ENERGY INSTITUTE AT HAAS

**EI @ Haas WP 219**

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August 2011



http://ei.haas.berkeley.edu

# Cleaning the Bathwater *with* the Baby: The Health Co-Benefits of Carbon Pricing in Transportation

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August 23, 2011

**Abstract**

Efforts to reduce greenhouse gas emissions in the US have relied on Corporate Average Fuel Economy (CAFE) Standards and Renewable Fuel Standards (RFS). Economists often argue that these policies are inefficient relative to carbon pricing because they ignore existing vehicles and do not adequately reduce the incentive to drive. This paper presents evidence that the *net* social costs of carbon pricing are significantly less than previous thought. The bias arises from the fact that the demand elasticity for miles travelled varies systematically with vehicle emissions; dirtier vehicles are more responsive to changes in gasoline prices. This is true for all four emissions for which we have data—nitrogen oxides, carbon monoxide, hydrocarbon, and greenhouse gases—as well as weight. This reduces the net social costs associated with carbon pricing through increasing the co-benefits. Accounting for this heterogeneity implies that the welfare losses from \$1.00 gas tax, or a \$110 per ton of $CO_2$ tax, are negative over the period of 1998 to 2008 even when we ignore the climate change benefits from the tax. Co-benefits increase by over 60 percent relative to ignoring the heterogeneity that we document. In addition, accounting for this heterogeneity raises the optimal gas tax associated with local pollution, as calculated by Parry and Small (2005), by as much as 57 percent. While our empirical setting is California, we present evidence that the effects may be larger for the rest of the US.

*This paper has benefited from conversations with Severin Borenstein, Michael Greenstone, Jonathan Hughes, Dave Rapson, Nicholas Sanders, and Catherine Wolfram. We gratefully acknowledge financial support from the University of California EEE and the Sustainable Transportation Center at UC Davis. A portion of the paper was written while Knittel was a visitor at the Energy Institute at Haas. *Knittel:* William Barton Rogers Professor of Energy Economics, Sloan School of Management, MIT and NBER, *email:* knittel@mit.edu. *Sandler:* Department of Economics, University of California, Davis, *email:* rsandler@ucdavis.edu.

# 1 Introduction

As concerns about climate change grow, so have debates about what policy tools to use to reduce emissions. The transportation sector accounts for nearly 37 percent of US greenhouse gas (GHG) emissions; it has therefore seen a number of policy changes during the past two decades. Within the transportation industry, greenhouse gas pricing, via either a carbon tax or cap & trade system, has succumbed to Corporate Average Fuel Economy (CAFE) standards to increase the new vehicle fleet fuel economy and the Renewable Fuel Standard (RFS) to decrease the carbon intensity of fuels. Economists have long viewed these policies with derision, arguing instead for the merits of Pigouvian taxes.

A large literature exists showing the inefficiency, relative to gasoline or carbon taxes, associated with both CAFE and the RFS. For the RFS, the main sources of inefficiency are that the policy over-incentivizes marginally cleaner fuels and suppresses fuel prices. CAFE, on the other hand, ignores the existing fleet and reduces the marginal cost of driving, increasing the number of miles driven. For example, Holland et al. (2011) find that even in the long run GHG reductions under the RFS are nearly three times more costly than equivalent reduction under a cap & trade system, while Jacobsen (2011) finds that CAFE standards are nearly seven times more costly than gasoline taxes in reducing GHG emissions.

In this paper we argue that the *net* social cost of GHG taxes have been *over*stated. The source of this bias comes from the heterogeneity in how different types of vehicles, in terms of the other externalities associated with driving, respond to changes in gasoline prices. We show that vehicles with higher externalities, both in terms of local pollution and weight, respond more to gasoline prices. This is true for all three vehicle emissions for which we have data: carbon monoxide, hydrocarbons, and nitrogen oxides. It is also true for vehicle weight and greenhouse gases. This heterogeneity increases the co-benefits associated with a greenhouse gas tax from reductions in criteria pollutants.[1]

We find that the average "two-year" elasticity is 0.26 across all vehicles, but the ratio of the elasticity for the dirtiest quarter of vehicles with the cleanest quarter of vehicles is 4.7, 4.5, and 3.4 for carbon monoxide, hydrocarbons, and nitrogen oxides, respectively. The ratio is 1.6 for

[1] Criteria air pollutants are the only air pollutants for which the Administrator of the U.S. Environmental Protection Agency has established national air quality standards defining allowable ambient air concentrations. Congress has focused regulatory attention on these pollutants (i.e., carbon monoxide, lead, nitrogen dioxide, ozone, particulate matter, and sulfur dioxide) because they endanger public health and they are widespread throughout the U.S.

greenhouse gases and 1.2 for vehicle weight. We also estimate how the hazard rate of scrapping a vehicle varies with criteria pollutant emissions. Here, the evidence is more mixed.

We use these estimates to simulate the co-benefits from a carbon tax. For each vehicle in our data, we calculate the change in miles driven from the tax and the change in the vehicle's probability of survival and the resulting change in vehicle emissions. We do this across our entire time period and in each year. We then quantify these reductions using the estimated marginal damages in Muller and Mendelsohn (2009) and Matthews and Lave (2000). We find that once the heterogeneous response is accounted for, there is essentially no change in near-term consumer surplus from a \$110 $CO_2$ tax from 1998 to 2008; the welfare near-term co-benefits are nearly 20 percent greater than the change in consumer surplus from the tax increase. If one fails to account for the heterogenous response, the simulated co-benefits fall to 74 percent of the consumer welfare loss from the tax. We discuss reasons why these effects should be interpreted as strict lower bounds.

Given that the vehicle fleet has, over time, become cleaner in terms of criteria pollutant emissions, we find that the co-benefits have fallen over our sample, but remain substantial even at the end. Early in the sample, we simulate that consumers would have been better off from the tax, with the co-benefits being twice as large as the welfare losses from the tax. In the last year of our sample, the co-benefits fall to 55 percent of the welfare losses from the tax. We argue that these are still substantial, reducing the cost per ton of carbon saved from \$83 to \$23. Again, not accounting for heterogeneity implies a net cost nearly twice as large as the net cost accounting for heterogeneity in the final year of our sample.

To put these numbers into context, Greenstone, Kopits, and Wolverton (2011) estimate the social cost of carbon for a variety of assumptions about the discount rate, relationship between emissions and temperatures, and models of economic activity. For 2010, using a 3 percent discount rate, they find an average SCC of \$21.40, with a 95th percentile of \$64.90. Using a 2.5 percent discount rate, the average SCC is \$35.10. Our results suggest that once the co-benefits are accounted for, a \$1.00 gas tax (i.e., a \$110 per ton of $CO_2$ tax) would be nearly cost-effective even at the lower of these three numbers.[2]

Our results also have implications for the optimal gas tax in the presence of multiple market failures. Parry and Small (2005) calculate that the optimal gasoline tax within the US accounting for local and global pollution, accidents, congestion, and inefficiencies associated with income taxes.

[2] Of course, a tax somewhere below this would likely maximize welfare.

They find that the optimal tax is \$1.01 in the US, while it is \$1.62 in the UK. We calculate the optimal gas tax for California with and without heterogeneity; with heterogeneity the optimal tax increases from \$0.92 to \$1.05 in 1998 and from \$0.85 to \$0.90 in 2008. The relatively small increase is due, in large part, to the fact that the Pigouvian tax associated with congestion dominates the tax. The portion of the optimal tax attributed to local pollution increases from \$0.22 to \$0.33 in 1998 and from \$0.08 to \$0.13 in 2008, a change of 52 and 57 percent, respectively.

We argue that these results should be viewed as strict lower bounds of the co-benefits for a variety of reasons. First, we have ignored all other negative externalities associated with vehicles; many of these, such as particulate matter, accidents, and congestion externalities, will be strongly correlated with VMT and the emissions of $NO_x$, HCs, and CO. Second, because of the rules of the California Smog Check program, from which our data come from, many vehicles that were produced prior to standards on emissions are not required to be tested, leading to their omission in this analysis. Third, a variety of behavior associated with smog check programs would lead the on-road emissions of vehicles to likely be higher than the tested levels. These include, but are not limited to: fraud, tampering with emission-control technologies between tests, failure to repair emission-control technologies until a test is required, etc.

We also present evidence that, while the marginal damages from $NO_x$ and HCs are larger within California, Californian vehicles are, on average, much cleaner that the rest of the US. We show, using county-level data from the EPA on average vehicle emission rates, that the county-level average per-mile externalities are roughly 30 percent *lower* in California compared to the rest of the US. Therefore, while are unable to estimate elasticities outside of California, this suggests that provided the heterogeneity is somewhat similar to what we observe in California, the co-benefits may be larger for other states.

Finally, we also investigate several sources of the heterogeneity. At the most general level, we show that while the age of the vehicle is a major driver in our results—older vehicles respond more to changes in gasoline prices—this does not explain all of the heterogeneity. There are at least two additional sources of criteria pollutant-related heterogeneity in the response of changes in gasoline prices. For one, income may be correlated with criteria pollutant emissions, and driving the difference. Second, it may come from within-household shifts in vehicles miles travelled, for example if a household has one newer and one older vehicle. As gas prices increase, they may shift miles away from the older vehicle and to the newer vehicle. Because age is, on average, correlated with both greenhouse gas and criteria pollutant emissions, this would lead to our result. Our data can speak to this. We find that while there is evidence of both a within household effect and an income effect, a significant amount of variation persists once these are accounted for.

We bring together a number of unique data sets. The first is the universe of test records for California's emissions inspection and maintenance program, Smog Check, for the period of 1996 to 2010. California requires vehicles older than six years to receive biennial testing. In addition, testing occurs each time a vehicle changes ownership and randomly for a small share of vehicles. Among other things, the inspection data report odometer readings, which we use to measure vehicle miles travelled between tests. The tests also measure criteria pollutant emissions. To measure greenhouse gas emissions, we link these data to EPA fuel economy ratings. In addition, the data are linked to EIA gas prices for the same years. For roughly 75 percent of the smog check records, we are able to link them to Department of Motor Vehicle address recordings. This allows us to aggregate vehicles to households, as well as match vehicles with Census tract demographic data. Finally, to capture scrappage decisions we use CARFAX data for roughly 32 million vehicles that track the last date a vehicle was recorded within the US or exported to a foreign country.

The paper proceeds as follows. Section 2 discusses the empirical setting. The data are discussed in Section 3. Section 4 provides graphical support for the empirical results. Sections 5 and 6 present empirical models and results on miles driven and scrappage . Section 7 presents the results from the two policy simulations. Section 8 discusses how our results apply to regions of the US outside of California. Finally, Section 9 concludes the paper.

# 2 Empirical Setting

Our empirical setting is California. California implemented its first inspection and maintenance program in 1984 in response to the 1977 Clean Air Act Amendments. The initial incarnation of the Smog Check program relied purely on a decentralized system of privately run, state-licensed inspection stations, and was plagued by cheating and lax inspections. Although the agreement between California and the federal EPA promised reductions in hydrocarbon and carbon monoxide emissions of more the 25 percent, estimates of actual reductions of the early Smog Check Program range from zero to half that amount (Glazer, Klein, and Lave (1995)).

The 1990 Clean Air Act Amendments required states to implement an enhanced inspection and maintenance program in areas with serious to extreme non-attainment of ozone limits. Several of

California's urban areas fell into this category, and in 1994, a redesigned inspection program was passed by California's legislature after reaching a compromise with the EPA. The program was updated in 1997 to address consumer complaints, and fully implemented by 1998. Among other improvements, California's new program introduced a system of centralized "Test-Only" stations and an electronic transmission system for inspection reports.[3] Today, more than a million Smog Checks take place each month.

An automobile appears in the data for a number of reasons. First, vehicles that are older than four years old must pass a smog check within 90 days of any change in ownership. Second, in parts of the state (details below) an emissions inspection is required every other year as a pre-requisite for renewing the registration on a vehicle that is six years old or older. Third, a test is required if a vehicle moves from out-of-state. Vehicles which fail an inspection must be repaired and receive another inspection before they can be registered and driven in the state. There is also a group of exempt vehicles. These are: vehicles of 1975 model-year or older, hybrid and electric vehicles, motorcycles, diesel powered vehicles, and large trucks powered by natural gas.

Since 1998, the state has been divided into three inspection regimes (recently expanded to four), the boundaries of which roughly correspond to the jurisdiction of the regional Air Quality Management Districts. "Enhanced" regions, designated because they fail to meet state or federal standards for carbon monoxide (CO) and ozone, fall under the most restrictive regime. All of the state's major urban centers are in Enhanced areas, including the greater Los Angeles, San Francisco, and San Diego metropolitan areas. Vehicles registered to an address in an Enhanced area must pass a biennial Smog Check in order to be registered, and they must take the more rigorous Acceleration Simulation Mode (ASM) test. The ASM test involves the use of a dynamometer, and allows for measurement of $NO_x$ emissions. In addition, a randomly selected two percent sample of all vehicles in these areas is directed to have their Smog Checks at Test-Only stations, which are not allowed to make repairs.[4] Vehicles which match a "High Emitter Profile" are also directed to Test-Only stations, as are vehicles which are flagged as "gross polluters" (this occurs when a vehicle fails an inspection with twice the legal limit of one or more pollutant in its emissions). More recently some "Partial-Enhanced" areas have been added, where a biennial ASM test is required, but no vehicles are directed to Test-Only stations.

[3] For more detailed background see http://www.arb.ca.gov/msprog/smogcheck/july00/if.pdf.

[4] Other vehicles can be taken to Test-Only stations as well if the owner chooses, although they must get repairs elsewhere if they fail.

Areas with poor air quality that does not exceed legal limits fall under the Basic regime. Cars in a Basic area must have biennial Smog Checks as part of registration, but they are allowed to take the simpler Two Speed Idle (TSI) test, and no vehicles are directed to Test-Only stations. The least restrictive regime, consisting of rural mountain and desert counties in the east and north of the state, is known as the Change of Ownership area. As the name suggests, inspections in these areas are only required upon change of ownership; no biennial Smog Check is required.

### 2.1 Automobiles, Criteria Pollutants, and Health

The tests report the emissions of three criteria pollutant: Nitrogen oxides, hydrocarbon, and carbon monoxide. All three of these pollutants are a direct consequences of the combustion process within either gasoline or diesel engines. Both $NO_x$ and HCs are precursors to ground-level ozone, but, as with CO, have been shown to have negative health effects individually.[5]

While numerous studies have found links between the exposure of either smog or these three pollutants directly and health outcomes, the direct mechanisms are still uncertain. These pollutants, as well as smog, may directly impact vital organs or indirectly cause trauma. For example, CO can bind to hemoglobin, thereby decreasing the amount of oxygen in the bloodstream. High levels of carbon monoxide have also been linked to heart and respiratory problems. On its own, $NO_x$ is also a fine-particle particulate matter (PM). PM has been shown to irritate lung tissue, lowers lung capacity and hinders long term-lung development. Extremely small PM can be absorbed through the lung tissue and cause damage on the cellular level. On its own, HC can interfere with oxygen intake and irritate lungs. Ground-level ozone is a known lung irritant, has been associated with lowered lung capacity, and can exacerbate existing prior heart problems as well as lung problems such as asthma or allergies.

## 3 Data

We bring together a number of large data sets. First, we have the universe of smog checks from 1996 to 2010 from California's Bureau of Automotive Repair (BAR). These data report the location of the test, the vehicle's VIN, odometer reading, the reason for the test, and test results. We decode the VIN to obtain the vehicles' make, model, engine, and transmission. Using this, we match the

[5]CO has also been shown to speed up the smog-formation process. For early work on this, see Westberg, Cohen, and Wilson (1971).

vehicles to EPA data on fuel economy. Because the VIN decoding only holds for vehicles made after 1981, our data are restricted to these models. We also restrict our sample to 1998 and beyond given the large changes that occurred in the smog check test program in 1997. This yields roughly 120 million observations.

The smog check data report nitrogen oxides and hydrocarbons in terms of parts per million and carbon monoxide levels as a percentage of the exhaust under two engine revolutions per minute (RPMs). The more relevant metric is a vehicles emissions per mile. We convert the smog check reading into emissions per mile using conversion equations developed by Sierra Research for California Air Resources Board for Morrow and Runkle (2005), an evaluation of the Smog Check program. The conversion equations are functions of all three pollutants, vehicle weight, model year, and truck status.

We also estimate scrappage decisions. For this we use data from CARFAX Inc for 32 million of the vehicles in the BAR data. These data report the last date and location a given vehicle was recorded by CARFAX in the United States, which includes registrations, emissions inspections, repairs, import/export records and accidents. The CARFAX data do not track vehicles that move outside of the US; we assume the vehicle continues to be driven if exported.

Finally, at times we use information about the household. For a subsample of our BAR data, we are able to match vehicles to given households using data come from confidential Department of Motor Vehicle records that track the registered address of the vehicle. We use this information to aggregate up to addresses, the stock of vehicles registered. Appendix A discusses how this is done. These data are from 2000 to 2008.

For vehicles required to get biennial smog checks, we construct the average gasoline price between the two test data using EIA's national average prices.

Table 1 reports means and standard deviations of the main variables used in our analysis, as well as these summary statistics split by vehicle vintage and 1998 and 2008. The average fuel economy of vehicles in our sample is 23.5 MPG, with fuel economy falling over our sample. The change in the average dollar per mile has been dramatic, more than doubling over our sample. The dramatic decrease in vehicle emissions is also clear in the data, with per-mile emissions of hydrocarbon, CO, and $NO_x$ falling considerable from 1998 to 2008. The tightening of standards has also meant that more vehicles fail the smog check late in the sample, although some of this is driven by the aging vehicle fleet.

# 4 Preliminary Evidence

One of the main driving forces behind our empirical results is whether vehicle elasticities, both in terms of their intensive and extensive margins, vary systematically with the magnitude of their externalities. In this section, we present evidence that:

- significant variation exists in terms of vehicle externalities across vehicles within a year,
- significant variation exists in terms of vehicle externalities across vehicles across years,
- significant variation exists in terms of vehicle externalities within the same make, model, model year, etc. within a year, and
- simple statistics, such as the average miles travelled by vehicle type, suggest that elasticities are correlated with externalities.

Figure 1 plots the distributions of $NO_x$, HCs, and CO emissions in 1998, 2004, and 2010. The distribution of criteria pollutant emissions tends to be right-skewed in any given year, with a standard deviation equal to roughly one to three times the mean, depending on the pollutant. This implies that there are a vehicles on the road that are quite "dirty" relative to the mean vehicle. Over time, the distribution has shifted to the left, as vehicles have been getting cleaner, but the range still remains.

Table 2 reports the means and standard deviations across all vehicles receiving smog checks in a given year. From 1998 to 2008 the average emissions of $NO_x$, HCs, and CO fell between 65 and 85 percent. However, the standard deviations, relative to the means, have increased over time. This is especially true for CO, where the standard deviation is over 4 times the mean at the end of the sample.

This variation is not only driven by the fact that different types of vehicles are on the road in a given year, but also variation within the *same* vehicle-type, defined as a make, model, model-year, engine, number of doors, drivetrain combination. To see this, Figure 2 plots the distributions of emissions for the most popular vehicle/year in our sample, the 2001 4-door Toyota Corolla in 2009. The vertical red line is at the mean of the distribution. Here, again, we see that even within the same vehicle-type in the same year, the distribution is wide and right skewed. The distribution of hydrocarbons is less skewed, but the standard deviation is 25 percent of the mean. Carbon monoxide is also less skewed, and has a standard deviation that is 36 percent of the mean. Across all years and vehicles, the mean emission rate of a given vehicle in a given year, on average, is roughly four times the standard deviation for all three pollutants (Table 2).

To understand how the distribution within a given vehicle changes over time, Figure 3 plots the distribution of the 1995 3.8L, front-wheel drive, Ford Windstar in 1999, 2001, 2004, and 2007.[6] These figures suggest that over time the distributions shift to the right, become more symmetric, and the standard deviation grows considerably, relative to the mean. Across all vehicles, the ratio of the mean emission rate of $NO_x$ and the standard deviation of $NO_x$ has increased from 3.16 in 1998 to 4.53 in 2010. For hydrocarbons, this has increased from 3.59 to 5.51; and, has increased from 3.95 to 5.72 for CO.

These distributions suggest that there is significant scope for meaningful emissions-correlated variation in elasticities across vehicles and within the same vehicle-type. We next present suggestive evidence that this, too, is the case. To do this, we categorize vehicles into four groups, based on the four quartiles of a given pollutant *within* a given year. We then plot how the log of daily miles driven has changed over our sample—a period where gas prices increased from roughly \$1.35 to \$3.20.

Figure 4 and 5 foreshadow our results on the intensive margin. Figure 4 plots the median of daily miles travelled across our sample split up by the emissions quartile of the vehicle. While the dirtiest quartile begins at a slightly lower daily-VMT, it appears to drop much further than the other quartiles. Indeed, the there is a general trend of monotonicity across the four emissions. To see this more clearly, Figure 5 rescales the median VMT in 1998 and plots the average of the log of VMT over time by quartiles of each pollutant. For each pollutant, the log change in bottom-quartile vehicles is larger than the first quartile, with the other two quartiles often exhibiting monotonic changes in miles driven.[7]

# 5 Vehicle Miles travelled Decisions

Our first set of empirical models estimates how vehicle miles travelled (VMT) decisions are affected by changes in gas prices, and how this elasticity varies with vehicle characteristics. Our empirical approach mirrors Figures 4 to 5. For each vehicle receiving a biennial smog check, we calculate average daily miles driven and the average gasoline price during the roughly two years between

[6] We chose this vehicle because the 1995 3.8L, front-wheel drive, Ford Windstar in 1999 is the second most popular entry in our data and it is old enough that we can track it over four 2-year periods.

[7] Constructing the graphs in this way hides variation in the average level of driving by quartile. We find some variation in this, with the first or second quartile vehicles being driven more in 1998 for the criteria pollutants. For fuel economy, the bottom quartile is driven the most in 1998.

smog checks. We will then allow the elasticity to vary based on the emissions of the vehicle. We begin by estimating:

$$\ln(VMT_{igt}) = \beta \ln(DPM_{igt}) + \gamma D_{truck} + \sum_{k=1998}^{2008} \omega_k \cdot time + \mu_t + \mu_i + \mu_g + \mu_v + \epsilon_{igt} \tag{1}$$

where $i$ indexes vehicle-types, $g$ geographic locations, $t$ time, and $v$ vehicle age, or vintage. $DPM_{igt}$ is the average dollars per mile of the vehicle between smog checks, $D_{truck}$ is an indicator for whether the vehicle is a truck, and $time$ is a time trend.[8]

We begin the analysis by including year, vintage, and zip code fixed effects. We then progressively include finer vehicle-type fixed effects by including make, then make-model-model year-engine, and ending with specific-vehicle fixed effects.

We next differentiate the influence of gas prices by vehicle attributes related to the magnitude of their negative externalities—criteria pollutants, $CO_2$ emissions, and weight. We do this in two ways. First, we split vehicles up by the quartile the vehicle falls into with respect to the within-year emissions of nitrogen oxides ($NO_x$), hydrocarbons (HC), and carbon monoxide (CO), fuel economy ($CO_2$), and weight. Second, we include a linear interaction of these variables and the log of gas prices. Below we investigate, in a semi-parametric way, the actual functional form of this relationship.

Tables 3 through 7 report the results across externality-type.

Model 1 controls for only the year, vintage of the vehicle, and zip code where the vehicle received its smog check. Model 2 adds vehicle-make fixed effects. Model 3 includes the quartile interactions and the quartiles themselves. Model 4 includes VIN x-prefix fixed effects which effectively are vehicle make/model/model year/drivetrain/engine fixed effects. Model 5 includes VIN fixed effects, or specific-vehicle fixed effects. Model 6 includes the quartile variables, and Model 7 allows for the relationship between externality and gas prices to be linear.

Table 3 focuses on nitrogen oxides. Moving from Models 1 to 5 illustrates the importance of controlling for vehicle-type fixed effects. Initially, the average elasticity falls from 0.399 to 0.140 when including fixed make effects, but then rises when including finer detailed vehicle fixed effects. Our final specification includes individual vehicle fixed effects yielding an average elasticity of 0.257.[9]

[8] Our dollars per mile variable uses the standard assumption that 45 percent of a vehicle miles driven are in the city and 55 percent are on the highway, along with the vehicles EPA fuel economy ratings.

[9] This is much larger than that found in Hughes, Knittel, and Sperling (2008) reflecting the longer run nature of our elasticity.

In general, we find that the more finely we control for vehicle-type the larger the heterogeneity in terms of the dollar-per-mile elasticity, while the average elasticity does not change much once we control for the vehicle's make. Focusing on Models 6 and 7, we find large heterogeneity. The DPM-elasticity for the cleanest vehicles, quartile one, is 0.094, while the DPM-elasticity for the dirtiest vehicles is over five times this, at 0.323. To put these numbers in context, the average per-mile $NO_x$ emissions of a quartile one vehicle is 0.163 grams, while the average per-mile $NO_x$ emissions of a quartile four vehicle is 1.68 grams. Model 7 assumes the relationship is linear in centiles of $NO_x$ and finds that each percentile increase in the per-mile $NO_x$ emission rate is associated with a change in the elasticity of .003, from a base of 0.078.

We find similar patterns across the three other pollutants. Table 4 reports the results for hydrocarbons. Here, the elasticity of the cleanest vehicles and the elasticity of the dirtiest vehicles differ by a factor of 4.5. Table 5 reports the results for carbon monoxide. Here there is almost a 4.7 times difference in the elasticity of the cleanest quartile vehicles and the dirtiest quartile vehicles. Table 6 reports the results for fuel economy, or $CO_2$ emissions. The lowest quartile here are the most polluting vehicles. Their elasticity is 1.6 times as large as the cleanest vehicles. It is important to note that this is not driven by the fact that a given change in gas prices implies a larger change in the price per miles, since the independent variable is the log of the price per mile.[10] The linear interaction implies that vehicles at the 100th percentile have an average elasticity of roughly zero. We come back to this below.

While the elasticities are larger for dirtier vehicles, the average miles driven are smaller at the beginning of the sample for these vehicles. In terms of levels, in 1998 vehicles in the bottom quartile in terms of $NO_x$ emissions are driven 2.23 more miles per day, on average, than vehicles in the top quartile; they are driven 0.10 and 1.03 miles more per day, on average, than vehicles in the second and third quartiles, respectively. Vehicles in the bottom quartile in terms of hydrocarbon emissions are driven 0.95 miles per day less, on average, than vehicles in the second quartile and 3.28 and 4.68 miles more, on average, than vehicles in the third and fourth quartiles, respectively (in 1998). Vehicles in the bottom quartile in terms of CO emissions are driven 3.00 miles per day less, on average, than vehicles in the second quartile, and 7.63 and 4.63 miles more, on average, than vehicles in the third and fourth quartiles, respectively (in 1998). Finally, vehicles in the bottom quartile in terms of fuel economy are driven 2.44, 2.04, and 1.7 miles per day more, on average,

[10] Also, note that this does not matter for the models with VIN fixed effects.

than vehicles in the second, third, and fourth quartiles, respectively (in 1998). We account for these differences in the policy simulations below.

Table 7 splits vehicles up into weight quartiles. Here, too, we find that those vehicles with the largest negative externality, heavier vehicles, are more responsive to changes in gas prices. However, the heterogeneity is not as stark.

We next investigate the functional forms of these relationships in a semi-parametric way. For each externality, we define vehicles by their percentile of that externality. We then estimate equation 1 separately for vehicles falling in the zero to first percentile, first to second, etc. Figure 7 plots a lowess smoothed line through these 100 separate elasticity estimates. For the three criteria pollutants, we find that the relationship is quite linear with the elasticity being positive for the cleanest 20 percent of vehicles. The dirtiest vehicles have elasticities that are roughly 0.4. For fuel economy, the relationship is fairly linear from the 60th percentile onwards, but begins steeply and flattens out from the 20th percentile to the 40th. The elasticity of the lowest fuel economy vehicles is nearly 0.6. To put these numbers into context across the different years, the average fuel economy of the 20th percentile is 18.7, while the average for the 40th percentile is 21.75. The variation in elasticities across weight is not monotonic. The relationship begins by increasing until roughly the 20th percentile, and then falls more or less linearly thereafter. The elasticity of the heaviest vehicles is roughly 0.3.

We next investigate whether the roughly-linear relationship between criteria pollutant emissions and the elasticity is due to "over smoothing". Figure 8 plots the lowess smoothed lines under different bandwidths. The top left figure simply reports the 100 elasticities. There is some evidence that the relationship is not monotonic early on, but from the 5th percentile on, the relationship appears monotonic. Doing this exercise for the other criteria pollutants yields similar results.

### 5.1 The Source of the Heterogeneity

While the co-pollutant benefits accrue regardless of the mechanism behind the heterogeneity, it is of independent interest to investigate the mechanism. We investigate three sources, which are not necessarily independent of each other. First, it may be driven entirely through a vintage effect. That is, older vehicles are both more responsive to changes in gas prices and have higher emissions. Second, it might be driven by differences in the incomes of consumers that drive dirtier versus cleaner vehicles. Third, it may result from households shifting which of their vehicles are driven in the face of rising gasoline prices.

To investigate whether it is simply a vintage effect, we redefine the quartiles based on the distribution of emissions within vintage bins. We split vehicles into three age categories: 4 to 9 years old, 10 to 15 years old, and 16 to 27 years old.

Tables 8 through 11 report the results across externality-type. These results suggest that while vintage is an important driver in the externality-based heterogeneity, it is not the only source. In all four externality types variation exists within age bin; furthermore, in all but fuel economy this variation would appear to be economically significant.

For a sub-sample of our smog check vehicles, we are able to group them into households. This grouping comes from access to California Department of Motor Vehicles (DMV) data. A number of steps are undertaken to "clean" the address entries in the DMV records. These are discussed in Appendix A. Ultimately, however, the subsample of vehicles that we are able to match likely draw more heavily from households residing in single-family homes. Given this selection, it is not surprising that we find average elasticities that differ from those presented above. In particular, they are smaller suggesting that the elasticity may be correlated with income.

The results from this sample are presented in Table 13. For this sample, we construct two additional variables meant to capture the household stock of vehicles. The variable "Higher MPG in HH" equals one if there is another vehicle in the household that has a higher MPG rating than the vehicle at question. Likewise, the variable "lower MPG in HH" equals one if there is another vehicle in the household that has a lower MPG rating than the vehicle at question.

If household shift usage from low MPG vehicles to high MPG vehicles, we would expect "Higher MPG in HH" to be negative and "Lower MPG in HH" to be positive. The results suggest that this is a mechanism, but not the only one. If there is a vehicle with higher fuel economy in the household, the elasticity is larger, while if there is a vehicle with a lower MPG, the elasticity is smaller. Column 2 of Table 13 adds these variables to our base specification. The point estimates suggest that a vehicle in the highest fuel economy quartile belonging to a household that also has a lower fuel economy vehicle has a near zero elasticity.[11]

For this same sample of vehicles, we also use the Census-tract information to categorize owners

[11]The sum of the two vehicle-stock variables is positive, but because lower fuel efficient vehicles are driven more earlier in the sample, the elasticities are not comparable in terms of what they imply for total miles driven.

into income quartiles. We interact these quartiles with the log of dollars per mile to see if differences in elasticities exist. Column 3 of Table 13 adds these interaction terms. There is some evidence that higher income consumers are less elastic, but these effects are not enough to reverse the emissions quartile effects; vehicles in the bottom quartile remain nearly three times more sensitive even after accounting for income differences.

Our smog check data report the zip code of the testing station the vehicle visited. For our more general sample, we can also use this information to construct measures of income. Table 14 compares these results with the DMV data. We find similar differences in the elasticities, despite the larger average elasticity. That is, the average elasticity of the top income quartile vehicles is roughly 0.03 less elastic, than the bottom quartile, in both samples.

## 6 Scrappage Decisions

Our next set of empirical models examine how vehicle owners' decisions to scrap their vehicles are affected by gasoline prices. Again we will also examine how this effect varies over emissions profiles.

We determine whether a vehicle has been scrapped using the data from CARFAX Inc. We begin by assuming that a vehicle has been scrapped if more than a year has passed between the last CARFAX record and the date when CARFAX produced our data extract (October 1, 2010). However, we treat a vehicle as being censored if the last CARFAX record was not in California, or if more than a year and a half passed between the last Smog Check in our data and the last CARFAX record. As well, to avoid treating late registrations as scrappage, we treat all vehicles with Smog Checks after 2008 as censored. Finally, to be sure we are dealing with scrapping decisions and not accidents or other events, we only examine vehicles which are at least 10 years old.

Some modifications to our data are necessary. To focus on the long-run response to gasoline prices, our model is specified in discrete time, denominated in years. Where vehicles have more than one Smog Check per calendar year, we use the last Smog Check in that year. Also, since it is generally unlikely that a vehicle is scrapped at the same time as its last Smog Check, we create an additional observation for scrapped vehicles either one year after the last Smog Check, or 6 months after the last CARFAX record, whichever is later. For these created observations, odometer is imputed based on the average VMT between the last two Smog Checks, and all other variables take their values from the vehicle's last Smog Check. An exception is if a vehicle fails the last Smog Check in our data. In this case, we assume the vehicle was scrapped by the end of that year.

Because many scrapping decisions will not take place until after our data ends, a hazard model is needed to deal with right censoring. Let $T_{jivg}$ be the year in which vehicle $j$, of vehicle type $i$, vintage $v$, and geography $g$ is scrapped. Assuming proportional hazards, our basic model is:

$$\Pr[t < T_{jivg} < t+1 | T > t] = h^0_{iv}(t) \cdot \exp\{\beta x DPM_{gt} + \gamma D_{fail_{jt}} + \psi G_{jgt} + \alpha X_{jt}\},$$

where $DPM_{gt}$ is defined as before, $D_{fail_{jt}}$ is a dummy equal to one if the vehicle failed a Smog Check any time during year $t$, $G$ is a vector of demographic variables, determined by the location of the Smog Check, $X$ is a vector of vehicle characteristics, including a dummy for truck and a 6th-order polynomial in odometer, and $h^0_{jiv}(t)$ is the baseline hazard rate, which varies by time but not the other covariates. In some specifications, we will allow each vehicle type and vintage to have its own baseline hazard rate.

We estimate this model using semi-parametric Cox proportional hazards regressions, leaving the baseline hazard unspecified. We report exponentiated coefficients, which may be interpreted as hazard ratios. For instance, a 1 unit increase in DPM will multiply the hazard rate by $\exp\{\beta\}$, or increase by $(\exp\{\beta\} - 1)$ percent. In practice, we scale the coefficients on DPM for a 5-cent change, corresponding to a \$1.00 increase in gasoline prices for a vehicle with fuel economy of 20 miles per gallon.

Tables 15 and 16 show the results of our hazard analysis. Models 1 and 2 assign all vehicles to the same baseline hazard function. Model 1 allows the effect of gas prices to vary by whether or not a vehicle failed a Smog Check. Model 2 also allows the effect of gas prices to vary by externality quartiles as well.[12] Models 3 and 4 are similar, but stratify the baseline hazard function, allowing each VIN prefix to have its own baseline hazard function. Finally, Model 5 allows the effect of gasoline prices to vary both by externality quartile and age group, separating vehicles 10 to 15 years old from vehicles 16 years and older.

Table 15 focuses on heterogeneity across emissions of $NO_x$. Models 1 and 2 indicate that increases in gasoline prices actually decrease scrapping on average, with the cleanest vehicles seeing the largest decreases. The effect is diminished once unobserved heterogeneity among vehicle types is controlled for. In Models 3 and 4, the decrease in the hazard rate from a 5 cent increase in dollars per mile is statistically insignificant, and while there are differences among $NO_x$ quartiles in model 4, we cannot reject the hypothesis that they are equal. Instead, the heterogeneity in the

[12] Quartiles in these models are calculated by year among only vehicles 10 years and older.

effect of gasoline prices on hazard seems to be over age groups. Model 5 shows that when the cost of driving a mile increases by 5 cents, the hazard of scrappage decreases by about 20% for vehicles between 10 and 15 years old, while it increases by around 7% for vehicles age 16 and older, with little variation across $NO_x$ quartiles within age groups. This suggests that when gasoline prices rise, very old cars are scrapped, increasing demand for moderately old cars and thus reducing the chance that they are scrapped. Results with HC and CO quartiles produce almost identical results.

Table 16 focuses on heterogeneity in fuel economy. Moving from model 2 to model 4, we see that heterogeneity appears when we stratify by VIN prefix, although the form is counter-intuitive. A 5-cent increase in DPM increases the hazard of scrappage by about 18% for the most fuel efficient vehicles, while deceasing the hazard of scrappage by about 17% for the most fuel efficient vehicles. Because we stratify by VIN prefix in model 4, this cannot be explained by differences in vehicle types, such as trucks surviving longer than cars. Model 5 shows that most but not all of these differences can be explained by differences in vehicle age. We cannot reject the hypothesis of no heterogeneity across MPG quartiles for vehicles age 10 to 15, but we can for vehicles age 16 and greater, where it seems that the hazard rate increases most for vehicles in the second and third quartiles.

In summary, increases in the cost of driving a mile over the long term increase the chance that old vehicles are scrapped, while middle aged vehicles are scrapped less, perhaps because of increased demand. Although vehicle age is highly correlated with emissions of criteria pollutants, there is little variation in the response to gasoline prices across emissions rates within age groups.

# 7 Policy Simulations

We use our empirical results to inform policy in two ways. First, we calculate the co-benefits associated with a gasoline, or carbon dioxide, tax in the transportation sector. Second, we extend the work by Parry and Small (2005) and calculate the optimal gasoline tax when one considers the heterogeneity in the VMT-elasticity.

## 7.1 Co-benefits and the Social Cost of Carbon Pricing

Our results indicate that a tax on gasoline will disproportionately affect the usage and, to a lesser extent, scrappage of cars with greater emissions of local pollutants. To quantify this, we use our data to simulate the change in emissions resulting from a \$1 increase in the tax on gasoline, or roughly a \$110 per ton of $CO_2$ tax.[13] We account for both the intensive and extensive margins, as well as all the dimensions of heterogeneity we have documented in Sections 5 and 6. For this simulation, we assume that the tax was imposed in 1998, and use our empirical models to estimate the level of gasoline consumption and emissions from 1998 until 2008, had gasoline prices been \$1 greater. Appendix C provides details of the steps we take for the simulation.

Tables 17, 18, and 19 show the results of our simulation for each year from 1998-2008, and the yearly average over the period. The two columns shows the total reduction in annual gasoline consumption and $CO_2$ emissions, in millions of gallons and millions of tons, respectively. The next two columns value the deadweight loss from the reduction in gasoline consumption. We approximate deadweight loss as $\frac{\Delta P \cdot \Delta Q}{2}$ and adjust for inflation. The next section of the table presents the social benefit resulting from the reduction in $NO_x$, HC, and CO due to the tax. Finally, the last column of the table shows the net cost of abating a ton of carbon dioxide, accounting for the reductions in criteria pollution.

Table 17 shows the results of a simulation that does not account for heterogeneity across emissions profiles. The reduction in gasoline consumption declines slightly over time from around 800 million gallons in 1998 down to around 625 in 2008. The reduction in criteria pollutants declines quickly as the fleet becomes cleaner. Nonetheless, the co-benefits of a gasoline tax are substantial, averaging 74% of the deadweight loss over the ten year period.

Table 18 adds heterogeneity on the intensive margin, but not the extensive margins. The total change in gasoline consumption is smaller, declining from 520 million gallons in 1998 to 208.5 million gallons in 2008. This is a result of more fuel efficient vehicles having a higher average VMT. However, the reductions in criteria pollutants are much larger. In 1998 the co-benefits are over 200% of the deadweight loss, with the net cost of abating a ton of carbon staying negative until 2004 and remaining low afterward. On average, we estimate that on average more than 130% of the deadweight loss resulting from a gasoline tax would be compensated for by a decrease in local air pollution between 1998 and 2008.

Finally, Table 19 adds heterogeneity on the extensive margins of scrappage and new car purchases. The net effect of the extensive margin is an increase in criteria pollutants, due to the

[13] We assume all of the tax is passed through to consumers. Our implicit assumption is that the supply elasticity is infinite. This is likely a fair assumption in the long-run and for policies that reduce gasoline consumption in the near-term.

decreased scrappage vehicles 10-15 years old, but an increase in greenhouse gas abatement. The amount and value of the co-benefits is reduced compared to the figures in Table 18, but the difference is relatively small. Now on average nearly 120% of the deadweight loss is compensated for by the co-benefits. The net cost of the tax remains negative through 2003. In the last year of our sample, the net cost is below $24 per ton of $CO_2$.

Consistent with the way smog is formed, the majority the benefits come from reductions in hydrocarbons. As discussed in the next section, most counties in California are "$NO_x$-constrained". In simplest terms this means that local changes in $NO_x$ emissions do not reduce smog, but changes in hydrocarbons do. In addition to the precursors to smog, we also find large co-benefits arising from CO reductions.

We argue that these results should be viewed as strict lower bounds of the co-benefits for a variety of reasons. First, we have ignored all other negative externalities associated with vehicles; many of these, such as particulate matter, accidents, and congestion externalities, will be strongly correlated with either VMT and the emissions of $NO_x$, HCs, and CO. Second, because of the rules of the Smog Check program many vehicles that emission standards are not required to be tested, leading to their omission in this analysis. For these reasons, we view our estimates as strict lower bounds. Third, a variety of behaviors associated with smog check programs would lead the on-road emissions of vehicles to likely be higher than the tested levels. These include, but are not limited to, fraud, tampering with emission-control technologies between tests, failure to repair emission-control technologies until a test is required, etc.

When we account for the heterogeneity in the responses to changes in gasoline prices, we see that the co-benefits from reduced air pollution would substantially ameliorate the costs of an increased gasoline tax. The co-benefits would have been especially substantial in the late 1990s, but persist in more recent years as well, even though the fleet has become cleaner. To put these numbers into context, Greenstone, Kopits, and Wolverton (2011) estimate the SCC for a variety of assumptions about the discount rate, relationship between emissions and temperatures, and models of economic activity. For 2010, using a 3 percent discount rate, they find an average social cost of carbon of $21.40, with a 95th percentile of $64.90. Using a 2.5 percent discount rate, the average social cost of carbon is $35.10. Our results suggest that once the co-benefits are accounted for, a $1.00 gas tax (i.e., a $110 per ton of $CO_2$ tax) would be nearly cost-effective even at the lower of these three numbers and well below the average social cost of capital using a 2.5 percent interest rate.[14]

The co-benefits vary considerably across counties. This variation comes from variation in the marginal damages, variation in the elasticities, and variation in the heterogeneity across vehicle types. Figures 9 through 11 illustrate the first two types of variation. Figures 9 and 10 plot the variation in the marginal damages for $NO_x$ and HC. While marginal damages for HC are positively correlated with population (correlation coefficient of 0.84), the marginal damage for $NO_x$ are negatively correlated with both HC (0.49) and population (0.36). The reason for this has to do with the chemistry of ground-level ozone formation. Ground-level ozone, or smog, is formed in the presence of $NO_x$, HCs, heat, and sunlight. When the ratio of $NO_x$ to HCs is not too large or small, the production function of smog, in the presence of sunlight and heat, is similar to that of a Leontiff production function. Therefore, a county can be in a region of the level-set where increasing $NO_x$ does not increase smog production because there are not enough HCs to mix with the additional $NO_x$. This is known as $NO_x$ constrained. In contrast, a county may have so much HCs such that increasing HC does not lead to more smog. This is known as HC, or VOC, -constrained.[15] Therefore, the marginal damages of $NO_x$ and HC are negatively correlated.[16] Given that vehicles emit roughly equal amounts of $NO_x$ and HCs, in some respects the average (or total) of marginal damages across $NO_x$ and HCs is more telling.

Figure 11 also shows that the absolute value of demand elasticities tend to be positively correlated with population, although the correlation coefficient is only 0.20.

This variation leads to the variation in the co-benefits in Figure 12. The distribution is slightly skewed with a non-population weighted mean of \$27.62 per ton of $CO_2$ and median of \$24.47; the standard deviation is \$24.46. More populated areas have greater co-benefits, on average. Figure 13 shows a scatterplot of the co-benefits across counties versus the log of the counties population.[17] Los Angeles is clearly an outlier with benefits of \$146.60 per ton of $CO_2$ over our sample, although as noted the median is nearly \$25 with 75 percent of counties exceeding average co-benefits of over \$10.

[14] Of course, a tax somewhere below this would likely maximize welfare.

[15] Of course, the chemistry is more complicated than this. In fact, the isoquants of the production process are backward bending in the sense that if there is so much $NO_x$, more $NO_x$ actually reduces smog (NO combines with $O_3$ (ozone) to form $NO_2$ and $O_2$). This is known as titration. See figure 14.

[16] For California the correlation is -0.36.

[17] County names are listed for a random 50 percent of the counties, plus Los Angeles.

## 7.2 Optimal Gasoline Tax in the Presence of Heterogeneity

Parry and Small (2005) derive a formula for the second-best optimal gasoline tax, with components accounting for the various external costs of transportation. They do not account for the possibility of heterogeneity in the response of VMT to gasoline prices, and use only one value for the damage per mile associated with pollution as a result. We extend this work by incorporating heterogeneity on the intensive margin of driving, and examine how this affects the calculated optimal gasoline tax.

Let $t_f^*$ be the optimal (ad-valorem) tax on gasoline. Parry and Small derive that:

$$t_f^* = \frac{MEC_f}{1+MEB_L} + \frac{(1-\eta_{MI})\varepsilon_{LL}^c}{\eta_{ff}} \cdot \frac{t_L(q_f+t_f)}{1-t_L} + \frac{\beta M}{F} E^C\{\varepsilon_{LL} - (1-\eta_{MI})\varepsilon_{LL}^c\}\frac{t_L}{1-t_L},$$

where $\eta_{MI}$ is the income elasticity of VMT, $\eta_{FF}$ is the price elasticity of gasoline, $\eta_{MF}$ is the price elasticity of VMT, $\beta \equiv \frac{\eta_{MF}}{\eta_{FF}}$, $t_L$ is the tax on labor, $M$ is total VMT, $F$ is total fuel consumption, $MEB_L$ is the marginal excess burden of the tax on labor, and $MEC_F$ is the marginal external cost of fuel use, defined by:

$$MEC_F \equiv E^{P_F} + (E^C + E^A + E^{P_M})\beta\frac{M}{F}.$$

$E^{P_F}$ is the marginal damage of carbon emissions, and $E^C$, $E^A$, and $E^{P_M}$ are the marginal damage of congestion, accidents and local pollution, respectively, denominated in cents per gallon. We focus on $MEC_F$ and maintain Parry and Small's assumptions for the other components. For derivation and definition of other terms, see Parry and Small (2005).

Parry and Small use a range of values for each parameter in their model; we use their "central values" in all cases, with only two exceptions: We use our own estimates for $\eta_{MF}$, and calculate a value for $E^{P_M}$ based on average emissions rates of $NO_x$, HC, and CO in the Smog Check data. $NO_x$ and HC are valued as in Muller and Mendelsohn (2009), using a population weighted average of the marginal damages for each county in California. CO is valued using the median value in Matthews and Lave (2000). We utilize the regression with heterogeneity over MPG, HC, $NO_x$, CO, weight, and age described in Section 7.1. To calculate the optimal gasoline tax without heterogeneity, we use the average elasticity of:

$$\bar{\beta} = \sum_q \beta_q s_q = \sum_q \frac{\eta_{MF}^q}{\eta_{FF}} s_q,$$

where $q$ denotes a quartile/age group, and $s_q$ the share of group $q$ in the Smog Check data. With heterogeneity, we modify $MEC_F$ to be:

$$MEC_F = E^{P_F} + [(E^C + E^A)\bar{\beta} + \sum_q E_q^{P_M}\beta_q s_q]\frac{M}{F},$$

such that the local pollution component is a weighted average damage rates times elasticities. We calculate average elasticity and emissions rates using the portion of the California fleet appearing in the 1998 and 2008 Smog Check data. All values are adjusted for inflation to year 2000 dollars.

Parry and Small calculate a second-best optimal gasoline tax rate of \$1.01 for the United States. Based on our average elasticity estimate and the average emissions rates in the Smog Check program, the optimal gasoline tax for California was \$0.92 in 1998 and \$0.85 in 2008. Once heterogeneity in the response to gasoline prices is taken into account, the optimal tax rises to \$1.05 in 1998, and \$0.90 in 2008. While these are modest increases, this is because a large portion of the optimal tax comes from the Pigouvian tax-like components for accidents and congestion. If we focus on that portion coming from local pollution, it increases from \$0.22 to \$0.33 in 1998 and from \$0.08 to \$0.13 in 2008, a change of 52 and 57 percent, respectively.

## 8 California versus the rest of the US

Given that our empirical setting is California, it is natural to ask whether our results are representative of the country as a whole. At the broadest level, the co-benefits from carbon pricing are a function of the per capita number of miles driven, the emission characteristics of the fleet of vehicles, and the marginal damages of the emissions. We present evidence that the benefits may, in fact, be larger outside of California. The reason for this is that while the marginal damages are indeed larger in California, the vehicle stock in California is much cleaner than the rest of the country because California has traditionally lead the rest of the US in terms of vehicle emission standards.

The results in Muller and Mendelsohn (2009) provide a convenient way to test whether California differs in terms of marginal damages. Table 20 presents points on the distribution of marginal damages for $NO_x$, HCs, and the sum of the two, weighted by each county's annual VMT.[18] Figure 15 plots the kernel density estimates of the distributions. We present the sum of because counties are typically either "$NO_x$ constrained" or "VOC (HC) constrained" and the sum is perhaps more

[18] All of the points on the distribution and densities discussed in this section weight each county by its total VMT.

informative. As expected, the marginal damages are higher in California for HCs, but lower for $NO_x$, as California counties tend to be VOC-constrained. The sum of the two marginal damages is 78 percent higher in California. Higher points in the distribution show an even larger disparity.

This effect is offset, however, by the cleaner vehicle stock within California—a result of California's stricter emission standards. To illustrate this, we collected county-level average per-mile emission rates for $NO_x$, HCs, and CO from the EPA Motor Vehicle Emission Simulator (MOVES). This reports total emissions from transportation and annual mileage for each county. Table 20 also presents points on the per-mile emissions and Figure 16 plots the distributions.[19] Mean county-level $NO_x$, HCs, and CO are 67, 36, and 31 percent lower in California, respectively. Other points in the distributions exhibit similar patterns.

Finally, we calculate the county-level average per-mile externality for each pollutant, as well as the sum of the three. Table 20 and Figure 17 illustrates these. As expected the HC damages are higher, but the average county-level per-mile externality from the sum the three pollutants is 30 percent lower in California compared to the rest of the country; the 25th percentile, median, and 75th percentile are 35, 30, and 9 percent lower, respectively. These calculations suggest that, provided the average VMT elasticities are not significantly smaller outside of California and/or the heterogeneity across vehicle types is not significantly different (in the reverse way), our estimates are likely to apply to the rest of the country.

# 9 Conclusions

This paper estimates how the sensitivity to gas prices varies by the emission rates and weight of vehicles. We find that those vehicles that have higher externalities are more price responsive. We show that this significantly increases the co-benefits associated with carbon taxes, as well as the optimal gas tax when gas taxes are used as a second-best policy tool in the presence of multiple market failures.

These results should be viewed in light of the fact that existing policies used to reduce greenhouse gas emissions from transportation—CAFE standards, ethanol subsidies, and the RFS—fail to take advantage of these co-benefits, and can even increase criteria pollutant emissions, because they

[19] We note that these are higher than the averages in our data. This may reflect the fact that smog checks are not required for vehicles with model years before 1975 and these vehicles likely have very high emissions since this pre-dates many of the emission standards within the US.

*reduce* the marginal cost of an extra mile travelled. Given that previous work that has analyzed the relative efficiency of these policies to gasoline or carbon taxes has ignored the heterogeneity that we document, such policies are less efficient than previous thought.

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# A Steps to clean smog check data

## A.1 Smog Check Data

Our data from the Smog Check Program are essentially the universe of test records from January 1, 1996 to December 31, 2010. We were only able to obtain test records going back to 1996 because this was the year when the Smog Check program introduced its electronic transmission system. Because the system seems to have been phased in during the first half of 1996, and major program changes took effect in 1998 we limit our sample to test records from January 1998 on. For our analyses, we use a 10% sample of VINs, selecting by the second to last digit of the VIN. We exclude tests which have no odometer reading, with a test result of "Tampered" or "Aborted" and vehicles which have more than 36 tests in the span of the data. Vehicles often have multiple Smog Check records in a year, whether due to changes of ownership or failed tests, but we argue that more than 36 in what is at most a 12 year-span indicates some problem with the data.[20]

A few adjustments must be made to accurately estimate VMT and emissions per mile.

First, we adjust odometer readings for roll-overs and typos. Many of the vehicles in our analysis were manufacturer withe 5-digit odometers–that is, five places for whole numbers plus a decimal. As such, any time one of these vehicles crosses over 100,000 miles, the odometer "rolls over" back to 0. To complicate matters further, sometimes either the vehicle owner or Smog Check technician notices this problem and records the appropriate number in the 100,000s place, and sometimes they do not. To address this problem, we employ an algorithm that increases the hundred thousands place in the odometer reading whenever a rollover seems to have occurred. The hundred thousands are incremented if the previous test record shows higher mileage, or if the next test record is shows more than 100,000 additional miles on the odometer (indicating that the odometer had already rolled over, but the next check took this into account). The algorithm also attempts to correct for typos and entry errors. An odometer reading is flagged if it does not fit with surrounding readings for the same vehicle–either it is less than the previous reading or greater the next–and cannot be explained by a rollover. The algorithm then tests whether fixing one of several common typos will make the flagged readings fit (e.g. moving the decimal over one place). If no correction will fit, the reading is replaced with the average of the surrounding readings. Finally, if after all our corrections

[20] For instance, there is one vehicle in particular, a 1986 Volvo station wagon, which has records for more than 600 Smog Checks between January 1996 and March 1998. The vehicle likely belonged to a Smog Check technician who used it to test the electronic transmission system.

any vehicle has an odometer reading above 800,000 or has implied VMT per day greater than 200 or less than zero, we exclude the vehicle from our analysis. All of our VMT analyses use this adjusted mileage.

Emissions results from smog checks are given in either parts per million (for HC and NOx) or percent ($O_2$, CO, and $CO_2$). Without knowing the volume of air involved, there is no straightforward way to convert this to total emissions. Fortunately, as part of an independent evaluation of the Smog Check program conducted in 2002-2003, Sierra Research Inc. and Eastern Research Group estimated a set of conversion equations to convert the proportional measurements of the ASM test to emissions in grams per mile travelled. These equations are reported in Morrow and Runkle (2005) and are reproduced below. The equations are for HCs, NOx and CO, and estimate grams per mile for each pollutant as a non-linear function of all three pollutants, model year and vehicle weight. The equations for vehicles of up to model year 1990 are

$$\begin{aligned} FTP\_HC = 1.2648 \cdot exp(-4.67052 \quad & +0.46382 \cdot HC^* + 0.09452 \cdot CO^* + 0.03577 \cdot NO^* \\ & +0.57829 \cdot \ln(weight) - 0.06326 \cdot MY^* + 0.20932 \cdot TRUCK) \end{aligned}$$

$$\begin{aligned} FTP\_CO = 1.2281 \cdot exp(-2.65939 \quad & +0.08030 \cdot HC^* + 0.32408 \cdot CO^* + 0.03324 \cdot CO^{*2} \\ & +0.05589 \cdot NO^* + 0.61969 \cdot \ln(weight) - 0.05339 \cdot MY^* \\ & +0.31869 \cdot TRUCK) \end{aligned}$$

$$\begin{aligned} FTP\_NOX = 1.0810 \cdot exp(-5.73623 \quad & +0.06145 \cdot HC^* - 0.02089 \cdot CO^{*2} + 0.44703 \cdot NO^* \\ & +0.04710 \cdot NO^{*2} + 0.72928 \cdot \ln(weight) - 0.02559 \cdot MY^* \\ & -0.00109 * MY^{*2} + 0.10580 \cdot TRUCK) \end{aligned}$$

Where

$$HC^* = \ln((Mode1_{HC} \cdot Mode2_{HC})^{.5}) - 3.72989$$
$$CO^* = \ln((Mode1_{CO} \cdot Mode2_{CO})^{.5}) + 2.07246$$
$$NO^* = \ln((Mode1_{NO} \cdot Mode2_{NO})^{.5}) - 5.83534$$
$$MY^* = modelyear - 1982.71$$
$$weight = \text{Vehicle weight in pounds}$$
$$TRUCK = 0 \text{ if a passenger car, } 1 \text{ otherwise}$$

And for model years after 1990 they are:

$$\begin{aligned} FTP\_HC = 1.1754 \cdot exp(-6.32723 \quad & +0.24549 \cdot HC^* + 0.09376 \cdot HC^{*2} + 0.06653 \cdot NO^* \\ & +0.01206 \cdot NO^{*2} + 0.56581 \cdot \ln(weight) - 0.10438 \cdot MY^* \\ & -0.00564 \cdot MY^{*2} + 0.24477 \cdot TRUCK) \end{aligned}$$

$$\begin{aligned} FTP\_CO = 1.2055 \cdot exp(-0.90704 \quad & +0.04418 \cdot HC^{*2} + 0.17796 \cdot CO^* + 0.08789 \cdot NO^* \\ & +0.01483 \cdot NO^{*2} - 0.12753 \cdot MY^* - 0.00681 \cdot MY^{*2} \\ & +0.37580 \cdot TRUCK) \end{aligned}$$

$$\begin{aligned} FTP\_NOX = 1.1056 \cdot exp(-6.51660 \quad & + + 0.25586 \cdot NO^* + 0.04326 \cdot NO^{*2} + 0.65599 \cdot \ln(weight) \\ & -0.09092 \cdot MY^* - 0.00998 * MY^{*2} + 0.24958 \cdot TRUCK) \end{aligned}$$

Where:

$$HC^* = \ln((Mode1_{HC} \cdot Mode2_{HC})^{.5}) - 2.32393$$
$$CO^* = \ln((Mode1_{CO} \cdot Mode2_{CO})^{.5}) + 3.45963$$
$$NO^* = \ln((Mode1_{NO} \cdot Mode2_{NO})^{.5}) - 3.71310$$
$$MY^* = modelyear - 1993.69$$
$$weight = \text{Vehicle weight in pounds}$$
$$TRUCK = 0 \text{ if a passenger car, } 1 \text{ otherwise}$$

# B Steps to clean DMV data

We deal with two issues associated with the DMV data. The main issue with the DMV data is that, often, entries for the same addresses will have slightly different formats. For example, 12 East Hickory Street may show up as 12 East Hickory St, 12 E. Hickory St., etc. To homogenize the entries, we input each of the DMV entries into mapquest.com and then replace the entry with the address that mapquest.com gives.

Second, the apartment number is often missing in the DMV data. This has the effect of yielding a large number of vehicles in the same "location". We omit observations that have over seven vehicles in a given address or more than three last names of registered owners.

# C Details of the gas tax policy simulation

For the intensive margin, we estimate a regression as in column 6 of Tables 3 to 7, except that we interact ln(DPM) with quartile of fuel economy, vehicle weight, and emissions of HC, $NO_x$, and CO, and dummies for vehicle age bins, again using bins of 4-9, 10-15, and 16-29 years, and control for the direct effects of quartiles of HC, $NO_x$, and CO emissions. As in Tables 8 to 12, we use quartiles calculated by year and age bin. The coefficients are difficult to interpret on their own, and too numerous to list. However, most are statistically different from zero, and the exceptions are due to small point estimates, not large standard errors.

As in Section 6, we compress our dataset to have at most one observation per vehicle per year. Each vehicle is then assigned an elasticity based on their quartiles and age bin. Vehicle $i$'s VMT in the counterfactual with an additional \$1 tax on gasoline is calculated by:

$$VMT^i_{counterfactual} = VMT^i_{BAU} * \left( \frac{P_i + 1}{P_i} \cdot \beta_i \right),$$

where $VMT^i_{BAU}$ is vehicle $i$'s actual average VMT per day between their current and previous Smog Check, $P_i$ is the average gasoline price over that time, and $\beta_i$ is the elasticity for the fuel economy/weight/HC/NO/CO/age cell that $i$ belongs to.

For the extensive margin, we estimate a Cox regression on the hazard of scrappage for vehicles 10 years and older, stratifying by VIN prefix and interacting DPM with all five type of quartiles and age bins 10-15 and 16-29. Similar to the intensive margin, we assign each vehicle a hazard coefficient based on their quartile-age cell. Cox coefficients can be transformed into hazard ratios, but to simulate the affect of an increase in gasoline prices on the composition of the vehicle fleet, we must convert these into changes in total hazard.

To do this, we first calculate the actual empirical hazard rate for prefix $k$ in year $t$ as:

$$OrigHazard_{kt} = \frac{D_{kt}}{R_{kt}},$$

where $D_{kt}$ is the number of vehicles in group $k$ which are scrapped in year $t$, and $R_{kt}$ is the number of vehicle at risk (that is, which have not previously been scrapped or censored). We then use the coefficients from our Cox regression to calculate the counterfactual hazard faced by vehicles of prefix $k$ in quartile-age group $q$ during year $t$ as:[21]

$$NewHazard_{qkt} = OrigHazard_{kt} * \exp\left\{\frac{1}{MPG_k} \cdot \gamma_q\right\},$$

where $MPG_k$ is the average fuel economy of vehicle of prefix $k$ and $\gamma_q$ is the Cox coefficient associated with quartile group $q$. We then use the change in hazard to construct a weight $H_{qkt}$ indicating the probability that a vehicle of prefix $k$ in quartile group $q$ in year $t$ would be in the fleet if a \$1 gasoline tax were imposed. Weights greater than 1 are possible, in which should be interpreted as a $H_{qkt}-1$ probability that another vehicle of the same type would be on the road, but which was scrapped under "Business as Usual." Since the hazard is the probability of scrappage in year $t$, conditional on survival to year $t$, this weight must be calculated interatively, taking into account the weight the previous year. Specifically, we have:

$$H_{qkt} = \prod_{j=1998}^{t} (1 - (NewHazard_{qkj} - OrigHazard_{kt})).$$

We also assign each vehicle in each year a population weight. This is done both to scale our estimates up to the size of the full California fleet of personal vehicles, and to account for the ways in which the age composition of the Smog Check data differs from that of the fleet. We construct these weights using the vehicle population estimates contained in CARB's EMFAC07 software, which are given by year, vehicle age, and truck status. Our population weight is the number of

[21] Note that age group is determined by model-year and year.

vehicles of a given age and truck status in a each year given by EMFAC07, divided by the number of such vehicle appearing in our sample. For instance, if EMFAC07 gave the number of 10 year old trucks in 2005 as 500, while our data contained 50, each 10 year old truck in our data would have a population weight of 10. Denote the population weight by $P_{tac}$, where $t$ is year, $a$ is age, and $c$ is truck status.

There is an additional extensive margin which we have not estimated in this paper, that of new car purchases. To ensure that the total vehicle population is accurate, we apply an *ad hoc* correction based on Busse, Knittel, and Zettelmeyer (2009), who find that a $1 increase in gas prices would decrease new car sales by 650,000 per year. Since California's vehicle fleet makes up about 13% of the national total, we decrease the population of model years 1998 and later by 84500 when constructing the population weight for the counterfactual. We apply 40% of the decrease to trucks, and 60% to passenger cars. Denote the "new car effect" $n_c$.

We estimate the total annual emissions by passenger vehicle in California of $NO_x$, HC, CO, and $CO_2$ as actually occurred, and under a counterfactual where a $1 gasoline tax was imposed in 1998. Let $i$ denote a vehicle, $a$ vehicle age, $c$ truck status, then the annual emissions of pollutant $p$ in year $t$ under "business as usual" are:

$$Emission_{BAU}^{pt} = \sum_i P_{tac} * VMT_{BAU}^i * r_i(p) * 365,$$

and under the counterfactual they are:

$$Emission_{counterfactual}^{pt} = \sum_i (P_{tac} - 1(\text{model year} >= 1998) * n_c) * H_{qkt} * VMT_{counterfactual}^i * r_i(p) * 365,$$

where $r_i(p)$ is the emissions rate per mile of pollutant $p$ for vehicle $i$. For $NO_x$, HC, and CO, this is the last Smog Check reading in grams per mile, while for $CO_2$ this is the vehicle's gallons per mile multiplied by 19.2 pounds per gallon.

# Figures and Tables

## A Figures

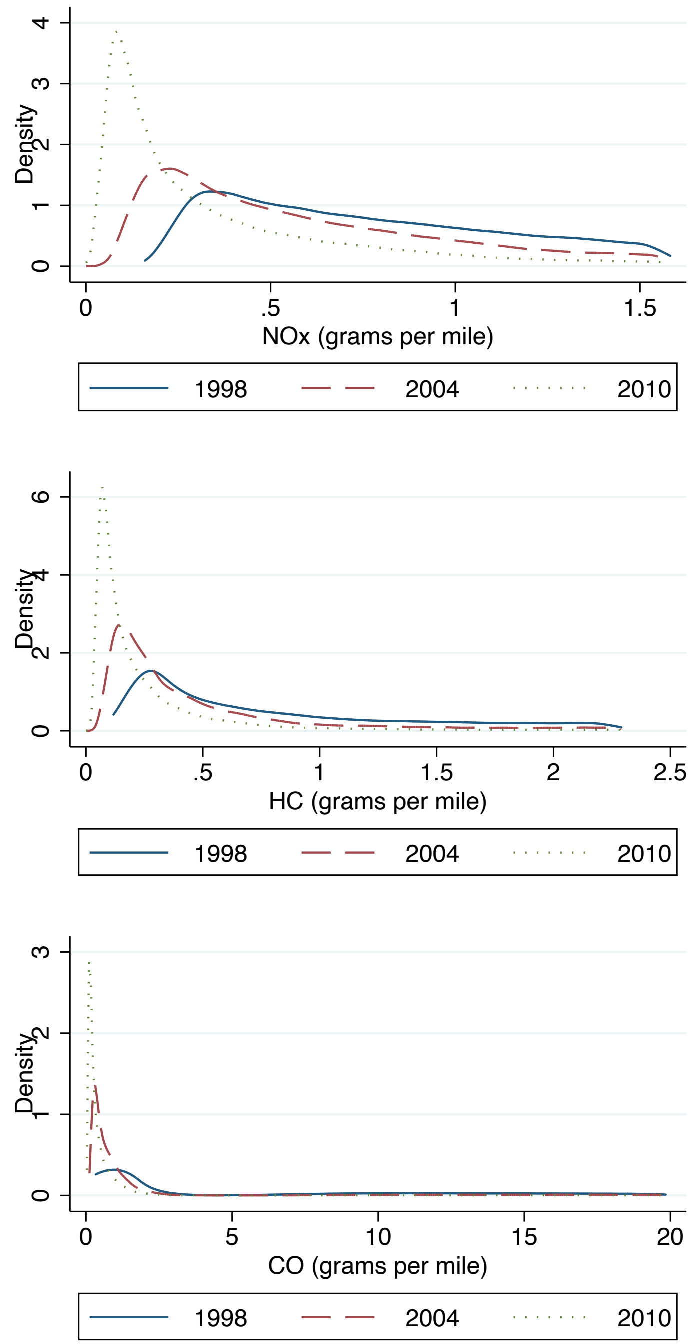


**Figure 1:** Distribution of three criteria pollutant emissions across all vehicles in 1998, 2004, and 2010 (observations above the 90th percentile are omitted)

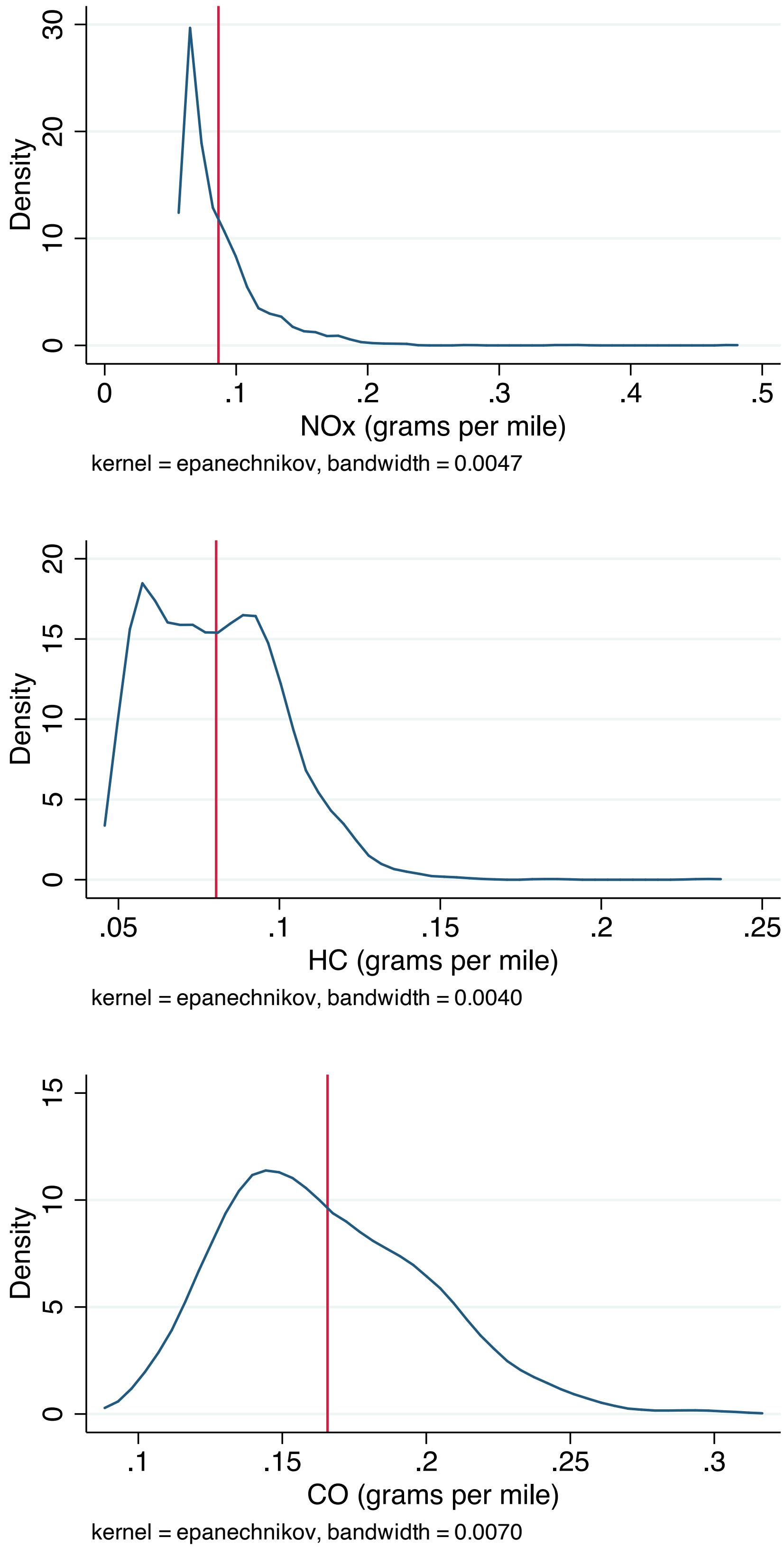


**Figure 2:** Distribution of three criteria pollutant emissions of a 2001 4-door, 1.8L, Toyota Corolla in 2009

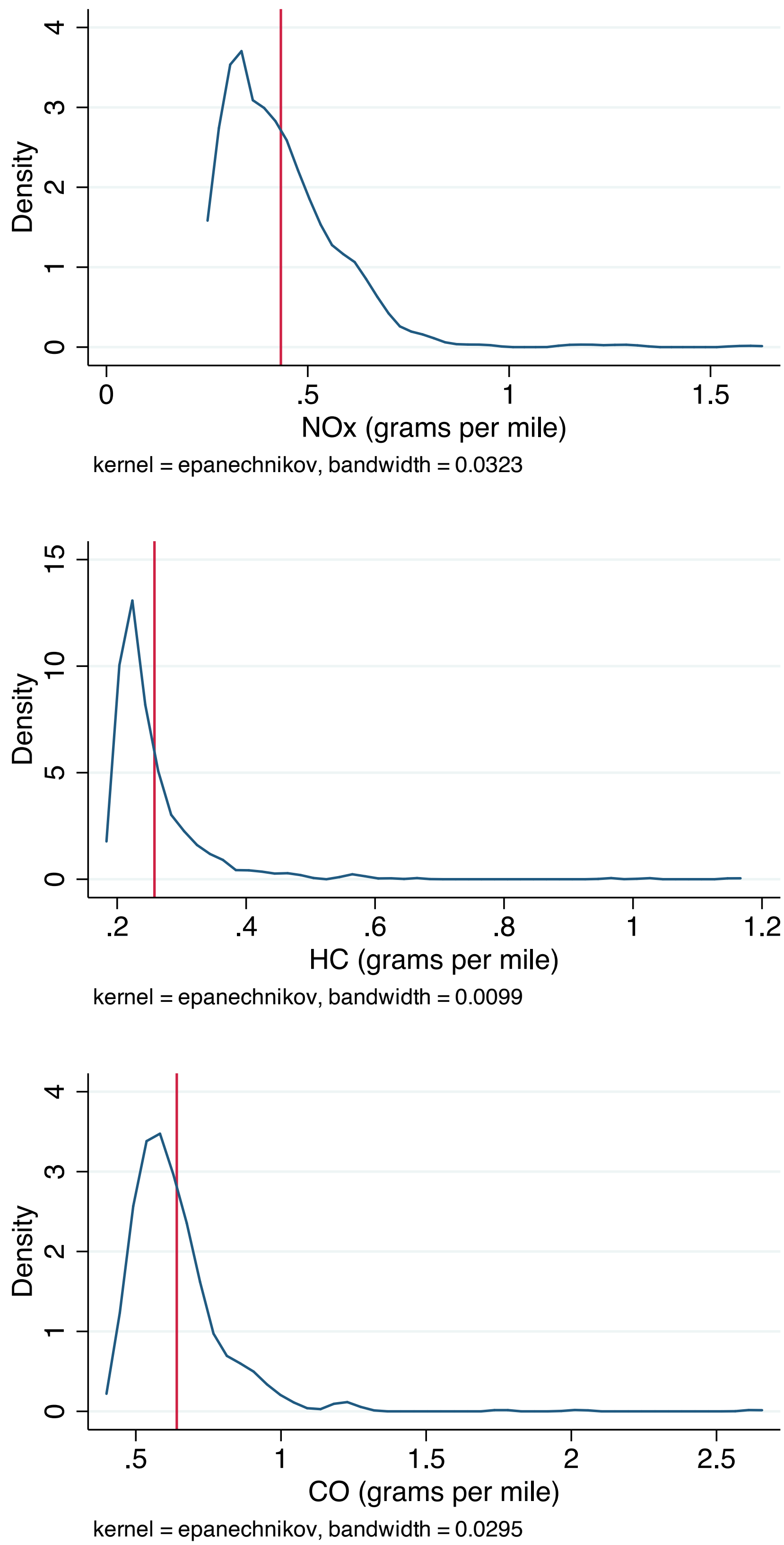


**Figure 3:** Distribution of three criteria pollutant emissions of a 1995 3.8L, FWD, Ford Windstar in 1999, 2001, 2005, and 2009 (observations above the 95th percentile are omitted)

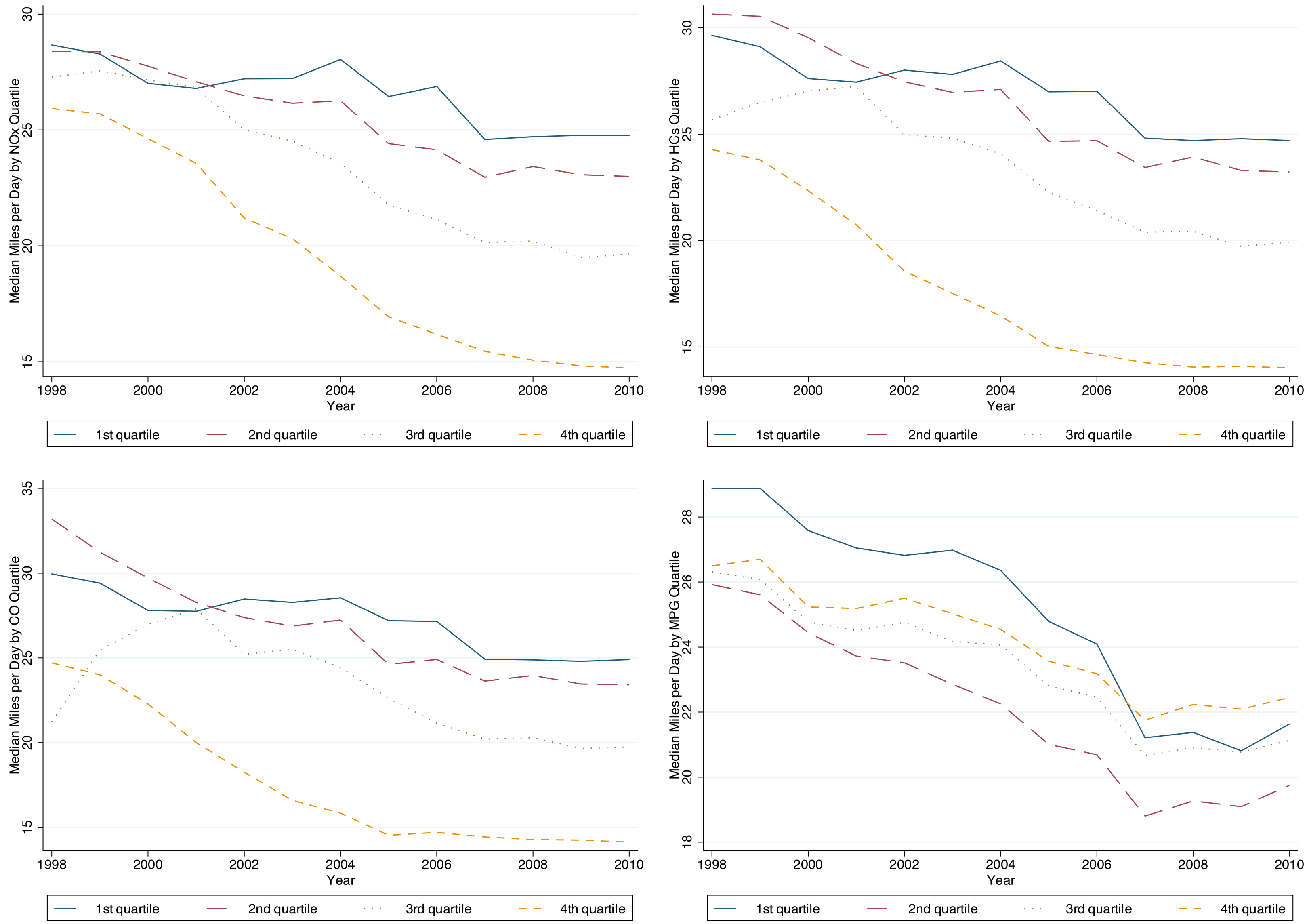


**Figure 4:** Change in VMT over sample by pollutant quartile

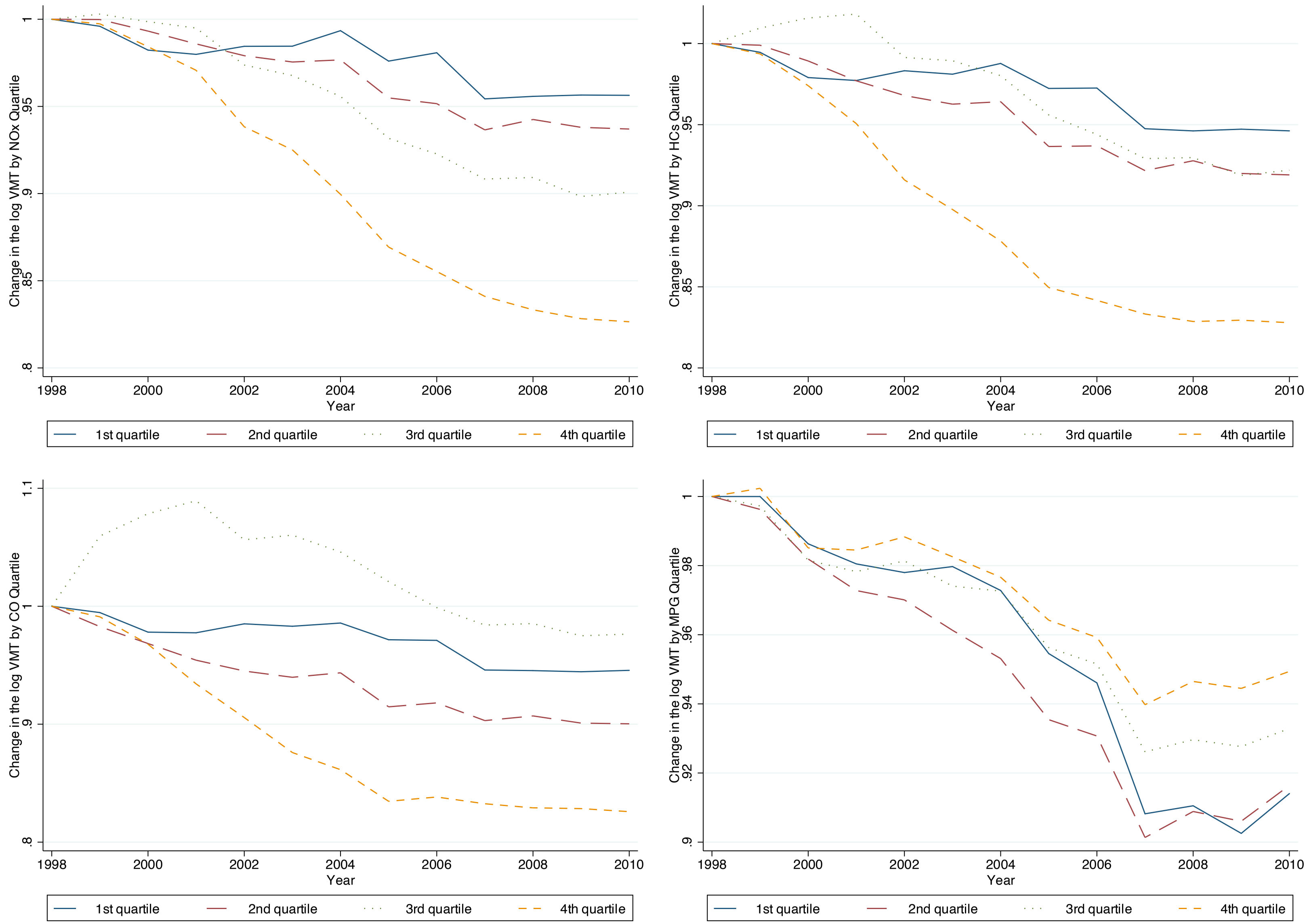


**Figure 5:** Change in the log of VMT over sample by pollutant quartile

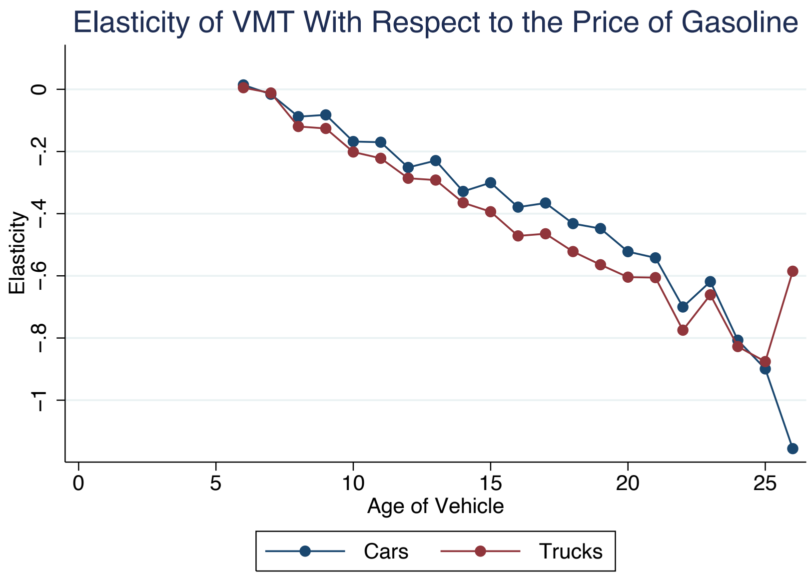


**Figure 6:** Elasticity by vehicles' vintage

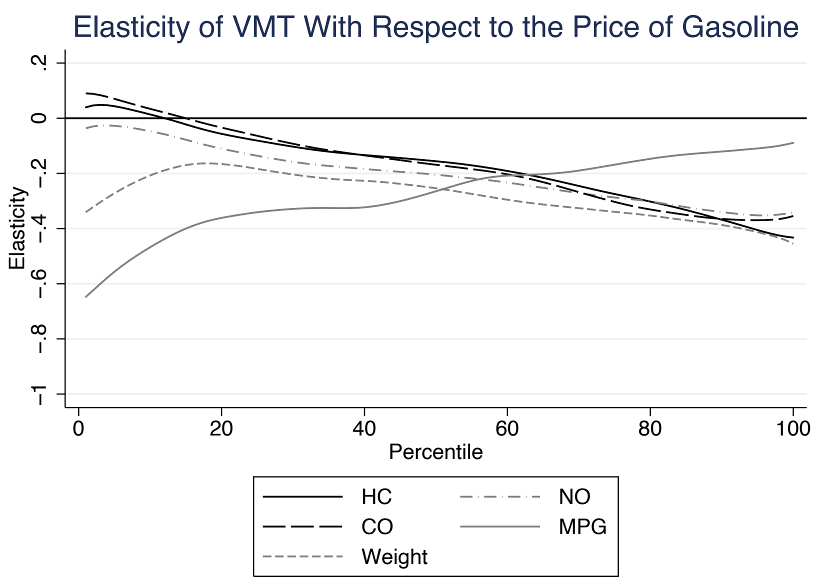


**Figure 7:** Non-parametric relationships between elasticity and externality

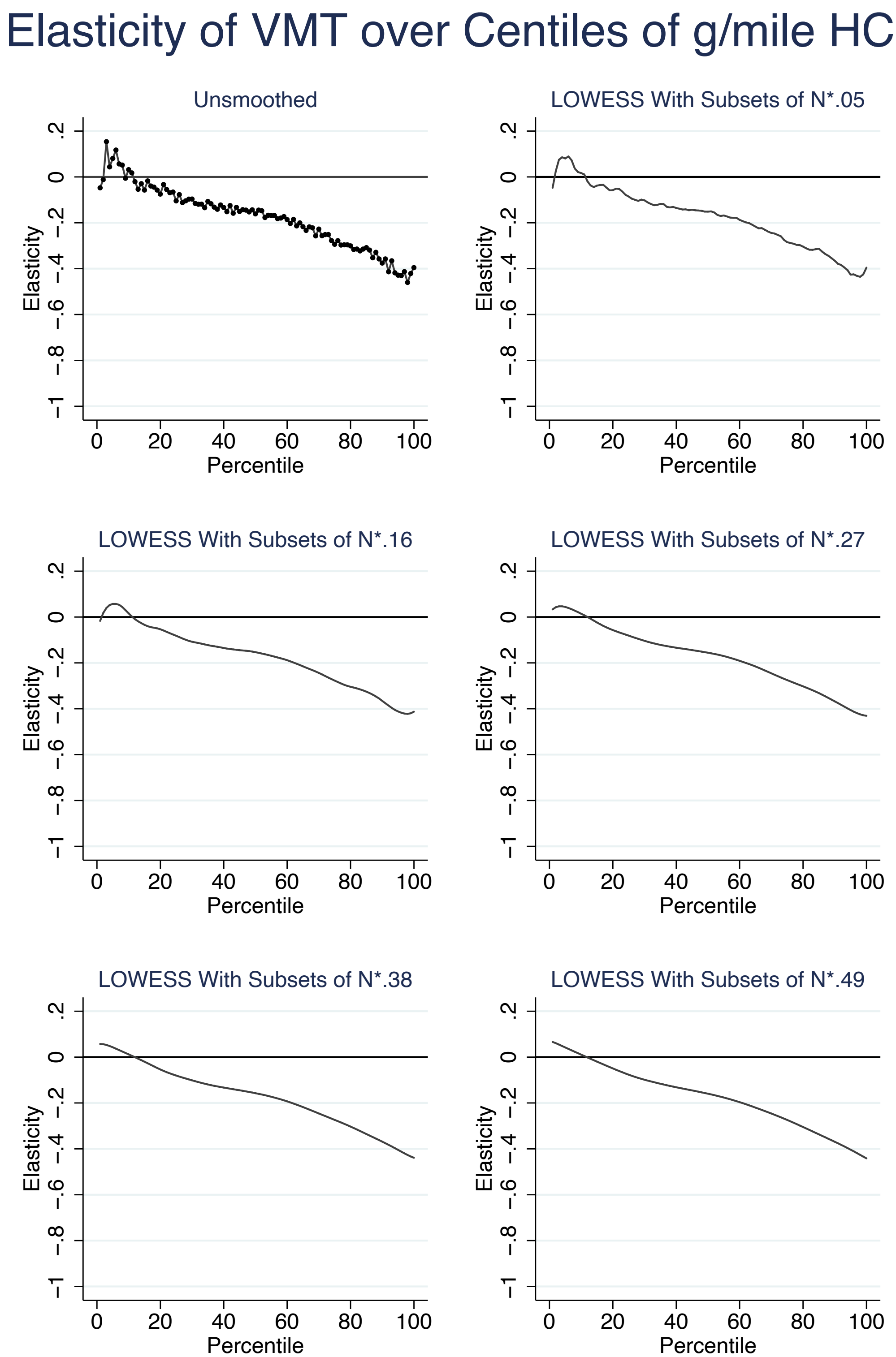


**Figure 8:** The effect of bandwidth on the non-parameteric function

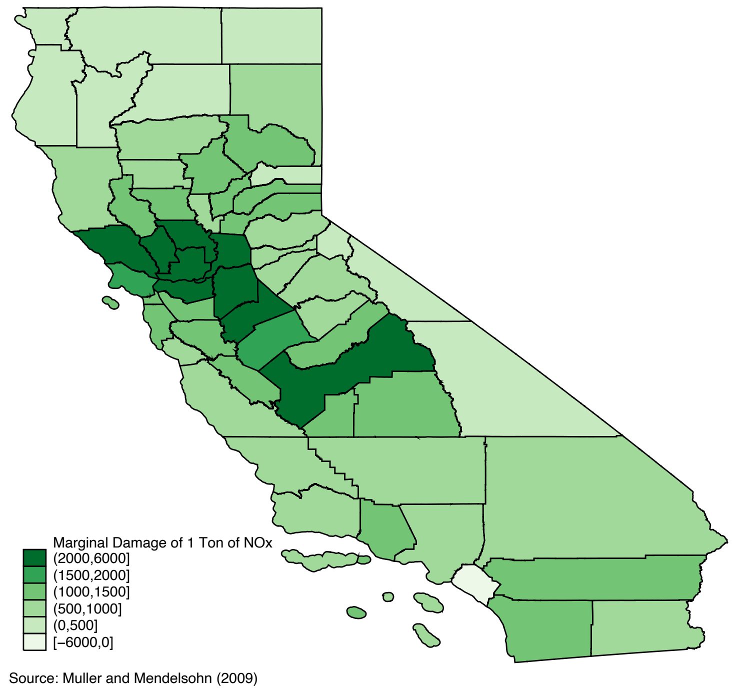


**Figure 9:** Marginal social damages from a ton of $NO_x$ by county

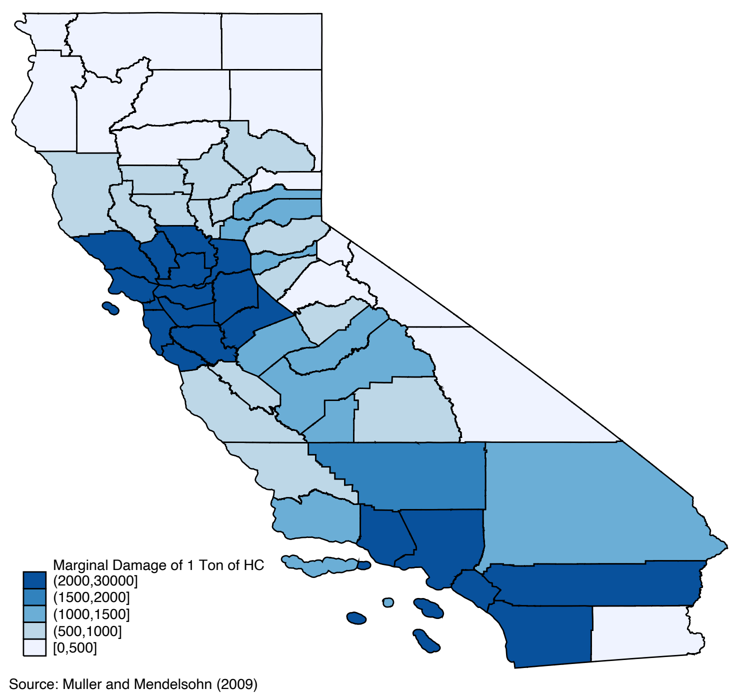


**Figure 10:** Marginal social damages from a ton of HC by county

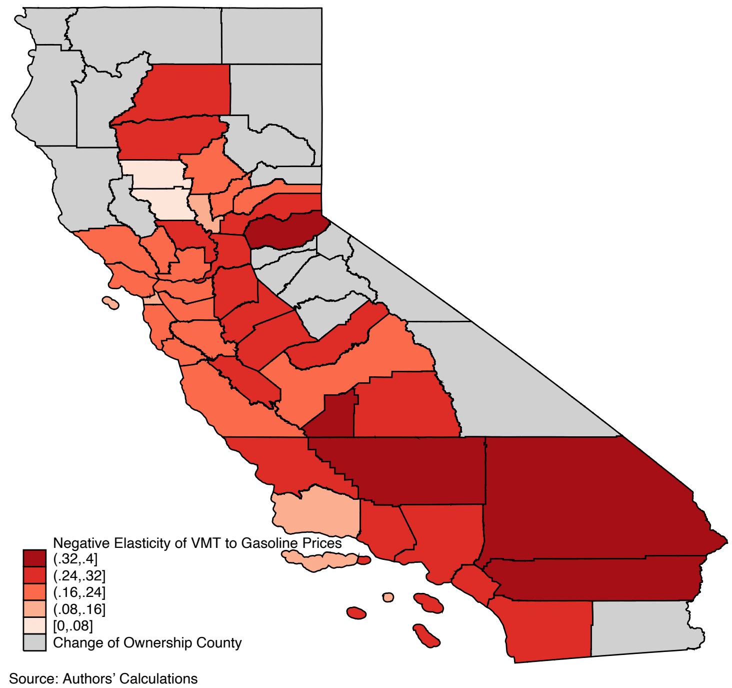


**Figure 11:** Estimated VMT elasticty by county

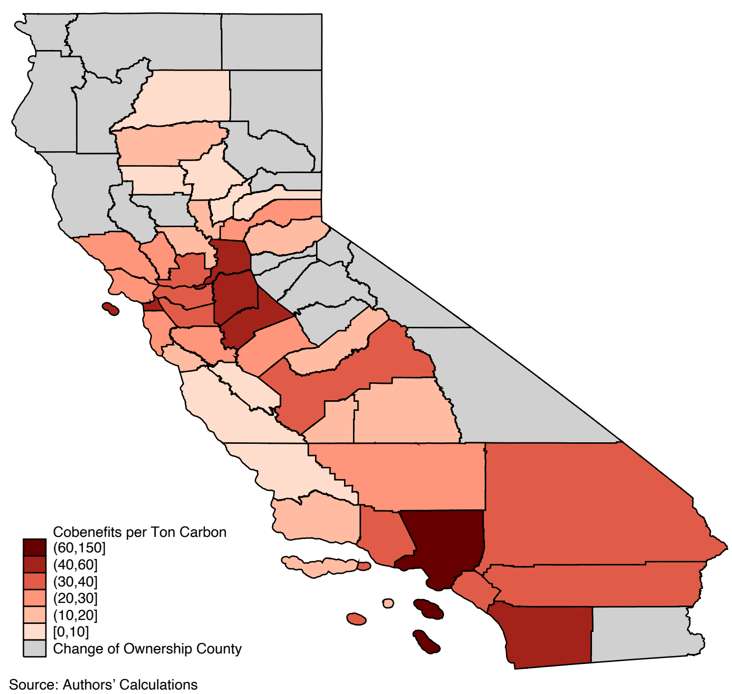


**Figure 12:** Estimated co-benefits by county

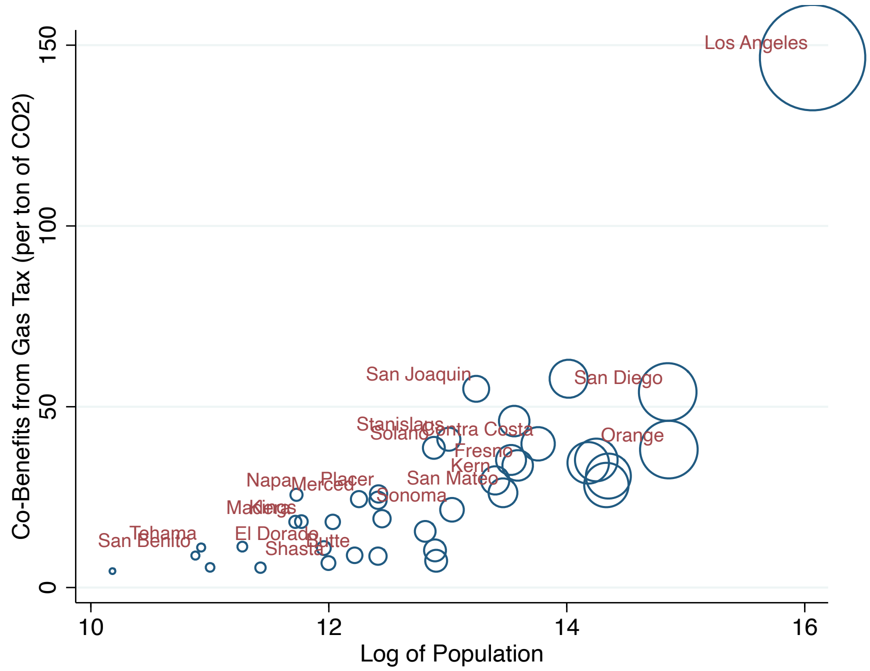


**Figure 13:** Estimated county-level co-benefits verse the log of county population

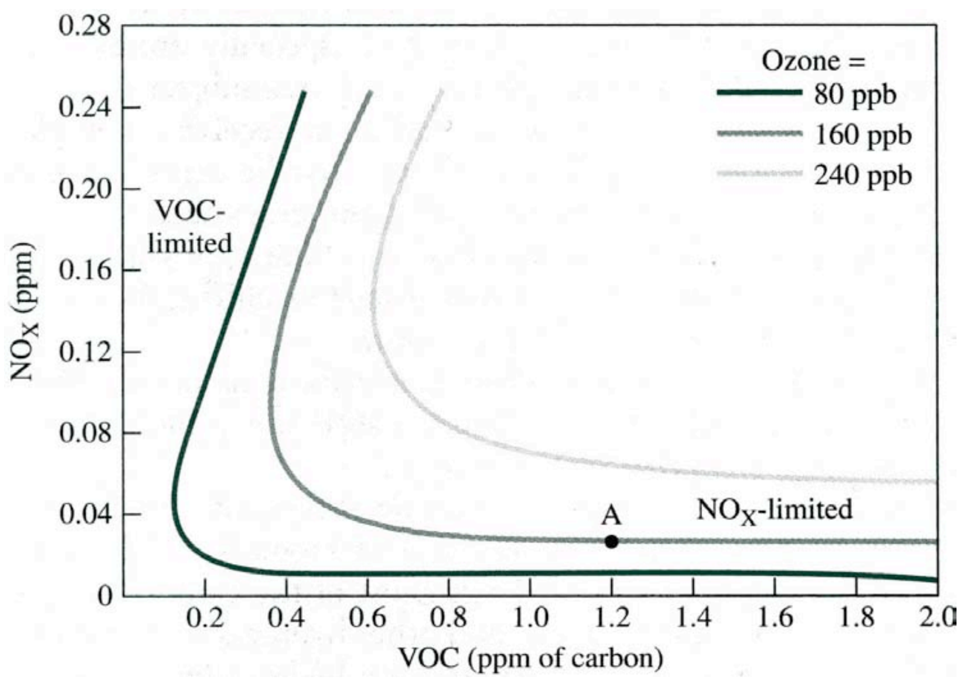


**Figure 14:** Level-sets of smog formation. Taken from
http://voh.chem.ucla.edu/vohtar/spring06/classes/103/pdf/Lect501.pdf.

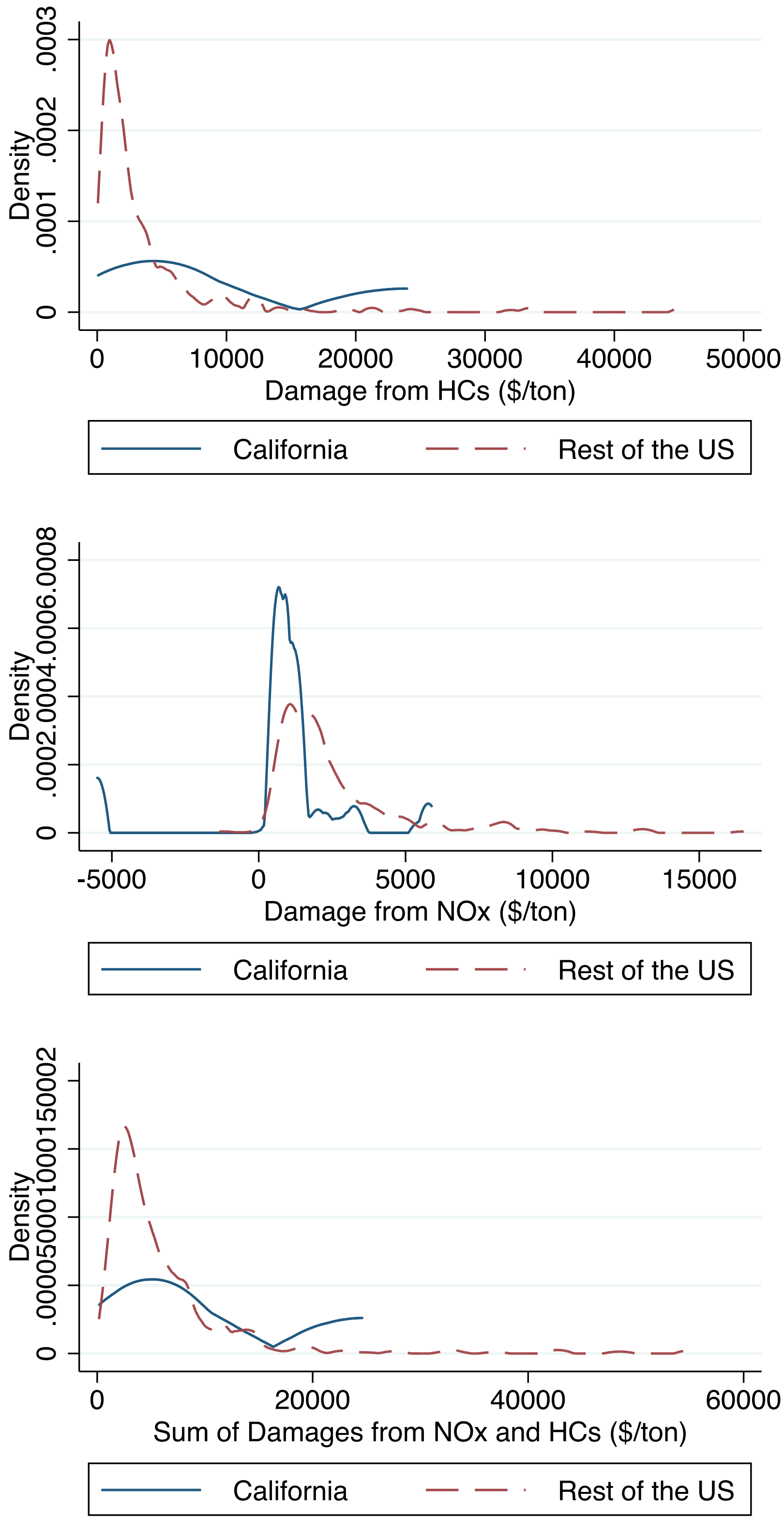


**Figure 15:** Distributions of marginal damages from Muller and Mendelsohn (2009) for California and the rest of the US

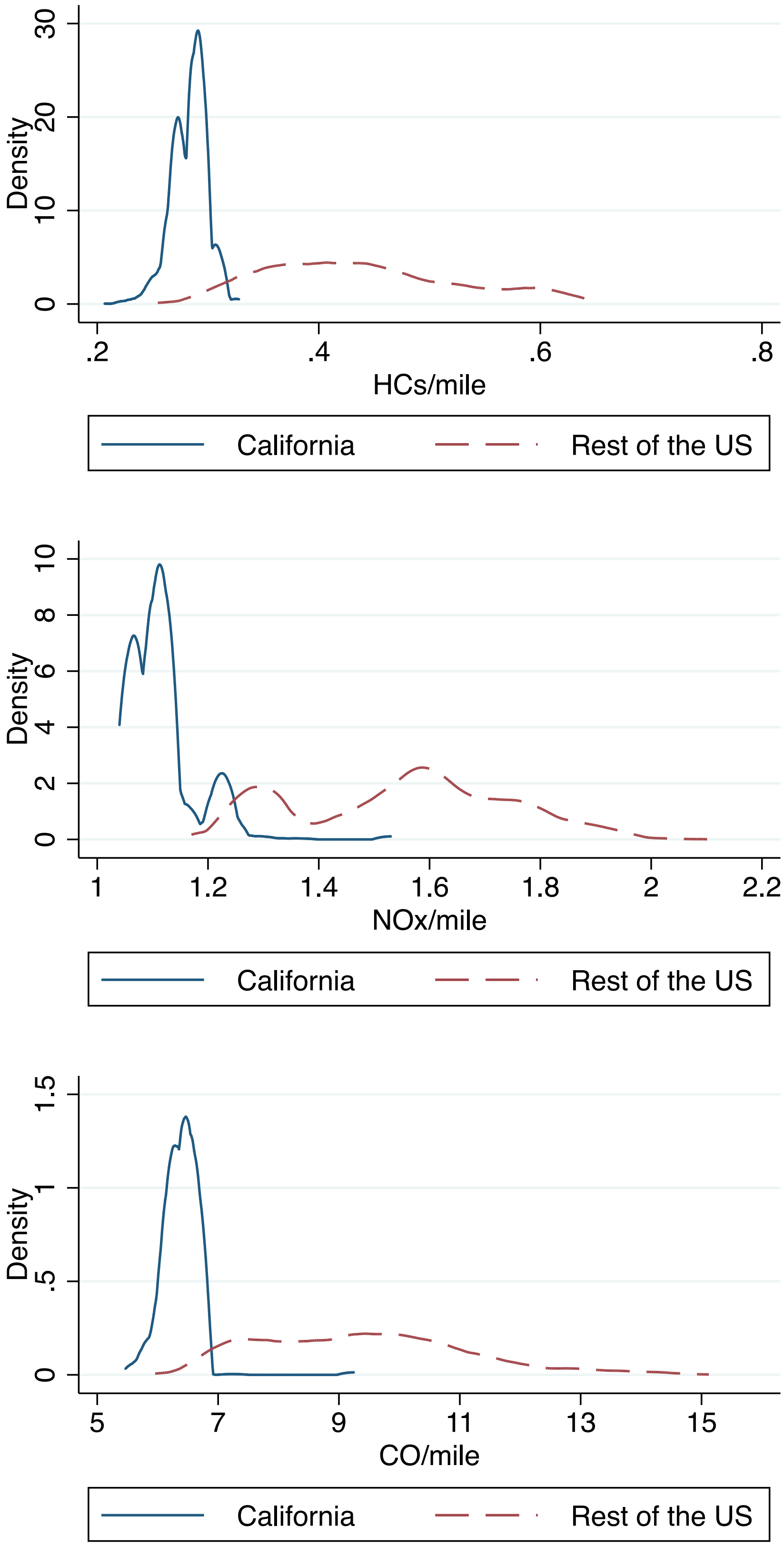


**Figure 16:** Distributions of per-mile emissions for California and the rest of the US

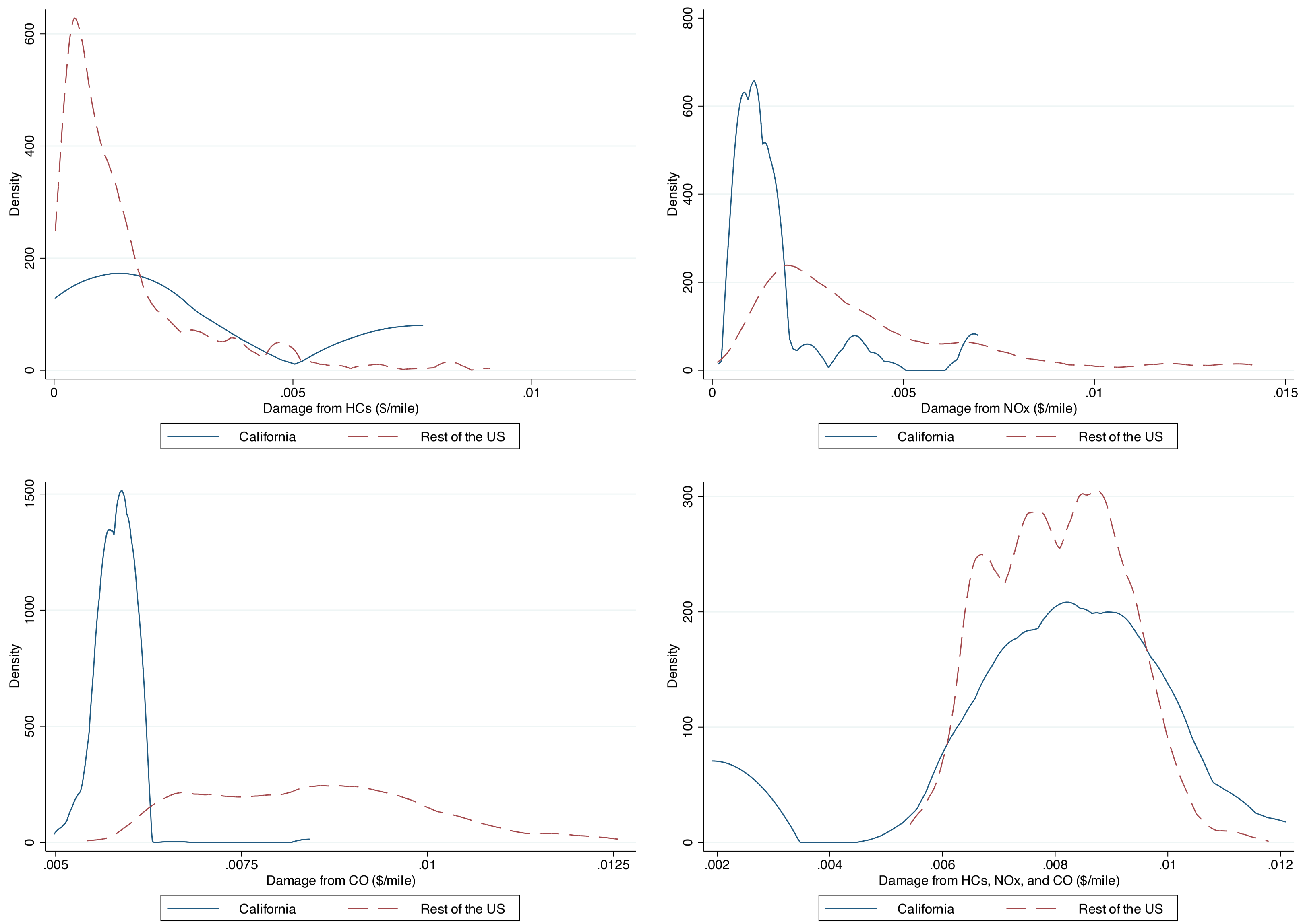


**Figure 17:** Distributions of per-mile damages for California and the rest of the US

## B Tables

**Table 1:** Summary Statistics

| | All | Vehicle Age | | | Year | |
|---|---|---|---|---|---|---|
| | | 4-9 | 10-15 | 16-28 | 1998 | 2008 |
| Weighted Fuel Economy | 23.49 | 23.29 | 23.67 | 23.67 | 24.09 | 23.04 |
| | (5.300) | (5.224) | (5.319) | (5.477) | (5.402) | (5.157) |
| Average $/mile | 0.0893 | 0.0843 | 0.0902 | 0.103 | 0.0581 | 0.128 |
| | (0.0394) | (0.0369) | (0.0400) | (0.0420) | (0.0133) | (0.0306) |
| Odometer (00000s) | 1.188 | 0.923 | 1.362 | 1.607 | 1.022 | 1.292 |
| | (0.594) | (0.448) | (0.564) | (0.684) | (0.521) | (0.606) |
| Grams/mile HC | 0.749 | 0.226 | 0.762 | 2.049 | 1.412 | 0.510 |
| | (1.180) | (0.281) | (1.064) | (1.712) | (1.524) | (0.973) |
| Grams/mile CO | 5.269 | 0.521 | 4.915 | 18.47 | 12.27 | 3.136 |
| | (12.84) | (1.664) | (11.07) | (21.25) | (18.95) | (10.26) |
| Grams/mile NOx | 0.664 | 0.328 | 0.751 | 1.321 | 1.060 | 0.498 |
| | (0.638) | (0.309) | (0.608) | (0.740) | (0.921) | (0.537) |
| Failed Smog Check | 0.0947 | 0.0455 | 0.117 | 0.202 | 0.0557 | 0.107 |
| | (0.293) | (0.208) | (0.321) | (0.401) | (0.229) | (0.309) |
| Average HH Income | 48277.8 | 49998.8 | 47279.1 | 45188.5 | 50228.4 | 48044.1 |
| | (17108.2) | (17702.9) | (16633.2) | (15628.0) | (18067.0) | (16887.5) |
| Truck | 0.386 | 0.403 | 0.367 | 0.375 | 0.331 | 0.426 |
| | (0.487) | (0.491) | (0.482) | (0.484) | (0.471) | (0.494) |
| Vehicle Age | 10.39 | 6.644 | 12.08 | 18.45 | 8.975 | 11.49 |
| | (4.477) | (1.615) | (1.682) | (2.424) | (3.448) | (4.741) |
| $N$ | 7015260 | 3333774 | 2699413 | 981234 | 386753 | 541246 |

Statistics are means with standard deviations presented below in parentheses. Weighted fuel economy is from EPA. Dollars per mile is the average gasoline price from EIA in between Smog Checks divided by fuel economy. Average household income is taken from the 2000 Census ZCTA where the Smog Check occurred. Dataset contains one observation per vehicle per year in which a Smog Check occurred.

**Table 2:** Average Pollutant Rates Per Mile Traveled by Year

| | Nitrogen Oxides | | | Hydrocarbons | | | Carbon Monoxide | | | Gasoline | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Mean | SD | Mean CV | Mean | SD | Mean CV | Mean | SD | Mean CV | Mean | SD |
| 1998 | 1.161 | 1.051 | 0.536 | 1.662 | 1.866 | 0.504 | 15.400 | 24.739 | 0.516 | 0.043 | 0.010 |
| 1999 | 1.187 | 0.983 | 0.455 | 1.665 | 1.864 | 0.464 | 15.227 | 24.952 | 0.485 | 0.043 | 0.010 |
| 2000 | 1.094 | 0.915 | 0.441 | 1.535 | 1.826 | 0.460 | 13.539 | 23.849 | 0.476 | 0.044 | 0.010 |
| 2001 | 0.982 | 0.857 | 0.427 | 1.354 | 1.769 | 0.464 | 11.689 | 23.123 | 0.461 | 0.044 | 0.010 |
| 2002 | 0.876 | 0.816 | 0.418 | 1.145 | 1.679 | 0.446 | 9.694 | 21.381 | 0.430 | 0.044 | 0.010 |
| 2003 | 0.791 | 0.780 | 0.401 | 0.997 | 1.563 | 0.432 | 7.940 | 19.503 | 0.395 | 0.045 | 0.010 |
| 2004 | 0.715 | 0.742 | 0.380 | 0.855 | 1.469 | 0.421 | 6.561 | 17.581 | 0.363 | 0.045 | 0.010 |
| 2005 | 0.735 | 0.713 | 0.393 | 0.852 | 1.444 | 0.455 | 6.375 | 17.519 | 0.379 | 0.045 | 0.010 |
| 2006 | 0.638 | 0.667 | 0.382 | 0.718 | 1.351 | 0.430 | 5.157 | 15.887 | 0.350 | 0.045 | 0.010 |
| 2007 | 0.572 | 0.634 | 0.377 | 0.628 | 1.261 | 0.431 | 4.308 | 14.509 | 0.334 | 0.045 | 0.010 |
| 2008 | 0.512 | 0.602 | 0.373 | 0.545 | 1.185 | 0.400 | 3.556 | 13.064 | 0.317 | 0.046 | 0.010 |
| 2009 | 0.478 | 0.590 | 0.379 | 0.496 | 1.148 | 0.412 | 3.120 | 12.147 | 0.316 | 0.046 | 0.011 |
| 2010 | 0.462 | 0.566 | 0.402 | 0.460 | 1.002 | 0.427 | 2.741 | 10.901 | 0.323 | 0.046 | 0.010 |
| $N$ | 10432374 | | | 10432374 | | | 10666348 | | | 13397795 | |

Note: Mean CV is the average VIN Prefix-level coefficient of variation (SD/Mean). Gasoline is measured in gallons per mile, while the remaining pollutant rates are measured in grams per mile.

**Table 3:** Vehicle Miles Traveled, Dollars Per Mile, and Nitrogen Oxides (Quartiles by year)

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 | (7) Model7 |
|---|---|---|---|---|---|---|---|
| ln(DPM) | -0.399** | -0.140** | | -0.224** | -0.257** | | -0.078 |
| | (0.068) | (0.040) | | (0.052) | (0.055) | | (0.068) |
| ln(DPM) * NO Q1 | | | -0.102** | | | -0.094 | |
| | | | (0.015) | | | (0.073) | |
| ln(DPM) * NO Q2 | | | -0.144** | | | -0.183** | |
| | | | (0.014) | | | (0.067) | |
| ln(DPM) * NO Q3 | | | -0.175** | | | -0.246** | |
| | | | (0.014) | | | (0.066) | |
| ln(DPM) * NO Q4 | | | -0.204** | | | -0.323** | |
| | | | (0.014) | | | (0.069) | |
| ln(DPM)*NO Centile | | | | | | | -0.003** |
| | | | | | | | (0.000) |
| NO Q2 | | | 0.212** | | | 0.226** | |
| | | | (0.014) | | | (0.023) | |
| NO Q3 | | | 0.409** | | | 0.408** | |
| | | | (0.019) | | | (0.038) | |
| NO Q4 | | | 0.630** | | | 0.636** | |
| | | | (0.022) | | | (0.043) | |
| NO Centile | | | | | | | 0.008** |
| | | | | | | | (0.001) |
| Truck | 0.125** | 0.097* | 0.073** | 0.038 | | | |
| | (0.042) | (0.048) | (0.010) | (0.075) | | | |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Make Fixed Effects | No | Yes | Yes | No | No | No | No |
| Vin Prefix Fixed Effects | No | No | No | Yes | No | No | No |
| Vehicle Fixed Effects | No | No | No | No | Yes | Yes | Yes |
| Observations | 3640436 | 3640436 | 2904026 | 3640436 | 3640436 | 2904026 | 2904026 |
| R-squared | 0.141 | 0.159 | 0.172 | 0.083 | 0.110 | 0.105 | 0.106 |

**Table 4:** Vehicle Miles Traveled, Dollars Per Mile, and Hydrocarbons (Quartiles by year)

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 | (7) Model7 |
|---|---|---|---|---|---|---|---|
| ln(DPM) | -0.399** | -0.140** | | -0.224** | -0.257** | | 0.003 |
| | (0.068) | (0.040) | | (0.052) | (0.055) | | (0.071) |
| ln(DPM) * HC Q1 | | | -0.118** | | | -0.075 | |
| | | | (0.015) | | | (0.069) | |
| ln(DPM) * HC Q2 | | | -0.129** | | | -0.160* | |
| | | | (0.014) | | | (0.066) | |
| ln(DPM) * HC Q3 | | | -0.141** | | | -0.225** | |
| | | | (0.014) | | | (0.064) | |
| ln(DPM) * HC Q4 | | | -0.197** | | | -0.336** | |
| | | | (0.014) | | | (0.066) | |
| ln(DPM)*HC Centile | | | | | | | -0.004** |
| | | | | | | | (0.000) |
| HC Q2 | | | 0.162** | | | 0.213** | |
| | | | (0.014) | | | (0.014) | |
| HC Q3 | | | 0.346** | | | 0.399** | |
| | | | (0.020) | | | (0.036) | |
| HC Q4 | | | 0.629** | | | 0.697** | |
| | | | (0.024) | | | (0.050) | |
| HC Centile | | | | | | | 0.011** |
| | | | | | | | (0.001) |
| Truck | 0.125** | 0.097* | 0.069** | 0.038 | | | |
| | (0.042) | (0.048) | (0.010) | (0.075) | | | |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Make Fixed Effects | No | Yes | Yes | No | No | No | No |
| Vin Prefix Fixed Effects | No | No | No | Yes | No | No | No |
| Vehicle Fixed Effects | No | No | No | No | Yes | Yes | Yes |
| Observations | 3640436 | 3640436 | 2904026 | 3640436 | 3640436 | 2904026 | 2904026 |
| R-squared | 0.141 | 0.159 | 0.170 | 0.083 | 0.110 | 0.104 | 0.105 |

**Table 5:** Vehicle Miles Traveled, Dollars Per Mile, and Carbon Monoxide (Quartiles by year)

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 | (7) Model7 |
|---|---|---|---|---|---|---|---|
| ln(DPM) | -0.399** | -0.140** | | -0.224** | -0.257** | | -0.008 |
| | (0.068) | (0.040) | | (0.052) | (0.055) | | (0.069) |
| ln(DPM) * CO Q1 | | | -0.046** | | | -0.071 | |
| | | | (0.015) | | | (0.067) | |
| ln(DPM) * CO Q2 | | | -0.072** | | | -0.168* | |
| | | | (0.014) | | | (0.064) | |
| ln(DPM) * CO Q3 | | | -0.097** | | | -0.237** | |
| | | | (0.014) | | | (0.061) | |
| ln(DPM) * CO Q4 | | | -0.129** | | | -0.333** | |
| | | | (0.015) | | | (0.066) | |
| ln(DPM)*CO Centile | | | | | | | -0.004** |
| | | | | | | | (0.000) |
| CO Q2 | | | 0.196** | | | 0.239** | |
| | | | (0.015) | | | (0.015) | |
| CO Q3 | | | 0.420** | | | 0.440** | |
| | | | (0.021) | | | (0.035) | |
| CO Q4 | | | 0.664** | | | 0.723** | |
| | | | (0.025) | | | (0.060) | |
| CO Centile | | | | | | | 0.012** |
| | | | | | | | (0.001) |
| Truck | 0.125** | 0.097* | 0.045** | 0.038 | | | |
| | (0.042) | (0.048) | (0.010) | (0.075) | | | |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Make Fixed Effects | No | Yes | Yes | No | No | No | No |
| Vin Prefix Fixed Effects | No | No | No | Yes | No | No | No |
| Vehicle Fixed Effects | No | No | No | No | Yes | Yes | Yes |
| Observations | 3640436 | 3640436 | 2965945 | 3640436 | 3640436 | 2965945 | 2965945 |
| R-squared | 0.141 | 0.159 | 0.169 | 0.083 | 0.110 | 0.104 | 0.105 |

**Table 6:** Vehicle Miles Traveled, Dollars Per Mile, and Fuel Economy (Quartiles by year)

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 | (7) Model7 |
|---|---|---|---|---|---|---|---|
| ln(DPM) | -0.399** | -0.140** | | -0.224** | -0.257** | | -0.500** |
| | (0.068) | (0.040) | | (0.052) | (0.055) | | (0.074) |
| ln(DPM) * MPG Q1 | | | -0.286** | | | -0.310** | |
| | | | (0.024) | | | (0.059) | |
| ln(DPM) * MPG Q2 | | | -0.245** | | | -0.288** | |
| | | | (0.024) | | | (0.058) | |
| ln(DPM) * MPG Q3 | | | -0.179** | | | -0.237** | |
| | | | (0.024) | | | (0.059) | |
| ln(DPM) * MPG Q4 | | | -0.154** | | | -0.198** | |
| | | | (0.022) | | | (0.066) | |
| ln(DPM)*MPG Centile | | | | | | | 0.005** |
| | | | | | | | (0.000) |
| Truck | 0.125** | 0.097* | 0.100** | 0.038 | | | |
| | (0.042) | (0.048) | (0.010) | (0.075) | | | |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Make Fixed Effects | No | Yes | Yes | No | No | No | No |
| Vin Prefix Fixed Effects | No | No | No | Yes | No | No | No |
| Vehicle Fixed Effects | No | No | No | No | Yes | Yes | Yes |
| Observations | 3640436 | 3640436 | 3640436 | 3640436 | 3640436 | 3640436 | 3640436 |
| R-squared | 0.141 | 0.159 | 0.160 | 0.083 | 0.110 | 0.110 | 0.111 |

**Table 7:** Vehicle Miles Traveled, Dollars Per Mile, and Weight (Quartiles by year)

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 | (7) Model7 |
|---|---|---|---|---|---|---|---|
| ln(DPM) | -0.399** | -0.140** | | -0.224** | -0.257** | | -0.157** |
| | (0.068) | (0.040) | | (0.052) | (0.055) | | (0.058) |
| ln(DPM) * Weight Q1 | | | -0.188** | | | -0.226** | |
| | | | (0.018) | | | (0.056) | |
| ln(DPM) * Weight Q2 | | | -0.159** | | | -0.252** | |
| | | | (0.017) | | | (0.056) | |
| ln(DPM) * Weight Q3 | | | -0.191** | | | -0.271** | |
| | | | (0.019) | | | (0.056) | |
| ln(DPM) * Weight Q4 | | | -0.222** | | | -0.282** | |
| | | | (0.017) | | | (0.059) | |
| ln(DPM)*Weight Centile | | | | | | | -0.002** |
| | | | | | | | (0.000) |
| Truck | 0.125** | 0.097* | 0.097** | 0.038 | | | |
| | (0.042) | (0.048) | (0.010) | (0.075) | | | |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Make Fixed Effects | No | Yes | Yes | No | No | No | No |
| Vin Prefix Fixed Effects | No | No | No | Yes | No | No | No |
| Vehicle Fixed Effects | No | No | No | No | Yes | Yes | Yes |
| Observations | 3640436 | 3640436 | 3619192 | 3640436 | 3640436 | 3619192 | 3619192 |
| R-squared | 0.141 | 0.159 | 0.160 | 0.083 | 0.110 | 0.110 | 0.110 |

**Table 8:** Vehicle Miles Traveled, Dollars Per Mile, and Nitrogen Oxides (Quartiles by age range)

| | (1)<br>4-9 | (2)<br>10-15 | (3)<br>16-27 | (4)<br>4-9 | (5)<br>10-15 | (6)<br>16-27 |
|---|---|---|---|---|---|---|
| ln(DPM) | -0.201** | -0.227** | -0.634** | | | |
| | (0.073) | (0.086) | (0.224) | | | |
| ln(DPM) * NO Q1 | | | | -0.166* | -0.109 | -0.531* |
| | | | | (0.073) | (0.075) | (0.239) |
| ln(DPM) * NO Q2 | | | | -0.197* | -0.181* | -0.594* |
| | | | | (0.076) | (0.080) | (0.240) |
| ln(DPM) * NO Q3 | | | | -0.215** | -0.224** | -0.691** |
| | | | | (0.075) | (0.080) | (0.236) |
| ln(DPM) * NO Q4 | | | | -0.226** | -0.250** | -0.722** |
| | | | | (0.075) | (0.083) | (0.249) |
| NO Q2 | | | | 0.081** | 0.191** | 0.175** |
| | | | | (0.022) | (0.027) | (0.031) |
| NO Q3 | | | | 0.130** | 0.310** | 0.428** |
| | | | | (0.023) | (0.034) | (0.054) |
| NO Q4 | | | | 0.174** | 0.395** | 0.539** |
| | | | | (0.032) | (0.046) | (0.055) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes |
| Vin Prefix Fixed Effects | No | No | No | No | No | No |
| Vehicle Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1548635 | 1535834 | 555967 | 1182350 | 1239393 | 482283 |
| R-squared | 0.040 | 0.064 | 0.083 | 0.038 | 0.066 | 0.081 |

**Table 9:** Vehicle Miles Traveled, Dollars Per Mile, and Hydrocarbons (Quartiles by age range)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 4-9 | 10-15 | 16-27 | 4-9 | 10-15 | 16-27 |
| ln(DPM) | -0.201** | -0.227** | -0.634** | | | |
| | (0.073) | (0.086) | (0.224) | | | |
| ln(DPM) * HC Q1 | | | | -0.162* | -0.118 | -0.467+ |
| | | | | (0.072) | (0.071) | (0.236) |
| ln(DPM) * HC Q2 | | | | -0.191* | -0.183* | -0.542* |
| | | | | (0.075) | (0.076) | (0.236) |
| ln(DPM) * HC Q3 | | | | -0.192* | -0.216** | -0.650** |
| | | | | (0.075) | (0.078) | (0.229) |
| ln(DPM) * HC Q4 | | | | -0.218** | -0.247** | -0.740** |
| | | | | (0.073) | (0.082) | (0.240) |
| HC Q2 | | | | 0.075** | 0.171** | 0.204** |
| | | | | (0.019) | (0.023) | (0.045) |
| HC Q3 | | | | 0.089** | 0.262** | 0.466** |
| | | | | (0.020) | (0.032) | (0.064) |
| HC Q4 | | | | 0.162** | 0.344** | 0.705** |
| | | | | (0.023) | (0.050) | (0.086) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes |
| Vin Prefix Fixed Effects | No | No | No | No | No | No |
| Vehicle Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1548635 | 1535834 | 555967 | 1182350 | 1239393 | 482283 |
| R-squared | 0.040 | 0.064 | 0.083 | 0.038 | 0.065 | 0.081 |

**Table 10:** Vehicle Miles Traveled, Dollars Per Mile, and Carbon Monoxide (Quartiles by age range)

| | (1)<br>4-9 | (2)<br>10-15 | (3)<br>16-27 | (4)<br>4-9 | (5)<br>10-15 | (6)<br>16-27 |
|---|---|---|---|---|---|---|
| ln(DPM) | -0.201** | -0.227** | -0.634** | | | |
| | (0.073) | (0.086) | (0.224) | | | |
| ln(DPM) * CO Q1 | | | | -0.162* | -0.090 | -0.483* |
| | | | | (0.074) | (0.071) | (0.226) |
| ln(DPM) * CO Q2 | | | | -0.204** | -0.170* | -0.571* |
| | | | | (0.073) | (0.075) | (0.225) |
| ln(DPM) * CO Q3 | | | | -0.218** | -0.203* | -0.662** |
| | | | | (0.074) | (0.082) | (0.231) |
| ln(DPM) * CO Q4 | | | | -0.241** | -0.237** | -0.721** |
| | | | | (0.073) | (0.084) | (0.236) |
| CO Q2 | | | | 0.095** | 0.209** | 0.234** |
| | | | | (0.015) | (0.021) | (0.045) |
| CO Q3 | | | | 0.139** | 0.302** | 0.467** |
| | | | | (0.018) | (0.038) | (0.078) |
| CO Q4 | | | | 0.205** | 0.410** | 0.632** |
| | | | | (0.034) | (0.053) | (0.104) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes |
| Vin Prefix Fixed Effects | No | No | No | No | No | No |
| Vehicle Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1548635 | 1535834 | 555967 | 1215664 | 1263957 | 486324 |
| R-squared | 0.040 | 0.064 | 0.083 | 0.038 | 0.066 | 0.081 |

**Table 11:** Vehicle Miles Traveled, Dollars Per Mile, and Fuel Economy (Quartiles by age range)

| | (1)<br>4-9 | (2)<br>10-15 | (3)<br>16-27 | (4)<br>4-9 | (5)<br>10-15 | (6)<br>16-27 |
|---|---|---|---|---|---|---|
| ln(DPM) | -0.201** | -0.227** | -0.634** | | | |
| | (0.073) | (0.086) | (0.224) | | | |
| ln(DPM) * MPG Q1 | | | | -0.217** | -0.248** | -0.678** |
| | | | | (0.073) | (0.088) | (0.224) |
| ln(DPM) * MPG Q2 | | | | -0.206** | -0.236** | -0.667** |
| | | | | (0.073) | (0.088) | (0.229) |
| ln(DPM) * MPG Q3 | | | | -0.195** | -0.218* | -0.627** |
| | | | | (0.073) | (0.084) | (0.225) |
| ln(DPM) * MPG Q4 | | | | -0.186* | -0.204* | -0.570* |
| | | | | (0.075) | (0.081) | (0.225) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes |
| Vin Prefix Fixed Effects | No | No | No | No | No | No |
| Vehicle Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1548635 | 1535834 | 555967 | 1548635 | 1535834 | 555967 |
| R-squared | 0.040 | 0.064 | 0.083 | 0.040 | 0.064 | 0.084 |

**Table 12:** Vehicle Miles Traveled, Dollars Per Mile, and Weight (Quartiles by age range)

| | (1)<br>4-9 | (2)<br>10-15 | (3)<br>16-27 | (4)<br>4-9 | (5)<br>10-15 | (6)<br>16-27 |
|---|---|---|---|---|---|---|
| ln(DPM) | -0.201** | -0.227** | -0.634** | | | |
| | (0.073) | (0.086) | (0.224) | | | |
| ln(DPM) * Weight Q1 | | | | -0.204** | -0.213* | -0.593** |
| | | | | (0.074) | (0.083) | (0.223) |
| ln(DPM) * Weight Q2 | | | | -0.207** | -0.223* | -0.640** |
| | | | | (0.074) | (0.085) | (0.223) |
| ln(DPM) * Weight Q3 | | | | -0.208** | -0.237** | -0.659** |
| | | | | (0.074) | (0.087) | (0.226) |
| ln(DPM) * Weight Q4 | | | | -0.213** | -0.240** | -0.673** |
| | | | | (0.073) | (0.086) | (0.226) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes |
| Vin Prefix Fixed Effects | No | No | No | No | No | No |
| Vehicle Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1548635 | 1535834 | 555967 | 1532126 | 1531382 | 555684 |
| R-squared | 0.040 | 0.064 | 0.083 | 0.040 | 0.064 | 0.083 |

**Table 13:** VMT Elasticity for a Sample of Households, 2000-2008

| | (1) | (2) | (3) |
|---|---|---|---|
| ln(DPM) * MPG Q1 | -0.131*** | -0.132*** | -0.148*** |
| | (0.0397) | (0.0396) | (0.0399) |
| ln(DPM) * MPG Q2 | -0.114** | -0.116** | -0.132*** |
| | (0.0396) | (0.0396) | (0.0399) |
| ln(DPM) * MPG Q3 | -0.0749 | -0.0796* | -0.0952* |
| | (0.0396) | (0.0396) | (0.0399) |
| ln(DPM) * MPG Q4 | -0.0339 | -0.0405 | -0.0559 |
| | (0.0398) | (0.0398) | (0.0400) |
| ln(DPM) * Higher MPG in HH | | -0.0274*** | -0.0284*** |
| | | (0.00423) | (0.00423) |
| Dollars per Mile * Lower MPG in HH | | 0.0503*** | 0.0499*** |
| | | (0.00433) | (0.00433) |
| Higher MPG in HH | | 0.0552*** | 0.0573*** |
| | | (0.00945) | (0.00945) |
| Lower MPG in HH | | -0.112*** | -0.111*** |
| | | (0.00867) | (0.00866) |
| ln(DPM) * HH Income Q2 | | | -0.00183 |
| | | | (0.00473) |
| ln(DPM) * HH Income Q3 | | | 0.0211*** |
| | | | (0.00492) |
| ln(DPM) * HH Income Q4 | | | 0.0322*** |
| | | | (0.00533) |
| Year Fixed Effects | Yes | Yes | Yes |
| Within-Year Time Trends | Yes | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes |
| Vehicle Fixed Effects | Yes | Yes | Yes |
| Observations | 7549359 | 7549359 | 7549359 |
| R-squared | 0.106 | 0.106 | 0.106 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 14:** VMT Elasticity by Income Quartile, 2000-2008

| | 40% Sample of HHs | 10% Sample of VINs |
|---|---|---|
| ln(DPM) * HH Income Q1 | -0.104** | -0.303*** |
| | (0.0398) | (0.0696) |
| ln(DPM) * HH Income Q2 | -0.106** | -0.300*** |
| | (0.0396) | (0.0695) |
| ln(DPM) * HH Income Q3 | -0.0841* | -0.297*** |
| | (0.0396) | (0.0697) |
| ln(DPM) * HH Income Q4 | -0.0753 | -0.274*** |
| | (0.0396) | (0.0695) |
| Year Fixed Effects | Yes | Yes |
| Within-Year Time Trends | Yes | Yes |
| Vintage Fixed Effects | Yes | Yes |
| Demographics | Yes | Yes |
| Vehicle Fixed Effects | Yes | Yes |
| Observations | 7549359 | 2489375 |
| R-squared | 0.105 | 0.088 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 15:** Hazard of Scrappage: Cox Proportional Hazard Model

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Dollars per Mile | 0.918+ | | 0.957 | | |
| | (0.045) | | (0.036) | | |
| DPM * Failed Smog Check | 1.099** | 1.069* | 1.058* | 1.038+ | |
| | (0.033) | (0.028) | (0.026) | (0.023) | |
| Failed Last Smog Check | 7.551** | 7.993** | 8.735** | 9.379** | |
| | (0.264) | (0.271) | (0.231) | (0.234) | |
| DPM * NO Quartile 1 | | 0.800** | | 0.922 | |
| | | (0.050) | | (0.049) | |
| DPM * NO Quartile 2 | | 0.841** | | 0.925 | |
| | | (0.046) | | (0.045) | |
| DPM * NO Quartile 3 | | 0.863** | | 0.956 | |
| | | (0.038) | | (0.030) | |
| DPM * NO Quartile 4 | | 0.924* | | 0.980 | |
| | | (0.037) | | (0.022) | |
| **Vehicle Ages 10-15** | | | | | |
| DPM * NO Quartile 1 | | | | | 0.815+ |
| | | | | | (0.087) |
| DPM * NO Quartile 2 | | | | | 0.790* |
| | | | | | (0.086) |
| DPM * NO Quartile 3 | | | | | 0.800* |
| | | | | | (0.081) |
| DPM * NO Quartile 4 | | | | | 0.765** |
| | | | | | (0.073) |
| Failed Smog Check | | | | | 7.460** |
| | | | | | (0.677) |
| DPM * Failed Smog Check | | | | | 1.124* |
| | | | | | (0.061) |
| **Vehicle Ages 16+** | | | | | |
| DPM * NO Quartile 1 | | | | | 1.087** |
| | | | | | (0.028) |
| DPM * NO Quartile 2 | | | | | 1.063* |
| | | | | | (0.028) |
| DPM * NO Quartile 3 | | | | | 1.073* |
| | | | | | (0.035) |
| DPM * NO Quartile 4 | | | | | 1.062+ |
| | | | | | (0.038) |
| Failed Smog Check | | | | | 10.862** |
| | | | | | (0.548) |
| DPM * Failed Smog Check | | | | | 0.992 |
| | | | | | (0.022) |
| Station ZIP Code Characteristics | Yes | Yes | Yes | Yes | Yes |
| Quadratic Time Trend in Days | Yes | Yes | Yes | Yes | Yes |
| Vehicle Characteristics | Yes | Yes | Yes | Yes | Yes |
| Quartiles of NO | No | Yes | No | Yes | Yes |
| Stratified on Vin Prefix | No | No | Yes | Yes | Yes |
| Observations | 3176325 | 2623649 | 3176325 | 2623649 | 2623649 |

Note: Coefficients on dollars per mile scaled for a 5-cent change

**Table 16:** Hazard of Scrappage: Cox Proportional Hazard Model

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Dollars per Mile | 0.918+ | | 0.957 | | |
| | (0.045) | | (0.036) | | |
| DPM * Failed Smog Check | 1.099** | 1.072+ | 1.058* | 1.096** | |
| | (0.033) | (0.038) | (0.026) | (0.028) | |
| Failed Last Smog Check | 7.551** | 7.778** | 8.735** | 8.210** | |
| | (0.264) | (0.293) | (0.231) | (0.229) | |
| DPM * MPG Quartile 1 | | 0.985 | | 0.828** | |
| | | (0.058) | | (0.050) | |
| DPM * MPG Quartile 2 | | 1.002 | | 0.924 | |
| | | (0.063) | | (0.048) | |
| DPM * MPG Quartile 3 | | 0.997 | | 1.014 | |
| | | (0.072) | | (0.074) | |
| DPM * MPG Quartile 4 | | 1.067 | | 1.173* | |
| | | (0.090) | | (0.082) | |
| **Vehicle Ages 10-15** | | | | | |
| DPM * MPG Quartile 1 | | | | | 0.740** |
| | | | | | (0.071) |
| DPM * MPG Quartile 2 | | | | | 0.746** |
| | | | | | (0.081) |
| DPM * MPG Quartile 3 | | | | | 0.862 |
| | | | | | (0.111) |
| DPM * MPG Quartile 4 | | | | | 0.944 |
| | | | | | (0.181) |
| Failed Smog Check | | | | | 6.780** |
| | | | | | (0.504) |
| DPM * Failed Smog Check | | | | | 1.161** |
| | | | | | (0.057) |
| **Vehicle Ages 16+** | | | | | |
| DPM * MPG Quartile 1 | | | | | 0.989 |
| | | | | | (0.034) |
| DPM * MPG Quartile 2 | | | | | 1.086* |
| | | | | | (0.036) |
| DPM * MPG Quartile 3 | | | | | 1.132* |
| | | | | | (0.061) |
| DPM * MPG Quartile 4 | | | | | 1.063 |
| | | | | | (0.040) |
| Failed Smog Check | | | | | 10.075** |
| | | | | | (0.469) |
| DPM * Failed Smog Check | | | | | 1.019 |
| | | | | | (0.022) |
| Station ZIP Code Characteristics | Yes | Yes | Yes | Yes | Yes |
| Quadratic Time Trend in Days | Yes | Yes | Yes | Yes | Yes |
| Vehicle Characteristics | Yes | Yes | Yes | Yes | Yes |
| Stratified on Vin Prefix | No | No | Yes | Yes | Yes |
| Observations | 3176325 | 3176325 | 3176325 | 3176325 | 3176325 |

Note: Coefficients on dollars per mile scaled for a 5-cent change

**Table 17:** Cobenefits of a Gasoline Tax, No Heterogeneity

| | Δ Consumption | Δ CO2 | DWL | Criteria Benefit | | | | | | **Net Cost** |
|---|---|---|---|---|---|---|---|---|---|---|
| | (Gallons) | (Tons) | ($) | (NOx $) | (HC $) | (CO $) | (Total $) | (% DWL) | (Per CO2) | (Per CO2) |
| 1998 | 798.2 | 7.662 | 548.0 | 3.262 | 227.4 | 92.86 | 322.5 | 134.9 | 96.46 | -24.94 |
| 1999 | 807.8 | 7.755 | 538.9 | 5.291 | 254.2 | 99.82 | 358.6 | 124.5 | 86.54 | -17.05 |
| 2000 | 835.8 | 8.023 | 537.4 | 5.791 | 250.9 | 93.12 | 349.4 | 114.9 | 76.97 | -9.982 |
| 2001 | 773.2 | 7.422 | 478.3 | 5.449 | 189.8 | 68.68 | 263.6 | 98.67 | 63.58 | 0.859 |
| 2002 | 735.8 | 7.064 | 444.4 | 8.176 | 229.0 | 80.83 | 317.6 | 80.92 | 50.91 | 12.00 |
| 2003 | 780.3 | 7.491 | 460.6 | 8.733 | 195.7 | 67.37 | 271.5 | 68.28 | 41.99 | 19.50 |
| 2004 | 821.1 | 7.883 | 472.4 | 10.18 | 159.8 | 55.34 | 225.0 | 53.77 | 32.22 | 27.70 |
| 2005 | 767.6 | 7.369 | 425.9 | 8.478 | 113.8 | 38.01 | 160.0 | 43.21 | 24.97 | 32.82 |
| 2006 | 637.2 | 6.117 | 340.3 | 6.740 | 85.04 | 27.30 | 118.9 | 40.48 | 22.52 | 33.11 |
| 2007 | 677.4 | 6.503 | 350.2 | 5.957 | 63.02 | 19.08 | 87.90 | 29.19 | 15.72 | 38.13 |
| 2008 | 604.1 | 5.799 | 302.0 | 4.419 | 48.82 | 13.75 | 66.85 | 26.55 | 13.83 | 38.26 |
| Average | 748.9 | 7.190 | 445.3 | 6.589 | 165.2 | 59.65 | 231.1 | 74.13 | 47.79 | 13.67 |

Note: All units are in millions. Dollar figures are inflation adjusted to 2008 terms. NOx and HC are valued as in Muller and Mendelsohn's (2009) USEPA scenario by the county where each vehicle received its Smog Check. The values vary substantially across counties, but a population-weighted average for the state values HC at $10109.81 per ton per year, and NOx at $826.34 per ton per year. CO is valued at $802.88, as per the median value of Matthews and Lave (2000).

**Table 18:** Cobenefits of a Gasoline Tax, Taking Heterogeneity into Account (No Extensive Margin Effect)

| | Δ Consumption | Δ CO2 | DWL | Criteria Benefit | | | | | | **Net Cost** |
|---|---|---|---|---|---|---|---|---|---|---|
| | (Gallons) | (Tons) | ($) | (NOx $) | (HC $) | (CO $) | (Total $) | (% DWL) | (Per CO2) | (Per CO2) |
| 1998 | 520.7 | 4.999 | 357.5 | 7.214 | 506.5 | 222.5 | 733.8 | 207.6 | 148.5 | -76.94 |
| 1999 | 505.4 | 4.852 | 337.1 | 8.575 | 444.9 | 190.5 | 642.8 | 191.5 | 133.1 | -63.59 |
| 2000 | 522.9 | 5.020 | 336.3 | 8.343 | 431.6 | 178.0 | 617.2 | 188.7 | 126.4 | -59.44 |
| 2001 | 485.7 | 4.662 | 300.4 | 8.574 | 344.4 | 142.2 | 494.7 | 165.4 | 106.6 | -42.12 |
| 2002 | 381.3 | 3.661 | 230.3 | 7.055 | 235.0 | 94.66 | 336.4 | 146.5 | 92.17 | -29.26 |
| 2003 | 373.3 | 3.584 | 220.4 | 7.398 | 199.8 | 78.60 | 285.5 | 130.0 | 79.93 | -18.43 |
| 2004 | 371.4 | 3.565 | 213.6 | 8.732 | 158.8 | 63.44 | 230.7 | 108.4 | 64.95 | -5.032 |
| 2005 | 294.4 | 2.826 | 163.3 | 6.970 | 110.8 | 43.22 | 160.8 | 98.90 | 57.16 | 0.634 |
| 2006 | 259.8 | 2.494 | 138.7 | 5.697 | 85.79 | 32.54 | 123.9 | 89.80 | 49.95 | 5.675 |
| 2007 | 221.3 | 2.124 | 114.4 | 4.529 | 64.65 | 24.21 | 93.27 | 82.06 | 44.19 | 9.661 |
| 2008 | 208.5 | 2.001 | 104.2 | 3.870 | 52.70 | 19.17 | 75.63 | 72.94 | 37.99 | 14.09 |
| Average | 376.8 | 3.617 | 228.8 | 6.996 | 239.5 | 99.00 | 345.0 | 134.7 | 85.53 | -24.07 |

Note: All units are in millions. Dollar figures are inflation adjusted to 2008 terms. NOx and HC are valued as in Muller and Mendelsohn's (2009) USEPA scenario by the county where each vehicle received its Smog Check. The values vary substantially across counties, but a population-weighted average for the state values HC at $10109.81 per ton per year, and NOx at $826.34 per ton per year. CO is valued at $802.88, as per the median value of Matthews and Lave (2000).

**Table 19:** Cobenefits of a Gasoline Tax, Taking Heterogeneity into Account

| | Δ Consumption | Δ CO2 | DWL | Criteria Benefit | | | | | | **Net Cost** |
|---|---|---|---|---|---|---|---|---|---|---|
| | (Gallons) | (Tons) | ($) | (NOx $) | (HC $) | (CO $) | (Total $) | (% DWL) | (Per CO2) | (Per CO2) |
| 1998 | 520.7 | 4.999 | 357.5 | 7.214 | 506.5 | 222.5 | 733.8 | 207.6 | 148.5 | -76.94 |
| 1999 | 524.7 | 5.037 | 350.0 | 9.202 | 444.6 | 190.3 | 643.0 | 184.5 | 128.2 | -58.70 |
| 2000 | 546.8 | 5.250 | 351.6 | 8.330 | 432.2 | 178.1 | 617.8 | 189.8 | 127.1 | -60.15 |
| 2001 | 563.7 | 5.412 | 348.7 | 9.014 | 351.3 | 143.8 | 503.8 | 145.0 | 93.45 | -29.01 |
| 2002 | 472.7 | 4.538 | 285.5 | 7.613 | 252.3 | 100.6 | 360.2 | 126.5 | 79.62 | -16.70 |
| 2003 | 511.7 | 4.912 | 302.1 | 8.339 | 224.3 | 87.17 | 319.5 | 106.1 | 65.28 | -3.781 |
| 2004 | 563.4 | 5.409 | 324.1 | 9.835 | 187.2 | 74.06 | 270.8 | 83.87 | 50.26 | 9.664 |
| 2005 | 489.6 | 4.701 | 271.7 | 8.430 | 139.7 | 55.22 | 203.1 | 75.10 | 43.40 | 14.39 |
| 2006 | 434.3 | 4.170 | 231.9 | 7.402 | 116.5 | 45.90 | 169.6 | 73.58 | 40.93 | 14.70 |
| 2007 | 463.3 | 4.448 | 239.5 | 6.681 | 97.78 | 38.21 | 142.5 | 59.86 | 32.24 | 21.61 |
| 2008 | 457.8 | 4.395 | 228.9 | 5.893 | 86.77 | 33.46 | 125.9 | 55.33 | 28.82 | 23.27 |
| Average | 504.4 | 4.843 | 299.2 | 7.996 | 258.1 | 106.3 | 371.8 | 118.8 | 76.16 | -14.70 |

Note: All units are in millions. Dollar figures are inflation adjusted to 2008 terms. NOx and HC are valued as in Muller and Mendelsohn's (2009) USEPA scenario by the county where each vehicle received its Smog Check. The values vary substantially across counties, but a population-weighted average for the state values HC at \$10109.81 per ton per year, and NOx at \$826.34 per ton per year. CO is valued at \$802.88, as per the median value of Matthews and Lave (2000).

**Table 20:** Percentage Difference Between California and the rest of the US

| | 25th Percentile | Median | 75th Percentile | Mean |
|---|---|---|---|---|
| NOx g/mi | -0.230 | -0.291 | -0.338 | -0.282 |
| NOx Damage/ton (MM) | -0.439 | -0.525 | -0.558 | -0.685 |
| NOx Damage/mi | -0.595 | -0.657 | -0.712 | -0.761 |
| HC g/mi | -0.262 | -0.321 | -0.410 | -0.354 |
| HC Damage/ton | 1.475 | 2.558 | 5.318 | 1.821 |
| HC Damage/mi | 0.602 | 1.134 | 3.358 | 1.035 |
| CO g/mi | -0.226 | -0.321 | -0.366 | -0.320 |
| CO Damage/mi | -0.226 | -0.321 | -0.366 | -0.320 |
| NOx + HC Damage/ton (MM) | 0.0191 | 0.994 | 2.337 | 0.787 |
| NOx + HC + CO Damage/mi | -0.353 | -0.299 | -0.0883 | -0.295 |

Notes: The table reports the coefficient on the California dummy divided by the constant. All differences are statistically significant at the 0.001 level, except for NOx g/mi and HC Damage/mi at the 25th percentile (significant at the 0.05 level), and NOx Damage/mi.