide (PPB)				
	(1)	(2)	(3)	(4)	(5)
000s of Re-Inspections Last 90 Days					
1975-1985 Vehicles	-26.61***	-38.81*	-26.59***	-24.21***	-28.81***
	(5.856)	(20.53)	(5.852)	(6.917)	(6.223)
1985+ Vehicles	-4.849**	-2.910	-4.830**	-5.929**	-5.723**
	(2.228)	(5.667)	(2.229)	(2.663)	(2.297)
County FE	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Calendar Week FE	Yes	Yes	Yes	Yes	Yes
County Time Trends	Yes	Yes	Yes	No	No
Exclude LA	No	Yes	No	No	No
Month-of-Year and Day-of Week FE	No	No	Yes	No	No
County-Year FE	No	No	No	Yes	No
	B: Outcome is NOx (PPB)				
	(1)	(2)	(3)	(4)	(5)
000s of Re-Inspections Last 90 Days					
1975-1985 Vehicles	-1.913***	-1.879	-1.909***	-1.831***	-2.051***
	(0.514)	(1.519)	(0.514)	(0.443)	(0.499)
1985+ Vehicles	-0.829***	-0.687**	-0.828***	-0.987***	-0.877***
	(0.164)	(0.311)	(0.164)	(0.241)	(0.158)
o.la		0			
		(.)			
County FE	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Calendar Week FE	Yes	Yes	Yes	Yes	Yes
County Time Trends	Yes	Yes	Yes	No	No
Month-of-Year and Day-of Week FE	No	No	Yes	No	No
County-Year FE	No	No	No	Yes	No
Observations	143440	139057	143440	143440	20505

* $p < .1$, ** $p < .05$, *** $p < .01$

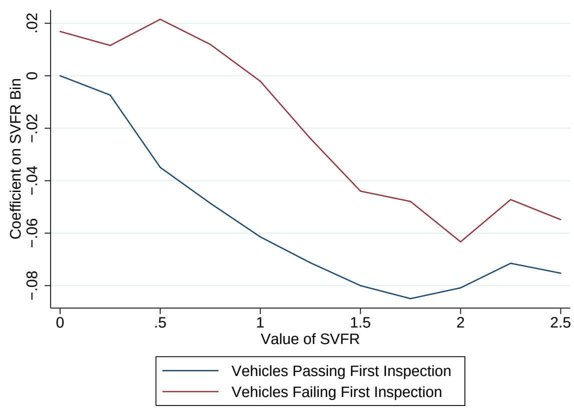
Note: Observations are county-days. Standard errors clustered by county reported in parentheses.

Table A3: Station Quality and County-Level Ozone

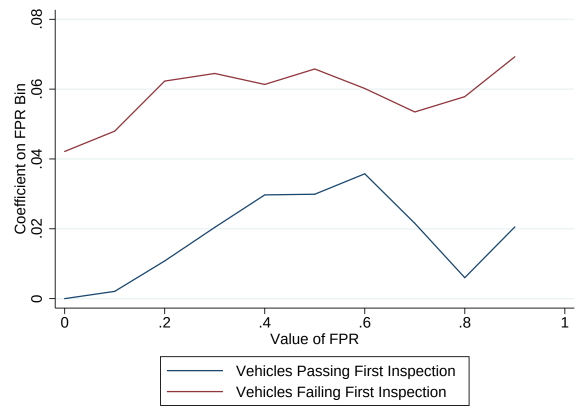
	(1)	(2)
Low NO_x Days		
1975-1985 Vehicles	0.163	0.449
	(0.195)	(0.464)
1975-1985 Vehicles · C-FPR		-0.933
		(1.199)
1985+ Vehicles Vehicles	0.207***	0.172
	(0.0621)	(0.239)
1985+ Vehicles · C-FPR		0.167
		(0.469)
High NO_x Days		
1975-1985 Vehicles	-0.193*	-0.442***
	(0.108)	(0.139)
1975-1985 Vehicles · C-FPR		0.425
		(0.401)
1985+ Vehicles Vehicles	0.0606	0.384***
	(0.0387)	(0.132)
1985+ Vehicles · C-FPR		-0.722**
		(0.274)
Observations	143049	143049

Note: Observations are county-days. All regressions control for daily weather, county fixed effects, calendar week fixed effects, and county-specific cubic time trends. Low and high NO_x days are days with NO_x levels below (above) the median NO_x level of 18 ppb. Standard errors clustered by county reported in parentheses.

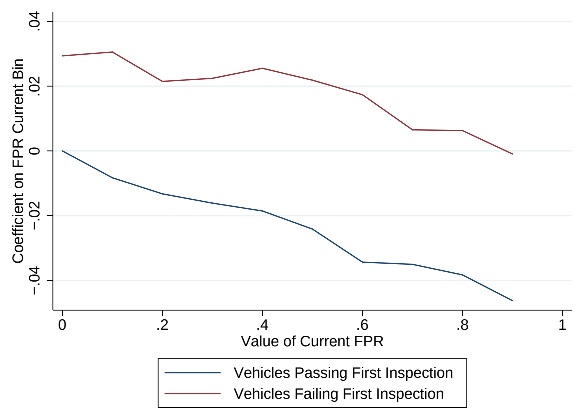
* $p < .1$, ** $p < .05$, *** $p < .01$



(A) STAR SVFR Score



(B) STAR FPR Score



(C) Contemporaneous FPR (C-FPR)

Figure A1: STAR Metrics of Re-inspection Station and Log NO_x Emissions at Next Inspection