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ABSTRACT

A basic tenet of economics posits that when consumers or firms don't face the true social cost of their actions, market outcomes are inefficient. In the case of negative externalities, Pigouvian taxes are one way to correct this market failure, where the optimal tax leads agents to internalize the true cost of their actions. A practical complication, however, is that the level of externality nearly always varies across economic agents and directly taxing the externality may be infeasible. In such cases, policy often taxes a product correlated with the externality. For example, instead of taxing vehicle emissions directly, policy makers may tax gasoline even though per-gallon emissions vary across vehicles. This paper estimates the implications of this approach within the personal transportation market. We have three general empirical results. First, we show that vehicle emissions are positively correlated with vehicle elasticities for miles traveled with respect to fuel prices (in absolute value)—i.e. dirtier vehicles respond more to fuel prices. This correlation substantially increases the optimal second-best uniform gasoline tax. Second, and perhaps more importantly, we show that a uniform tax performs very poorly in eliminating deadweight loss associated with vehicle emissions; in many years in our sample over 75 percent of the deadweight loss remains under the optimal second-best gasoline tax. Substantial improvements to market efficiency require differentiating based on vehicle type, for example vintage. Finally, there is a more positive result: because of the positive correlation between emissions and elasticities, the health benefits from a given gasoline tax increase by roughly 90 percent, compared to what one would expect if emissions and elasticities were uncorrelated.

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1 Introduction

A basic tenet of economics posits that when consumers or firms do not face the true social cost of their actions, market outcomes are inefficient. In the case of externalities, Pigouvian taxes provide one way to correct this market failure, and the optimal tax or subsidy leads agents to internalize the true cost of their actions. A practical complication, however, is that the level of externality nearly always varies across economic agents, and directly taxing the externality may be infeasible. In such cases, policy often taxes or subsidizes a product correlated with the externality. For example, instead of taxing vehicle emissions directly, policy makers may tax gasoline even though per-gallon emissions vary across vehicles. Similarly, a uniform alcohol or tobacco tax may be imposed as a means of reducing the negative externalities associated with their use, even though externalities likely vary by person or alcohol type. Or, in the case of positive externalities associated with research and development activities, policy might subsidize R&D uniformly across firms.

In this paper, we address three related questions. First, what is the size of the optimal uniform tax rate for gasoline? Second, how much deadweight loss (DWL) remains once this tax is imposed? Finally, how does variation in responses to gasoline taxes affect the benefits associated with gasoline or carbon taxes? Our empirical setting is the personal transportation market in California between 1998 and 2008. We show three things.

First, we observe substantial variation in vehicle-level emissions (externalities) in the light-duty vehicle market and, more importantly, that variation is correlated with the vehicle-specific elasticity of miles driven with respect to gasoline prices. Dirtier vehicles are more price responsive. Using detailed vehicle-specific data on miles driven, we show that the positive correlation between emissions and elasticities (in absolute value) holds for all three local pollutant emissions—known as criteria pollutant emissions—for which we have data: carbon monoxide (CO), hydrocarbons (HCs), and nitrogen oxides (NO_x).[1] It also holds for fuel economy and vehicle weight. We find that the average "two-year" elasticity of miles traveled is -0.15 across all vehicles, but the differences across vehicle types are substantial.

[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 are widespread throughout the United States

The elasticity for the dirtiest quartile of vehicles with respect to NO_x is -0.29. The second, third, and fourth quartile elasticities are -0.16, -0.06, and 0.04, respectively. Similar variation exists for CO and HCs. This correlation drives a wedge between the optimal uniform Pigouvian tax associated with emissions, which should weight vehicles' externalities by their responsiveness to the tax, and what we call the "naive" tax, which is based on the average externalities. The optimal tax is substantially larger, on the order of 50 percent, in each of the years of our sample.

Second, we show that even when instituting the optimal uniform Pigouvian tax, the uniform tax performs very poorly in eliminating DWL. Across our sample, we estimate that the optimal uniform Pigouvian tax, a gasoline tax in this case, eliminates only 30 percent of DWL associated with these pollutants. During the second half of our sample, 75 percent of DWL remains under the optimal uniform tax.[2]

We investigate ways to improve upon this. We find that allowing gasoline taxes to be county specific leads to a small improvement, increasing the amount of DWL eliminated by less than 5 percentage points. We find moderate benefits from "homogenizing" the fleet, potentially through vehicle retirement (e.g., "Cash-for-Clunkers") programs; scrapping the dirtiest 10 percent of vehicles reduces the remaining DWL by 14 percentage points. The largest pay-offs come from conditioning taxes on vehicle type, in particular vehicle's age.

Finally, we report some good news. We show that the positive correlation between emissions and the miles-driven elasticity implies that health benefits from a given gasoline, or carbon, tax are larger than would be suggested by ignoring this correlation. We estimate that across our sample, the health benefits of a gasoline tax, per gallon of gasoline reduced, increase by 90 percent once one accounts for the the heterogeneity that we document. Furthermore, these differences are large enough to push a substantial gasoline tax of $1.00 per gallon from harming welfare to improving welfare late in the sample.

We also investigate several sources of the heterogeneity in the responsiveness to gasoline prices. At the most general level, we show that while the age of the vehicle contributes to

[2]The closest paper in the literature to ours, in terms of this contribution, is Fullerton and West (2010). They also investigate the amount of DWL eliminated by a uniform gasoline tax by calibrating a numerical model with approximate miles and emissions obtained by matching inspection data from a small CARB program to quarterly gasoline expenditures in the Consumer Expenditure Survey. Our estimates are based on actual emissions, miles traveled, and gasoline prices from the universe of California vehicles. We find that a uniform tax removes much less of the DWL of pollution compared to their calculations.

our results—older vehicles respond more to changes in gasoline prices—this does not explain all or even most 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, low-income consumers may both own dirtier vehicles and respond more to changes in gasoline prices. Second, the heterogeneity may come from within-household shifts in vehicle miles traveled across household vehicles. For example if a household has one newer, more fuel efficient vehicle, and one older vehicle, as gasoline prices increase, the household may shift miles away from the older vehicle to the newer vehicle. Because age is, on average, correlated with both fuel economy and criteria pollutant emissions, this would lead to our result. Our data 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.

The paper proceeds as follows. Section 2 draws on Diamond (1973) to derive the optimal uniform gasoline tax and the amount of remaining DWL. Section 3 discusses the empirical setting and data. Section 4 provides graphical support for the empirical results. Section 5 presents the main empirical model and results on miles driven. Section 6 estimates empirically the optimal uniform tax and welfare effects, and Section 7 presents the results from our policy simulation. Section 8 concludes the paper.

2 Optimal Uniform Taxes

In this section, we derive the optimal uniform tax in the presence of heterogeneity in the externality, following closely the model of Diamond (1973). We reiterate that the optimal uniform Pigouvian tax is second best, because heterogeneity would imply taxing different agents differently. We then add more structure to the problem to analytically solve for the amount of remaining DWL.

Consumer h derives utility (indirectly, of course) from her gasoline purchases, α_h, but is also affected by the gasoline consumption of others, α_{-h} (the externality). We assume single-car households and discuss robustness to this assumption. Assuming quasi-linear preferences, consumer h's utility can be written as:

$$U^h(\alpha_1, \alpha_2, ..., \alpha_h, ..., \alpha_n) + \mu_h. \quad (1)$$

We assume utility is monotone in own consumption, i.e., $\frac{\partial U^h}{\partial \alpha_h} \geq 0$.

These assumptions, along with assuming an interior solution for each consumer, lead to:

Proposition 1. *The second-best tax is* (from Diamond (1973))*:*

$$\tau^* = \frac{-\sum_h \sum_{i \neq h} \frac{\partial U^h}{\partial \alpha_i} \alpha_i'}{\sum_h \alpha_h'}. \tag{2}$$

Proof. See Appendix A. □

The optimal uniform Pigouvian tax becomes a weighted average of vehicles' externalities where the weights are the derivative of the externality with respect to the tax. When the price responsiveness and emissions are positively correlated, i.e. dirtier cars are more price responsive, this will increase the optimal uniform Pigouvian tax.[3]

As Diamond explicitly discusses, there is no requirement that all of the $\alpha_h' s$ must be negative, although the optimal second-best tax loses the interpretation as a weighted average. Indeed, if households hold multiple vehicles, it is conceivable that miles traveled is shifted from the low-mileage vehicle to the high-mileage vehicle. This also implies that the second-best tax can be negative. For example, suppose the dirty vehicles had a positive miles-traveled elasticity, while clean vehicles were very price sensitive. In this case, it may be optimal for policy to *subsidize* gasoline.

Also, note that the elasticity of the negative externality with respect to price accounts for any changes on the extensive margin. That is, if the gasoline tax increases the scrappage rate of some vehicles, then the relevant derivative of the externality with respect to price is the expected change in miles driven, not the change in miles driven, conditional on survival.

The presence of heterogeneity also implies that the uniform tax will not achieve the first-best outcome. In short, the uniform tax will under-tax high externality agents and over-tax low externality agents. We extend Diamond (1973) to solve for the amount of DWL remaining in the presence of a uniform Pigouvian tax applied to a market with heterogenous externalities. This requires a bit more structure.

[3]As an intuitive example, imagine the case where there are only two vehicle types. The first emits little pollution, while the second is dirtier. Also imagine the clean vehicles are completely price insensitive, while the dirty vehicles are price sensitive. The naive Pigouvian tax would tax based on the average emissions of the two vehicle types. However, the marginal emission is the emission rate of the dirty vehicles; the clean cars are driven regardless of the tax level. In this case, we can achieve first best by setting the tax rate at the externality rate of the dirty vehicle. There is no distortion to owners of clean vehicles since their demand is completely inelastic, so we can completely internalize the externality to those driving the dirty vehicles.

Proposition 2. *Suppose drivers are homogenous in their demand for miles driven, but vehicles emissions differ. In particular, each consumer has a demand for miles driven given as:*

$$m = \beta_0 - \beta_1 dpm(p_g + \tau). \tag{3}$$

If the distribution of the externality per mile, E, is log normal, with probability density function:

$$\varphi(E_i) = \frac{1}{E_i\sqrt{2\sigma_E^2}} \exp\left(\frac{-(E_i - \mu_E)^2}{2\sigma_E^2}\right), \tag{4}$$

the DWL absent any market intervention will be given as:

$$D = \frac{1}{2\beta_1} e^{2\mu_E + 2\sigma_E^2}.$$

Proof. See Appendix A. □

This leads to the following calculation of remaining DWL under the optimal uniform Pigouvian tax.

Proposition 3. *Under the assumptions in Proposition 2, the ratio of remaining DWL after the tax is imposed to the DWL absent the tax:*

$$R = \frac{D - \frac{e^{2\mu_E + \sigma_E^2}}{2\beta_1}}{D} = 1 - \frac{e^{2\mu_E + \sigma_E^2}}{e^{2\mu_E + 2\sigma_E^2}} = 1 - e^{-\sigma_E^2}. \tag{5}$$

Proof. See Appendix A. □

With externalities uncorrelated with the demand for miles driven, the remaining DWL from a uniform tax depends only on the shape parameter of the externality distribution. The larger σ_E^2 is, the wider and more skewed will the distribution of the externality be, causing the uniform tax to "overshoot" the optimal quantity of miles for more vehicles.

If the demand for miles driven is not homogeneous, and in fact is correlated with externalities per mile, the calculation changes. For ease, define $B_i = \frac{1}{\beta_i}$, and assume that B_i is distributed lognormal with parameters μ_B and σ_B^2. Define ρ as the dependence parameter of the bivariate lognormal distribution (the correlation coefficient of $\ln E$ and $\ln B$). We then have:

Proposition 4. *When B_i and E_i are distributed lognormal with dependence parameter ρ, the optimal tax is:*

$$\tau^* = e^{\mu_E + \frac{\sigma_E^2}{2} + \rho\sigma_E\sigma_B}$$

Proof. See Appendix A. □

As we would expect, the optimal tax does not depend on the scale of the elasticity distribution, only on the extent to which externalities are correlated with elasticities. We can next calculate the amount of remaining DWL under both the naive and optimal uniform Pigouvian tax.

Proposition 5. *When B_i and E_i are distributed lognormal with dependence parameter ρ, the ratios of the remaining DWL after the optimal uniform Pigouvian tax to the original DWL will be:*

$$R(\tau^*) = 1 - e^{-\sigma_E^2}, \tag{6}$$

And, the ratios of the remaining DWL after the naive uniform tax to the original DWL will be:

$$R(\tau_{naive}) = 1 - e^{-\sigma_E^2}(2e^{-\rho\sigma_E\sigma_B} - e^{-2\rho\sigma_E\sigma_B}). \tag{7}$$

Proof. See Appendix A. □

As we would expect, the optimal tax correctly accounts for the correlation between the externality and demand responses, and thus the remaining DWL depends only on the variance and skewness of the externality distribution. However, in the presence of correlation the naive tax reduces less of the DWL from the externality, reducing it by a proportion related to the degree of correlation and the spread of the two distributions. The term in parentheses in Equation (7) is strictly less than 1, and strictly greater than zero if $\rho > 0$, but may be negative if $\rho < 0$ and the shape parameters are sufficiently large.

In Section 6, we will show that σ_E^2 is such that $R(\tau^*)$ is surprisingly large, and that while $R(\tau_{naive})$ is measurably larger, it is not much larger.

3 Empirical Setting

3.1 Data

Our empirical setting is the California personal transportation market. We bring together a number of large data sets. First, we have the universe of smog checks from 1996 to 2010 from California's vehicle emissions testing program, the Smog Check Program, which is administered by the California Bureau of Automotive Repair (BAR). An automobile appears in the data for a number of reasons. First, vehicles more 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 or older. Third, a test is required if a vehicle moves to California from out-of-state. Vehicles that 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 natural-gas powered trucks.

These data report the location of the test, the unique vehicle identification number (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 information, we match the vehicles to EPA data on fuel economy. Because the VIN decoding is only feasible for vehicles made after 1981, our data are restricted to these models. We also restrict our sample to 1998 and beyond, given large changes that occurred in the Smog Check Program in 1997. This yields roughly 120 million observations.

The smog check data report two measurements each for NO_x and HCs in terms of parts per million and CO levels as a percentage of the exhaust, taken under two engine speeds. As we are interested in the quantity of emissions, the more relevant metric is a vehicle's 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 in Morrow and Runkle (2005), an evaluation of the Smog Check Program. The conversion equations are functions of both measurements of all three pollutants, vehicle weight, model year, and truck status.

We also estimate scrappage decisions using data reported to CARFAX Inc. for 32 million vehicles in the smog check data. We detail this analysis in Appendix G. These data contain the date and location of the last record of the vehicle reported to CARFAX. This includes registrations, emissions inspections, repairs, import/export records and accidents.

At times we use information about the household. For a subsample of our smog check data, we are able to match vehicles to households using confidential data from Department of Motor Vehicle records that track the registered address of the vehicle. We use this information to aggregate up the stock of vehicles registered to an address. Appendix C discusses how this is done. These data are from 2000 to 2008. Finally, we use gasoline prices from EIA's weekly California average price series to construct average prices between inspections.

Table 1 reports means and standard deviations of the main variables used in our analysis, as well as these summary statistics split by both vehicle vintage and for 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 average per-mile emissions of HCs, CO, and NO_x falling considerably 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.

3.2 Automobiles, Criteria Pollutants, and Health

The tests report the emissions of three criteria pollutant: NO_x, HCs, and CO. All three of these result directly from 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 on their own.[4]

While numerous studies have found links between exposure to either smog or these three pollutants and health outcomes, the 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 CO have also been linked to heart and respiratory problems. NO_x reacts with other compounds to create nitrate aerosols, which are fine-particle particulate matter (PM). PM has been shown to irritate lung tissue, lower lung capacity, and hinder long-term lung development. Extremely small PM can be absorbed through the lung tissue and cause damage on the cellular level. On their own, HCs 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 heart problems and lung ailments such as asthma or allergies.

[4] CO has also been shown to speed up the smog-formation process. For early work on this, see Westberg et al. (1971).

4 Preliminary Evidence

One of the main driving forces behind our empirical results is how 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 within a year, across years, and even within the same vehicle type (make, model, model year, etc.) within a year. Further, simple statistics, such as the average miles traveled by vehicle type, suggest that elasticities may be correlated with externalities.[5]

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 some vehicles on the road are quite dirty relative to the mean vehicle. Over time, the distribution has shifted to the left, as vehicles have gotten cleaner, but the range remains.

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, and drivetrain combination. To see this, Figure 2 plots the distributions of emissions for the most popular vehicle/year in our sample, the 2001 four-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 HCs is less skewed, but the standard deviation is 25 percent of the mean. CO 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 A.1).

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

[5] We are not the first to document the large variation across vehicles in emissions. See, for example, Kahn (1996). Instead, our contribution is in finding a link between elasticities and emissions.

[6] We chose this vehicle because the 1995 3.8L, front-wheel drive, Ford Windstar in 1999 is the second-most

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 HCs, this increased from 3.59 to 5.51; and, for CO it increased from 3.95 to 5.72.

These distributions demonstrate significant variation in emissions across vehicles and within vehicle type, and thus significant scope for meaningful emissions-correlated variation in elasticities along those lines. We next present suggestive evidence that this is the case. To do this, we categorize vehicles into four groups, based on the quartiles of a given pollutant *within* a given year. Next we scale the median annual miles traveled in the groups relative to their 1998 values, and plot how this has changed over our sample—a period where gasoline prices increased from roughly \$1.35 to \$3.20. Figure 4 foreshadows our results on the intensive margin. 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] For each pollutant, we see that the dirtiest quartile saw the largest decreases in miles driven during the run up gasoline prices. The ordering of the relative decreases suggests that dirtier vehicles were more responsive over this period.

5 Vehicle Miles Traveled Decisions

Our first set of empirical models estimates how changes in gasoline prices affect decisions about vehicle miles traveled (VMT), and how this elasticity varies with vehicle characteristics. Our empirical approach mirrors Figure 4. 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 smog checks. We then allow the elasticity to vary based on the emissions of the vehicle. We begin by estimating:

$$\ln(VMT_{ijgt}) = \beta \ln(DPM_{ijgt}) + \gamma D_{truck} + \omega time + \mu_t + \mu_j + \mu_g + \mu_v + \epsilon_{igt} \qquad (8)$$

where i indexes vehicles, j vehicle-types, g geographic locations, t time, and v vehicle age, or vintage. DPM_{ijgt} is the average DPM of the vehicle between smog checks, D_{truck} is an

popular entry in our data and it is old enough that we can track it over four 2-year periods.

[7]The levels also differ. Appendix Figure A.1 plots the median of daily miles traveled across our sample split up by the emissions quartile of the vehicle.

indicator variable for whether the vehicle is a truck, and *time* is a time trend.[8]

Table 2 shows our basic results. 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 finally individual vehicle fixed effects. We also differentiate the influence of gasoline 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 in which the vehicle falls with respect to the within-year emissions of NO_x, HCs, and CO, fuel economy (CO_2), and weight. Second, we include a linear interaction of the percentiles of these variables and the log of gasoline prices. In Appendix B we investigate, in a semi-parametric way, the actual functional form of this relationship and the robustness of our results to alternative sources of variation in DPM.

Tables 2 shows our results, focusing on NO_x. The changes from Models 1 to 5 illustrates the importance of controlling for vehicle-type fixed effects. Initially, the average elasticity falls from -0.265 to -0.117 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 -0.147.[9] In Models 6 and 7 we examine heterogeneity with vehicle fixed effects. Model 6 includes interactions with quartiles of NO_x, as in Model 3. The DPM-elasticity for the cleanest vehicles, quartile one, is positive at 0.041, while the DPM-elasticity for the dirtiest vehicles is twice the average elacticity at -0.288. 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 .001, from a base of essentially zero. This heterogeneity is also robust to allowing our other covariates to vary with NO_x quartiles, leveraging cross-sectional instead of time-series variation, allowing a semi-parametric functional form for the heterogeneity and to employing a log-linear specification with the level of dollars miles as the variable of interest. The details

[8]Our DPM variable uses the standard assumption that 45 percent of a vehicle's miles driven are in the city and 55 percent are on the highway. This is the standard approach used by the EPA for combined fuel economy ratings.

[9]This is larger than that found in Hughes et al. (2008) reflecting the longer run nature of our elasticity.

of these robustness checks are reported in Appendix B.

We find similar patterns across the other externalities. There is slightly more heterogeneity over HCs and CO emissions than over NO_x, with the dirtiest quartiles around -0.30 and the cleanest around 0.05. For CO_2 the cleanest vehicles are those with the highest fuel economy, and here we see the least fuel-efficient vehicles having an elasticity of -0.183, compared to -0.108. We observe some heterogeneity over weight as well, although it is smaller than the other externalities. For the full set of results, see Appendix Table A.2.

5.1 The Source of the Heterogeneity

While the optimal uniform Pigouvian tax is not affected by the mechanism behind the heterogeneity, it is of independent interest to investigate the mechanism. We investigate three sources, which are not necessarily mutually exclusive. First, it may be driven entirely by a vintage effect. That is, older vehicles are both more responsive to changes in gasoline prices and have higher emissions. Second, it might be driven by differences in the incomes of consumers that drive dirtier versus cleaner vehicles.[10] 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 and calendar year bins. We split vehicles into three age categories: 4 to 9 years old, 10 to 15 years old, and 16 to 27 years old.

Table 3 reports the results for heterogeneity over NOx emissions.[11] These results suggest that while vintage is a factor in the externality-based heterogeneity, it is not the only source or even the most important source. While middle-aged and older vehicles are more elastic than new vehicles on average, within age bin there is still substantial heterogeneity. For new vehicles, the difference between the dirtiest and cleanest quartiles is two thirds of the range for the whole sample. Middle-aged vehicles have three quarters as much range, and the oldest vehicles, 16 years and older, have a range nearly as large as for the whole sample.

We are able to group a subsample of our smog check vehicles into households. This grouping comes from access to California Department of Motor Vehicles (DMV) confidential

[10] West (2005) also documents a positive correlation between income and emissions. She does not separately estimate elasticities, however.

[11] Results for the other four externality types are quite similar.

data. A number of steps are undertaken to "clean" the address entries in the DMV records. These are discussed in Appendix C. 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 and the fact that the sample period differs from our base specification, it is not surprising that we find average elasticities that differ from those presented above.

Table 4 presents the results from this subsample. 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 in 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 in question.

If households 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. Column 2 of Table 4 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 an elasticity greater than a third lower. We cannot reject the null hypothesis that the sum of the interactions with quartile four and "Higher MPG in HH" is zero.[12]

For this same sample of vehicles, we also use U.S. Census information based on zip-code of residence to categorize owners into income quartiles. We interact these quartiles with the log of DPM to see if differences in elasticities exist. Column 3 of Table 4 adds these interaction terms. There is some evidence that higher-income consumers are less elastic, as the emissions quartile effects persist; 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 also use this information to construct measures of income. Table 5 compares these results with the DMV data. We find similar differences in the elasticities, despite the smaller average elasticity.

[12]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.

6 Efficiency of Uniform Pigouvian Taxes

In this section, we consider the efficiency of using a uniform Pigouvian tax to abate the externalities caused by driving, specifically those resulting from emissions of NO_x, HCs, and CO. We begin by calculating both the naive and optimal second-best Pigouvian tax, and then compare the remaining DWL left over from these second-best taxes to the optimal outcome obtained by a vehicle-specific tax.

6.1 Optimal Uniform Pigouvian Tax

We calculate the naive Pigouvian tax per gallon of gasoline as the simple average of the externality per gallon caused by all vehicles on the road in California in a particular year. We value the externalities imposed by NO_x and HCs using the marginal damages calculated by Muller and Mendelsohn (2009), based on the county in which each vehicle has its smog check.[13] For CO, we use the median marginal damage estimate from Matthews and Lave (2000). Let the marginal damage per gram of pollutant p in county c be θ_c^p, with emissions rates in grams per mile by vehicle i of ϵ_i^p. Then the externality per mile of vehicle i, E_i is:

$$E_i = \theta^{hc} \cdot \epsilon_i^h c + \theta_c^{HC} \cdot \epsilon_i^H C + \theta^{NOx} \cdot \epsilon_i^N Ox_c + \theta^{CO} \cdot \epsilon_i^C O_c. \tag{9}$$

The naive tax in year y will then be simply:

$$\tau_{naive} = \frac{1}{N^y} \sum_{i=1}^{N^y} \frac{E_i}{MPG_i}. \tag{10}$$

Following Proposition 1, we calculate the second-best optimal Pigouvian tax, taking into account the heterogeneity in both levels of the externality and the responsiveness to gasoline prices. We estimate a regression similar to Equation (8), but allowing the elasticity of VMT with respect to DPM to vary over all our dimensions of heterogeneity. For more details, see Appendix E. Let the group-specific elasticity for vehicle i be ε_i^q, where q indexes cells by HC emissions, NO_x emissions, CO emissions, MPG, weight, and age, with the externalities again

[13] Note that the values used in this paper differ from those used in the published version of Muller and Mendelsohn (2009). The published values were calculated using incorrect baseline mortality numbers that were too low for older age groups. Using corrected mortality data increases the marginal damages substantially. We are grateful to Nicholas Muller for providing updated values, and to Joel Wiles for bringing this to our attention.

in quartiles by year. Further, let the average price per gallon and the quantity of gasoline consumed per year in gallons in year y be P_i^y and Q_i^y, respectively. Then the optimal tax in year y based on the marginal externality will be

$$\tau^y_{marginal} = \tau^* = \frac{-\sum_h \sum_{i \neq h} \frac{\partial U^h}{\partial \alpha_i} \alpha'_i}{\sum_h \alpha'_h}, \tag{11}$$

with

$$\alpha'_i = -\varepsilon_i^q \cdot \frac{Q_i^y}{P_i^y}.\text{[14]} \tag{12}$$

Table 6 shows the taxes based on the average and marginal externalities for each year from 1998 to 2008. The average externality is 61.2 cents per gallon of gasoline consumed in 1998, while the marginal externality is 86 cents, 39 percent higher. The ratio of the average and marginal tax increases even as the level of the externalities declines over time. From 2002 on, the marginal tax is at least 50 percent larger than the naive tax in each year.

We also account for vehicle owners' decisions to scrap their vehicles are affected by gasoline prices. Appendix G discusses the details and results of this exercise. To summarize, we allow gasoline price to affect scrappage decisions, and allow this to vary over emissions profiles and vintages. We find that the main source of heterogeneity occurs across vintages; specifically, increases in gasoline prices increase the hazard rate of very old vehicles, but decrease the hazard rate of middle-aged vehicles. Because emissions of criteria pollutants are positively correlated with age, this has the effect of decreasing criteria pollutants.

6.2 Welfare with Uniform Taxes

We have shown that because of the correlation between elasticities and externality rates, the optimal uniform Pigouvian tax is much higher than the naive tax calculated as the average of per-gallon externalities. We now turn to the question of how much the optimal tax improves welfare beyond what is achieved by the naive tax. We note again that even the optimal uniform tax is still a second-best policy. Because of the heterogeneity in externality levels, the most polluting vehicles will be taxed by less than their external costs to society, leaving remaining dead weight loss. Vehicles that are cleaner than the weighted average will be taxed

[14] We also weight vehicles based on the number of vehicles of that age and class that appear in the fleet as a whole; see Appendix E.

too much, overshooting the optimal quantity of consumption and creating more DWL.

In each of the following analyses, we compare the remaining DWL resulting from the local pollution externality with both the naive and marginal tax to the DWL without any additional tax.

6.2.1 Simulation Results

We begin by approximating the ratios of DWL with and without tax using our data to simulate the change in miles driven and thus in gasoline consumption from a tax. Let $miles_i^y$ be the actual average miles per day traveled by vehicle i between its last smog check and the current one, observed in year y, and let $\hat{miles}_i^y(\tau)$ be the miles per day that a vehicle would travel if the average price of gasoline were raised by a tax of τ that is fully passed through to consumers. We approximate DWL as a triangle, such that the ratio of interest is:

$$r(\tau) = \frac{\sum_i \frac{1}{2} \cdot \left| \frac{miles_i^y - \hat{miles}_i^y(\tau)}{MPG_i} \right| \cdot \left| \frac{E_i}{MPG_i} - \tau \right|}{\sum_i \frac{1}{2} \cdot \left| \frac{miles_i^y - \hat{miles}_i^y(\frac{E_i}{MPG_i})}{MPG_i} \right| \cdot \frac{E_i}{MPG_i}}$$

The fully optimal tax would have a ratio of 0, while a tax that actually increased the DWL from gasoline consumption would be greater than 1. Table 7 shows these ratios for various taxes. The first two columns show ratios for a statewide tax based on the average and marginal externalities, respectively, of all vehicles in California in each year. Deadweight loss from the uniform naive tax averages 72.8 percent of DWL with no additional tax over the sample period, and rises over time as the fleet becomes cleaner. The uniform marginal tax is little better, averaging 69.8 percent of DWL with no tax during our sample period.

How can policy makers improve upon these results? The remaining columns of Table 7 allows the tax to vary so that it is uniform by groups, but not uniform over the entire state. The marginal damages from Muller and Mendelsohn (2009) vary substantially at the county level,[15] due to both baseline emissions levels and the extent to which population is exposed to harmful emissions. As such, a county-specific tax on emissions might be expected to target externality levels more precisely. The third and fourth columns of Table 7 shows

[15] We discuss this further in Appendix F.

the DWL ratios for an average and marginal tax computed this way, and it turns out there is relatively little improvement. The average ratios over our sample are 0.684 for the naive tax and 0.653 for the optimal uniform tax tax. Since emissions rates are highly correlated with vintage, another approach would be to tax the average or marginal externality rate by age.[16] The fifth and sixth columns of the table show this, and here we see a substantial improvement: 0.342 for the naive tax and 0.34 for a marginal tax. Combining these and having the tax vary by both vintage and location, shown in the last two columns, reduces the ratios to 0.276 and 0.274, respectively.

This analysis shows two striking results. First, a uniform Pigouvian tax does a terrible job of addressing the market failure from pollution externalities. The dirtiest vehicles are not taxed enough, and many clean vehicles are over-taxed. This is true even when the uniform tax is calculated taking heterogeneity into account. The roughly 50 percent increase in the tax level from a marginal tax correctly abates more emissions from the dirtiest vehicles, but also over-taxes the cleanest vehicles by a larger amount. This is still an improvement over the naive tax, but not by much. The number of vehicles for which the uniform tax overshoots is remarkable. Table 8 shows the proportion of vehicle-years over the 11 years of our sample for which each tax overshoots. Because the distribution of emissions is so strongly right skewed, the naive uniform tax overshoots for more than 72 percent of vehicles, and the optimal uniform tax for even more. Second, there is enough heterogeneity in the distribution of the per-gallon externality that even a tax targeting broad groups leaves a substantial portion of DWL. Overshooting is again an issue—when the tax is allowed to vary by county and vintage, only the average tax by county and vintage overshoots for less than 70 percent of vehicles.

The variance and skewness in the distribution of externality per gallon causes a uniform tax to be less efficient than might otherwise be expected. Figure 5 shows this clearly, plotting the kernel density of the externality per gallon in 1998 and 2008, with vertical lines indicating the naive tax and the optimal tax, respectively. The long right tail of the distribution requires that either tax greatly exceed the median externality.

We next examine how the optimal uniform tax would compare to the optimal vehicle

[16] Such a system could be built within the Smog Check Program, with vehicle taxes based on mileage since the previous test.

specific tax if the distribution became less skewed. That is, how would a uniform tax perform if the right tail of the distribution—the oldest, dirtiest vehicles—were removed from the road? This could be achieved directly from a Cash for Clunkers-style program, or indirectly through tightening emissions standards in the Smog Check Program. Sandler (2012) shows that vehicle retirement programs are not cost-effective in reducing criteria emissions, and possibly grossly over pay for emissions; however the overall welfare consequences of this sort of scheme may be more favorable if they improve the efficiency of a uniform gasoline tax. Table 9 shows the ratios of DWL with the optimal Pigouvian tax to DWL with no tax, with increasing proportions of the top of the externality distribution removed. Removing the top 1 percent increases the DWL reduction from 30 percent to 38 percent of the total with no tax. Scrapping more of the top end of the distribution improves the outcome further. If the most polluting 25 percent of vehicles were removed from the road and the optimal Pigouvian tax was imposed based on the weighted externality of the remaining 75 percent, this would remove 58.3 percent of remaining DWL. Of course, the practical complications of scrapping this large a proportion of the vehicle fleet might make this cost-prohibitive.

6.2.2 Analytical Results

We can also calculate the ratio of remaining DWL to original DWL by calibrating Equations (6) and (7) and with the moments in our data. The average value in our sample for the lognormal shape parameters σ_E^2 and σ_B^2 are 1.47 and 1.51, respectively. The average value of ρ, the correlation coefficient for the logs of externality and inverse elasticity, is 0.28.[17] These parameter values produce remaining DWL estimates in line with the simulation results in Table 7. With σ_E^2 around 1.47, the optimal uniform tax can only decrease DWL by 23 percent.

6.3 Treatment of Other Externalities

In the previous section we assumed that the difference between the socially optimal consumption of gasoline and actual consumption was entirely driven by externalities from local pollution. In practice, there are several other externalities from automobiles, as well as

[17] This is the average of parameters calculated separately for each year from 1998 to 2008. The parameters do not vary much over time. For the year-by-year parameter estimates, see Table A.7 in the online appendix.

existing federal and state taxes on gasoline. Examples of additional externalities include congestion, accidents, infrastructure depreciation, and other forms of pollution. The combined state and federal gasoline tax in California was \$0.47 during our sample period.

Many of these other externalities are similar to criteria pollution emissions in the sense that they also vary across vehicles. Congestion and accident externalities depend on when and where vehicles are driven. Accident and infrastructure depreciation depend to some degree on vehicle weight.[18] We lack vehicle-specific measures of these other externalities to measure how they impact our calculations of the amount of remaining DWL after imposing a uniform Pigouvian tax. Insofar as additional variation exists we are understating the *level* of remaining DWL, although not necessarily the *share* of remaining DWL. One way to interpret our results is that by ignoring the existing taxes we are assuming that existing taxes exactly equal the uniform Pigouvian tax associated with these other externalities, and that we are also ignoring the remaining DWL due to the fact that these externalities are not uniform across vehicles.

One externality that does not vary across vehicles is the social cost of CO_2 emissions due to their contribution to climate change. Because CO_2 emissions are, to a first-order approximation, directly proportional to gasoline consumption, in this case a per-gallon gasoline tax is the optimal policy instrument. The larger the climate change externality, the greater the *share* of DWL eliminated from the uniform Pigouvian tax will be. To get a sense of how climate change externalities affect our calculations, we repeat the analysis for a range of social costs of carbon (SCC). The "correct" social cost of carbon depends on a number of factors, such as assumptions about the mappings between temperature and GDP, between GDP and CO_2 emissions, and between CO_2 emissions and temperatures, as well as assumptions on the discount rate and the relevant set of economic agents. Greenstone et al. (2011) estimate the SCC for a variety of assumptions about the discount rate, relationship between emissions and temperatures, and models of economic activity. For each of their sets of assumptions, they compute the *global* SCC; focusing only on the US impacts would reduce the number considerably. For 2010, using a 3 percent discount rate, they find an average SCC of \$21.40 per ton of CO_2 or roughly 19.5 cents per gallon of gasoline, with a 95th percentile of \$64.90

[18]For estimates on the degree of this heterogeneity, see Anderson and Auffhammer (2011) and Jacobsen (Forthcoming).

(59 cents per gallon).[19] Using a 2.5 percent discount rate, the average SCC is \$35.10 (38.6 cents per gallon).

We calculate the remaining DWL, varying the SCC from zero cents per gallon to \$1.00 per gallon (\$91 per to of CO_2). While our discussion focuses on the externalities associated with CO_2, we stress that these calculations are relevant for *any* externalities for which a per-gallon tax is the first-best instrument. They also represent the lower bound on the remaining DWL when we consider any other externality for which a per-gallon tax is a second-best instrument. For example, if one considers externalities associated with accidents or congestion to be \$0.30 per gallon on average, then insofar that a per-gallon tax is not optimal, more DWL will remain than what we report.

Figure 6 summarizes the results across all years in our sample. The points associated with an extra per-gallon externality of zero correspond to Table 7.[20] Not until the extra per-gallon externality exceeds \$0.20 per gallon does a uniform gasoline tax eliminate the majority of DWL associated with both the criteria pollutants and per-gallon externality. Even if the per-gallon externality is \$1.00, nearly 20 percent of combined DWL remains under both the optimal naive and marginal taxes.

7 Benefits from Gasoline or Carbon Taxes

We have shown that the positive correlation between emissions and sensitivity to gasoline prices increases the optimal gasoline tax. At the same time, the large variation in automobile emissions implies that a uniform gasoline tax does a poor job eliminating the DWL associated with both local and global pollution. The positive correlation between emissions and sensitivity to gasoline prices has a second effect: because a given gasoline tax (or carbon tax) affects dirty vehicles more, the positive correlation increases the amount of local-pollution benefits arising from a given gasoline or carbon tax. This, in turn, reduces the net social cost of such a policy, and to our knowledge, has been ignored in the discussion surrounding the desirability of carbon tax or cap-and-trade policy.

We calculate the cost of a relatively high tax on CO_2 net of local-pollution benefits.

[19] These calculations assume that the lifecycle emissions of gasoline are 22 pounds per gallon.

[20] Note that the figure plots the weighted averages across the years, while the last row in Table 7 is a simple average of the annual weighted averages.

Specifically, we use our data to simulate the change in emissions resulting from a \$91 tax on CO_2, which translates to a \$1 increase in the gasoline tax.[21] This is much higher than permit prices in Europe's cap-and-trade program, which peaked at \$40 per ton of CO_2-equivalent in 2008 and have plummeted since. It is also higher than permit prices expected in California's cap-and-trade program which are estimated to reach of roughly \$30 per ton of CO_2-equivalent. The Waxman-Markey Bill of 2009 expected a similar permit price.

We account for the intensive margin of driving, including all the dimensions of heterogeneity we have documented in Section 5. For completeness, we also include heterogeneity in the extensive margin of scrappage, using results that we document in Appendix G. The extensive margin has little impact on our results. 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, if gasoline prices had been \$1 greater. Appendix E provides details of the steps we take for the simulation.

Tables 11 and 12 show the results of our simulation for each year from 1998-2008, and the yearly average over the period.[22] The first 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 DWL from the reduction in gasoline consumption.[23] The next section of the table presents the social benefit resulting from the reduction in NO_x, HC, and CO due to the tax. Social benefits are valued using the marginal damages of NO_x and HC calculated by Muller and Mendelsohn (2009) and the median CO value from Matthews and Lave (2000). Finally, the last column of the table shows the net cost per ton of carbon dioxide abated, accounting for the reductions in criteria pollution.

Table 11 shows the results of a simulation that does not account for heterogeneity across emissions profiles. The reduction in gasoline consumption declines over time, from around 470 million gallons in 1998 to around 219 in 2008. The reduction in criteria pollutants declines quickly as the fleet becomes cleaner. Nonetheless, the local-pollution benefits of a gasoline tax are substantial, averaging 42 percent of the DWL over the ten-year period.

[21] 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.

[22] Additionally, Table A.9 shows results excluding effects on the extensive margin. These results are very similar to Table 12.

[23] We approximate DWL as $\frac{\Delta P \cdot \Delta Q}{2}$ and adjust for inflation.

Table 12 adds heterogeneity in the intensive and extensive margins. The total change in gasoline consumption is smaller, declining from 272 million gallons in 1998 to 110 million gallons in 2008. This results from more fuel-efficient vehicles having a higher average VMT. However, reductions in criteria pollutants are much larger. In 1998 the local-pollution benefits are over 126 percent of the DWL, and the net cost of abating a ton of carbon is negative until 2002. On average, we estimate that benefits of a decrease in local air pollution from a gasoline tax would be about 85 percent of the change in surplus between 1998 and 2008.

Consistent with the way smog is formed, the majority of benefits come from reductions in HCs, because 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 HCs do. In addition to the smog benefits from reducing HCs and NO_x, we also find significant local-pollution benefits arising from CO reductions.

We argue that these results should be viewed as strict lower bounds of the local-pollution benefits for a variety of reasons. First, we have valued the benefits from NO_x and HCs using the most conservative marginal damages from Muller and Mendelsohn (2009). Muller and Mendelsohn's estimates depend heavily on the value placed upon mortality. Their baseline, used here in Tables 11 and 12, assumes the value of a statistical life (VSL) to be \$2 million, weighted by remaining years of life, and they acknowledge this may not be the correct value. For instance, the U.S. EPA assumes a VSL of \$6 million. Muller and Mendelsohn also calculate a scenario, with a VSL of \$6 million, constant over ages, that yields much higher marginal damages. If we use the marginal damages from this scenario, we find that with heterogeneity, the benefits average more than three times the DWL over the period, and remain twice as large in 2008.[24]

There are other reasons why our estimates should be considered a lower bound. 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 or the emissions of NO_x, HCs, and CO. Second, because of the rules of the Smog Check Program, many vehicles are not required to be tested, leading to their omission in this analysis. Third, a variety of behaviors associated with smog check programs would lead the

[24] Full results using Muller and Mendelsohn's "USEPA" values may be found in the online appendix in tables A.10 and A.11.

on-road emissions of vehicles to likely exceed the tested levels. These include, but are not limited to, fraud, tampering with emission-control technologies between tests, and failure to repair emission-control technologies until a test is required. Appendix F also suggests that these results may also represent a lower bound across other states.

When we account for the heterogeneity in responses to changes in gasoline prices, we see that local-pollution benefits would substantially ameliorate the costs of an increased gasoline tax. These 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, recall that Greenstone et al. (2011) estimate a SCC for 2010, using a 3 percent discount rate, 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 local-pollution benefits are accounted for, a $1.00 gasoline tax (i.e., a tax of $91 per ton of CO_2) 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.[25]

8 Conclusions

In this paper we show three general empirical results. First, the sensitivity to a given vehicle's miles traveled to gasoline prices is correlated with the vehicle's emissions. Dirtier vehicles are more price responsive. This increases the size of the optimal uniform gasoline tax by as much as 50 percent.

Second, gasoline taxes are an inefficient policy tool to reduce vehicle emissions. Gasoline taxes are often promoted as a means of reducing vehicle emissions. The optimal policy would differentially tax vehicles based on their emissions, not gasoline consumption. While gasoline consumption and emissions are positively correlated, we show that gasoline taxes are a poor substitute for vehicle-specific Pigouvian taxes. The remaining DWL under the optimal gasoline tax exceeds 75 percent in the second half of our sample, and surpasses 70 percent across all years.

Finally, the correlation we document leads to a positive result. We show that this correlation significantly increases the health benefits associated with gasoline taxes. This final

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

result increases the attractiveness of carbon taxes as a means of reducing greenhouse gas emissions, especially considering that existing policies used to reduce greenhouse gasoline emissions from transportation—CAFE standards, ethanol subsidies, and the RFS—fail to take advantage of these local-pollution benefits. In fact, they can even increase criteria pollutant emissions, because they *reduce* the marginal cost of an extra mile traveled. Given that previous work analyzing the relative efficiency of these policies to gasoline or carbon taxes has ignored the heterogeneity that we document, such policies are less efficient than previously thought.

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Figures and Tables

Figures

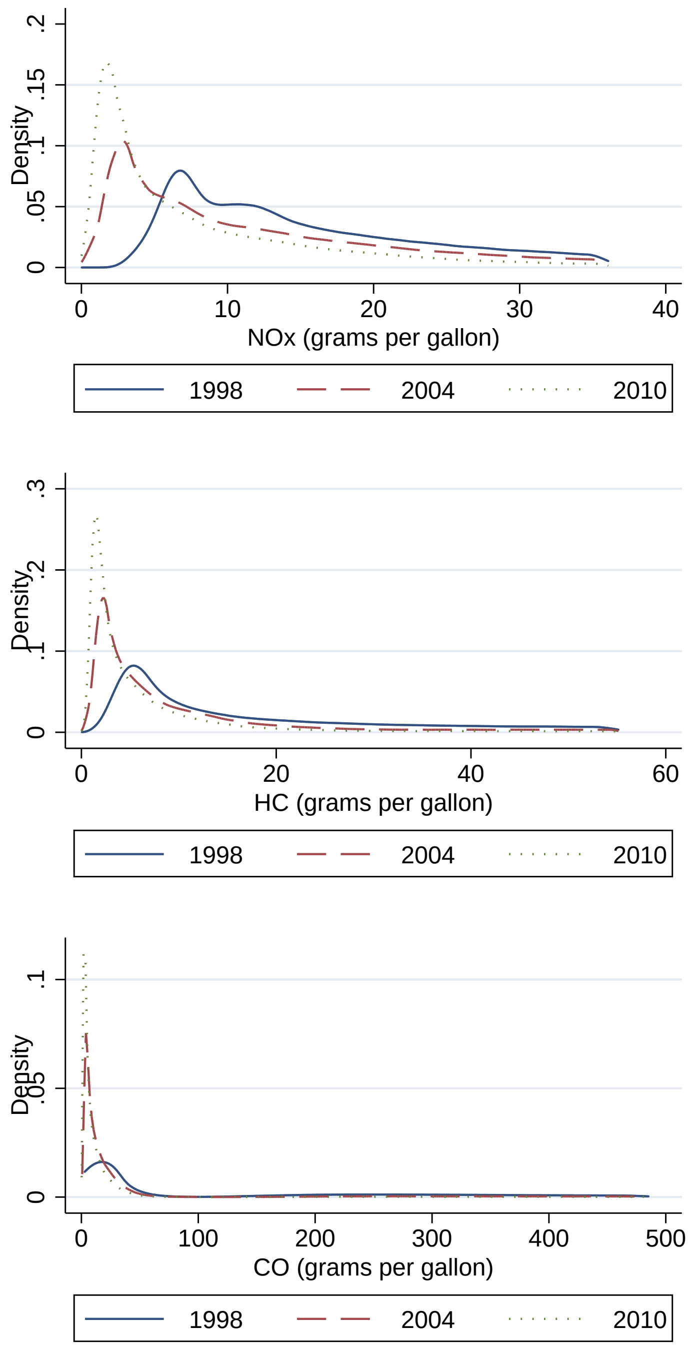

Figure 1: Distribution of three criteria pollutant emissions across all vehicles in 1998, 2004, and 2010 (observations above the 90th percentile are omitted)

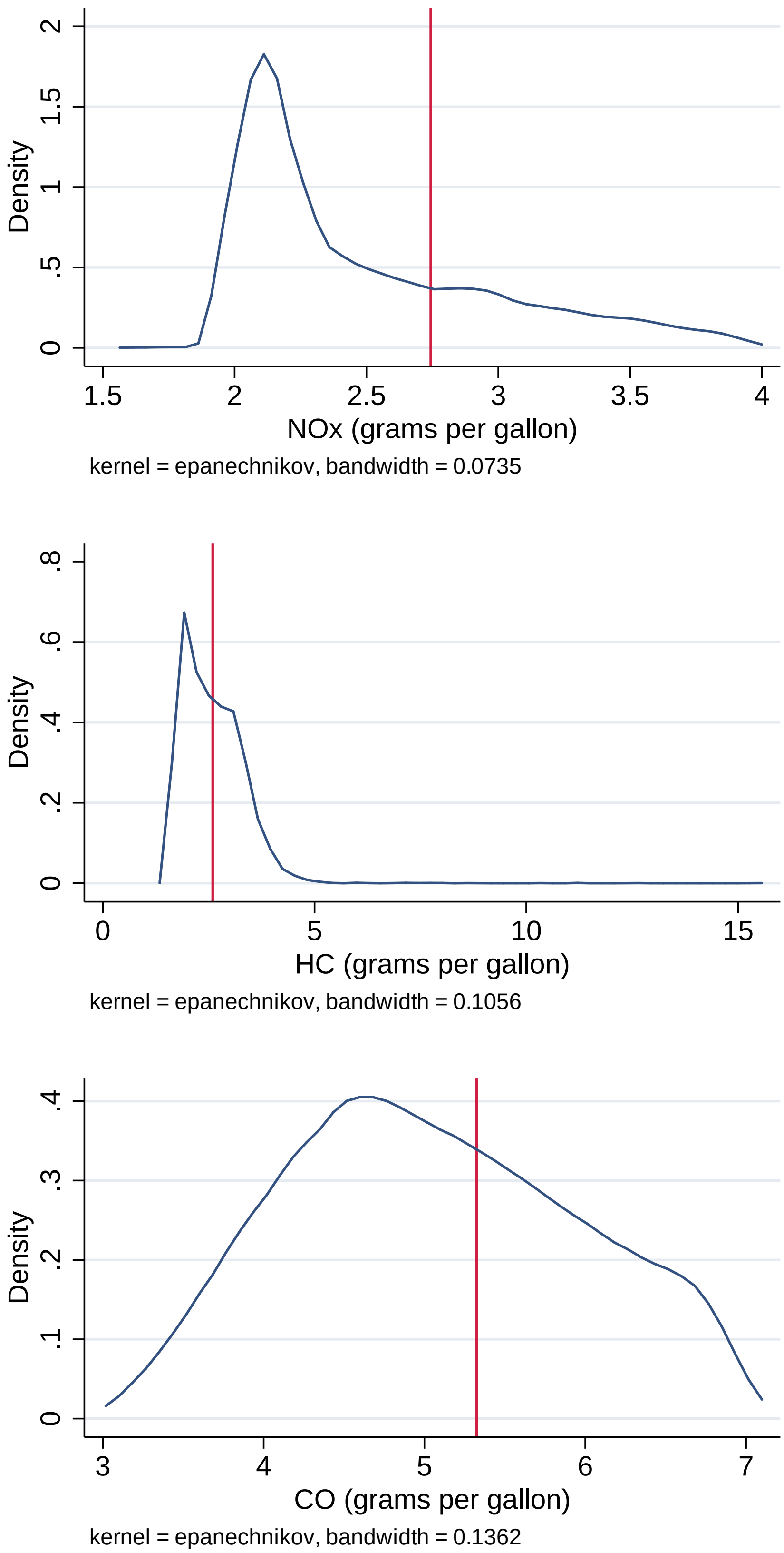

Figure 2: Distribution of three criteria pollutant emissions of a 2001 4-door, 1.8L, Toyota Corolla in 2009 (observations above the 90th percentile are omitted)

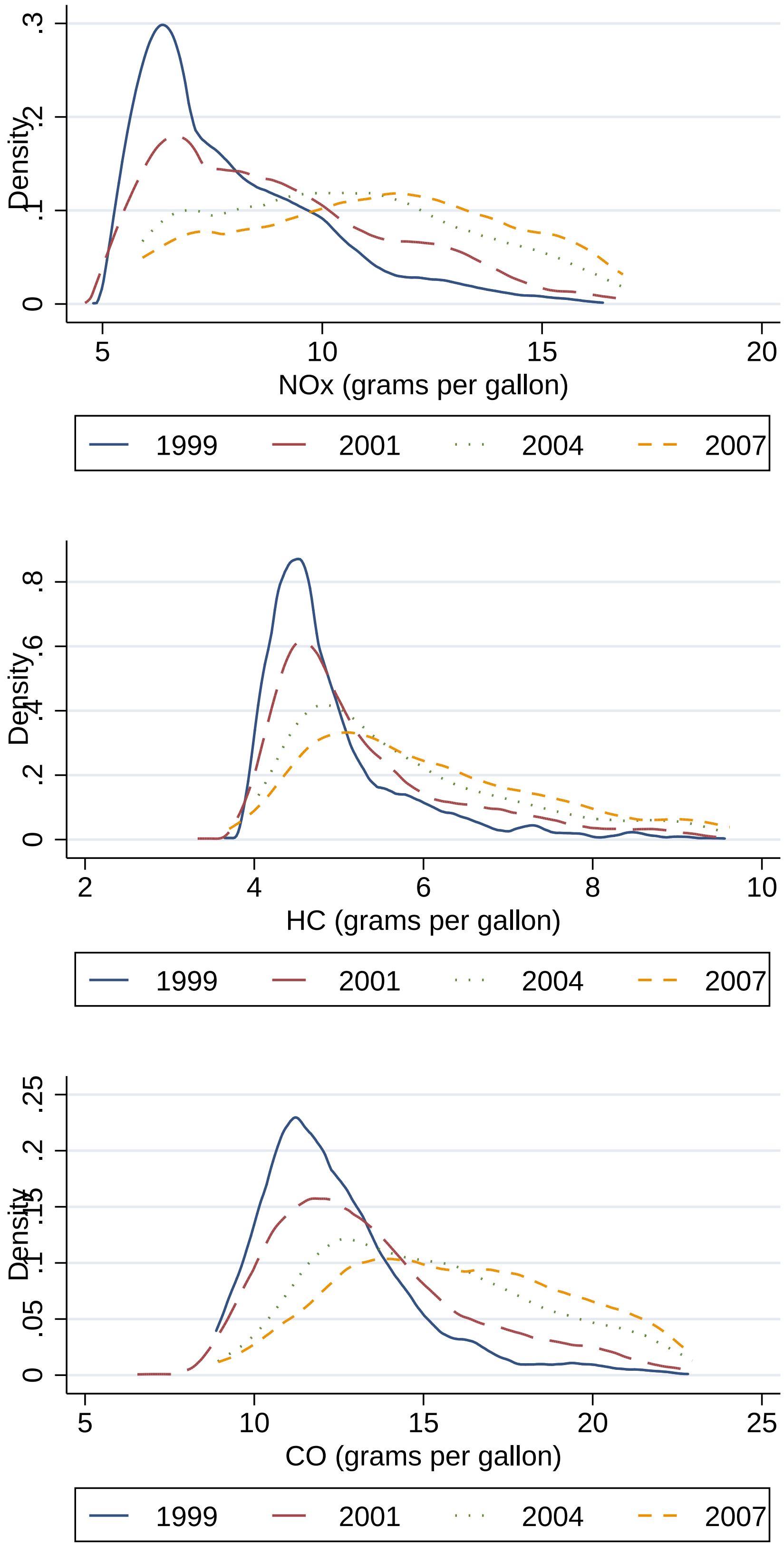

Figure 3: Distribution of three criteria pollutant emissions of a 1995 3.8L, FWD, Ford Windstar in 1999, 2001, 2005, and 2009 (observations above the 90th percentile are omitted)

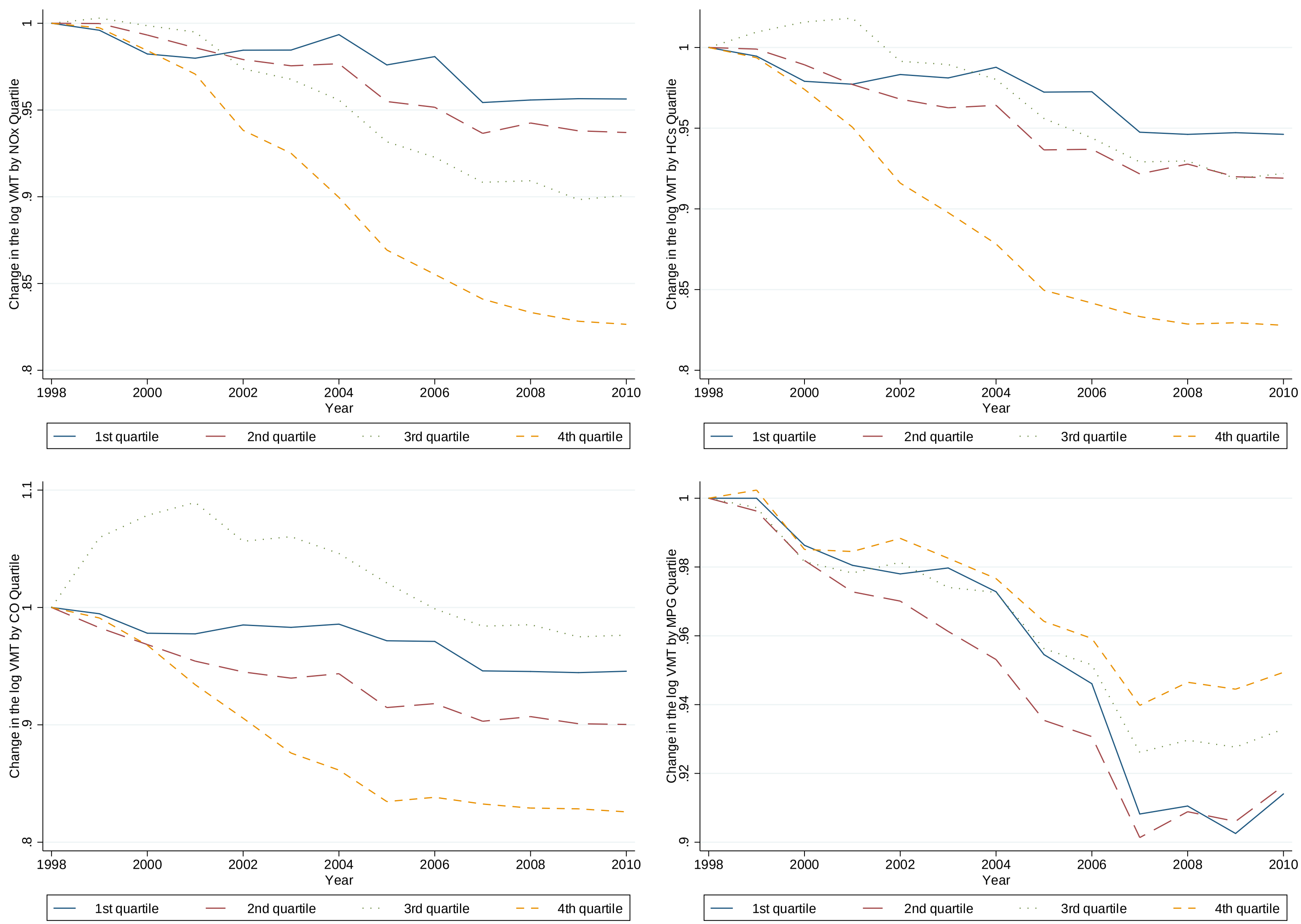

Figure 4: Change in the log of VMT over sample by pollutant quartile

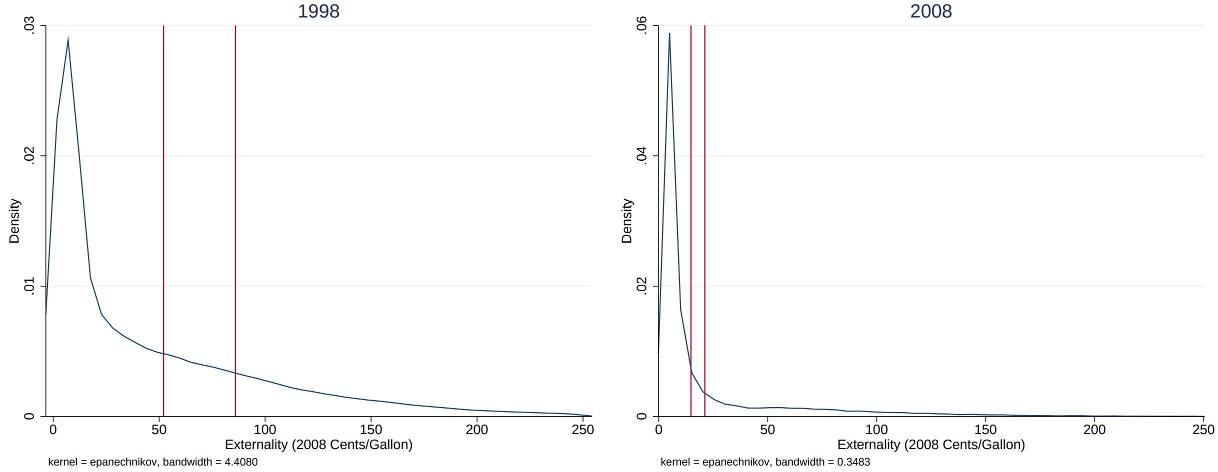

Figure 5: Distribution of externality per gallon—vertical lines indicate naive and marginal uniform tax

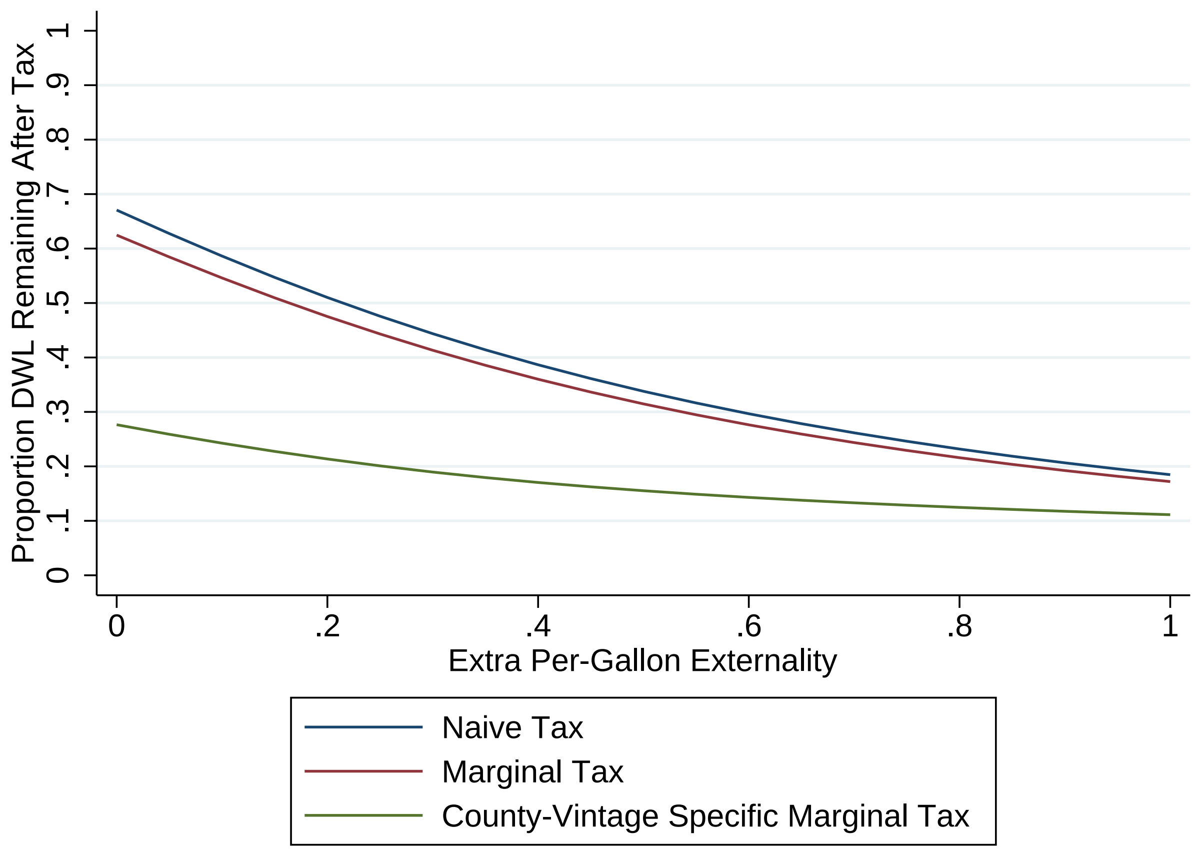

Figure 6: Remaining deadweight loss under alternatives gasoline-specific externalities

Tables

Table 1: Summary Statistics

		Vehicle Age			Year	
	All	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

Note: 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: 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) Model 7
ln(DPM)	-0.265**	-0.117**		-0.177**	-0.147**		-0.044
	(0.045)	(0.038)		(0.027)	(0.025)		(0.032)
ln(DPM) * NO Q1			-0.037**			0.041+	
			(0.011)			(0.023)	
ln(DPM) * NO Q2			-0.086**			-0.062*	
			(0.011)			(0.026)	
ln(DPM) * NO Q3			-0.133**			-0.158**	
			(0.011)			(0.027)	
ln(DPM) * NO Q4			-0.189**			-0.288**	
			(0.012)			(0.030)	
ln(DPM)*NO Centile							-0.001**
							(0.000)
NO Q2			-0.083**			0.378	
			(0.012)			(0.800)	
NO Q3			-0.144**			-1.246	
			(0.016)			(1.012)	
NO Q4			-0.166**			-2.297*	
			(0.020)			(1.116)	
NO Centile							-0.001
							(0.001)
Truck	0.058+	0.062	0.049**	0.006			
	(0.035)	(0.046)	(0.009)	(0.057)			
Time Trend	-0.281**	-0.355**	-0.388**	-0.318**	-0.019	-0.027	-0.046
	(0.040)	(0.029)	(0.026)	(0.023)	(0.041)	(0.070)	(0.053)
Time Trend-Squared	0.002**	0.003**	0.003**	0.002**	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Year Fixed Effects	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	3640433	3640433	2979289	3640433	3640433	2979289	2979289
R-squared	0.216	0.224	0.234	0.149	0.120	0.116	0.117

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

	(1) 4-9	(2) 10-15	(3) 16-27	(4) 4-9	(5) 10-15	(6) 16-27
ln(DPM)	-0.013	-0.126**	-0.119+			
	(0.020)	(0.027)	(0.064)			
ln(DPM) * NO Q1				0.119**	-0.002	0.035
				(0.036)	(0.029)	(0.073)
ln(DPM) * NO Q2				0.026	-0.076**	0.002
				(0.018)	(0.021)	(0.066)
ln(DPM) * NO Q3				-0.029	-0.153**	-0.151*
				(0.019)	(0.034)	(0.073)
ln(DPM) * NO Q4				-0.099**	-0.249**	-0.248**
				(0.025)	(0.031)	(0.065)
NO Q2				-0.113	-1.351*	-2.616
				(0.694)	(0.647)	(2.241)
NO Q3				-0.516	-2.797**	-7.279**
				(0.959)	(0.897)	(1.949)
NO Q4				-3.574**	-4.890**	-7.861**
				(1.230)	(0.817)	(1.842)
Time Trend	0.362**	0.208**	0.016	0.463**	0.108	-0.186
	(0.049)	(0.062)	(0.146)	(0.094)	(0.081)	(0.181)
Time Trend-Squared	-0.003**	-0.002*	-0.001	-0.004**	-0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Year Fixed Effects	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	1548634	1535833	555966	1215676	1269332	494281
R-squared	0.124	0.096	0.091	0.121	0.097	0.091

Table 4: VMT Elasticity for a Sample of Households, 2000-2008

	(1)	(2)	(3)
ln(DPM) * MPG Q1	-0.0881***	-0.0902***	-0.0970***
	(0.0145)	(0.0145)	(0.0149)
ln(DPM) * MPG Q2	-0.0882***	-0.0910***	-0.0976***
	(0.0145)	(0.0145)	(0.0148)
ln(DPM) * MPG Q3	-0.0324*	-0.0385**	-0.0448**
	(0.0145)	(0.0145)	(0.0148)
ln(DPM) * MPG Q4	-0.0263	-0.0339*	-0.0401**
	(0.0148)	(0.0148)	(0.0152)
ln(DPM) * Higher MPG in HH		-0.0290***	-0.0296***
		(0.00402)	(0.00402)
ln(DPM) * Lower MPG in HH		0.0628***	0.0626***
		(0.00418)	(0.00417)
Higher MPG in HH		-0.0739***	-0.0753***
		(0.00932)	(0.00932)
Lower MPG in HH		0.150***	0.149***
		(0.0106)	(0.0106)
ln(DPM) * HH Income Q2			-0.00514
			(0.00455)
ln(DPM) * HH Income Q3			0.00763
			(0.00473)
ln(DPM) * HH Income Q4			0.0224***
			(0.00520)
Year Fixed Effects	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	0.113	0.113	0.113

Standard errors in parentheses

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

Table 5: VMT Elasticity by Income Quartile, 2000-2008

	40% Sample of HHs	HHs, with HH FE	10% Sample of VINs
ln(DPM) * HH Income Q1	-0.0659***	-0.0560***	-0.0524*
	(0.0146)	(0.00560)	(0.0242)
ln(DPM) * HH Income Q2	-0.0706***	-0.0591***	-0.0559*
	(0.0145)	(0.00555)	(0.0241)
ln(DPM) * HH Income Q3	-0.0588***	-0.0451***	-0.0679**
	(0.0144)	(0.00552)	(0.0239)
ln(DPM) * HH Income Q4	-0.0461**	-0.0316***	-0.0527*
	(0.0146)	(0.00553)	(0.0242)
Year Fixed Effects	Yes	Yes	Yes
Vintage Fixed Effects	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Vehicle Fixed Effects	Yes	No	Yes
Observations	7549359	7549359	2489373
R-squared	0.112	0.165	0.107

Standard errors in parentheses

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

Table 6: Average and Marginal Pollution Externality

	Average Externality (¢/gal)	Marginal Externality (¢/gal)
1998	61.20	86.00
1999	54.28	76.58
2000	48.52	70.90
2001	41.12	61.51
2002	33.92	51.10
2003	28.68	43.93
2004	24.23	36.54
2005	21.17	31.59
2006	18.64	27.46
2007	16.19	23.87
2008	14.38	21.12

Dollar figures inflation adjusted to year 2008.

Table 7: Ratios of DWL with Tax to DWL With No Tax

	Statewide Tax		County-Level Taxes		Vintage Tax		County/Vintage Tax	
	Average	Marginal	Average	Marginal	Average	Marginal	Average	Marginal
1998	0.616	0.564	0.570	0.516	0.351	0.346	0.299	0.293
1999	0.631	0.568	0.587	0.519	0.329	0.324	0.266	0.262
2000	0.638	0.582	0.590	0.530	0.328	0.326	0.261	0.258
2001	0.698	0.633	0.657	0.587	0.365	0.362	0.297	0.295
2002	0.700	0.671	0.652	0.621	0.349	0.346	0.284	0.282
2003	0.719	0.698	0.665	0.643	0.321	0.319	0.251	0.250
2004	0.763	0.752	0.719	0.707	0.359	0.358	0.293	0.292
2005	0.769	0.762	0.726	0.717	0.329	0.328	0.260	0.259
2006	0.819	0.811	0.782	0.774	0.397	0.397	0.335	0.334
2007	0.814	0.810	0.776	0.772	0.313	0.312	0.243	0.243
2008	0.837	0.831	0.801	0.794	0.320	0.320	0.249	0.247
Average	0.728	0.698	0.684	0.653	0.342	0.340	0.276	0.274

Notes: DWL with no tax calculated based on the difference in emissions from imposing a tax equal to the actual externality per gallon consumed by a particular car. Marginal tax computed as the weighted average of externality per gallon, using the negative slope of the vehicle's demand curve as the weight.

Table 8: Proportion of Vehicles for which a Uniform Tax Overshoots the Optimal Tax

	Mean
Fleet Average	0.724
Fleet Marginal	0.794
County Average	0.714
County Marginal	0.784
Vintage Average	0.706
Vintage Marginal	0.726
County/Vintage Average	0.671
County/Vintage Marginal	0.706
N	3605189

mean coefficients

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

Table 9: Ratios of DWL with Tax to DWL With No Tax, Scrapping Most Polluting Vehicles

	Percentile Scrapped					
	None	1%	2%	5%	10%	25%
1998	0.564	0.466	0.441	0.415	0.405	0.415
1999	0.568	0.474	0.458	0.442	0.437	0.444
2000	0.582	0.493	0.478	0.462	0.459	0.460
2001	0.633	0.528	0.511	0.495	0.491	0.437
2002	0.671	0.585	0.573	0.560	0.556	0.496
2003	0.698	0.629	0.619	0.608	0.604	0.472
2004	0.752	0.675	0.666	0.654	0.645	0.439
2005	0.762	0.699	0.689	0.672	0.648	0.371
2006	0.811	0.731	0.720	0.700	0.658	0.344
2007	0.810	0.759	0.748	0.725	0.658	0.355
2008	0.831	0.780	0.768	0.737	0.612	0.349
Average	0.698	0.620	0.606	0.588	0.561	0.417

Notes: DWL with no tax calculated based on the difference in emissions from imposing a tax equal to the actual externality per gallon consumed by a particular car. Marginal tax computed as the weighted average of externality per gallon, using the negative slope of the vehicle's demand curve as the weight.

Table 10: Ratios of DWL with Tax to DWL With No Tax

	Statewide Tax		County-Level Taxes		Vintage Tax		County/Vintage Tax	
	Average	Marginal	Average	Marginal	Average	Marginal	Average	Marginal
1998	0.571	0.434	0.536	0.397	0.318	0.295	0.280	0.254
1999	0.590	0.426	0.558	0.390	0.301	0.279	0.256	0.235
2000	0.591	0.433	0.556	0.397	0.299	0.281	0.250	0.235
2001	0.648	0.472	0.619	0.440	0.329	0.312	0.280	0.266
2002	0.619	0.490	0.586	0.459	0.324	0.310	0.281	0.268
2003	0.625	0.503	0.589	0.469	0.314	0.303	0.268	0.259
2004	0.647	0.544	0.619	0.516	0.351	0.341	0.309	0.301
2005	0.644	0.548	0.617	0.522	0.347	0.336	0.306	0.296
2006	0.692	0.595	0.669	0.573	0.397	0.390	0.360	0.353
2007	0.674	0.585	0.653	0.564	0.368	0.362	0.329	0.325
2008	0.701	0.605	0.682	0.586	0.388	0.383	0.349	0.345
Average	0.636	0.512	0.608	0.483	0.340	0.327	0.297	0.285

Notes: DWL with no tax calculated based on the difference in emissions from imposing a tax equal to the actual externality per gallon consumed by a particular car. Marginal tax computed as the weighted average of externality per gallon, using the negative slope of the vehicle's demand curve as the weight.

Table 11: Cobenefits of a Gasoline Tax, No Heterogeneity, Muller and Mendelsohn (2009) Baseline Values

	Δ Consumption	Δ CO2	DWL		Criteria Benefit						**Net Cost**
	(Gallons)	(Tons)	($)	(Per CO2)	(NOx $)	(HC $)	(CO $)	(Total $)	(% DWL)	(Per CO2)	(Per CO2)
1998	470.6	4.518	323.1	71.53	-0.676	115.7	134.2	247.8	77.51	55.44	16.09
1999	478.1	4.589	318.9	69.49	-0.138	105.2	117.7	222.1	70.11	48.72	20.77
2000	450.1	4.321	289.4	66.98	-0.0765	89.26	94.95	183.8	63.85	42.77	24.22
2001	389.8	3.742	241.1	64.44	0.136	64.63	67.78	132.4	55.16	35.55	28.89
2002	380.8	3.655	230.0	62.92	0.299	50.05	50.32	100.5	43.86	27.60	35.32
2003	386.3	3.708	228.0	61.50	0.461	41.59	40.25	82.18	36.18	22.25	39.25
2004	372.4	3.575	214.2	59.92	0.634	31.48	31.46	63.45	29.76	17.83	42.09
2005	321.7	3.088	178.5	57.79	0.532	21.86	21.92	44.22	24.89	14.39	43.41
2006	249.1	2.391	133.0	55.62	0.395	16.41	16.57	33.29	25.18	14.01	41.62
2007	261.8	2.513	135.3	53.85	0.385	13.00	13.22	26.55	19.73	10.63	43.22
2008	219.3	2.105	109.7	52.08	0.257	10.57	10.90	21.66	19.87	10.35	41.73
Average	361.8	3.473	218.3	61.47	0.201	50.88	54.48	105.3	42.37	27.23	34.24

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) Baseline 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 $3638.62 per ton per year, and NOx at $125.26 per ton per year. CO is valued at $802.88, as per the median value of Matthews and Lave (2000).

Table 12: Cobenefits of a Gasoline Tax, Taking Heterogeneity into Account, Muller and Mendelsohn (2009) Baseline Values

	Δ Consumption	Δ CO2	DWL		Criteria Benefit						**Net Cost**
	(Gallons)	(Tons)	($)	(Per CO2)	(NOx $)	(HC $)	(CO $)	(Total $)	(% DWL)	(Per CO2)	(Per CO2)
1998	272.1	2.612	186.8	71.53	-0.540	105.6	130.3	234.0	126.6	90.58	-19.05
1999	265.2	2.546	176.9	69.49	-0.134	92.45	111.7	203.4	115.8	80.44	-10.95
2000	252.8	2.426	162.5	66.98	-0.128	83.42	97.79	180.7	111.8	74.86	-7.874
2001	225.5	2.164	139.5	64.44	0.116	65.15	77.23	142.3	102.5	66.02	-1.581
2002	210.1	2.017	126.9	62.92	0.228	51.73	59.82	111.6	88.18	55.48	7.436
2003	206.3	1.980	121.8	61.50	0.343	44.47	50.23	94.87	78.18	48.08	13.42
2004	194.1	1.863	111.6	59.92	0.540	34.60	40.49	75.46	67.85	40.66	19.26
2005	153.9	1.477	85.37	57.79	0.454	24.72	29.08	54.13	63.69	36.81	20.98
2006	131.7	1.264	70.32	55.62	0.370	20.10	23.89	44.23	63.27	35.19	20.43
2007	118.7	1.140	61.37	53.85	0.312	16.96	20.46	37.63	61.70	33.22	20.63
2008	110.2	1.058	55.12	52.08	0.266	14.88	18.05	33.08	60.35	31.43	20.65
Average	194.6	1.868	118.0	61.47	0.166	50.37	59.91	110.1	85.44	53.89	7.577

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) Baseline 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 $3638.62 per ton per year, and NOx at $125.26 per ton per year. CO is valued at $802.88, as per the median value of Matthews and Lave (2000).

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A Proofs of Propositions

Proposition 1. *The second-best tax is (from Diamond (1973)):*

$$\tau^* = \frac{-\sum_h \sum_{i \neq h} \frac{\partial U^h}{\partial \alpha_i} \alpha'_i}{\sum_h \alpha'_h}. \tag{13}$$

Proof. Consumers have quasi-linear utility functions, given as:

$$\max_{\alpha_h} \quad U^h(\alpha_1, \alpha_2, ..., \alpha_h, ..., \alpha_n) + \mu_h, \tag{14}$$

$$s.t. \quad (p + \tau)\alpha_h + \mu_h = m_h. \tag{15}$$

Where p is the price and τ the tax per gallon. Assuming an interior solution, we have:

$$\frac{\partial U^h}{\partial \alpha_h} = (p + \tau). \tag{16}$$

This yields demand curves, given by:

$$\alpha^*_h = \alpha_h (p + \tau). \tag{17}$$

The optimal uniform Pigouvian tax maximizes social welfare, or the sum of utilities:

$$W(\tau) = \sum_h U^h[\alpha^*_1, ..., \alpha^*_h, ...\alpha^*_n] - p \sum_h \alpha^*_h + \sum_h m_h. \tag{18}$$

The first-order condition for the optimal uniform Pigouvian tax is given as:

$$W'(\tau) = \sum_h \sum_i \frac{\partial U^h}{\partial \alpha_i} \alpha'_i - p \sum_h \alpha'_h = 0. \tag{19}$$

Rewriting this and plugging in the result from the consumers' problem, $\frac{\partial U^h}{\partial \alpha_h} - p = \tau$, we have:

$$W'(\tau) = \sum_h \sum_{i \neq h} \frac{\partial U^h}{\partial \alpha_i} \alpha'_i + \tau \sum_h \alpha'_h = 0. \tag{20}$$

Solving for the second-best tax yields:

$$\tau^* = \frac{-\sum_h \sum_{i \neq h} \frac{\partial U^h}{\partial \alpha_i} \alpha'_i}{\sum_h \alpha'_h}. \tag{21}$$

□

Proposition 2. *Suppose the drivers are homogenous in their demand for miles driven, but vehicles differ in terms of emissions. In particular, each consumer has a demand for miles drive given as:*

$$m = \beta_0 - \beta_1 dpm(p_g + \tau). \tag{22}$$

If the distribution of the externality per mile, E, is log normal, with probability density function of:

$$\varphi(E_i) = \frac{1}{E_i\sqrt{2\sigma_E^2}} \exp\left(\frac{-(E_i - \mu_E)^2}{2\sigma_E^2}\right), \tag{23}$$

the deadweight loss absent any market intervention will be given as:

$$D = \frac{1}{2\beta_1} e^{2\mu_E + 2\sigma_E^2}.$$

Proof. Given these assumptions, the deadweight loss absent any market intervention will be given as:

$$\begin{aligned} D &= \int_0^\infty \frac{(E_i)^2}{2\beta_1}\varphi(E_i)dE_i \\ &= \frac{1}{2\beta_1}\mathbb{E}[E_i^2] \\ &= \frac{1}{2\beta_1}e^{2\mu_E + 2\sigma_E^2}. \end{aligned} \tag{24}$$

□

Proposition 3. *Under the assumptions in Proposition 2, the ratio of the remaining DWL with the deadweight loss after the tax is:*

$$R = \frac{D - \frac{e^{2\mu_E + \sigma_E^2}}{2\beta_1}}{D} = 1 - \frac{e^{2\mu_E + \sigma_E^2}}{e^{2\mu_E + 2\sigma_E^2}} = 1 - e^{-\sigma_E^2}. \tag{25}$$

Proof. The level of the externality is given as:

$$\overline{E} = \tau = e^{\mu_E + \sigma_E^2/2}. \tag{26}$$

The deadweight loss associated with all vehicles is given as:

$$
\begin{aligned}
D(\tau) &= \int_0^\infty \frac{(\tau - E_i)^2}{2\beta_1}\varphi(E_i)dE_i \\
&= \frac{1}{2\beta_1}\mathbb{E}[\tau^2 - 2\tau E_i + E_i^2] \\
&= \frac{1}{2\beta_1}(\tau^2 - 2\tau\mathbb{E}[E_i] + \mathbb{E}[E_i^2]) \\
&= \frac{1}{2\beta_1}(\tau^2 - 2\tau e^{\mu_E+\frac{\sigma_E^2}{2}} + e^{2\mu_E+2\sigma_E^2}) \\
&= \frac{1}{2\beta_1}(\tau^2 - 2\tau e^{\mu_E+\frac{\sigma_E^2}{2}}) + D \\
&= D - \frac{e^{2\mu_E+\sigma_E^2}}{2\beta_1}.
\end{aligned} \tag{27}
$$

The ratio of remaining DWL with the deadweight loss absent the tax is therefore:

$$
R = \frac{D - \frac{e^{2\mu_E+\sigma_E^2}}{2\beta_1}}{D} = 1 - \frac{e^{2\mu_E+\sigma_E^2}}{e^{2\mu_E+2\sigma_E^2}} = 1 - e^{-\sigma_E^2}. \tag{28}
$$

□

Proposition 4. *When $B_i = \frac{1}{\beta_i}$ and E_i are distributed lognormal with dependence parameter ρ, the optimal tax is:*

$$
\tau^* = e^{\mu_E+\frac{\sigma_E^2}{2}+\rho\sigma_E\sigma_B}
$$

Proof. The slope of the demand curve with respect to the cost of driving, defined as $B_i = \frac{1}{\beta_i}$, is distributed lognormal with parameters μ_B and σ_B^2. ρ is the dependence parameter of the bivariate lognormal distribution (the correlation coefficient of $\ln E$ and $\ln B$). The optimal tax is:

$$
\begin{aligned}
\tau^* &= \frac{\sum E_i\beta_i}{\sum \beta_i} \\
&= \frac{\frac{1}{N}\sum E_i\beta_i}{\frac{1}{N}\sum \beta_i} \\
&= \frac{\mathbb{E}[E_i\beta_i]}{\mathbb{E}[\frac{1}{B_i}]} \\
&= \frac{e^{\mu_E+\frac{\sigma_E^2}{2}-\mu_B+\frac{\sigma_B^2}{2}}e^{\rho\sigma_E\sigma_B}}{e^{-\mu_B+\frac{\sigma_B^2}{2}}} \\
&= e^{\mu_E+\frac{\sigma_E^2}{2}+\rho\sigma_E\sigma_B}.
\end{aligned} \tag{29}
$$

□

Proposition 5. *When $B_i = \frac{1}{\beta_i}$ and E_i are distributed lognormal with dependence parameter*

ρ, the ratios of the remaining deadweight loss after the optimal uniform Pigouvian tax to the original deadweight loss will be:

$$R(\tau^*) = 1 - e^{-\sigma_E^2}, \tag{30}$$

and, the ratios of the remaining deadweight loss after the naive uniform tax to the original deadweight loss will be:

$$R(\tau_{naive}) = 1 - e^{-\sigma_E^2}(2e^{-\rho\sigma_E\sigma_B} - e^{-2\rho\sigma_E\sigma_B}). \tag{31}$$

Proof. The deadweight loss with no gasoline tax is:

$$\begin{aligned}
\mathcal{D} &= \int_0^\infty \left(\int_0^\infty \frac{(E_i)^2 B_i}{2} \varphi(E_i) dE_i \right) \varphi_B(B_i) dB_i \\
&= \frac{1}{2}\mathbb{E}[E_i^2 B_i] \\
&= \frac{1}{2} e^{2\mu_E + 2\sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + 2\rho\sigma_E\sigma_B}.
\end{aligned} \tag{32}$$

The deadweight loss with the optimal uniform tax is:

$$\begin{aligned}
\mathcal{D}(\tau^*) &= \int_0^\infty \left(\int_0^\infty \frac{(\tau - E_i)^2 B_i}{2} \varphi(E_i) dE_i \right) \varphi_B(B_i) dB_i \\
&= \frac{1}{2}\mathbb{E}[\tau^2 B_i - 2\tau E_i B_i + E_i^2 B_i] \\
&= \frac{1}{2}(\tau^2 \mathbb{E}[B_i] - 2\tau\mathbb{E}[E_i B_i] + \mathbb{E}[E_i^2 B_i]) \\
&= \frac{1}{2}(\tau^2 e^{\mu_B + \frac{\sigma_B^2}{2}} - 2\tau e^{\mu_E + \frac{\sigma_E^2}{2} + \mu_B + \frac{\sigma_B^2}{2} + \rho\sigma_E\sigma_B} + e^{2\mu_E + 2\sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + 2\rho\sigma_E\sigma_B}) \\
&= \frac{1}{2} e^{2\mu_E + \sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + 2\rho\sigma_E\sigma_B} - e^{2\mu_E + \sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + 2\rho\sigma_E\sigma_B} + \mathcal{D} \\
&= \mathcal{D} - \frac{1}{2} e^{2\mu_E + \sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + 2\rho\sigma_E\sigma_B},
\end{aligned} \tag{33}$$

while the deadweight loss with the naive tax, equal to the average externality level is:

$$\mathcal{D}(\tau_{naive}) = \mathcal{D} - \frac{1}{2}(2e^{2\mu_E + \sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + \rho\sigma_E\sigma_B} - e^{2\mu_E + \sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2}}). \tag{34}$$

Then the ratios of the remaining deadweight loss after a tax to the original deadweight loss will be:

$$\begin{aligned}
R(\tau^*) &= 1 - \frac{e^{2\mu_E + \sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + 2\rho\sigma_E\sigma_B}}{e^{2\mu_E + 2\sigma_E^2 + \mu_B + \frac{\sigma_B^2}{2} + 2\rho\sigma_E\sigma_B}} \\
&= 1 - e^{-\sigma_E^2},
\end{aligned} \tag{35}$$

$$
\begin{aligned}
R(\tau_{naive}) &= 1 - \frac{2e^{2\mu_E+\sigma_E^2+\mu_B+\frac{\sigma_B^2}{2}\rho\sigma_E\sigma_B} - e^{2\mu+\sigma_E^2+\mu_B+\frac{\sigma_B^2}{2}}}{e^{2\mu_E+2\sigma_E^2+\mu_B+\frac{\sigma_B^2}{2}+2\rho\sigma_E\sigma_B}} \\
&= 1 - e^{-\sigma_E^2}(2e^{-\rho\sigma_E\sigma_B} - e^{-2\rho\sigma_E\sigma_B}). \qquad (36)
\end{aligned}
$$

□

B Robustness Checks

In this appendix, we report the results of several robustness checks to our main results on the intensive margin. Table A.2 reports elasticities by quartile for all five categories of externality.

Our base specification controls for the fixed effect of a each NO_x quartile on miles traveled. One might be concerned, however, that variation in dollars per mile (DPM) might be correlated with other characteristics such as age, odometer, and demographics, and that the DPM-quartile interactions may be picking up this correlation, rather than true heterogeneity. To test for this, in Table A.5 we present results with vehicle fixed effects and interactions between NOx quartiles and various control variables. Adding these interaction terms actually makes the heterogeneity in the effect of DPM more pronounced.

Table A.6 repeats the same exercise, but uses levels rather than logs of DPM as the variable of interest. The results are qualitatively similar, with substantial heterogeneity in every specification. However, with a log-linear specification we do not observe the cleanest vehicles having a positive coefficient.

We also 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 (8) with separate elasticities for vehicles falling in the zero to first percentile, first to second, etc. Appendix Figure A.2 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 10 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.

Note that the roughly linear relationship between criteria pollutant emissions and the elasticity is not due to "over smoothing." Appendix Figure A.3 plots the LOWESS smoothed lines for HCs 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.

C Steps to Clean Smog Check Data

C.1 Smog Check Data

California implemented its first inspection and maintenance program (the Smog Check Program) in 1984 in response to the 1977 Clean Air Act Amendments. 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, California's legislature passed 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.[26] Today, more than a million smog checks take place each month.

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 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

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

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.[27] Vehicles that match a "High Emitter Profile" are also directed to Test-Only stations, as are vehicles that are flagged as "gross polluters" (those that fail an inspection with twice the legal limit of one or more pollutant in emissions). More recently some "Partial-Enhanced" areas that require a biennial ASM test have been added, but no vehicles are directed to Test-Only stations.

Areas with poor air quality not exceeding 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 are not directed to Test-Only stations. The least restrictive regime, consisting of rural mountain and desert counties in the east and north, 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.

Our data from the Smog Check Program essentially comprise the universe of test records from January 1, 1996 to December 31, 2010. We were able to obtain test records only 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 percent sample of VINs, selecting by the second to last digit of the VIN. We exclude tests that have no odometer reading, with a test result of "Tampered" or "Aborted" and vehicles that 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.[28]

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

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

[28] 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.

First, we adjust odometer readings for "roll overs" and typos. Many of the vehicles in our analysis were manufactured with 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 than 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 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 NO_x) 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 traveled. These equations are reported in Morrow and Runkle (2005) and are reproduced below. The equations are for HCs, NO_x, 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

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

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:

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

D Steps to Clean DMV Data

We deal with two issues associated with DMV data. The main issue is that DMV entries for the same addresses will often 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 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.

E Details of the Gasoline Tax Policy Simulation

For the intensive margin, we estimate a regression as in column 6 of Tables 2 and A.2, 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 Table 3, 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 G, we compress our dataset to have at most one observation per vehicle per year. Each vehicle is then assigned an elasticity based on its quartiles and age bin. Vehicle i's VMT in the counterfactual with an additional \$1 tax on gasoline is calculated by:

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

where VMT^i_{BAU} is vehicle i's actual average VMT per day between its current and previous smog check, P_i is the average gasoline price over that time, and β_i is the elasticity for the fuel economy/weight/HC/NO/CO/age cell to which i belongs.

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 its 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, that 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:[29]

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

where MPG_k is the average fuel economy of vehicle of prefix k and γ_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, 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." Because 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 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 that we have not estimated in this paper: new car purchases. To ensure that the total vehicle population is accurate, we apply an *ad hoc* correction based on Busse et al. (forthcoming), who find that a \$1 increase in gasoline prices would decrease new car sales by 650,000 per year. Because California's vehicle fleet makes up about 13 percent of the national total, we decrease the population of model years 1998 and later by 84,500 when constructing the population weight for the counterfactual. We

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

apply 40 percent of the decrease to trucks, and 60 percent 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:

$$Emission^{pt}_{BAU} = \sum_i P_{tac} \cdot VMT^i_{BAU} \cdot r_i(p) \cdot 365,$$

and under the counterfactual they are:

$$Emission^{pt}_{counterfactual} = \sum_i (P_{tac} - 1(\text{model year} >= 1998) \cdot n_c) \cdot H_{qkt} \cdot VMT^i_{counterfactual} \cdot r_i(p) \cdot 365,$$

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.

F California versus the Rest of the United States

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 local-pollution 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 led the rest of the U.S. 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 A.12 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.[30] Figure A.6 plots the kernel density estimates of the distributions.

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

We present the sum of because counties are typically either "NO_x constrained" or "VOC (HC) constrained," and the sum is perhaps more 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 A.12 also presents points on the per-mile emissions, and Figure A.7 plots the distributions.[31] 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 A.12 and Figure A.8 illustrates these. As expected, the HC damages are higher, but the average county-level per-mile externality from the sum of the three pollutants is 30 percent lower in California than 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.

G Scrappage Decisions

Our next set of empirical models examines how vehicle owners' decisions to scrap their vehicles due to 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 record reported to CARFAX and the date when CARFAX produced our

[31] We note that these exceed 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 because this pre-dates many of the emission standards within the U.S.

data extract (October 1, 2010). However, we treat a vehicle as being censored if the last record reported to CARFAX was not in California, or if more than a year and a half passed between the last smog check in our data and that last 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 that are at least 10 years old.

Some modifications to our data are necessary. To focus on the long-term 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, because 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 six 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 i, of vehicle type j, vintage v, and geography g, is scrapped. Assuming proportional hazards, our basic model is:

$$\Pr[t < T_{ijvg} < t+1 | T > t] = h^0_{jv}(t) \cdot \exp\{\beta x DPM_{igt} + \gamma D_{fail_{it}} + \psi G_{igt} + \alpha X_{it}\},$$

where DPM_{igt} is defined as before; $D_{fail_{it}}$ 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 sixth-order polynomial in odometer; and $h^0_{ijv}(t)$ 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 it 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 A.3 and A.4 show the results of our hazard analysis. Models 1 and 2 of Table A.3 assign all vehicles to the same baseline hazard function. Model 1 allows the effect of gasoline prices to vary by whether or not a vehicle failed a smog check. Model 2 also allows the effect of gasoline prices to vary by quartiles of NO_x.[32] Models 3 and 4 are similar, but stratify the baseline hazard function, allowing each VIN prefix to have its own baseline hazard function. 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.

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, but is still statistically significant. However, the true heterogeneity in the 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 five cents, the hazard of scrappage decreases by about 23 percent for vehicles between 10 and 15 years old, while it increases by around 3 percent 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.

Table A.4 presents the quartile by age by DPM interactions for each of the 5 externality dimensions. Hydrocarbons and CO have the identical pattern to NO_x, with no heterogeneity within age-group. With fuel economy and vehicle weight, there is within-age heterogeneity, although the form is counter-intuitive. The heaviest and least fuel-efficient vehicles are relatively less likely thank the lightest and most fuel-efficient vehicles to be scrapped when gasoline prices increase. That is, while all 10- to 15-year-old vehicles are less likely to be scrapped, the decrease in hazard rate is larger for heavy, gas-guzzling vehicles. For vehicles 16 years and older, the heaviest quartile is less likely to be scrapped when gasoline prices

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

increase, even though the lightest (and middle quartiles) are more likely. As the model stratifies by VIN prefix, this cannot be simply that more durable vehicles have lower fuel economy.

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.

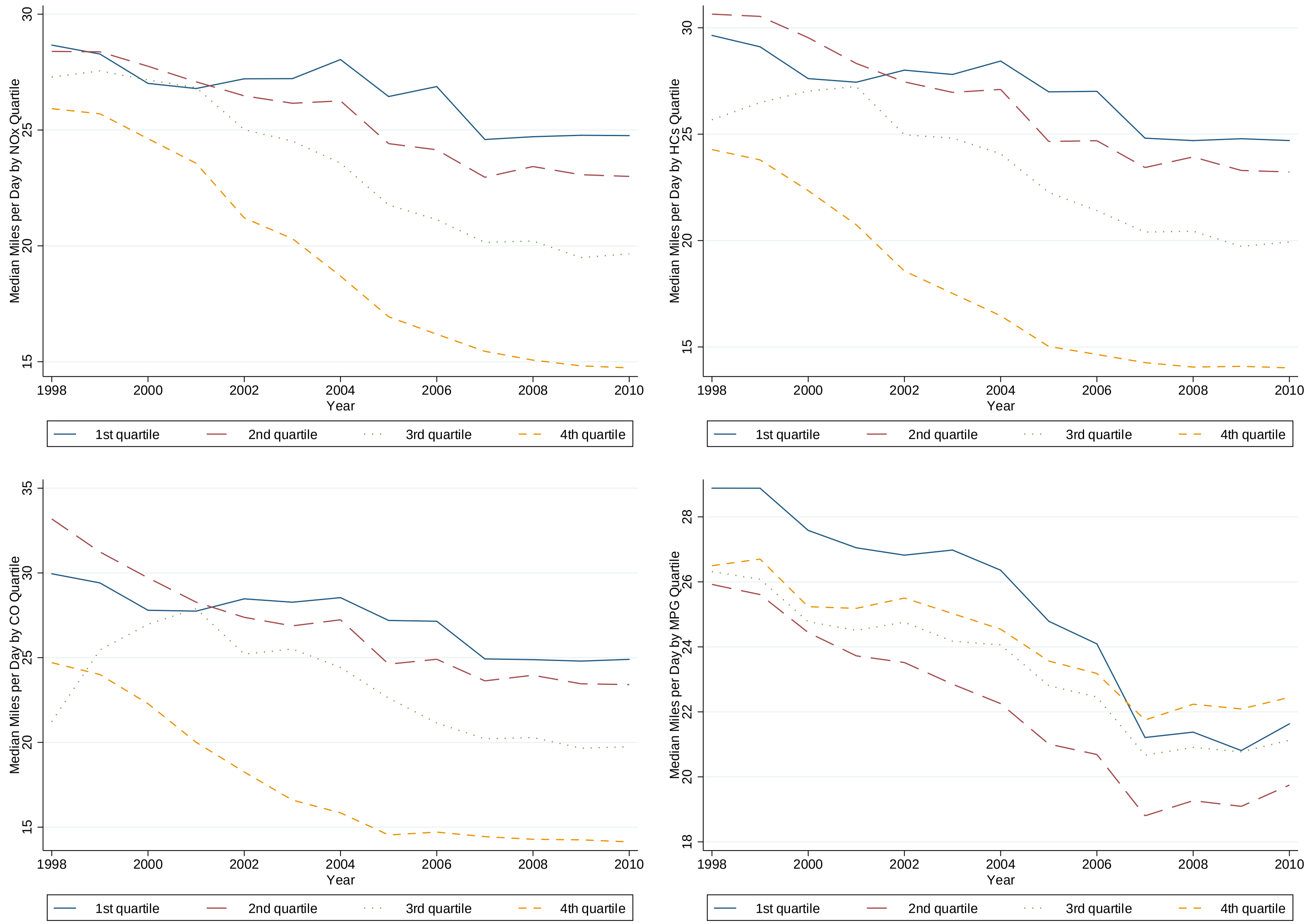


Figure A.1: Change in VMT over sample by pollutant quartile

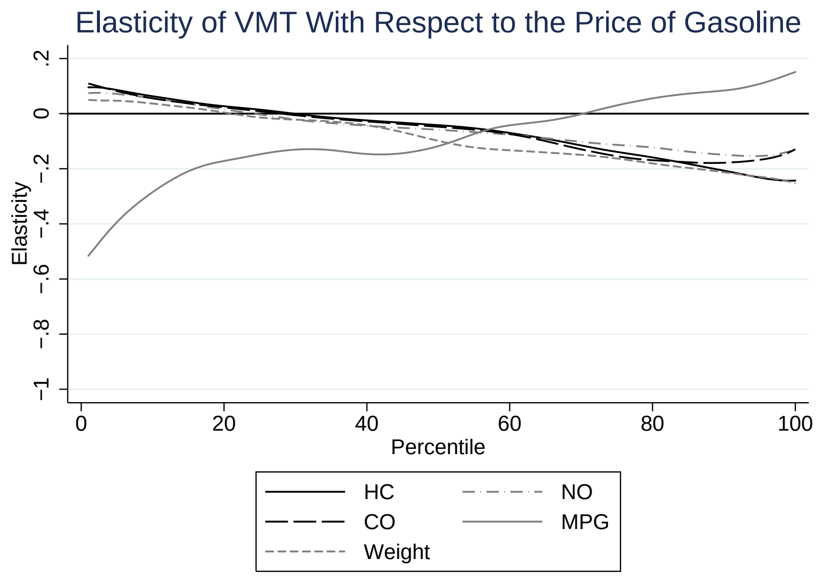


Figure A.2: Non-parametric relationships between elasticity and externality

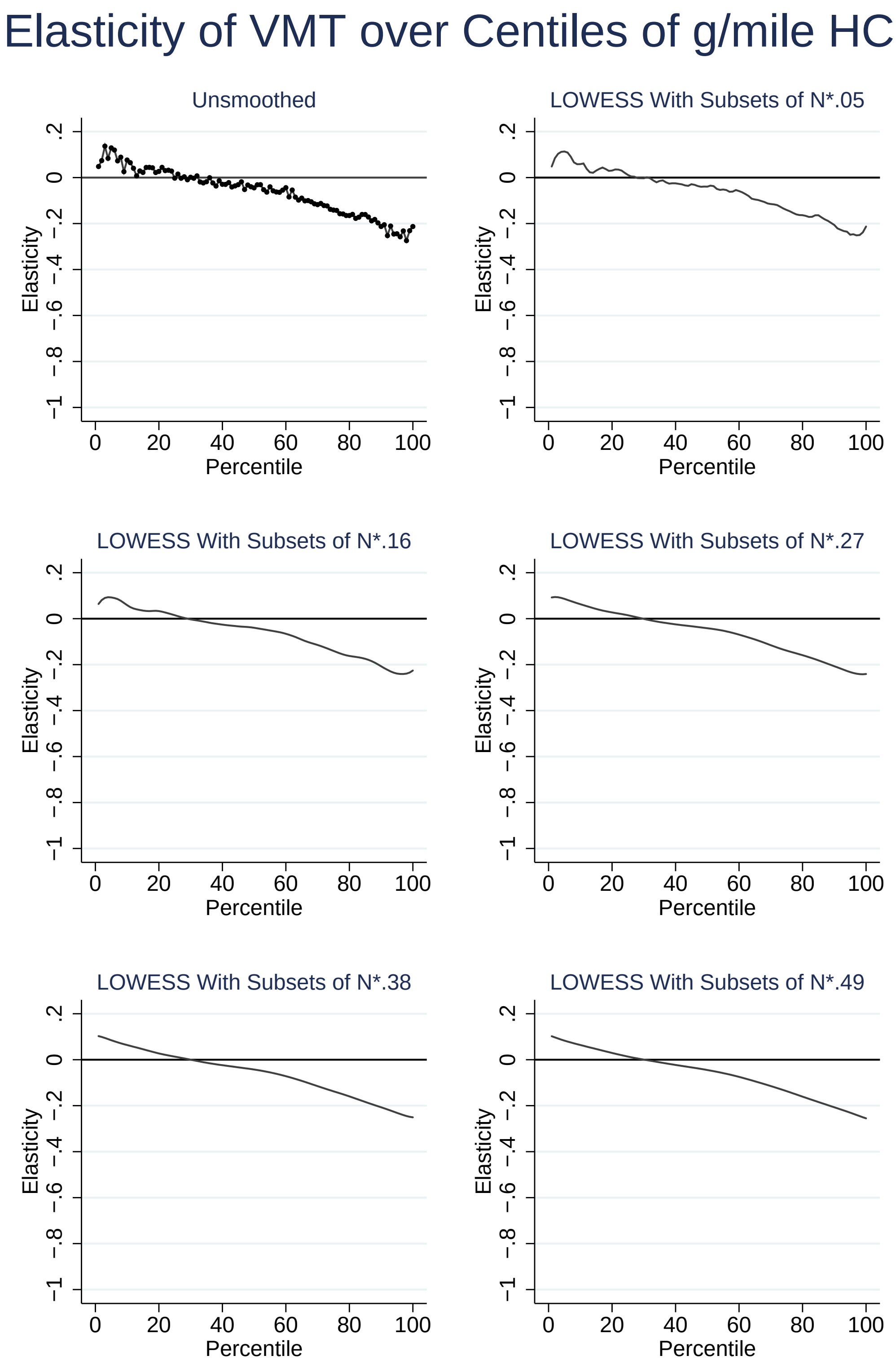
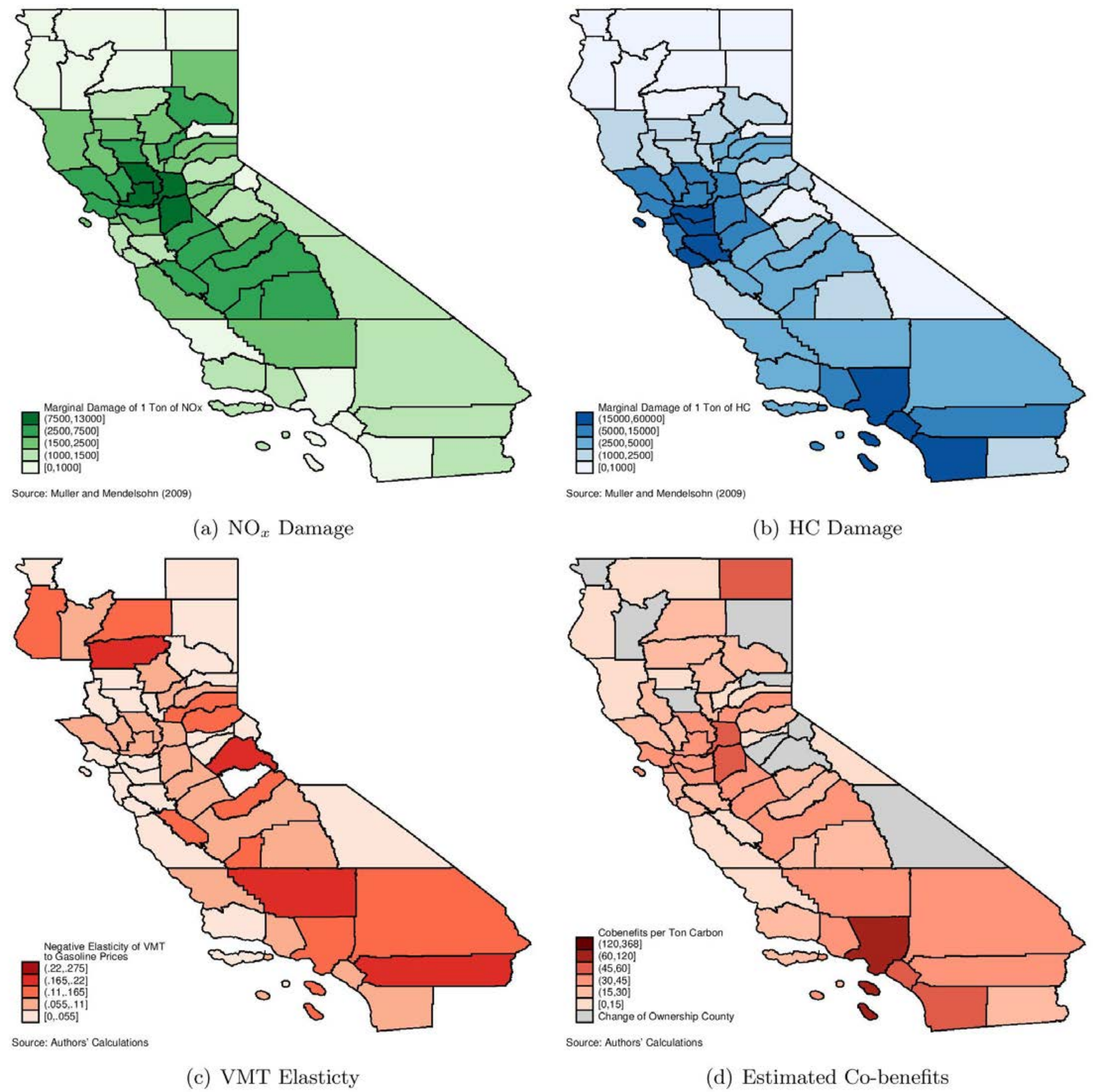


Figure A.3: The effect of bandwidth on the non-parametric function



(a) NO_x Damage

(b) HC Damage

(c) VMT Elasticty

(d) Estimated Co-benefits

Figure A.4: Social damages of pollution, VMT elasticity, and local-pollution benefits of a gasoline tax, by county

Figure A.5: Estimated county-level local-pollution benefits versus the log of county population

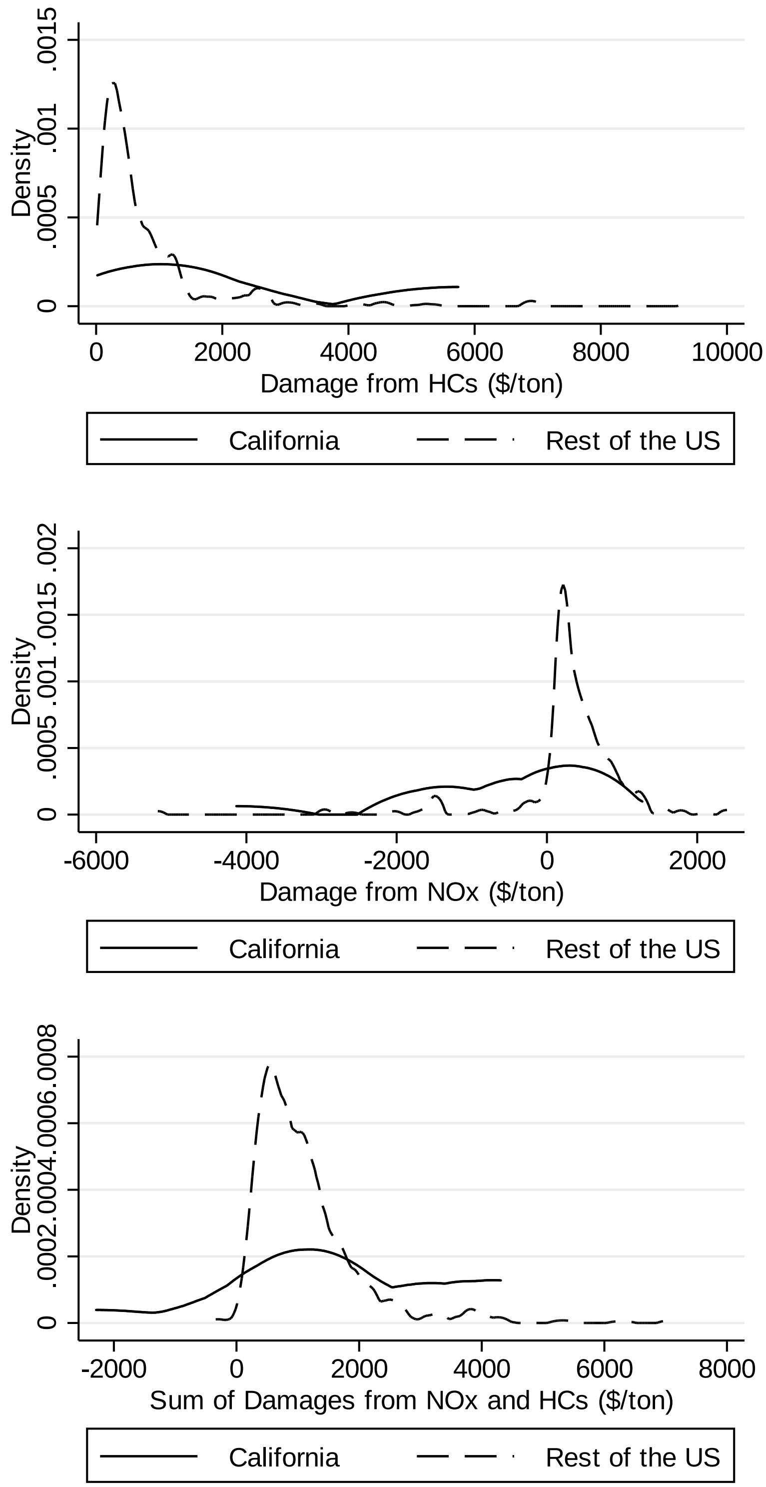


Figure A.6: Distributions of marginal damages from Muller and Mendelsohn (2009) for California and the rest of the U.S.

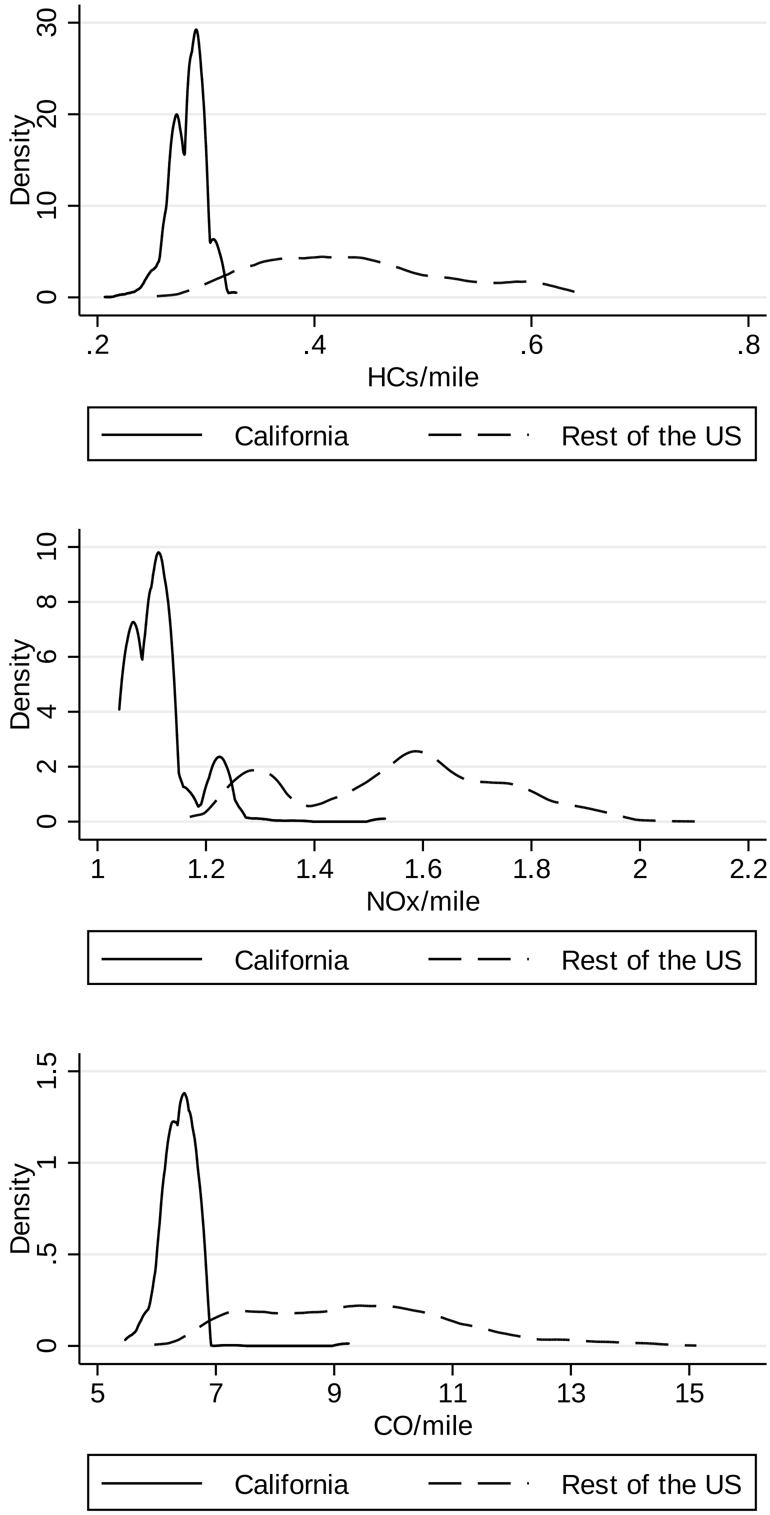


Figure A.7: Distributions of per-mile emissions for California and the rest of the U.S.

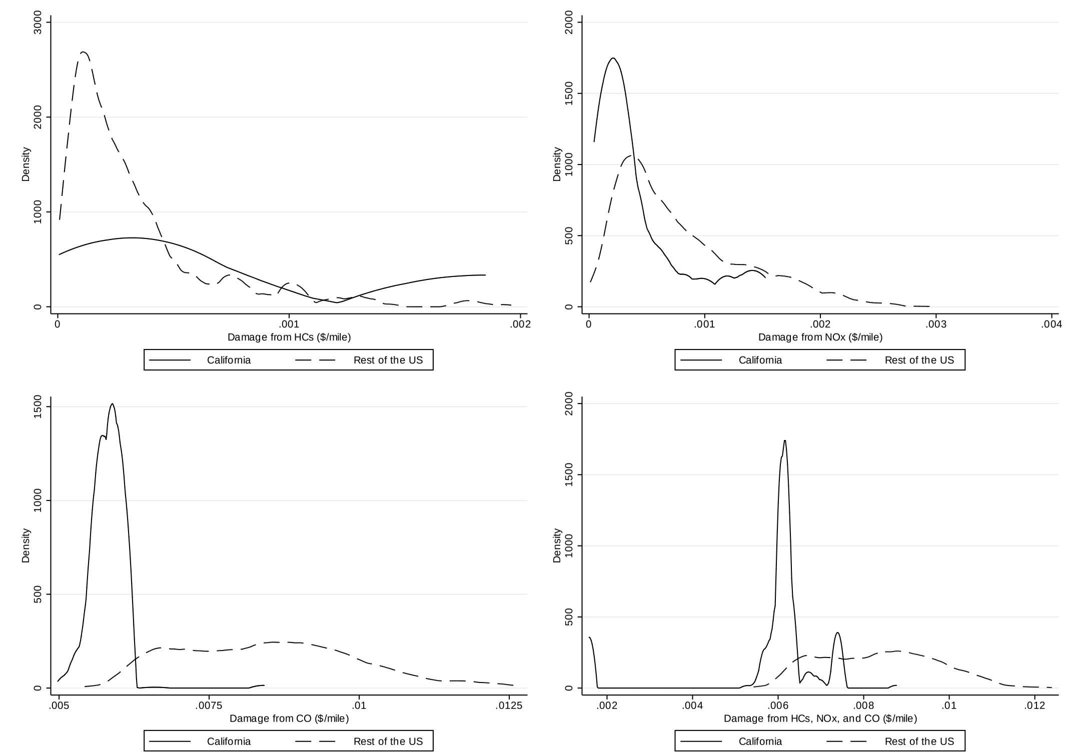


Figure A.8: Distributions of per-mile damages for California and the rest of the US

Table A.1: 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 A.2: Vehicle Miles Traveled, Dollars Per Mile, and Externality Quartiles

Quartile	Nitrogen Oxides	Hydrocarbons	Carbon Monoxide	Fuel Economy	Vehicle Weight
1	0.0406	0.0505	0.0442	-0.183	-0.124
2	-0.0617	-0.0645	-0.0625	-0.173	-0.129
3	-0.158	-0.154	-0.156	-0.119	-0.158
4	-0.288	-0.315	-0.317	-0.108	-0.179

Table A.3: Hazard of Scrappage: Cox Proportional Hazard Model

	Model 1	Model 2	Model 3	Model 4	Model 5
Dollars per Mile	0.917*		0.926**		
	(0.040)		(0.024)		
DPM * Failed Smog Check	1.109**	1.080**	1.085**	1.068**	
	(0.029)	(0.025)	(0.021)	(0.020)	
Failed Last Smog Check	7.293**	7.686**	8.282**	8.819**	
	(0.234)	(0.241)	(0.187)	(0.199)	
DPM * NO Quartile 1		0.792**		0.867**	
		(0.046)		(0.040)	
DPM * NO Quartile 2		0.859**		0.891**	
		(0.039)		(0.031)	
DPM * NO Quartile 3		0.874**		0.916**	
		(0.034)		(0.021)	
DPM * NO Quartile 4		0.927*		0.940**	
		(0.032)		(0.015)	
Vehicle Ages 10-15					
DPM * NO Quartile 1					0.774**
					(0.070)
DPM * NO Quartile 2					0.761**
					(0.067)
DPM * NO Quartile 3					0.770**
					(0.063)
DPM * NO Quartile 4					0.745**
					(0.058)
Failed Smog Check					7.156**
					(0.558)
DPM * Failed Smog Check					1.143**
					(0.050)
Vehicle Ages 16+					
DPM * NO Quartile 1					1.037+
					(0.023)
DPM * NO Quartile 2					1.028
					(0.025)
DPM * NO Quartile 3					1.034
					(0.030)
DPM * NO Quartile 4					1.034
					(0.035)
Failed Smog Check					10.150**
					(0.487)
DPM * Failed Smog Check					1.022
					(0.019)
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	3170553	2682641	3170553	2682641	2682641

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

Table A.4: Effect of a 5-cent/mile Increase in Driving Cost on the Hazard of Scrappage

	Nitrogen Oxides	Hydrocarbons	Carbon Monoxide	Fuel Economy	Vehicle Weight
Vehicle Ages 10-15					
Quartile 1	0.774	0.781	0.775	0.714	0.905
Quartile 2	0.761	0.764	0.776	0.724	0.771
Quartile 3	0.770	0.770	0.765	0.835	0.757
Quartile 4	0.745	0.746	0.741	0.909	0.697
Vehicle Ages 16+					
Quartile 1	1.037	1.031	1.027	0.957	1.280
Quartile 2	1.028	1.024	1.038	1.060	1.054
Quartile 3	1.034	1.045	1.025	1.130	1.014
Quartile 4	1.034	1.050	1.048	1.104	0.906

Statistics are exponentiated coeficients of a Cox proportional hazards model. Interpret as hazard ratios.

Table A.5: Robustness Check—Intensive Margin Interacting NOx Quartiles With Other Controls

	(1)	(2)	(3)	(4)	(5)	(6)
ln(DPM) * NO Q1	0.0406	0.0381	0.0678*	0.0605	0.0590	0.0666
	(0.0231)	(0.0250)	(0.0339)	(0.0335)	(0.0333)	(0.121)
ln(DPM) * NO Q2	-0.0617*	-0.0581*	-0.0453	-0.0478	-0.0484	-0.0410
	(0.0261)	(0.0269)	(0.0309)	(0.0310)	(0.0308)	(0.121)
ln(DPM) * NO Q3	-0.158***	-0.155***	-0.166***	-0.165***	-0.165***	-0.157
	(0.0271)	(0.0272)	(0.0282)	(0.0291)	(0.0294)	(0.120)
ln(DPM) * NO Q4	-0.288***	-0.298***	-0.355***	-0.353***	-0.351***	-0.344**
	(0.0300)	(0.0302)	(0.0325)	(0.0332)	(0.0331)	(0.120)
NO Q2	0.378	0.327	-2.622	-3.925*	-3.954*	-4.916**
	(0.800)	(0.735)	(1.622)	(1.693)	(1.673)	(1.732)
NO Q3	-1.246	-1.447	-5.233***	-6.846***	-6.793***	-7.987***
	(1.012)	(0.899)	(1.447)	(1.524)	(1.508)	(1.566)
NO Q4	-2.297*	-2.951**	-9.696***	-11.39***	-11.26***	-12.60***
	(1.116)	(1.084)	(2.257)	(2.253)	(2.271)	(2.301)
Quartile-Time Trend Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Vintage-Quartile Interactions	No	Yes	Yes	Yes	Yes	Yes
Quartile-Year Interactions	No	No	Yes	Yes	Yes	Yes
Quartile-Lagged Odometer Interactions	No	No	No	Yes	Yes	Yes
Quartile-Demographics Interactions	No	No	No	No	Yes	Yes
Calendar Month Fixed-Effects	No	No	No	No	No	Yes
N	2979289	2979289	2979289	2979289	2979289	2979289

Note: All regressions include vehicle fixed-effects, year fixed effects, vintage/truck fixed effects, a quadratic time trend, a sixth order polynomial in the odometer reading at previous Smog Check, and ZIP code level demographic characteristics.

Table A.6: Robustness Check—Intensive Margin Interacting NOx Quartiles With Other Controls

	(1)	(2)	(3)	(4)	(5)	(6)
DPM * NO Q1	-2.676***	-2.807***	-2.294***	-2.412***	-2.421***	-5.089***
	(0.359)	(0.350)	(0.301)	(0.347)	(0.345)	(0.696)
DPM * NO Q2	-3.337***	-3.358***	-3.075***	-3.128***	-3.129***	-5.339***
	(0.359)	(0.357)	(0.334)	(0.355)	(0.354)	(0.631)
DPM * NO Q3	-3.925***	-3.941***	-3.858***	-3.881***	-3.875***	-5.728***
	(0.389)	(0.391)	(0.397)	(0.395)	(0.394)	(0.631)
DPM * NO Q4	-4.642***	-4.720***	-4.970***	-4.974***	-4.957***	-6.482***
	(0.425)	(0.433)	(0.444)	(0.440)	(0.442)	(0.653)
NO Q2	0.958	0.821	-5.997***	-7.404***	-7.433***	-4.917**
	(0.674)	(0.613)	(1.330)	(1.391)	(1.384)	(1.567)
NO Q3	0.242	-0.00702	-8.999***	-10.74***	-10.69***	-6.708***
	(0.889)	(0.798)	(1.563)	(1.619)	(1.605)	(1.527)
NO Q4	0.615	0.124	-12.63***	-14.43***	-14.34***	-9.222***
	(1.015)	(0.999)	(2.173)	(2.181)	(2.205)	(2.227)
Quartile-Time Trend Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Vintage-Quartile Interactions	No	Yes	Yes	Yes	Yes	Yes
Quartile-Year Interactions	No	No	Yes	Yes	Yes	Yes
Quartile-Lagged Odometer Interactions	No	No	No	Yes	Yes	Yes
Quartile-Demographics Interactions	No	No	No	No	Yes	Yes
Calendar Month Fixed-Effects	No	No	No	No	No	Yes
N	2979289	2979289	2979289	2979289	2979289	2979289

Note: All regressions include vehicle fixed-effects, year fixed effects, vintage/truck fixed effects, a quadratic time trend, a sixth order polynomial in the odometer reading at previous Smog Check, and ZIP code level demographic characteristics.

Table A.7: Ratio of Remaining Deadweight Loss With Tax to Deadweight Loss with No Tax: Calibration

	σ^2	σ_B^2	ρ	$R(\tau_{naive})$	$R(\tau^*)$
1998	1.407	1.465	0.322	0.789	0.755
1999	1.408	1.471	0.299	0.785	0.755
2000	1.438	1.486	0.308	0.794	0.763
2001	1.457	1.496	0.311	0.799	0.767
2002	1.492	1.506	0.283	0.802	0.775
2003	1.517	1.535	0.283	0.807	0.781
2004	1.525	1.531	0.265	0.806	0.782
2005	1.474	1.539	0.265	0.796	0.771
2006	1.482	1.539	0.251	0.795	0.773
2007	1.487	1.547	0.247	0.796	0.774
2008	1.498	1.533	0.252	0.799	0.777
Average	1.471	1.513	0.281	0.797	0.770

Table A.8: Ratios of DWL with Tax to DWL With No Tax, Scrapping Most Polluting Vehicles

	Percentile Scrapped					
	None	1%	2%	5%	10%	25%
1998	0.434	0.338	0.316	0.293	0.286	0.323
1999	0.426	0.338	0.323	0.308	0.307	0.374
2000	0.433	0.350	0.336	0.323	0.323	0.405
2001	0.472	0.373	0.358	0.347	0.358	0.514
2002	0.490	0.407	0.396	0.388	0.398	0.546
2003	0.503	0.433	0.424	0.419	0.436	0.624
2004	0.544	0.464	0.456	0.455	0.485	0.686
2005	0.548	0.485	0.479	0.482	0.520	0.708
2006	0.595	0.511	0.506	0.518	0.577	0.757
2007	0.585	0.534	0.532	0.552	0.625	0.779
2008	0.605	0.556	0.558	0.590	0.681	0.806
Average	0.512	0.435	0.426	0.425	0.454	0.593

Notes: DWL with no tax calculated based on the difference in emissions from imposing a tax equal to the actual externality per gallon consumed by a particular car. Marginal tax computed as the weighted average of externality per gallon, using the negative slope of the vehicle's demand curve as the weight.

Table A.9: Cobenefits of a Gasoline Tax, Taking Heterogeneity into Account (No Extensive Margin Effect), Muller and Mendelsohn (2009) Baseline Values

	Δ Consumption	Δ CO2	DWL		Criteria Benefit						**Net Cost**
	(Gallons)	(Tons)	($)	(Per CO2)	(NOx $)	(HC $)	(CO $)	(Total $)	(% DWL)	(Per CO2)	(Per CO2)
1998	272.1	2.612	186.8	71.53	-0.540	105.6	130.3	234.0	126.6	90.58	-19.05
1999	267.0	2.564	178.1	69.49	-0.129	92.91	112.3	204.5	115.5	80.29	-10.80
2000	259.3	2.489	166.7	66.98	-0.121	84.70	99.62	183.8	110.8	74.22	-7.237
2001	233.6	2.243	144.5	64.44	0.135	65.65	78.15	143.7	99.86	64.35	0.0904
2002	218.9	2.101	132.2	62.92	0.256	51.74	60.05	111.8	84.86	53.39	9.525
2003	213.3	2.047	125.9	61.50	0.383	43.79	49.69	93.69	74.67	45.92	15.58
2004	195.3	1.875	112.3	59.92	0.577	32.79	38.13	71.36	63.76	38.21	21.71
2005	153.1	1.470	84.95	57.79	0.466	22.32	25.16	47.83	56.56	32.69	25.10
2006	131.1	1.258	69.98	55.62	0.375	17.02	18.69	35.98	51.71	28.76	26.86
2007	113.5	1.090	58.68	53.85	0.311	13.23	14.40	27.86	47.77	25.73	28.13
2008	106.9	1.027	53.47	52.08	0.267	10.88	11.50	22.58	42.46	22.11	29.97
Average	196.7	1.889	119.4	61.47	0.180	49.15	58.00	107.0	79.51	50.57	10.90

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) Baseline 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 $3638.62 per ton per year, and NOx at $125.26 per ton per year. CO is valued at $802.88, as per the median value of Matthews and Lave (2000).

Table A.10: Cobenefits of a Gasoline Tax, No Heterogeneity, Muller and Mendelsohn (2009) USEPA Values

	Δ Consumption	Δ CO2	DWL		Criteria Benefit						**Net Cost**
	(Gallons)	(Tons)	(\$)	(Per CO2)	(NOx \$)	(HC \$)	(CO \$)	(Total \$)	(% DWL)	(Per CO2)	(Per CO2)
1998	470.6	4.518	323.1	71.53	26.46	760.5	134.2	919.7	287.7	205.8	-134.2
1999	478.1	4.589	318.9	69.49	28.24	691.1	117.7	836.4	264.0	183.5	-114.0
2000	450.1	4.321	289.4	66.98	23.44	586.4	94.95	704.5	244.7	163.9	-96.93
2001	389.8	3.742	241.1	64.44	18.34	424.6	67.78	510.5	212.8	137.1	-72.67
2002	380.8	3.655	230.0	62.92	16.14	328.7	50.32	395.0	172.4	108.5	-45.54
2003	386.3	3.708	228.0	61.50	14.75	273.1	40.25	328.0	144.4	88.79	-27.29
2004	372.4	3.575	214.2	59.92	13.40	206.8	31.46	251.5	118.0	70.68	-10.76
2005	321.7	3.088	178.5	57.79	10.18	143.6	21.92	175.6	98.86	57.13	0.663
2006	249.1	2.391	133.0	55.62	7.582	107.8	16.57	131.8	99.73	55.47	0.152
2007	261.8	2.513	135.3	53.85	6.480	85.41	13.22	105.1	78.09	42.05	11.80
2008	219.3	2.105	109.7	52.08	4.804	69.41	10.90	85.05	78.03	40.64	11.44
Average	361.8	3.473	218.3	61.47	15.44	334.3	54.48	403.9	163.5	104.9	-43.39

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 \$23897.10 per ton per year, and NOx at \$1995.43 per ton per year. CO is valued at \$802.88, as per the median value of Matthews and Lave (2000).

Table A.11: Cobenefits of a Gasoline Tax, Taking Heterogeneity into Account, Muller and Mendelsohn (2009) USEPA Values

	Δ Consumption	Δ CO2	DWL		Criteria Benefit						**Net Cost**
	(Gallons)	(Tons)	($)	(Per CO2)	(NOx $)	(HC $)	(CO $)	(Total $)	(% DWL)	(Per CO2)	(Per CO2)
1998	272.1	2.612	186.8	71.53	21.49	694.1	130.3	844.5	457.0	326.9	-255.4
1999	265.2	2.546	176.9	69.49	21.66	607.5	111.7	740.2	421.2	292.7	-223.2
2000	252.8	2.426	162.5	66.98	18.30	547.9	97.79	663.7	410.4	274.9	-207.9
2001	225.5	2.164	139.5	64.44	15.41	427.9	77.23	520.4	374.7	241.4	-177.0
2002	210.1	2.017	126.9	62.92	13.49	339.7	59.82	412.8	326.3	205.3	-142.4
2003	206.3	1.980	121.8	61.50	12.38	292.0	50.23	354.4	292.1	179.6	-118.1
2004	194.1	1.863	111.6	59.92	11.72	227.3	40.49	279.3	251.1	150.5	-90.57
2005	153.9	1.477	85.37	57.79	9.037	162.4	29.08	200.4	235.8	136.3	-78.48
2006	131.7	1.264	70.32	55.62	7.306	132.0	23.89	163.1	233.3	129.8	-74.13
2007	118.7	1.140	61.37	53.85	6.126	111.4	20.46	137.9	226.0	121.7	-67.86
2008	110.2	1.058	55.12	52.08	5.320	97.72	18.05	121.0	220.7	114.9	-62.86
Average	194.6	1.868	118.0	61.47	12.93	330.9	59.91	403.4	313.5	197.6	-136.2

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 $23897.10 per ton per year, and NOx at $1995.43 per ton per year. CO is valued at $802.88, as per the median value of Matthews and Lave (2000).

Table A.12: 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.